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METHODS AND SYSTEMS FOR USING CONSUMER ALIASES AND IDENTIFIERS

ABSTRACT

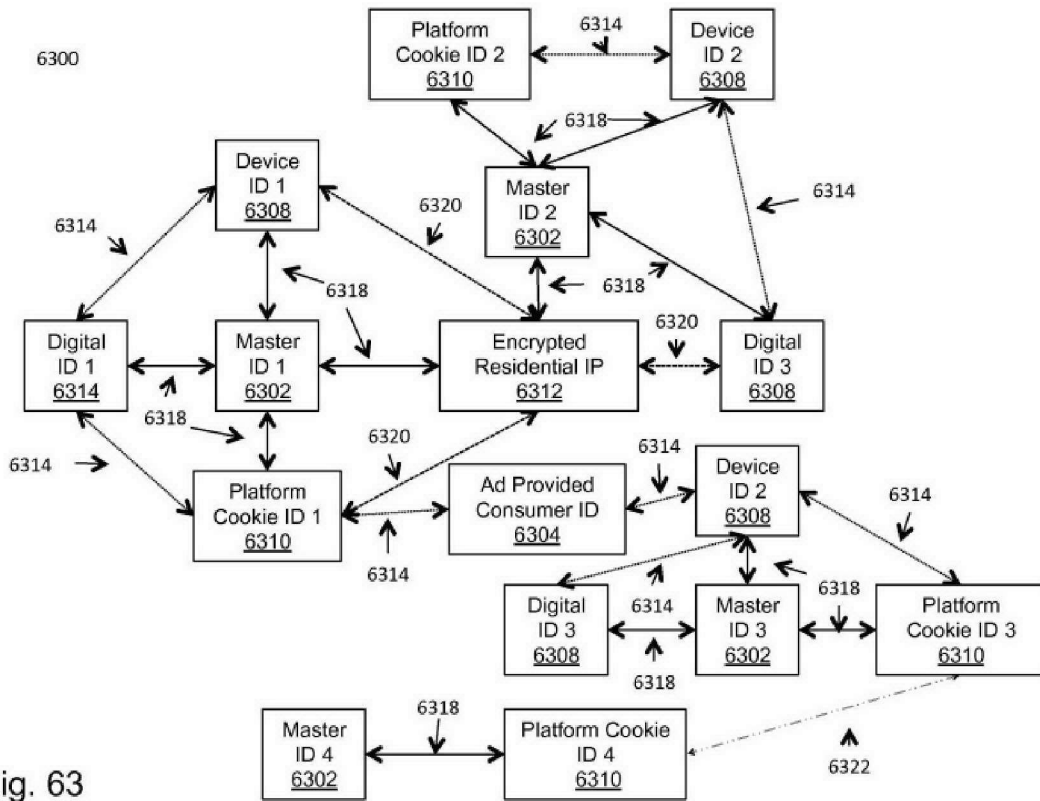


Fig. 63

Systems and methods are disclosed for creating a digital consumer profile that may be dynamically and transiently generated, drawing upon attribute data that is available at time of the digital consumer profile creation. The digital consumer profile may further provide for dynamic and transient generations of a plurality of user profiles to fit definitions and use cases not anticipated at the outset of targeting or attribution efforts and attribute data collection. Regulatory conditions, privacy policies, enterprise rules and the like may determine, at least in part, the collection, analysis, and auditing of attribute data, and the merging of such data to form aliases that may be associated with consumers. The digital consumer service may comprise binding expression syntax to dynamically, and transiently, identify profiles to give flexibility and extensibility beyond having a flat match table.

**METHODS AND SYSTEMS FOR USING CONSUMER
ALIASES AND IDENTIFIERS**

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application is a divisional of Australian Patent Application No. 2014237961, which claims the benefit of United States Provisional Patent Application Ser. No. 61/792,701, filed March 15, 2013, and to United States Patent Application Ser. No. 14/057,188, filed October 18, 2013, both of which are hereby incorporated by reference herein in their entireties.

[0002] United States Patent Application Ser. No. 14/057,188, filed October 18, 2013, is a Continuation-in-Part of the following co-pending United States Non-Provisional Patent Applications, each of which is hereby incorporated by reference herein in its entirety: United States Non-Provisional Patent Application Serial No. 13/537,991, entitled CREATION AND USAGE OF SYNTHETIC USER IDENTIFIERS WITHIN AN ADVERTISEMENT PLACEMENT FACILITY, filed June 29, 2012; United States Non-Provisional Patent Application Ser. No. 12/856,547, entitled DYNAMIC TARGETING ALGORITHMS FOR REAL-TIME VALUATION OF ADVERTISING PLACEMENTS, filed August 13, 2010; United States Non-Provisional Patent Application Ser. No. 12/856,552, entitled MACHINE LEARNING FOR COMPUTING AND TARGETING BIDS FOR THE PLACEMENT OF ADVERTISEMENTS, filed August 13, 2010; United States Non-Provisional Patent Application Ser. No. 12/856,554, entitled USING COMPETITIVE ALGORITHMS FOR THE PREDICTION AND PRICING OF ONLINE ADVERTISEMENT OPPORTUNITIES, filed August 13, 2010; United States Non-Provisional Patent Application Ser. No. 12/856,565, entitled LEARNING SYSTEM FOR THE USE OF COMPETING VALUATION MODELS FOR REAL-TIME ADVERTISEMNT BIDDING, filed August 13, 2010; and United States Non-Provisional Patent Application Ser. No. 12/856,560, entitled LEARNING SYSTEM FOR ADVERTISING BIDDING AND VALUATION of Third Party Data, filed August 13, 2010.

[0003] United States Non-Provisional Patent Application Ser. No. 13/537,991 claims priority to United States Non-Provisional Patent Application Ser. Nos. 12/856,547, 12/856,552, 12/856,554, 12/856,565, and 12/856,560; and to United

States Provisional Patent Application Serial Nos. 61/503,682, filed July 1, 2011, and 61/649,142, filed May 18, 2012.

[0004] United States Non-Provisional Patent Application Ser. Nos. 12/856,547, 12/856,552, 12/856,554, 12/856,565, and 12/856,560 each claim the benefit of United States Provisional Application Ser. No. 61/234,186, entitled REAL-TIME BIDDING SYSTEM FOR DELIVERY OF ADVERTISING, filed August 14, 2009.

[0005] Each of the above applications is incorporated by reference in its entirety.

FIELD OF THE INVENTION

[0006] The invention is related to using historical and real-time data associated with digital media and its use to adjust the pricing and delivery of advertising media among a plurality of available advertising channels.

BACKGROUND

[0007] The ability to measure advertising campaign results is a priority of a majority of advertising systems. Measured advertising campaign results, including results that are categorized by user, user groups, and the like, may be subsequently utilized by advertisers to modify advertising campaigns to maximize the effect of the advertisement messages on intended user and/or user group targets. For example, an advertiser may modify its campaigns by reallocating budgets and prices, from lower performing ones to focus on user groups that have a history of responsiveness to the campaign, similar campaigns, or advertisements that share an attribute(s) with material contained within an advertising campaign. Additionally, a plurality of media channels may be used for communicating the advertising campaign to consumers. For online advertising, it may be possible to measure the effect of advertisements by using consumer identifiers stored in cookies. This enables an advertiser to distinguish individuals, while keeping their identity anonymous. However, there are cases where it is not possible or desirable to distinguish individuals.

[0008] Therefore, there is a need for a method and system for providing an advertising measurement solution for cases where it may not be possible or desirable to identify individuals.

SUMMARY

[0009] The management of presenting advertisements to digital media users is often characterized by a batch mode optimization scheme in which advertising content is selected for presentation to a chosen group of users, performance data is collected and analyzed, and optimization steps are then carried out to better future ad performance. This process is then iteratively run in a sequence of optimization analyses with the intention of improving an ad performance criterion, such as a completed transaction, through more informed ad-user pairings and other techniques. However, this optimization framework is limited in several important respects. For example, given the growth of digital media users brought about by popular innovations such as social networking, there is an over-abundance of data relating to digital media usage that cannot be accommodated and analyzed by the pre-planned, batch mode analytics of much of the current advertising performance modeling conducted in the industry. Furthermore, the batch mode of advertising analytics may force content groupings that do not correspond to the actual, and ever-changing, ad impression sequences that are occurring within a user's behavior, or across a pool of users. As a result, publishers of advertising content may be forced to unnecessarily utilize a number of ad networks to distribute their advertisements based at least in part on the plurality of optimization techniques and criteria used by the different ad networks. This may create redundancies and limit the ability to value the worth of an advertisement's impression and its performance over time within the totality of digital media users.

[0010] In embodiments, the systems and methods disclosed herein may include a computer program product embodied in a non-transitory computer readable medium that, when executing on one or more computers, performs the step of first acquiring a first alias. The first alias may include a first plurality of attributes, wherein each of the first plurality of attributes includes at least one of a first device identifier datum, a first behavioral datum, and a first demographic datum. The program product may then include acquiring a second alias, wherein the second alias includes a second plurality of attributes, wherein each of the second plurality of attributes is comprised of at least one of a second device identifier datum, a second behavioral datum, and a second demographic datum. Furthermore, the program product may dynamically and transiently link the first alias and the second alias to form a Master ID. The dynamic link of the first and second aliases may be based, at least in part, on analysis of the

first and the second pluralities of attributes using a binding expression that expresses a statistical confidence threshold required for grouping aliases. Also, the program product may target advertising to a consumer device based at least in part on the Master ID. The computer program product may perform the alias acquiring and dynamically linking steps iteratively over a plurality of aliases so that a plurality of attributes are merged into a single Master ID. The computer program product may also perform a step of analyzing at least one of an advertising campaign targeted to the Master ID, consumer behavior associated with the Master ID, and consumer traits associated with the Master ID. In embodiments, at least one of the first alias and the second alias is acquired from at least one of a consumer database of an organization and a third party database. Additionally, the first device identifier datum and the second device identifier datum may include at least one of an IP address and a device ID. In embodiments, dynamic linking of aliases is further based at least in part on a rules engine. The rules engine may include rules for the dynamic linking of aliases based at least in part on at least one of a regulatory constraint, a business agreement, a privacy policy, or a consumer preference. Dynamic linking of aliases may prohibit linking aliases based on an identification of an IP address in certain predetermined geographical locations. Furthermore, the dynamic linking of aliases may be performed based on a link type including at least one of self, household, and friend. In embodiments, the first and the second aliases may be linked only for a predetermined time period. In embodiments, aliases may be stored in memory and may include additional time attributes. In embodiments, the computer program may perform advertising which may be targeted to a plurality of linked consumer computing devices based on the Master ID. In embodiments, the statistical confidence threshold may vary depending on the alias attributes that are linked.

[0011] In accordance with various illustrative but non-limiting embodiments, the systems and methods disclosed herein may include a computer program product embodied in a non-transitory computer readable medium that, when executing on one or more computers, performs the steps of first acquiring a first alias, wherein the first alias is comprised of a first plurality of attributes. Each of the first plurality of attributes may include at least one of a first device identifier datum, a first consumer datum, a first behavioral datum, and a first demographic datum. The computer program product may then acquire a second alias, wherein the second alias is comprised of a second plurality of attributes. Each of the second plurality of

attributes may include at least one of a second device identifier datum, a second consumer datum, a second behavioral datum, and a second demographic datum. The computer program product may additionally dynamically and transiently link the first alias and the second alias to form a Master ID. The dynamic linking of the first and second aliases may be based at least in part on analysis of the first and the second pluralities of attributes using a binding expression that expresses a statistical confidence threshold required for grouping aliases. In embodiments, the alias acquiring and dynamically linking steps are performed iteratively over a plurality of aliases so that a plurality of attributes are merged into a single Master ID. Additionally, the computer program product may target an advertising campaign to a consumer device based at least in part on the Master ID and analyze results of the advertising campaign targeted to the Master ID. In embodiments, at least one of the first alias and the second alias may be acquired from at least one of a consumer database of an organization and a third party database. In embodiments, dynamic linking may be achieved by matching attributes of aliases including at least one of an IP address, a device ID, an e-mail address, and cookie tracking information. Additionally, the dynamic linking of alias may be based on a rules engine. The rules engine may include rules for dynamic linking of aliases based at least in part on at least one of a regulatory constraint, a business agreement, a privacy policy, and a consumer preference. In embodiments, the rules engine may include different rules for different geographic locations.

[0012] In accordance with various illustrative but non-limiting embodiments, the systems and methods disclosed herein may include a computer program product embodied in a non-transitory computer readable medium that, when executing on one or more computers, first performs the step of acquiring a first alias. The first alias may include a first plurality of attributes, wherein each of the first plurality of attributes may include of at least one of a first device identifier datum, a first consumer datum, a first behavioral datum, or a first demographic datum. The computer program product may then acquire a second alias, wherein the second alias may include of a second plurality of attributes. Each of the second plurality of attributes may include of at least one of a second device identifier datum, a second consumer datum, a second behavioral datum, and a second demographic datum. Also, the computer program product may then perform the step of dynamically and transiently linking the first alias and the second alias to form a first Master ID. The

dynamic linking of the first and second aliases may be based, at least in part, on analysis of the first and the second pluralities of attributes using a first binding expression that expresses a statistical confidence threshold required for grouping aliases. In addition, the computer program product may perform the step of acquiring a third alias, wherein the third alias may include a third plurality of attributes, wherein each of the third plurality of attributes may include of at least one of a third device identifier datum, a third consumer datum, a third behavioral datum, and a third demographic datum. The computer program may additionally perform the step of acquiring a fourth alias, wherein the fourth alias includes a fourth plurality of attributes. Each of the fourth plurality of attributes may include least one of a fourth device identifier datum, a fourth consumer datum, a fourth behavioral datum, and a fourth demographic datum. The computer program may then dynamically and transiently link the third alias and the fourth alias to form a second Master ID. The dynamic linking of the third and fourth aliases may be based at least in part on analysis of the first and the second pluralities of attributes using a second binding expression that expresses a statistical confidence threshold required for grouping aliases. The computer program product may then merge the first Master ID and the second Master ID to form a circle set. The merging may be based on a recognition that the Master IDs are related to each other by one of a type of self, household, and friend. Additionally, the computer program product may perform the step of targeting an advertising campaign to multiple consumer devices based at least in part on the circle set. In embodiments, the dynamic linking may be achieved by matching attributes of aliases including at least one of an IP address, a device ID, an e-mail address, and cookie tracking information.

[0013] While the invention has been described in connection with certain preferred embodiments, other embodiments would be understood by one of ordinary skill in the art and are encompassed herein.

BRIEF DESCRIPTION OF THE FIGURES

[0014] The invention and the following detailed description of certain embodiments thereof may be understood by reference to the following figures:

[0015] Fig. 1A depicts a real-time bidding method and system for the delivery of advertising.

[0016] Fig. 1B depicts the execution of the real-time bidding system across multiple exchanges.

[0017] Fig. 2 depicts a learning method and system for optimizing bid management.

[0018] Fig. 3 depicts sample data domains that may be used to predict media success associated with key performance indicators.

[0019] Fig. 4 depicts training multiple algorithms relating to an advertising campaign, in which better performing algorithms may be detected.

[0020] Fig. 5A depicts the use of micro-segmentation for bid valuation.

[0021] Fig. 5B depicts a microsegmentation analysis of an advertising campaign.

[0022] Fig. 5C depicts optimization of pricing through frequency analysis.

[0023] Fig. 5D depicts how pacing may be optimized through recency analysis within the real-time bidding system.

[0024] Fig. 6 depicts the use of nano-segmentation for bid valuation.

[0025] Fig. 7 depicts a sample integration of a real-time bidding method and system within a major media supply chain.

[0026] Fig. 8A depicts a hypothetical case study using a real-time bidding method and system.

[0027] Fig. 8B depicts a second hypothetical case study comparing two advertising campaigns using a real-time bidding method and system.

[0028] Fig. 9 depicts a simplified use case in the form of a flow chart summarizing key steps that a user may take in using a real-time bidding method and system.

[0029] Fig. 10 depicts an exemplary embodiment of a user interface for a pixel provisioning system that may be associated with the real-time bidding system.

[0030] Fig. 11 depicts an exemplary embodiment of impression level data that may be associated with the real-time bidding system.

[0031] Fig. 12 depicts a hypothetical advertising campaign performance report.

[0032] Fig. 13 illustrates a bidding valuation facility for real-time bidding and valuation for purchases of online advertising placements.

[0033] Fig. 14 illustrates a method for real-time bidding and economic valuation for purchases of online advertising placements.

[0034] Fig. 15 illustrates a method for determining a bid amount.

[0035] Fig. 16 illustrates a method automatically placing a bid on the optimum placement for an advertisement

[0036] Fig. 17 illustrates facilities of the analytic platform that may be used for targeting bids for online advertising purchases in accordance with an embodiment of the invention.

[0037] Fig. 18 illustrates a method for selecting and presenting to a user at least one of a plurality of available placements based on an economic valuation.

[0038] Fig. 19 illustrates a method for the prioritization of available advertising placements derived from an economic valuation.

[0039] Fig. 20 illustrates a real-time facility for selecting alternative algorithms for predicting purchase price trends for bids for online advertising.

[0040] Fig. 21 illustrates a method for predicting performance of advertising placements based on current market conditions

[0041] Fig. 22 illustrates a method for determining a preference between a primary model and a second model for predicting economic valuation.

[0042] Fig. 23 illustrates a method for determining a preference between a primary model and a second model for predicting economic valuation.

[0043] Fig. 24 illustrates a method for selecting one among multiple competing valuation models in real-time bidding for advertising placements.

[0044] Fig. 25 illustrates a method for replacing a first economic valuation model by a second economic valuation model for deriving a recommended bid amount for an advertising placement.

[0045] Fig. 26 illustrates a method for evaluating multiple economic valuation models and selecting one valuation as a future valuation of an advertising placement.

[0046] Fig. 27 illustrates a method for evaluating in real time multiple economic valuation models and selecting one valuation as a future valuation of an advertising placement.

[0047] Fig. 28 illustrates a method for evaluating multiple bidding algorithms to select a preferred algorithm for placing an advertisement.

[0048] Fig. 29 illustrates a method for replacing a bid recommendation with a revised bid recommendation for an advertising placement.

[0049] Fig. 30 illustrates a real-time facility for measuring the value of additional third party data.

[0050] Fig. 31 illustrates a method for advertising valuation that has the ability to measure the value of additional third party data.

[0051] Fig. 32 illustrates a method for computing a valuation of a third party dataset and billing an advertiser a portion of the valuation.

[0052] Fig. 33 illustrates a method for computing a valuation of a third party dataset and calibrating a bid amount recommendation for a publisher to pay for a placement of an ad content based at least in part on the valuation.

[0053] Fig. 34 depicts a data visualization embodiment presenting a summary of advertising performance by time of day versus day of the week.

[0054] Fig. 35 depicts a data visualization embodiment presenting a summary of advertising performance by population density.

[0055] Fig. 36 depicts a data visualization embodiment presenting a summary of advertising performance by geographic region in the United States.

[0056] Fig. 37 depicts a data visualization embodiment presenting a summary of advertising performance by personal income.

[0057] Fig. 38 depicts a data visualization embodiment presenting a summary of advertising performance by gender.

[0058] Fig. 39 illustrates an affinity index, by category, for an advertising campaign.

[0059] Fig. 40 depicts a data visualization embodiment presenting a summary of page visits by the number of impressions.

[0060] Fig. 41 depicts an example of matrix operations that may be used to map the number of impressions as expressed through the channel ID to affect the store sales may be provided.

[0061] Fig. 42 illustrates an example of parameters that may create a SUID partition of the advertisement inventory.

[0062] Fig. 43 illustrates an example of a feedback loop for offline data and online data to advertising.

[0063] Referring to Fig. 44, a number of internal machines that may be used for managing and tracking advertisement activities.

[0064] Fig. 45 illustrates a simplified embodiment of the chain among publisher and advertisement networks

[0065] Fig. 46 depicts the temporal relationship between multiple inventories and advertising campaigns with multiple starting and ending dates for available budgets.

[0066] Fig. 47 depicts an exemplary GYM for buyers using a proxy translator in real time bidding calls, in accordance with an embodiment of the present invention.

[0067] Fig. 48 depicts an exemplary GYM for sellers using a proxy translator in real time bidding calls, in accordance with an embodiment of the present invention.

[0068] Fig. 49 depicts another example of a GYM for sellers using real time bidding system for valuation, in accordance with an embodiment of the present invention.

[0069] Fig. 50 depicts a simplified example of variables that may be used within a virtual global consumer ID.

[0070] Fig. 51 depicts a simplified framework for analyzing and utilizing advertising placement opportunities.

[0071] Fig. 52 depicts a simplified framework for providing impression level decisioning for guaranteed buys towards audience optimization.

[0072] Fig. 53 depicts an embodiment flow for depicting a bid request as related to bid request valuation, bid response, RTB exchanges, and optimization parameters.

[0073] Fig. 54 shows an embodiment of a process flow from an RTB branding bidding function, to a campaign, survey, responses, and valuation algorithms leading to an optimization engine.

[0074] Figs. 55-56 illustrate embodiments of how exposed market increments may be adjusted as survey results tally from a campaign.

[0075] Fig. 57 illustrates a method of creating a plurality of Synthetic User Identifiers that may be used to select a targeted advertisement.

[0076] Fig. 58 illustrates a method of creating and using a Synthetic User Identifier to present an advertisement to a user.

[0077] Fig. 59 illustrates a system for varying the intensity level of advertising based on a plurality of Synthetic User Identifiers.

[0078] Fig. 60 depicts an example embodiment of a method and system for the delivery of advertising, including the uses of offline panel data.

[0079] Fig. 61 depicts elements that may be associated with a Master ID.

[0080] Fig. 62 depicts a simplified network of associations among attributes, aliases, and consumers.

[0081] Fig. 63 depicts a simplified network of associations among identifiers and a Master ID.

DETAILED DESCRIPTION

[0082] Referring to Fig. 1A, a real-time bidding system 100A that may be used according to the methods and systems as described herein for selecting and valuing sponsored content buying opportunities, real-time bidding, and placing sponsored content, such as advertisements, across a plurality of content delivery channels. The real-time bidding facility may inform buying opportunities to place sponsored content across multiple advertisement (“ad”) delivery channels. The real-time bidding facility may further enable the collection of data regarding ad performance and use this data to provide ongoing feedback to parties wanting to place ads, and automatically adjust and target the ad delivery channels used to present sponsored content. The real-time bidding system 100A may facilitate the selection of a particular ad type to show in each placement opportunity, and the associated costs of the ad placements over time (and, for example, adjusted by time of placement). The real-time facility may facilitate valuation of ads, using valuation algorithms, and may further optimize return on investment for an advertiser 104.

[0083] The real-time bidding system 100A may include, and/or be further associated with, one or more distribution service consumers, such as an advertising agency 102 or advertiser 104, an ad network 108, an ad exchange 110, or a publisher 112, an analytics facility 114, an ad tagging facility 118, an advertising order sending and receiving facility 120, and advertising distribution service facility 122, an advertising data distribution service facility 124, an ad display client facility 128, an advertising performance data facility 130, a contextualizer service facility 132, a data integration facility 134, and one or more databases providing different types of data relating to ads and/or ad performance. In an embodiment of the invention, the real-time bidding system 100A may include an analytic facility that may, at least in part, include a learning machine facility 138, a valuation algorithms facility 140, a real-

time bidding machine facility 142, a tracking machine facility 144, an impression/click/action logs facility 148, and a real-time bidding logs facility 150.

[0084] In embodiments, the one or more databases providing data to the real-time bidding system 100A and to the learning machine facility 138 relating to ads, ad performance, or ad placement context, may include an agency database and/or an advertiser database 152. The agency database may include campaign descriptors, and may describe the channels, timelines, budgets, and other information, including historical information, relating to the use and distribution of advertisements. The agency data 152 may also include campaign and historic logs that may include the placement for each advertisement shown to users. The agency data 152 may also include one or more of the following: an identifier for the user, the web page context, time, price paid, ad message shown, and resulting user actions, or some other type of campaign or historic log data. The advertiser database may include business intelligence data, or some other type of data, which may describe dynamic and/or static marketing objectives, or may describe the operation of the advertiser 104. In an example, the amount of overstock of a given product (that the advertiser 104 has in its warehouses) may be described by the advertiser data 152. In another example, the data may describe purchases executed by costumers when interacting with the advertiser 104,

[0085] In embodiments, the one or more databases may include an historic event database. The historic event data 154, may be used to correlate the time of user events with other events happening in, for example, a region in which the user is located. In an example, response rates to certain types of advertisements may be correlated to stock market movements. The historic event data 154 may include, but is not limited to, weather data, events data, local news data, or some other type of data.

[0086] In embodiments, the one or more databases may include a user data 158, database. The user data 158, may include data may be internally sourced and/or provided by third parties that may contain personally linked information about advertising recipients. This information may associate users with preferences, or other indicators, which may be used to label, describe, or categorize the users.

[0087] In embodiments, the one or more databases may include a real-time event database. The real-time event data 160 may include data similar to historic data, but more current. The real-time event data 160 may include, but is not limited

to, data that is current to the second, minute, hour, day, or some other measure of time. In an example, if the learning machine facility 138 finds a correlation between ad performance and historic stock market index values, the real-time stock market index value may be used to value advertisements by the real-time bidding machine facility 142.

[0088] In embodiments, the one or more databases may include a contextual database that may provide contextual data 162, associated with publisher's, publisher's content (e.g., a publisher's website), and the like. Contextual data 162, may include, but is not limited to, keywords found within the ad; an URL associated with prior placements of the ad, or some other type of contextual data 162, and may be stored as a categorization metadata relating to publisher's content. In an example, such categorization metadata may record that a first publisher's website is related to financial content, and a second publisher's content is predominantly sports-related.

[0089] In embodiments, the one or more databases may further include a third party/commercial database. A third party/commercial database may include data 164, relating to consumer transactions, such as point-of-sale scanner data obtained from retail transactions, or some other type of third party or commercial data.

[0090] In embodiments of the present invention, data from the one or more databases may be shared with the analytic facilities 114, of the real-time bidding system 100A through a data integration facility 134. In an example, the data integration facility 134 may provide data from the one or more databases to the analytics facilities of the real-time bidding system 100A for the purposes of evaluating a potential ad and/or ad placement. For example, the data integration facility 134, may combine, merge, analyze or integrate a plurality of data types received from the available databases (e.g., user data 158 and real-time event data 160). In an embodiment, a contextualizer may analyze web content to determine whether a web page contains content about sports, finance, or some other topic. This information may be used as an input to the analytics platform facility 114 in order to identify the relevant publishers and/or web pages where ads will appear.

[0091] In embodiments, the analytics facilities of the real-time bidding system 100A may receive an ad request via the advertising order sending and receiving facility 120. The ad request may come from an advertising agency 102, advertiser 104, ad network 108, ad exchange 110, and publisher 112 or some other party requesting advertising content. For example, the tracking machine facility 144

may receive the ad request via the advertising order sending and receiving facility 120, and provide a service that may include attaching an identifier, such as an ad tag using an ad tagging facility 118, to each ad order, and resulting ad placement. This ad tracking functionality may enable the real-time bidding system 100A to track, collect and analyze advertising performance data 130. For example an online display ad may be tagged using a tracking pixel. Once a pixel is served from the tracking machine facility 144, it may record the placement opportunity as well as the time and date of the opportunity. In another embodiment of the invention, the tracking machine facility 144 may record the ID of the ad requestor, the user, and other information that labels the user including, but not limited to, Internet Protocol (IP) address, context of an ad and/or ad placement, a user's history, geo-location information of the user, social behavior, inferred demographics or some other type of data Ad impressions, user clickthroughs, action logs, or some other type of data, may be produced by the tracking machine facility 144.

[0092] In embodiments, the recorded logs, and other data types, may be used by the learning machine facility 138 to improve and customize the targeting and valuation algorithms 140, as described herein. The learning machine facility 138 may create rules regarding advertisements that are performing well for a given client and may optimize the content of an advertising campaign based on the created rules. Further, in embodiments of the invention, the learning machine facility 138 may be used to develop targeting algorithms for the real-time bidding machine facility 142. The learning machine facility 138 may learn patterns, including Internet Protocol (IP) address, context of an ad and/or ad placement, URL of the ad placement website, , a user's history, geo-location information of the user, social behavior, inferred demographics, or any other characteristic of the user or that can be linked to the user, ad concept, ad size, ad format, ad color, or any other characteristic of an ad or some other type of data, among others, that may be used to target and value ads and ad placement opportunities. In an embodiment of the invention, the learning patterns may be used to target ads. Further, the learning machine facility 138 may be coupled to one or more databases, as depicted in Fig. 1, from which it may obtain additional data needed to further optimize targeting and/or valuation algorithms 140.

[0093] In an embodiment of the invention, an advertiser 104 may place an "order" with instructions limiting where and when an ad may be placed. The order from the advertiser 104 may be received by the learning machine facilities or another

element of the platform. The advertiser 104 may specify the criteria of ‘goodness’ for the ad campaign to be successful. Further, the tracking machine facility 144 may be used to measure the ‘goodness’ criteria. The advertiser 104 may also provide historic data associated with the ‘order’ in order to bootstrap the outcome of the analysis. Thus, based on data available from the one or more databases and the data provided by the advertiser 104, the learning machine facility 138 may develop customized targeting algorithms for the advertisement. The targeting algorithms may calculate an expected value of the advertisement under certain conditions (using, for example, real-time event data 160 as part of the modeling). The targeting algorithms may also seek to maximize the specified ‘goodness’ criteria. The targeting algorithms developed by the learning machine facility 138 may be received by the real-time bidding machine 142, which may wait for opportunities to place the advertisement. In an embodiment of the invention, the real-time bidding machine facility 142 may also receive an ad and/or bid request via the advertising order sending and receiving facility 120. The real-time bidding machine facility 142 may be considered a “real-time” facility since it may reply to an ad or bid request that is associated with a time constraint. The real-time bidding machine facility 142 may use a non-stateless method to calculate which advertising message to show, while the user waits for the system to decide. The real-time bidding machine facility 142 may perform the real-time calculation using algorithms provided by the learning machine facility 138, dynamically estimating an optimal bid value. In embodiments, an alternative real-time bidding machine facility 142 may have a stateless configuration to determine an advertisement to present.

[0094] The real-time bidding machine facility 142 may blend historical and real-time data to produce a valuation algorithm for calculating a real-time bid value to associate with an ad and/or ad placement opportunity. The real-time bidding machine facility 142 may calculate an expected value that combines information about the Internet Protocol (IP) address, context of an ad and/or ad placement, a user’s history, geo-location information of the user, social behavior, inferred demographics or some other type of data. In embodiments, the real-time bidding machine facility 142 may use an opportunistic algorithm update by using tracking machine 144 or ad performance data to order and prioritize the algorithms based at least in part on the performance of each algorithm. The learning machine facility 138 may use and select from an open list of multiple, competing algorithms in the machine learning facility

and real-time bidding facility. The real-time bidding machine 142 may use control systems theory to control the pricing and speed of delivery of a set of advertisements. Further, the real-time bidding machine facility 142 may use won and lost bid data to build user profiles. Also, the real-time bidding machine 142 may correlate expected values with current events in the ad recipient's geography. The real-time bidding machine facility 142 may trade ad buys across multiple exchanges and thus, treat multiple exchanges as a single source of inventory, selecting and buying ads based at least in part on the valuation that is modeled by the real-time bidding system 100A.

[0095] In embodiments, the real-time bidding system 100A may further include a real-time bidding log facility that may record a bid request received and a bid response sent by the real-time bidding machine facility 142. In an embodiment of the invention, the real-time bidding log may log additional data related to a user. In an example, the additional data may include the details of the websites the user may visit. These details may be used to derive user interests or browsing habits. Additionally, the real-time bidding log facility may record the rate of arrival of advertising placement opportunities from different ad channels. In an embodiment of the invention, the real-time bidding log facility may also be coupled to the learning machine facility 138.

[0096] In embodiments, the real-time bidding machine 142 may dynamically determine an anticipated economic valuation for each of the plurality of potential placements for an advertisement based at least in part on valuation algorithms 140 associated with the learning machine facility 138. In response to receiving a request to place an advertisement, the real-time bidding machine facility 142 may dynamically determine an anticipated economic valuation for each of the plurality of potential placements for the advertisement, and may select and decide whether to present the available placements based on the economic valuation to the one or more distribution service consumers.

[0097] In embodiments, the real-time bidding machine 142 may include altering a model for dynamically determining the economic valuation prior to processing a second request for a placement. The alteration of the model may be based at least in part on a valuation algorithm associated with the learning facility. In an embodiment of the invention, prior to selecting and presenting the one or more of the available placements, the behavior of an economic valuation model may be altered to produce a second set of valuations for each of the plurality of placements.

[0098] In embodiments, the valuation algorithms 140 may evaluate performance information relating to each of the plurality of ad placements. A dynamically variable economic valuation model may be used to determine the anticipated valuation. The valuation model may evaluate bid values in relation to the economic valuations for a plurality of placements. A step in bidding for the plurality of available placements and/or plurality of advertisements may be based on the economic valuation. In an exemplary case, the real-time bidding machine facility 142 may adopt the following sequence: At Step 1, the real-time bidding machine 142 may filter possible ads that are to be shown using the valuation algorithms 140. At Step 2, the real-time bidding machine facility 142 may check if the filtered ads have remaining budget funds, and may remove any ads from the list that do not have available budget funds from the list. At Step 3, the real-time bidding machine facility 142 may run an economic valuation algorithm for the ads in order to determine the economic value for each ad. At Step 4, the real-time bidding machine 142 may adjust the economic values by the opportunity cost of placing an ad. At Step 5, the real-time bidding machine facility 142 may select the ad with the highest economic value, after adjusting by the opportunity cost. At Step 6, the information about the first request, which may include information about the publisher 112 content of a request, may be used to update the dynamic algorithm before the second request is received and processed. Finally, at Step 7, the second ad may be processed in the same sequence as the first, with updates to the dynamic algorithm before the third ad is placed. In embodiments, a plurality of competing valuation algorithms 140 may be used at each step in selecting an ad to present. By tracking the advertising performance of the ad that eventually is placed, the competing algorithms may be evaluated in order to determine their relative performance and utility.

[0099] In an embodiment of the present invention, competing algorithms may be tested by dividing portions of data into separate training and validation sets. Each of the algorithms may be trained on a training set of data, and then validated (measured) for predictiveness against the validation set of data. Each bidding algorithm may be evaluated for its predictiveness against the validation set using metrics such as receiver operating characteristic (ROC) area, Lift, Precision/Recall, Return on Advertising Spend, other signal processing metrics, other machine learning metrics, other advertising metrics, or some other analytic method, statistical technique or tool. It will be understood that general analytic methods, statistical techniques, and

tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention. Predictiveness of an algorithm may be measured by how well it predicts the likelihood that showing a particular advertisement to a particular consumer in a particular context is likely to influence a consumer to engage in a desirable action, such as purchasing one of the advertiser's products, engaging with the advertiser product, affecting the consumer perception about the advertiser's product, visiting a web page, or taking some other kind of action which is valued by the advertiser.

[00100] In an embodiment of the present invention, cross-validation may be used to improve the algorithm evaluation metrics. Cross-validation describes a methodology where a training set-validation set procedure for evaluating competing algorithms and/or models is repeated multiple times by changing the training and validation sets of data. Cross-validation techniques that may be used as part of the methods and systems described herein include, but are not limited to, repeated random sub-sampling validation, k-fold cross-validation, k x 2 cross-validation, leave-one-out cross-validation, or some other type of cross-validation technique.

[00101] In embodiments, competing algorithms may be evaluated using the methods and systems as described herein, in real-time, in batch mode processing, or using some other periodic processing framework. In embodiments, competing algorithms may be evaluated online, such as using the Internet or some other networked platform, or the competing algorithms may be evaluated offline and made available to an online facility following evaluation. In a sample embodiment, one algorithm may be strictly better than all other algorithms, in terms of its predictiveness, and it may be chosen offline in the learning facility 138. In another sample embodiment, one algorithm from a set may be more predictive given a particular combination of variables, and more than one algorithm may be made available to the real-time bidding facility 142 and the selection of the best performing algorithm may take place in real-time, for example, by examining the attributes of a particular placement request, then determining which algorithm from the set of trained algorithms is most predictive for that particular set of attributes.

[00102] In embodiments, data corresponding to the valuation of an ad from the real-time bidding system 100A may be received by the advertising distribution service facility 122 and delivered to a consumer of the valuation data, such as an advertising agency 102, advertiser 104, ad network 108, ad exchange 110, publisher 112, or some other type of consumer. In another embodiment of the invention, the advertising distribution service facility 122 may be an ad server. The advertising distribution service facility 122 may distribute an output of the real-time bidding system 100A, such as a selected ad, to the one or more ad servers. In embodiments, the advertising distribution service facilities 122 may be coupled to the tracking machine facility 144. In another embodiment of the invention, the advertising distribution service facility 122 may be coupled to an ad display client 128. In embodiments, an ad display client 128 may be a mobile device, a PDA, cell phone, a computer, a communicator, a digital device, a digital display panel or some other type of device able to present advertisements.

[00103] In embodiments, an ad received at the ad display client 128 may include interactive data; for example, popping up of an offer on movie tickets. A user of the ad display client 128 may interact with the ad and may perform actions such as making a purchase, clicking an ad, filling out a form, or performing some other type of user action. The user actions may be recorded by the advertising performance data facility 130. In an embodiment, the advertising performance data facility 130 may be coupled to the one or more databases. In an example, the performance data facility may be coupled to the contextual database for updating the contextual database in real-time. In an embodiment, the updated information may be accessed by the real-time bidding system 100A for updating the valuation algorithms 140. In embodiments, the advertising performance data facility 130 may be coupled to the one or more distribution service consumers.

[00104] Data corresponding to the valuation of an ad from the analytics platform facility 114 may also be received by the advertising distribution service facility 122. In an embodiment of the invention, the advertising distribution service facility 122 may utilize the valuation data for reordering/rearranging/reorganizing the one or more ads. In another embodiment, the advertising distribution service facility 122 may utilize the valuation data for ranking ads based on predefined criteria. The predefined criteria may include, time of the day, location, and the like.

[00105] The advertising data distribution service facility 124 may also provide valuation data to the one or more consumers of ad valuation data. In embodiments, an advertising data distribution service facility 124 may sell the valuation data or may provide subscription of the valuation data to the one or more consumers of ad valuation data. In embodiments, the advertising distribution service facility 122 may provide the output from the real-time bidding system 100A or from the learning machine facility 138 to the one or more consumers of ad valuation data. The consumers of ad valuation data may include, without any limitation, advertising agencies 102/advertisers 104, an ad network 108, an ad exchange 110, a publisher 112, or some other type of ad valuation data customer. In an example, an advertising agency 102 may be a service business dedicated to creating, planning, and handling of advertisements for its clients. The ad agency 102 may be independent from the client and may provide an outside point of view to the effort of selling the client's products or services. Further, the ad agencies 102 may be of different types, including without any limitation, limited-service advertising agencies, specialist advertising agencies, in-house advertising agencies, interactive agencies, search engine agencies, social media agencies, healthcare communications agencies, medical education agencies, or some other type of agency. Further, in examples, an ad network 108 may be an entity that may connect advertisers 104 to websites that may want to host their advertisements. Ad networks 108 may include, without any limitation, vertical networks, blind networks, and targeted networks. The Ad networks 108 may also be classified as first-tier and second-tier networks. The first-tier advertising networks may have a large number of their own advertisers 104 and publishers, they may have high quality traffic, and they may serve ads and traffic to second-tier networks. The second-tier advertising networks may have some of their own advertisers 104 and publishers, but their main source of revenue may come from syndicating ads from other advertising networks. An ad exchange 110 network may include information related to attributes of ad inventory such as price of ad impression, number of advertisers 104 in a specific product or services category, legacy data about the highest and the lowest bid for a specific period, ad success (user click the ad impression), and the like. The advertisers 104 may be able to use this data as part of their decision-making. For example, the stored information may depict the success rate for a particular publisher 112. In addition, advertisers 104 may have an option of choosing one or more models for making financial transactions. For example, a cost-

per-transaction pricing structure may be adopted by the advertiser 104. Likewise, in another example, advertisers 104 may have an option to pay cost-per-click. The ad exchange 110 may implement algorithms, which may allow the publisher 112 to price ad impressions during bidding in real-time.

[00106] In embodiments, a real-time bidding system 100A for advertising messages delivery may be a composition of machines intended for buying opportunities to place advertising messages across multiple delivery channels. The system may provide active feedback in order to automatically fine-tune and target the channels used to present the advertising messages, as well as to select what advertising messages to show in each placement opportunity, and the associated costs over time. In embodiments, the system may be composed of interconnected machines, including but not limited to: (1) a learning machine facility 138, (2) a real-time bidding machine 142, and (3) a tracking machine 144. Two of the machines may produce logs, which may be internally used by the learning machine facility 138. In embodiments, the inputs to the system may be from both real-time and non-real time sources. Historical data may be combined with real-time data to fine-tune pricing and delivery instructions for advertising campaigns.

[00107] In embodiments, a real-time bidding system 100A for advertising messages delivery may include external machines and services. External machines and services may include, but are not limited to, agencies 102, advertisers 104, agency data 152, such as campaign descriptors and historic logs, advertiser data 152, key performance indicators, historic event data 154, user data 158, a contextualizer service 132, real-time event data 160, an advertising distribution service 122, an advertising recipient, or some other type of external machine and/or service.

[00108] In embodiments, agencies and/or advertisers 104 may provide historical ad data, and may be beneficiaries of the real-time bidding system 100A.

[00109] In embodiments, agency data 152, such as campaign descriptors, may describe the channels, times, budgets, and other information that may be allowed for diffusion of advertising messages.

[00110] In embodiments, agency data 152, such as campaign and historic logs may describe the placement for each advertising message show to a user, including one or more of the following: an identifier for the user, the channel, time, price paid, ad message shown, and user resulting user actions, or some other type of campaign or historic log data. Additional logs may also record spontaneous user

actions, for example a user action that is not directly traceable to an advertising impression, or some other type of spontaneous user action.

[00111] In embodiments, advertiser data 152 may consist of business intelligence data, or some other type of data, that describes dynamic and/or static marketing objectives. For example, the amount of overstock of a given product that the advertiser 104 has in its warehouses may be described by the data.

[00112] In embodiments, key performance indicators may include a set of parameters that expresses the ‘goodness’ for each given user action. For example, a product activation may be valued at \$X, and a product configuration may be valued at \$Y.

[00113] In embodiments, historic event data 154 may be used by the real-time bidding system 100A to correlate the time of user events with other events happening in their region. For example, response rates to certain types of advertisements may be correlated to stock market movements. Historic event data 154 may include, but is not limited to weather data, events data, local news data, or some other type of data.

[00114] In embodiments, user data 158 may include data provided by third parties that contains personally linked information about advertising recipients. This information may show users preferences, or other indicators, that label or describe the users.

[00115] In embodiments, a contextualizer service 132 may identify the contextual category of a medium for advertising. For example, a contextualizer may analyze web content to determine whether a web page contains content about sports, finance, or some other topic. This information may be used as an input to the learning system 138, to refine which types of pages on which ads will appear.

[00116] In embodiments, real-time event data 160 may include data similar to historic data, but that is more current. Real-time event data 160 may include, but is not limited to data that is current to the second, minute, hour, day, or some other measure of time. For example, if the learning machine facility 138 finds a correlation between ad performance and historic stock market index values, the real-time stock market index value may be used to value advertisements by the real-time bidding machine 142.

[00117] In embodiments, an advertising distribution service 122 may include, but is not limited to ad networks 108, ad exchanges 110, sell-side optimizers, or some other type of advertising distribution service 122.

[00118] In embodiments, an advertising recipient may include a person who receives an advertising message. Advertising content may be specifically requested (“pulled”) as part of or attached to content requested by an advertising recipient, or “pushed” over the network by, for example, an advertising distribution service 122. Some non-limiting examples of modes of receiving advertising include the Internet, mobile phone display screens, radio transmissions, television transmissions, electronic bulletin boards, printed media, and cinematographic projections.

[00119] In embodiments, a real-time bidding system 100A for advertising messages delivery may include internal machines and services. Internal machines and services may include, but are not limited to, a real-time bidding machine 142, a tracking machine 144, a real-time bidding log, impression, click and action logs, a learning machine facility 138, or some other type of internal machine and/or service.

[00120] In embodiments, a real-time bidding machine 142 may receive a bid request message from an advertising distribution service 122. A real-time bidding machine 142 may be considered a “real-time” system, since it may reply to a bid request that is associated with a time constraint. The real-time bidding machine 142 may use a non-stateless method to calculate which advertising message to show, while the user is waiting for the system to decide. The system may perform the real-time calculation using algorithms provided by the learning machine facility 138, dynamically estimating an optimal bid value. In embodiments, an alternative system may have a stateless configuration to determine an advertisement to present.

[00121] In embodiments, a tracking machine 144 may provide a service that will attach tracking IDs to each advertisement. For example, an online display ad may be followed by a pixel. Once a pixel is served from the tracking machine 144, it may record the placement opportunity as well as the time and date; additionally, the machine may record the ID of the user, and other information that labels the user, including but not limited to IP address, geographic location, or some other type of data.

[00122] In embodiments, a real-time bidding log may record a bid request received and a bid response sent by the real-time bidding machine 142. This log may contain additional data about which sites a user has visited that could be used to

derive user interests or browsing habits. Additionally, this log may record the rate of arrival of advertising placement opportunities from different channels.

[00123] In embodiments, impression, click and action logs may be records that are produced by the tracking system, which can be used by the learning machine facility 138.

[00124] In embodiments, a learning machine facility 138 may be used to develop targeting algorithms for the real-time bidding machine 142. The learning machine facility 138 may learn patterns, including social behavior, inferred demographics, among others, that may be used to target online ads.

[00125] In an example, an advertiser 104 may place an “order” with instructions limiting where and when an ad may be placed. The order may be received by the learning machine facility 138. The advertiser 104 may specify the criteria of ‘goodness’ for the campaign to be successful. Such ‘goodness’ criteria may be measurable using the tracking machine 144. The advertiser 104 may provide historic data to bootstrap the system. Based on available data, the learning system 138 may develop customized targeting algorithms for the advertisement. The algorithms may calculate an expected value of the advertisement given certain conditions, and seek to maximize the specified ‘goodness’ criteria. Algorithms may be received by the real-time bidding machine 142, which may wait for opportunities to place the advertisement. Bid requests may be received by the real-time bidding machine 142. Each one may be evaluated for its value for each advertiser 104, using the received algorithms. Bid responses may be sent for ads that have an attractive value. Lower values may be bid if estimated appropriate. The bid response may request that an ad be placed at a particular price. Ads may be tagged with a tracking system, such as a pixel displayed in a browser. The tracking machine 144 may log ad impressions, user clicks, and user actions. And/or other data. The tracking machine logs may be sent to the learning system 138, which may use the ‘goodness criteria,’ and decide which algorithms to improve, and further customize them. This process may be iterative. The system may also correlate expected values with current events in the ad recipient’s geo-region.

[00126] In embodiments, a real-time bidding machine 142 may dynamically update targeting algorithms.

[00127] In embodiments, a real-time bidding machine 142 may blend historical and real-time data to produce an algorithm for calculating a real-time bid value.

[00128] In embodiments, a real-time bidding machine 142 may calculate an expected value that combines information about the context of an ad placement, a user's history and geo-location information, and the ad itself, or some other type of data, to calculate an expected value of showing a particular advertisement at a given time.

[00129] In embodiments, a real-time bidding machine 142 may use algorithms rather than targeting "buckets."

[00130] In embodiments, a real-time bidding machine 142 may use an opportunistic algorithm update, by using tracking machine facility 144 feedback to prioritize the worst performing algorithms.

[00131] In embodiments, a real-time bidding machine 142 may use an open list of multiple, competing algorithms in the learning system 138 and real-time bidding system 100A.

[00132] In embodiments, a real-time bidding machine 142 may use control systems theory to control the pricing and speed of delivery of a set of advertisements.

[00133] In embodiments, a real-time bidding machine 142 may use won and lost bid data to build user profiles.

[00134] As shown in Fig. 1B, in embodiments, a real-time bidding machine may trade ad buys across multiple exchanges 100B. Treating multiple exchanges as a single source of inventory.

[00135] Referring to Fig. 2, the analytic algorithms of the real-time bidding system may be used to optimize the management of bids associated with advertisements and advertisement impressions, conversions, or some other type of ad-user interaction 200. In embodiments, the learning system embodied, for example, by the learning machine 138 may create rules regarding which advertisements are performing well for a given client and optimize the content mix of an advertising campaign based at least in part on the rules. In an example, a digital media user's behavior, such as an advertisement clickthrough, impression, webpage visit, transaction or purchase, or third party data associated with the user may be associated with, and used by the learning system of the real-time bidding system. The real-time bidding system may use the output of the learning system (e.g., rules and algorithms)

to pair a request for an advertisement with an advertisement selection that conforms to the rules and/or algorithms created by the learning machine. A selected advertisement may come from an ad exchange, inventory partner, or some other source of advertising content. The selected advertisement may then be associated with an ad tag, as described herein, and sent to the digital media user for presentation, such as on a webpage. The ad tag may then be tracked and future impressions, clickthroughs, and the like recorded in databases associated with the real-time bidding system. The rules and algorithms may then be further optimized by the learning machine based at least in part on new interactions (or lack thereof) between the selected advertisement and the digital media user.

[00136] In embodiments, a computer program product embodied in a computer readable medium that, when executing on one or more computers, may dynamically determine an anticipated economic valuation for each of a plurality of potential placements for an advertisement based at least in part on receiving a request to place an advertisement for a publisher. In response to receiving a request to place an advertisement for a publisher, the method and system of the present invention may dynamically determine an anticipated economic valuation for each of a plurality of potential placements for the advertisement, and/or plurality of advertisements, and select and decide whether to present to the publisher at least one of the plurality of available placements and/or plurality of advertisements based on the economic valuation.

[00137] In embodiments, the method and system enabled by the computer program may comprise altering a model for dynamically determining the economic valuation prior to processing a second request for a placement. Alteration of the model may be based at least in part on machine learning.

[00138] In embodiments, prior to selecting and presenting at least one of the plurality of available placements, and/or plurality of advertisements, the behavior of an economic valuation model may be altered to produce a second set of valuations for each of the plurality of placements, wherein the selecting and the presenting steps are based at least in part on the second set of valuations. The request for the placement may be a time limited request.

[00139] In embodiments, the economic valuation model may evaluate performance information relating to each of the plurality of advertisement placements.

[00140] In embodiments, a dynamically variable economic valuation model may be used to determine the anticipated economic valuation. The dynamically variable economic valuation model may evaluate bid values in relation to economic valuations for a plurality of placements. A step of bidding for at least one of the plurality of available placements, and/or plurality of advertisements, may be based on the economic valuation.

[00141] Referring still to Fig. 2, the real-time bidding system may contain an algorithm fitting the description above 200. Given a plurality of possible ads to show the real-time bidding system may follow the following exemplary sequence: 1) All possible ads may be filtered to show using targeting rules, and an output a listed ads may be shown; 2) the system may check if possible ads have remaining budget funds, and may remove those ads that do not have available budget funds from the list; 3) the system may run an economic valuation dynamic algorithm for the ads in order to determine the economic value for each ad; 4) the values may be adjusted by the opportunity cost of placing an ad on a given site, instead of alternative sites. 5) the ad with the highest value may be selected, after adjusting by the opportunity cost; 6) Information about the first request, which may include information about the publisher content of a request, may be used to update the dynamic algorithm before the second request is received and processed. This information may be used to determine whether or not a particular type of publisher content is available frequently or infrequently, and 7) the second ad may be processed in the same sequence as the first, with the updates to the dynamic algorithm before the third ad is placed.

[00142] In embodiments, the dynamic algorithm may be analogous to an algorithm used in airplane flight control systems, which adjust for atmospheric conditions as they change, or an automobile cruise control system, which dynamically adjusts the gas pedal positions as wind drag changes or the automobile climbs or descends a hill.

[00143] Referring to Fig. 3, data relating to context, the consumer (i.e., the digital media user), and the message/advertisement may be used to predict the success of an advertisement based at least in part on specified key performance indicators 300. Contextual data may include data relating to the type of media, the time of day or week, or some other type of contextual data. Data relating to a consumer, or digital media user, may include demographics, geographic data, and data relating to consumer intent or behavior, or some other type of consumer data. Data relating to

the message and/or advertisement may include data associated with the creative content of the message/advertisement, the intention or call to action embodied in the message/advertisement, or some other type of data.

[00144] As depicted in Fig. 4, the real-time bidding system may be used to produce advertising campaign-specific models and algorithms that are continuously produced, tested, and run using data associated with campaign results (e.g., clickthroughs, conversions, transactions, and the like) as they become available in real-time 400. In embodiments, multiple models may be tested using preparatory datasets to design sample advertising campaigns. The multiple models may be run against multiple training algorithms that embody specified objectives, such as key performance indicators. Advertising content that performs well against the algorithms may be retained and presented to a plurality of digital media users. Additional data may be collected based at least in part on the interactions of the plurality of digital media users and the selected advertising content, and this data may be used to optimize the algorithms and select new or different advertising content for presentation to the plurality of digital media users.

[00145] Still referring to Fig. 4, in embodiments, a computer program product embodied in a computer readable medium that, when executing on one or more computers, may deploy an economic valuation model that may be refined through machine learning to evaluate information relating to a plurality of available placements, and/or plurality of advertisements, to predict an economic valuation for each of the plurality of placements 400. At least one of the plurality of available placements, and/or plurality of advertisements, may be selected and presented to the publisher based at least in part on the economic valuation.

[00146] In embodiments, data may be taken from various formats, including but not limited to information that is not about advertisements, such as successful market demographics data, and the like. This may include specific data streams, translating data into a neutral format, specific machine learning techniques, or some other data type or technique. In embodiments, the learning system may perform an auditing and/or supervisory function, including but not limited to optimizing the methods and systems as described herein. In embodiments, the learning system may learn from multiple data sources, and base optimization of the methods and systems as described herein based at least in part on the multiple data sources.

[00147] In embodiments, the methods and systems as described herein may be used in Internet-based applications, mobile applications, fixed-line applications (e.g., cable media), or some other type of digital application.

[00148] In embodiments, the methods and systems as described herein may be used in a plurality of addressable advertising media, including but not limited to set top boxes, digital billboards, radio ads, or some other type of addressable advertising media.

[00149] Examples of machine learning algorithms may include, but are not limited to, Naïve Bayes, Bayes Net, Support Vector Machines, Logistic Regression, Neural Networks, and Decision Trees. These algorithms may be used to produce classifiers, which are algorithms that classify whether or not an advertisement is likely to produce an action or not. In their basic form, they return a “yes” or “no” answer and a score indicated the strength of certainty of the classifier. When calibration techniques are applied, they return a probability estimate of the likelihood of a prediction to be correct. They can also return what specific advertising is most likely to produce an action or which characteristics describe advertisings most likely to produce an action. These characteristics can include advertisings concept, advertisings size, advertisings color, advertisings text, or any other characteristic of an advertisement. Furthermore, they can also return what version of the advertiser website is most likely to create an action or what characteristics describe the version of the advertiser website most likely to produce an action. These characteristics can include website concept, products presented, colors, images, prices, text, or any other characteristic of the website. In embodiments, a computer implemented method of the present invention may comprise applying a plurality of algorithms to predict performance of online advertising placements, and tracking performance of the plurality of algorithms under a variety of market conditions. Preferred performance conditions for a type of algorithm may be determined, and market conditions tracked, and an algorithm may be selected for predicting performance of advertising placements based at least in part on current market conditions. In embodiments, the plurality of algorithms may include three algorithms.

[00150] In embodiments, a computer program product embodied in a computer readable medium that, when executing on one or more computers, may predict, using a primary model, the economic valuation of each of a plurality of available web publishable advertisement placements based in part on past

performance and prices of similar advertisement placements. The economic valuation of each of the plurality of web publishable advertisement placements may be predicted, through a second model, and the valuations produced by the primary model and the second model may be compared to determine a preference between the primary model and the second model. In embodiments, the primary model may be an active model responding to purchase requests. The purchase requested may be a time limited purchase request.

In embodiments, the second model may replace the primary model as the active model responding to purchase requests. The replacement may be based at least in part on a prediction that the second model will perform better than the primary model under the current market conditions.

[00151] In embodiments, a computer implemented method of the present invention may apply a plurality of algorithms to predict performance of online advertising placements, track performance of the plurality of algorithms under a variety of market conditions, and determine preferred performance conditions for a type of algorithm. Market conditions may be tracked, and an algorithm for predicting performance of advertising placements may be refined based at least in part on current market conditions.

[00152] In embodiments, a computer implemented method of the present invention may monitor a set of algorithms that are each predicting purchase price value of a set of advertisements and selecting the best algorithm from the set of algorithms based at least in part on a current market condition.

[00153] Referring again to Fig. 4, new data may be entered into a sorting mechanism (depicted by a funnel in Fig. 4) 400. This data may be prepared for machine learning training by labeling each ad impression with an indicator of whether or not it leads to a click or action. Alternative machine learning algorithms may be trained on the labeled data. A portion of the labeled may be saved for a testing phase. This testing portion may be used to measure the prediction performance of each alternative algorithm. Algorithms which are most successful in predicting the outcome of the hold-out training data set may be forwarded to the real-time decision system.

[00154] In embodiments, a computer program product embodied in a computer readable medium that, when executing on one or more computers, may deploy a plurality of competing economic valuation models, in response to receiving

to place an advertisement for a publisher, to predict an economic valuation for each of the plurality of advertisement placements. The valuations produced by each of the plurality of competing economic valuation models may be evaluated to select one of the models for a current valuation of an advertising placement. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00155] In embodiments, a computer program product embodied in a computer readable medium that, when executing on one or more computers, may deploy a plurality of competing economic valuation models, in response to receiving a request to place an advertisement, to evaluate information relating to a plurality of available advertisement placements. The economic valuation models may be used to predict an economic valuation for each of the plurality of advertisement placements. The valuations produced by each of the plurality of competing economic valuation models may be evaluated to select one of the models for future valuations. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00156] In embodiments, data may be evaluated to determine if it supports a winning algorithm in a learning system. The incremental value of buying additional data may be determined and auditing and testing of data samples may be used to determine whether the data increases the effectiveness of prediction. For example, the system may use data derived from an ad server log, combined with demographical information, to derive a valuation model, with a certain level of accuracy. Such a model may enable the acquisition of online advertising ads, for the benefit of an appliance manufacturer, below the market price. The addition of an additional data source, such as a list of consumers that have expressed their interest in buying a specific appliance, may increase the accuracy of the model, and as a consequence the

benefit to the appliance manufacturer. It is stated that the increased benefit received would be linked to the addition of the new data source, and hence, such data source may be assigned a value linked to the incremental benefit. Although this example presents a case of online advertising, it should be appreciated by one skilled in the art that the application can be generalized to advertising through different channels, using data sources of different types, as well as models to predict economic value or pricing for advertising.

[00157] As depicted in Figs. 5A and 5B, an advertisement inventory may be divided into many segments, or micro-segments (500, 502). The real-time bidding system may produce and continuously revise algorithms, for example by using the learning machine, based at least in part on data received on the performance of the advertisements in the inventory and its micro-segments (e.g., the number of impressions or conversions associated with each advertisement). Based at least in part on the learning system's algorithms, the real-time bidding system may produce a bid value that is thought to be "fair" relative to the advertising performance data. This bid value data may, in turn, be used to determine an average bid value to associate with advertisements located in the inventory. In embodiments, each micro-segment may be associated with a rule, algorithm, or set of rules and/or algorithms, a price-to-paid, and/or a budget. Rules may be used to buy advertising placement opportunities in groups of one or more opportunities. The size of the group of placement opportunities may be determined by the budget allocated to the rule. Rules may be transmitted to sellers of advertising placement opportunities through a server-to-server interface, through other electronic communication channel, including phone and fax, through a paper based order, through a verbal communication or any other way to convey an order to buy advertising placement opportunities. Fig. 5C depicts the use of frequency analysis for the purpose of pricing optimization 504. Fig. 5D depicts how pacing may be optimized through recency analysis within the real-time bidding system 508. Referring now to Fig. 6, the real-time bidding system may enable the automated analysis of an advertising inventory down to a nano-segment level (e.g., a bidding value for each impression) in order to identify valuable segments (i.e., advertisements) of an otherwise low-value advertisement inventory 600. The real-time bidding system may produce and continuously revise algorithms, for example by using the learning machine, based at least in part on data received on the performance of the advertisements in the nano-segment of the advertising inventory

(e.g., the number of impressions associated with each advertisement). Based at least in part on the learning system's algorithms, the real-time bidding system may produce a bid value that is thought to be "fair" relative to the advertisement(s) in the nano-segment, based at least in part on the performance data. In embodiments, the average bid price associated with the nano-segment may be adjusted based on other criteria, for example the number of impressions associated with the advertisement. In embodiments, each nano-segment may be associated with a rule, algorithm, or set of rules and/or algorithms.

[00158] In embodiments, a computer program product embodied in a computer readable medium that, when executing on one or more computers, may predict a purchase price for each of a plurality of available web publishable advertisement placements based at least in part on performance information and past bid prices for each of the plurality of advertisement placements. The purchase price for each of the plurality of advertisements may be tracked and predicted to determine a pricing trend.

[00159] In embodiments, the pricing trend may include a prediction of whether the valuation is going to change in the future.

[00160] In embodiments, a computer program product embodied in a computer readable medium that, when executing on one or more computers, may predict an economic valuation for each of a plurality of available web publishable advertisement placements based at least in part on performance information and past bid prices for each of the plurality of advertisement placements. Economic valuations for each of the plurality of advertisements may be tracked and predicted to determine a pricing trend.

[00161] In an example, the system may present bids for buying ads in an auction, expecting a fraction of them to be successful, and be awarded the ads for which it sends bids. As the system operates, the fraction of bids that is successful might fall below the expected goal. Such behavior can happen for the universe of available ads or for a subset of them. The price trend predicting algorithm may estimate what correction should be done to the bid price, so that, the fraction of ads successfully bought becomes closer to the intended goal, and may finally reach the intended goal.

[00162] As depicted in Fig. 7, the real-time bidding method and system as described herein may be integrated, associated, and/or affiliated with a plurality of

organizations and organization types, including but not limited to advertisers and advertising agencies 700. The real-time bidding system may perform buy-side optimization using the learning algorithms and techniques, as described herein, to optimize the selection of advertisements from sell-side aggregators, such as sell-side optimizers, ad networks, and/or exchanges, that receive advertisements from content publishers. This may optimize the pairing of messages and advertisements that are available within the inventories with digital media users. Advertising agencies may include Internet-based advertising companies, advertising sellers, such as organizations that sell advertisement impressions that display to a digital media user, and/or advertising buyers. Advertisers and advertising agencies may provide the real-time bidding system advertising campaign descriptors. A campaign descriptor may include, but is not limited to, a channel, time, budget, or some other type of campaign descriptor data. In embodiments, advertising agency data may include historic logs that describe the placement of each advertisement and user impression, conversion, and the like, including, but not limited to an identifier associated with a user, a channel, time, price paid, advertisement shown, resulting user actions, or some other type of historic data relating to the advertisement and/or impression. Historic logs may also include data relating to spontaneous user actions. In embodiments, advertiser data utilized by the real-time bidding system may include, but is not limited to, metadata relating to the subject matter of an advertisement, for example, inventory levels of a product that is the subject of the advertisement. Valuation, bid amounts, and the like may be optimized according to this and other metadata. Valuation, bid amounts, and the like may be optimized according to key performance indicators.

[00163] Figs. 8A and 8B depict hypothetical case studies using a real-time bidding method and system (800, 802). In embodiments, the learning system may create rules and algorithms, as described herein, using training data sets, such as that derived from a prior retailer advertising campaign. The training dataset may include a record of prior impressions, conversions, actions, clickthroughs and the like performed by a plurality of digital media users with the advertisements that were included in the prior campaign. The learning system may then identify a subset of advertising content from the prior campaign that was relatively more successful than other of the advertisements in the campaign, and recommend this advertising content for future use on the basis of its higher expected value.

[00164] In embodiments, a computer program product embodied in a computer readable medium that, when executing on one or more computers, may deploy an economic valuation model, in response to receiving a request to place an advertisement, in order to evaluate information relating to a plurality of available advertisement placements. The economic valuation model may be used to predict an economic valuation or the pricing for bids for each of the plurality of advertisement placements. A hypothesis as to a market opportunity may be determined, and the economic valuation model may be updated in response to the hypothesized market opportunity.

[00165] In an example, the system may find every few seconds, a data set or identify changes to the model that improves the accuracy of the valuation model used to predict economic value of ads. The system may have limitations on its ability to replace the valuation model on its whole, at the same rate as new data or changes to the model are created. As a consequence it may be beneficial to select which parts are less effective at providing economic valuation. The opportunistic updating component may select what is the order and priority for replacing sections of the valuation model. Such prioritization may be based on the economic valuation of the section to replace versus the new section to incorporate. As a result the system may create a prioritized set of instructions as to what data or sections of the model to add to the valuation system and in what order to do so.

[00166] In embodiments, the method and system of the present invention may split an advertising campaign, and compare the performance of a first set from the campaign using the methods and systems as described herein with a second set from the campaign not using the methods and systems. The analytic comparison may show the lift and charge based on the lift between the first set and the second set (e.g., third party campaign).

[00167] In an example, the system may separate a fraction of ads for creating a baseline sample on which the system is not applied, and thus, its benefits may not be delivered. Such process may be automatic. Such separation may be done by a random selection, across the universe of available ads, or to a randomly selected panel of users. The remaining ads that do not belong to the baseline sample may be placed using the system.

[00168] In embodiments, as the ad campaign presents some objectives that are possible to measure, and the greater the benefit, the better is the campaign judged

to be, it stands to believe an advertiser is willing to pay a premium for ad campaigns that deliver increased benefits.

[00169] In embodiments, the pricing model may calculate the difference between the benefit created by ads placed using the system and those placed without the system, as on the baseline sample. The system benefit is such net difference. The price charged to the advertiser may be a fraction of the system benefit.

[00170] Fig. 9 depicts a simplified flow chart summarizing key steps that may be involved in using a real-time bidding method and system 900.

[00171] Fig. 10 depicts an exemplary embodiment of a user interface for a pixel provisioning system that may be associated with the real-time bidding system 1000.

[00172] Fig. 11 depicts an exemplary embodiment of impression level data that may be associated with the real-time bidding system 1100.

[00173] Fig. 12 depicts a hypothetical advertising campaign performance report 1200.

[00174] Fig. 13 illustrates a bidding valuation facility 1300 for real-time bidding and valuation for purchases of online advertising placements in accordance with an embodiment of the invention. The bidding valuation facility 1300 may further include (apart from other facilities) a publisher facility 112, an analytics platform facility 114, an advertising order sending and receiving facility 120, a contextualizer service facility 132, a data integration facility 134, one or more databases providing different types of data for use by the analytics facility. In an embodiment of the invention, the analytics platform facility 114 may include a learning machine facility 138, valuation algorithm facility 140, a real-time bidding machine facility 142, a tracking machine facility 144, an Impression/Click/Action Logs facility 148, and a real-time bidding logs facility 150.

[00175] In embodiments of the invention, a learning machine 138 may be used to develop targeting algorithms for the real-time bidding machine facility 142. The learning machine 138 may learn patterns, including social behavior and inferred demographics among others, which may be used to target online ads. Further, the learning machine facility 138 may be coupled to one or more databases. In embodiments of the invention, the one or more databases may include an ad agency/advertiser database 152. The ad agency data 152 may include campaign descriptors, and may describe the channels, times, budgets, and other information that

may be allowed for diffusion of advertising messages. The ad agency data 152 may also include campaign and historic logs that may be the placement for each advertising message to be shown to the user. The ad agency data 152 may include one or more of the following: an identifier for the user, the channel, time, price paid, ad message shown, and user resulting user actions, or some other type of campaign or historic log data. Further, the advertiser data 152 may include business intelligence data, or some other type of data, which may describe dynamic and/or static marketing objectives. In an example, the amount of overstock of a given product that the advertiser 104 has in its warehouses may be described by the advertiser data 152. Further, the one or more databases may include an historic event database. The historic event data 154 may be used to correlate the time of user events with other events happening in their region. In an example, response rates to certain types of advertisements may be correlated to stock market movements. The historic event data 154 may include, but is not limited to, weather data, events data, local news data, or some other type of data. Further, the one or more databases may include a user database. The user data 158 may include data provided by third parties that may contain personally linked information about advertising recipients. This information may provide users with preferences, or other indicators, which may label or describe the users. Further, the one or more databases may include a real-time event database. The real-time event data 160 may include data similar to historic data, but that is more current. The real-time event data 160 may include, but is not limited to, data that is current to the second, minute, hour, day, or some other measure of time. In an example, if the learning machine facility 138 finds a correlation between advertising performance and historic stock market index values, the real-time stock market index value may be used to value advertisements by the real-time bidding machine facility 142. Further, the one or more databases may include a contextual database that may provide contextual data 162 associated with a publisher 112, publisher's website and the like. The one or more databases may further include a third party/commercial database.

[00176] Further, in embodiments of the invention, a data integration facility 134 and the contextualizer service facility 132 may be associated with the analytics platform facility 114 and the one or more databases. The data integration facility 134 may facilitate the integration of different types of data from one or more databases into the analytics platform facility 114. The contextualizer service facility 132 may

identify the contextual category of a medium for advertising and/or publisher content, website, or other publisher ad context. In an example, a contextualizer may analyze web content to determine whether a web page contains content about sports, finance, or some other topic. This information may be used as an input to the learning machine facility in order to identify the relevant publishers and/or web pages where ads may appear. In another embodiment, the location of the ad on the publisher 112 web page may be determined based on the information. In an embodiment of the invention, the contextualizer service facility 132 may also be associated with the real-time bidding machine facility 142 and/or with the one or more databases.

[00177] In embodiments of the invention, the real-time bidding machine facility 142 may receive a bid request message from the publisher facility 112. A real-time bidding machine facility 142 may be considered a “real-time” facility since it may reply to a bid request that is associated with a time constraint, where the reply occurs substantially simultaneous to the request receipt, and/or very near in time to the request receipt. The real-time bidding machine facility 142 may use a non-stateless method to calculate which advertising message to show, while the user waits for the system to decide. The real-time bidding machine facility 142 may perform the real-time calculation using algorithms provided by the learning machine 138, dynamically estimating an optimal bid value. In embodiments, an alternative real-time bidding machine facility 142 may have a stateless configuration to determine an advertisement to present.

[00178] Further, in an embodiment of the invention, the real-time bidding machine facility 142 may dynamically determine an anticipated economic valuation for each of the plurality of potential placements for an advertisement based on receiving the request to place an advertisement for the publisher facility 112. In response to receiving a request to place an advertisement for the publisher facility 112, the real-time bidding machine facility 142 may dynamically determine an anticipated economic valuation for each of the plurality of potential placements for the advertisement, and may select and decide whether to present the available placements based on the economic valuation to the publisher facility 112.

[00179] In embodiments, the real-time bidding machine facility 142 may include altering a model for dynamically determining the economic valuation prior to processing a second request for a placement. The alteration of the model may be based at least in part on the machine learning facility. In an embodiment of the

invention, prior to selecting and presenting at least one of the plurality of available placements, and/or plurality of advertisements, the behavior of an economic valuation model may be altered to produce a second set of valuations for each of the plurality of placements. In embodiments, the steps for selecting and presenting may be based on the second set of valuations. Further, in an embodiment of the invention, the request for the placement may be a time-limited request. Further, the economic valuation model may evaluate performance information relating to each of the plurality of advertisement placements. The dynamically variable economic valuation model may also be used to determine an anticipated economic valuation. In an embodiment of the invention, the dynamically variable economic valuation model may evaluate bid values in relation to economic valuations for a plurality of placements. Dynamic determination of an anticipated economic valuation for each of the plurality of potential placements for an advertisement may be based at least in part on advertiser data 152, historical event data 154, user data 158, real-time event data 160, contextual data 162, and third-party commercial data 164.

[00180] In embodiments, the real-time bidding machine facility 142, in response to receiving a request to place an advertisement for a publisher 112, may dynamically determine an anticipated economic valuation for each of a plurality of potential placements for an advertisement. After the economic valuation model has been determined, the real-time bidding machine facility 142 may determine a bid amount based at least in part on the anticipated economic valuation for each of the plurality of potential placements for the advertisement. The determination of the bid amount may include analysis of real-time bidding logs. In another embodiment, the determination of the bid amount may include analytic modeling based at least in part on machine learning. Analytic modeling based at least in part on machine learning may include the analysis of historical log data summarizing at least one of: ad impressions, ad clickthroughs, and user actions taken in association with an ad presentation. Further, in an embodiment of the invention, the determination of the bid amount may include analysis of data from the contextualizer service facility 132.

[00181] In an embodiment of the invention, the real-time bidding machine facility 142, in response to receiving a request to place an advertisement for a publisher 112, may dynamically determine an anticipated economic valuation for each of a plurality of potential placements for the advertisement. After the economic valuation model has been determined, the real-time bidding machine facility 142 may

determine a bid amount based at least in part on the anticipated economic valuation for each of the plurality of potential placements for the advertisement. Thereafter, the real-time bidding machine facility may select an optimum placement for the advertisement, from among the plurality of potential placements. Further, the real-time bidding machine facility 142 may automatically place a bid on the optimum placement for the advertisement.

[00182] Fig. 14 illustrates a method 1400 for selecting and presenting to a publisher at least one of the plurality of available placements, and/or plurality of advertisements, based on an economic valuation. The method initiates at step 1402. At step 1404, in response to receiving a request to place an advertisement for a publisher, an anticipated economic valuation may be dynamically determined for each of a plurality of potential placements for the advertisement. Thereafter at step 1408, at least one of the plurality of available placements, and/or plurality of advertisements, may be selected and presented to the publisher based at least in part on the economic valuation. In an embodiment of the invention, a model for dynamically determining the economic valuation may be altered prior to processing a second request for a placement. In an embodiment the model may be altered based at least in part on machine learning. In an embodiment of the invention, prior to the steps of selecting and presenting, the behavior of an economic valuation model may be altered to produce a second set of valuations for each of the plurality of placements. In an embodiment, the steps of selecting and presenting steps may be based on the second set of valuations, which are used in place of the first valuation(s). In embodiments, the request for the placement may be a time limited request. In embodiments, the economic valuation model, as described herein, may evaluate performance information relating to each of a plurality of advertisement placements. A dynamically variable economic valuation model may be used to determine the anticipated economic valuation and to evaluate bid values in relation to economic valuations for a plurality of placements. An anticipated economic valuation for each of a plurality of potential placements for an advertisement may be based at least in part on advertiser data, historical event data, user data, real-time event data, contextual data or third-party commercial data. The method terminates at step 1410.

[00183] Fig. 15 illustrates a method 1500 for determining a bid amount, in accordance with an embodiment of the invention. The method initiates at step 1502. At step 1504, in response to receiving a request to place an advertisement for a

publisher, an anticipated economic valuation for each of a plurality of potential placements for the advertisement may be dynamically determined. Thereafter at step 1508, a bid amount based at least in part on the anticipated economic valuation for each of the plurality of potential placements for the advertisement is determined. In an embodiment of the invention, the determination of the bid amount may include analysis of real-time bidding logs and/or analytic modeling based at least in part on machine learning. In an embodiment of the invention, the analytic modeling may include the analysis of historical log data summarizing at least one of: ad impressions, ad clickthroughs, and user actions taken in association with an ad presentation. In an embodiment of the invention, determination of the bid amount may include analysis of data from a contextualizer service.

[00184] Fig. 16 illustrates a method 1600 for automatically placing a bid on an optimum placement for an advertisement, where the optimum placement is selected based at least in part on an anticipated economic valuation. The method initiates at step 1602. At step 1604, in response to receiving a request to place an advertisement for a publisher, an anticipated economic valuation for each of a plurality of potential placements for the advertisement is dynamically determined. Thereafter at step 1608, a bid amount based at least in part on the anticipated economic valuation for each of the plurality of potential placements for the advertisement is determined. Further at step 1610, an optimum placement for the advertisement is selected, from among the plurality of potential placements, based at least in part on the bid amount. Finally at step 1612, a bid on the optimum placement for the advertisement is automatically placed. The method terminates at step 1614.

[00185] Fig. 17 illustrates a real-time facility 1700 for targeting bids for online advertising purchases in accordance with an embodiment of the invention. The real-time facility may include a learning machine facility 138 and a real-time bidding machine facility 142. In an embodiment of the invention, the real-time bidding machine facility 142 may receive a bid request message from the publisher facility 112. The real-time bidding machine facility 142 may be considered a “real-time” facility since it may reply to a bid request that is associated with a time constraint. The real-time bidding machine facility 142 may perform the real-time calculation using targeting algorithms provided by the learning machine 138, dynamically estimating an optimal bid value.

[00186] Further, in an embodiment of the invention, the real-time bidding machine facility 142 may deploy an economic valuation model that may dynamically determine an economic valuation (based on receiving the request to place an advertisement for the publisher facility 112) for each of one or more potential placements for an advertisement. In response to receiving a request to place an advertisement for the publisher facility 112, the real-time bidding machine facility 142 may dynamically determine an economic valuation for each of one or more potential placements for the advertisement. After the economic valuation has been determined, the real-time bidding machine facility 142 may select and present to a user at least one of the plurality of available placements, and/or plurality of advertisements, based on the economic valuation. In an embodiment, the selection and presentation to the publisher 112 may include a recommended bid amount for the at least one of the plurality of available placements, and/or plurality of advertisements. The bid amount may be associated with a time constraint. Further, in an embodiment, the refinement through machine learning may include comparing economic valuation models by retrospectively comparing the extent to which the models reflect actual economic performance of advertisements. In embodiments of the invention, the economic valuation model may be based at least in part on advertising agency data 152, real-time event data 160, historic event data 154, user data 158, third party commercial data 164, and contextual data 162. In an embodiment, the advertising agency data 152 may include at least one campaign descriptor. In embodiments, the campaign descriptor may be historic log data, advertising agency campaign budget data, and a datum indicating a temporal restraint on an advertising placement.

[00187] In embodiments, the learning machine facility 138 may receive an economic valuation model. The economic valuation model may be based at least in part on analysis of real-time bidding log data 150 from the real time bidding machine facility 142. Thereafter, the learning machine facility 138 may refine the economic valuation model. The refinement may be based at least in part on analysis of an advertising impression log. In an embodiment of the invention, the refinement of the economic valuation model may include a data integration step during which data to be used in the learning machine facility 138 may be transformed into a data format that may be read by the learning machine facility 138. The format may be a neutral format. Further in embodiments, the refinement of the economic valuation model

using the learning machine may be based at least in part on a machine learning algorithm. The machine learning algorithms may be based at least in part on naïve bayes analytic techniques and on logistic regression analytic techniques. Further, the real-time bidding machine facility 142 may use the refined economic valuation model to classify each of a plurality of available advertising placements. The classification may be a datum indicating a probability of each of the available advertising placements achieving an advertising impression. The real-time bidding machine facility 142 may then prioritize the available advertising placements based at least in part on the datum indicating the probability of achieving an advertising impression. Thereafter, the real-time bidding machine facility 142 may select and present to a user at least one of the plurality of available placements, and/or plurality of advertisements, based on the prioritization.

[00188] In an embodiment of the invention, an economic valuation model deployed by the real-time bidding machine facility 142 may be refined by the machine learning facility to evaluate information relating to one or more available placements to predict an economic valuation for each of the one or more placements. Further, in embodiments, the learning machine facility 138 may obtain different types of data to refine the economic valuation model. The different types of data may include, without any limitation, agency data 152 which may include campaign descriptors, and may describe the channels, times, budgets, and other information that may be allowed for diffusion of advertising messages. The agency data 152 may also include campaign and historic logs that may be the placement for each advertising message to be shown to the user. The agency data 152 may also include one or more of the following: an identifier for the user, the channel, time, price paid, ad message shown, and user resulting user actions, or some other type of campaign or historic log data. Further, the different types of data may include business intelligence data, or some other type of data, which may describe dynamic and/or static marketing objectives.

[00189] In embodiments of the invention, the learning machine facility 138 may perform an auditing and/or supervisory function, including, but not limited to, optimizing the methods and systems as described herein. In other embodiments of the information, the learning system 138 may learn from multiple data sources, and base optimization of the methods and systems as described herein at least in part on the multiple data sources. In embodiments, the methods and systems as described herein

may be used in Internet-based applications, mobile applications, fixed-line applications (e.g., cable media), or some other type of digital application. In embodiments, the methods and systems as described herein may be used in one or more addressable advertising media, including, but not limited to, set top boxes, digital billboards, radio ads, or some other type of addressable advertising media.

[00190] Further, in embodiments of the invention, the learning machine facility 138 may utilize various types of algorithms to refine the economic valuation models of the real-time bidding machine facility 142. The algorithms may include, without any limitations, decision tree learning, association rule learning, artificial neural networks, genetic programming, inductive logic programming, support vector machines, clustering, Bayesian networks, and reinforcement learning. In an embodiment of the invention, the various types of algorithms may produce classifiers, which are algorithms that may classify whether or not an advertisement is likely to produce an action. In their basic form, they may return a “yes” or “no” answer and/or a score indicating the strength of certainty of the classifier. When calibration techniques are applied, they may return a probability estimate of the likelihood of a prediction to be correct.

[00191] Fig. 18 illustrates a method 1800 for selecting and presenting to a user at least one of a plurality of available advertising placements based on an economic valuation. The method initiates at step 1802. At step 1804, an economic valuation model may be deployed, in response to receiving a request to place an advertisement for a publisher. The economic valuation model may be refined through machine learning to evaluate information relating to a plurality of available placements, and/or plurality of advertisements, to predict an economic valuation for each of the plurality of placements. In an embodiment, the refinement through machine learning may include comparing economic valuation models by retrospectively comparing the extent to which the models reflect actual economic performance of advertisements. Further, the economic valuation model may be based at least in part on advertising agency data, real time event data, historic event data, user data, third-party commercial data and contextual data. Furthermore, the advertising agency data may include at least one campaign descriptor. Moreover, the campaign descriptor may be historic log data, is advertising agency campaign budget data and advertising agency campaign budget data. At step 1808, at least one of the plurality of available placements, and/or plurality of advertisements, based on the

economic valuation may be selected and presented to a user. In an embodiment, the selection and presentation to the publisher may include a recommended bid amount for the at least one of the plurality of available placements, and/or plurality of advertisements. Further, the bid amount may be associated with a time constraint. The method 1800 terminates at step 1810.

[00192] Fig. 19 illustrates a method 1900 for selecting from a plurality of available advertising placements a prioritized placement opportunity based at least in part on an economic valuation model using real-time bidding log data. The method 1900 initiates at step 1902. At step 1904, an economic valuation model at a learning machine may be received. The economic valuation model may be based at least in part on analysis of a real-time bidding log from a real time bidding machine. At step 1908, the economic valuation model may be refined using the learning machine. In an embodiment, the refinement may be based at least in part on analysis of an advertising impression log. Further, the refinement of the economic valuation model may include a data integration step during which data to be used in the learning machine may be transformed into a data format that can be read by the learning machine. In an embodiment, the format may be a neural format. Furthermore, the refinement of the economic valuation model using the learning machine may be based at least in part on a machine learning algorithm. The machine learning algorithm may be based at least in part on naïve bayes analytic techniques. Moreover, the machine learning algorithm may be based at least in part on logistic regression analytic techniques. At step 1910, the refined economic valuation model may be used to classify each of a plurality of available advertising placements. Each classification may be summarized using a datum indicating a probability of each of the available advertising placements achieving an advertising impression. Further, at step 1912, the available advertising placements may be prioritized based at least in part on the datum. In addition, at step 1914, at least one of the plurality of available placements, and/or plurality of advertisements, may be selected and presented to a user based on the prioritization. The method 1900 terminates at step 1918.

[00193] Fig. 20 illustrates a real-time facility 2000 for selecting alternative algorithms for predicting purchase price trends for bids for online advertising, in accordance with an embodiment of the invention. The real-time facility 1700 may include a learning machine facility 138, a valuation algorithm facility 140, a real-time bidding machine facility 142, a plurality of data 2002, and a bid request message 2004

from a publisher facility 112. In an embodiment of the invention, the real-time bidding machine facility 142 may receive a bid request message 1704 from the publisher facility 112. The real-time bidding machine facility 142 may be considered a “real-time” facility since it may reply to a bid request that is associated with time constraint. The real-time bidding machine facility 142 may perform a real-time calculation using targeting algorithms provided by the learning machine facility 138 to predict purchase price trends for bids for online advertising. In an embodiment of the invention, the learning machine facility 138 may select an alternative algorithm based on the performance of a currently operating algorithm for predicting purchase price trends for bids for online advertising. In another embodiment of the invention, the learning machine facility 138 may select an alternative algorithm based on the predicted performance of the alternative algorithm for predicting purchase price trends for bids for online advertising. Further, in an embodiment of the invention, learning machine facility 138 may obtain the alternative algorithms from the valuation algorithm facility 140.

[00194] In embodiments, the real-time bidding machine facility 142 may apply a plurality of algorithms to predict performance of online advertising placements. Once the plurality of algorithms is applied, the real-time bidding machine facility 142 may track the performance of the plurality of algorithms under a variety of market conditions. The real-time bidding machine facility 142 may then determine the performance conditions for a type of algorithm from the plurality of algorithms. Thereafter, the real-time bidding machine facility 142 may track the market conditions and may select the algorithm for predicting performance of advertising placements based on the current market conditions.

[00195] In embodiments, at least one of the plurality of algorithms to predict performance may include advertiser data 152. The advertiser data 152 may include business intelligence data, or some other type of data, which may describe dynamic and/or static marketing objectives. In another embodiment of the invention, at least one of the plurality of algorithms to predict performance may include historic event data 154. The historic event data 154 may be used to correlate the time of user events with the occurrence of other events in their region. In an example, response rates to certain types of advertisements may be correlated to stock market movements. The historic event data 154 may include, but is not limited to, weather data, events data, local news data, or some other type of data. In yet another embodiment of the

invention, at least one of the plurality of algorithms to predict performance may include user data 158. The user data 158 may include data provided by third parties, which may contain personally linked information about advertising recipients. This information may provide users with preferences, or other indicators, which may label or describe the users. In yet another embodiment of the invention, at least one of the plurality of algorithms to predict performance may include real-time event data 160. The real-time event data 160 may include data similar to historic data, but more current. The real-time event data 160 may include, but is not limited to, data that is current to the second, minute, hour, day, or some other measure of time. In yet another embodiment of the invention, at least one of the plurality of algorithms to predict performance may include contextual data 162. In yet another embodiment of the invention, at least one of the plurality of algorithms to predict performance may include third party commercial data.

[00196] Further, in an embodiment of the invention, the real-time bidding machine facility 142 may use a primary model for predicting an economic valuation of each of a plurality of available web publishable advertisement placements based in part on past performance and prices of similar advertisement placements. The real-time bidding machine facility 142 may also use a second model for predicting an economic valuation of each of the plurality of web publishable advertisement placements. After predicting the economic valuations using both the primary model and the second model, the real-time bidding machine facility 142 may compare the valuations produced by the primary model and the second model to determine a preference between the primary model and the second model. In an embodiment of the invention, the comparison of the valuations may include retrospectively comparing the extent to which the models reflect actual economic performance of advertisements. Further, in an embodiment of the invention, the primary model may be an active model responding to purchase requests. The purchase request may be a time limited purchase request. In an embodiment of the invention, the second model may replace the primary model as the active model responding to purchase requests. Further, the replacement may be based on a prediction that the second model may perform better than the primary model under the current market conditions. In embodiments of the invention, the prediction may be based at least in parts on machine learning, historical advertising performance data 130, historical event data, and real-time event data 160.

[00197] In another embodiment of the invention, the real-time bidding machine facility 142 may use a primary model for predicting an economic valuation of each of a plurality of available mobile device advertisement placements based in part on past performance and prices of similar advertisement placements. The real-time bidding machine facility 142 may also use a second model for predicting an economic valuation of each of the plurality of mobile device advertisement placements. After predicting the economic valuations using both the primary model and the second model, the real-time bidding machine facility 142 may compare the valuations produced by the primary model and the second model to determine a preference between the primary model and the second model. In an embodiment of the invention, the comparison of the valuations may include retrospectively comparing the extent to which the models reflect actual economic performance of advertisements. Further, in an embodiment of the invention, the primary model may be an active model responding to purchase requests. The purchase request may be a time limited purchase request. In an embodiment of the invention, the second model may replace the primary model as the active model responding to purchase requests. Further, the replacement may be based on a prediction that the second model may perform better than the primary model under the current market conditions.

[00198] In an embodiment of the invention, the economic valuation model deployed by the real-time bidding machine facility 142 may be refined by the machine learning facility 138 to evaluate information relating to one or more available placements to predict an economic valuation for each of the one or more placements.

[00199] In embodiments, the learning machine facility 138 may obtain different types of data to refine the economic valuation model. The different types of data may include, without any limitation, advertiser data 152, historic event data 154, user data 158, real-time event data 160, contextual data 162, and third party commercial data. The different types of data may have different formats and information that may not directly relate to the advertisements, such as market demographics data, and the like. In embodiments of the invention, the different types of data in different formats may be translated into a neutral format or specific to a format compatible with the learning machine facility 138, or some other data type suitable for the learning machine facility 138.

[00200] In embodiments, the learning machine facility 138 may utilize various types of algorithms to refine the economic valuation model of the real-time

bidding machine facility 142. The algorithms may include, without any limitations, decision tree learning, association rule learning, artificial neural networks, genetic programming, inductive logic programming, support vector machines, clustering, Bayesian networks, and reinforcement learning.

[00201] Fig. 21 illustrates a method 2100 of the present invention for predicting performance of advertising placements based on current market conditions. The method initiates at step 2102. At step 2104, a plurality of algorithms to predict performance of online advertising placement may be applied. In embodiments of the invention, at least one of the plurality of algorithms to predict performance may include advertiser data, historic event data, user data, real-time event data, contextual data, and third-party commercial data, of some other type of data. Thereafter, at step 2108, the performance of the plurality of algorithms may be tracked under various market conditions. Further, at step 2110, the performance for a type of algorithm may be determined and then the market conditions may be tracked at step 2112. Finally, at step 2114, an algorithm for predicting performance of advertising placements based on the current market conditions may be selected. The method terminates at step 2118.

[00202] Fig. 22 illustrates a method 2200 for determining a preference between a primary model and a second model for predicting an economic valuation, in accordance with an embodiment of the invention. The method initiates at step 2202. At step 2204, using a primary model, an economic valuation of each of a plurality of available web publishable advertisement placements may be predicted. The economic valuation may be based in part on past performance and prices of similar advertisement placements. At step 2208, using a second model, an economic valuation of each of the plurality of available web publishable advertisement placements may be predicted. Thereafter, at step 2210, the economic valuations using both the primary model and the second model may be compared to determine a preference between the primary model and the second model. In an embodiment of the invention, the comparison of the valuations may include retrospectively comparing the extent to which the models reflect actual economic performance of advertisements. Further, in an embodiment of the invention, the primary model may be an active model responding to purchase requests. The purchase request may be a time limited purchase request. In an embodiment of the invention, the second model may replace the primary model as the active model responding to purchase requests.

Further, the replacement may be based on a prediction that the second model may perform better than the primary model under the current market conditions. In embodiments of the invention, the prediction may be based at least in parts on machine learning, historical advertising performance data, historical event data, and real-time event data. The method terminates at step 2212.

[00203] Referring now to Fig. 23, which illustrates a method 2300 for determining a preference between a primary model and a second model for predicting economic valuation, in accordance with another embodiment of the invention. The method initiates at step 2302. At step 2304, using a primary model, an economic valuation of each of a plurality of available mobile device advertisement placements may be predicted. The economic valuation may be based in part on past performance and prices of similar advertisement placements. At step 2308, using a second model an economic valuation of each of the plurality of available mobile device advertisement placements may be predicted. Thereafter, at step 2310, the economic valuations using both the primary model and the second model may be compared to determine a preference between the primary model and the second model. In an embodiment of the invention, the comparison of the valuations may include retrospectively comparing the extent to which the models reflect actual economic performance of advertisements. Further, in an embodiment of the invention, the primary model may be an active model responding to purchase requests. The purchase request may be a time limited purchase request. In an embodiment of the invention, the second model may replace the primary model as the active model responding to purchase requests. Further, the replacement may be based on a prediction that the second model may perform better than the primary model under the current market conditions. The method terminates at step 2312.

[00204] Further in an embodiment of the invention, the real-time bidding machine facility 142 may receive a request to place an advertisement from a publisher facility 112. In response to this request, the real-time bidding machine facility 142 may deploy a plurality of competing economic valuation models to predict an economic valuation for each of a plurality of available advertisement placements. After deploying the plurality of economic valuation models, the real-time bidding machine facility 142 may evaluate each valuation produced by each of the plurality of competing economic valuation models to select one economic valuation model as a current valuation of an advertising placement.

[00205] In an embodiment of the invention, the economic valuation model may be based at least in part on real-time event data 160. The real-time event data 160 may include data similar to historic data, but more current. The real-time event data 160 may include, but is not limited to, data that is current to the second, minute, hour, day, or some other measure of time. In another embodiment of the invention, the economic valuation model may be based at least in part on historic event data 154. The historic event data 154 may be used to correlate the time of user events with the occurrence of other events in their region. In an example, response rates to certain types of advertisements may be correlated to stock market movements. The historic event data 154 may include, but is not limited to, weather data, events data, local news data, or some other type of data. In yet another embodiment of the invention, the economic valuation model may be based at least in part on the user data 158. The user data 158 may include data provided by third parties, which may contain personally linked information about advertising recipients. This information may provide users with preferences, or other indicators, which may label or describe the users. In yet another embodiment of the invention, the economic valuation model may be based at least in part on the third party commercial data. In an embodiment of the invention, the third party commercial data may include financial data relating to historical advertisement impressions. In yet another embodiment of the invention, the economic valuation model may be based at least in part on contextual data 162. In yet another embodiment of the invention, the economic valuation model may be based at least in part on advertiser data 152. The advertiser data 152 may include business intelligence data, or some other type of data, which may describe dynamic and/or static marketing objectives. In yet another embodiment of the invention, the economic valuation model may be based at least in part on ad agency data 152. The ad agency data 152 may also include campaign and historic logs that may be the placement for each advertising message to be shown to the user. The ad agency data 152 may also include one or more of the following: an identifier for the user, the channel, time, price paid, ad message shown, and user resulting user actions, or some other type of campaign or historic log data. In yet another embodiment of the invention, the economic valuation model may be based at least in part on the historical advertising performance data 130. In yet another embodiment of the invention, the economic valuation model may be based at least in part on the machine learning.

[00206] In an embodiment of the invention, an economic valuation model deployed by the real-time bidding machine facility 142 may be refined by the machine learning facility 138 to evaluate information relating to one or more available placements to predict an economic valuation for each of the one or more placements.

[00207] In an embodiment of the present invention, after the real-time bidding machine facility 142 receives a request to place an advertisement from a publisher facility 112, the real-time bidding machine facility 142 in response to this request may deploy a plurality of competing economic valuation models to predict an economic valuation for each of the plurality of advertisement placements. After deploying the plurality of economic valuation models, the real-time bidding machine facility 142 may evaluate each valuation produced by each of the plurality of competing economic valuation models to select one as a first valuation of an advertising placement. Upon selecting the first valuation, the real-time bidding machine facility 142 may reevaluate each valuation produced by each of the plurality of competing economic valuation models to select one as a revised valuation of an advertising placement. In an embodiment of the invention, the revised valuation may be based at least in part on analysis of an economic valuation model using real-time event data 160 that was not available at the time of selecting the first valuation. Thereafter, real-time bidding machine facility 142 may replace the first valuation by the second revised valuation for use in deriving a recommended bid amount for the advertising placement. In an embodiment of the invention, the request may be received from a publisher 112 and the recommended bid amount may be automatically sent to the publisher 112. In another embodiment of the invention, the request may be received from a publisher 112 and a bid equaling the recommended bid amount may be automatically placed on behalf of the publisher 112. In an embodiment of the invention, the recommended bid amount may be associated with a recommended time of ad placement. In another embodiment of the invention, the recommended bid amount may be further derived by analysis of a real-time bidding log that may be associated with a real-time bidding machine facility 142. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to

evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00208] In another embodiment of the invention, after the real-time bidding machine facility 142 receives a request to place an advertisement from a publisher facility 112, the real-time bidding machine facility 142 may deploy a plurality of competing economic valuation models to evaluate information relating to a plurality of available advertisement placements. The real-time bidding machine facility 142 may deploy the competing economic valuation models to predict an economic valuation for each of the plurality of advertisement placements. After deploying the plurality of economic valuation models, the real-time bidding machine facility 142 may evaluate each valuation produced by each of the plurality of competing economic valuation models to select one valuation as a future valuation of an advertising placement. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00209] In another embodiment of the invention, after the real-time bidding machine facility 142 receives a request to place an advertisement from a publisher facility 112 the real-time bidding machine facility 142 may deploy a plurality of competing economic valuation models to evaluate information relating to a plurality of available advertisement placements. The real-time bidding machine facility 142 may deploy the competing economic valuation models to predict an economic valuation for each of the plurality of advertisement placements. After deploying the plurality of economic valuation models, the real-time bidding machine facility 142 may evaluate in real time, each valuation produced by each of the plurality of competing economic valuation models to select one valuation as a future valuation of an advertising placement. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention. In an

embodiment of the invention, the future valuation may be based at least in part on simulation data describing a future event. In an embodiment of the invention, the future event may be a stock market fluctuation. Further, in an embodiment of the invention, the simulation data describing future event may be derived from analysis of historical event data.

[00210] In an embodiment of the invention, after the real-time bidding machine facility 142 receives a request to place an advertisement from a publisher facility 112, the real-time bidding machine facility 142 may deploy a plurality of competing real-time bidding algorithms relating to a plurality of available advertisement placements to bid for advertisement placements. After deploying the plurality of competing real-time bidding algorithms, the real-time bidding machine facility 142 may evaluate each bidding algorithm to select a preferred algorithm. In an embodiment of the invention, the competing real-time bidding algorithms may use data from a real-time bidding log. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00211] In another embodiment of the invention, after the real-time bidding machine facility 142 receives a request to place an advertisement from a publisher facility 112, the real-time bidding machine facility 142 may deploy a plurality of competing real-time bidding algorithms relating to a plurality of available advertisement placements. The real-time bidding machine facility 142 may deploy the plurality of competing real-time bidding algorithms to bid for advertisement placements. After deploying the plurality of competing real-time bidding algorithms, the real-time bidding machine facility 142 may evaluate each bid recommendation created by the competing real-time bidding algorithms. The real-time bidding machine facility 142 may reevaluate each bid recommendation created by the competing real-time bidding algorithms to select one as a revised bid recommendation. In an embodiment of the invention, the revised bid recommendation may be based at least in part on a real-time bidding algorithm using real-time event data 160 that was not available at the time of selecting the bid recommendation. Thereafter, the real-time bidding machine facility 142 may replace

the bid recommendation with the revised bid recommendation for use in deriving a recommended bid amount for the advertising placement. In an embodiment of the invention, the replacement may occur in real-time relative to the receipt of the request to place an advertisement.

[00212] Referring now to Fig. 24 which illustrates a method 2400 for selecting one among multiple competing valuation models in real-time bidding for advertising placements, in accordance with an embodiment of the invention. The method initiates at step 2402. At step 2404, in response to receiving a request to place an advertisement, a plurality of competing economic valuation models may be deployed to predict an economic valuation for each of the plurality of advertisement placements. Thereafter at step 2408, each valuation produced by each of the plurality of competing economic valuation models may be evaluated to select one of the valuation models as a current valuation of an advertising placement. In embodiments of the invention, the economic valuation model may be based at least in part on real-time event data, historic event data, user data, contextual data, advertiser data, ad agency data, historical advertising performance data, machine learning and third-party commercial data. In an embodiment of the invention, the third party commercial data may include financial data relating to historical advertisement impressions. The method terminates at step 2410. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00213] Fig. 25 illustrates a method 2500 for replacing a first economic valuation model by a second economic valuation model for deriving a recommended bid amount for an advertising placement. The method initiates at step 2502. At step 2504, in response to receiving a request to place an advertisement, a plurality of competing economic valuation models may be deployed to predict an economic valuation for each of the plurality of advertisement placements. Thereafter at step 2508, valuations produced by each of the plurality of competing economic valuation models may be evaluated and a first valuation of an advertising placement may be then selected. Further at step 2510, each valuation produced by each of the plurality of competing economic valuation models may be reevaluated. One of the competing

economic valuation models may then be selected as a revised valuation of an advertising placement. The revised valuation may be based at least in part on analysis of an economic valuation model using real-time event data that was not available at the time of selecting the first valuation. Further at step 2512, the first valuation may be replaced with the second revised valuation for use in deriving a recommended bid amount for the advertising placement. In an embodiment of the invention, the request may be received from a publisher and the recommended bid amount may be automatically sent to the publisher. In another embodiment of the invention, the request may be received from a publisher and a bid equaling the recommended bid amount may be automatically placed on behalf of the publisher. In yet another embodiment of the invention, recommended bid amount may be associated with a recommended time of ad placement. Still in another embodiment of the invention, recommended bid amount may be further derived by analysis of a real-time bidding log that is associated with a real-time bidding machine. The method terminates at step 2514. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00214] Fig. 26 illustrates a method 2600 for evaluating multiple economic valuation models and selecting one valuation as a future valuation of an advertising placement, in accordance with an embodiment of the invention. The method initiates at step 2602. At step 2604, in response to receiving a request to place an advertisement, a plurality of competing economic valuation models may be deployed. Information relating to a plurality of available advertisement placements may be evaluated to predict an economic valuation for each of the plurality of advertisement placements. Further at step 2608, each valuation produced by each of the plurality of competing economic valuation models may be evaluated to select one valuation as a future valuation of an advertising placement. The method terminates at step 2610. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to

evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00215] Fig. 27 illustrates a method 2700 for evaluating in real time multiple economic valuation models and selecting one valuation as a future valuation of an advertising placement, in accordance with an embodiment of the invention. The method initiates at step 2702. At step 2704, in response to receiving a request to place an advertisement, a plurality of competing economic valuation models may be deployed. Information relating to a plurality of available advertisement placements may be evaluated to predict an economic valuation for each of the plurality of advertisement placements. Thereafter at step 2708, each valuation produced by each of the plurality of competing economic valuation models may be evaluated in real-time to select one valuation as a future valuation of an advertising placement. In an embodiment of the invention, the future valuation may be based at least in part on simulation data describing a future event. In another embodiment of the invention, the future event may be a stock market fluctuation. In an embodiment of the invention, the simulation data describing future event may be derived from analysis of historical event data that may be chosen based at least in part on contextual data relating to an advertisement to be placed in the advertising placement. The method terminates at step 2710. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00216] Fig. 28 illustrates a method 2800 for evaluating multiple bidding algorithms to select a preferred algorithm for placing an advertisement, in accordance with an embodiment of the invention. The method initiates at step 2802. At step 2804, in response to receiving a request to place an advertisement, a plurality of competing real-time bidding algorithms may be deployed. The bidding algorithms may be related to a plurality of available advertisement placements to bid for advertisement placements. Thereafter at step 2808, each bidding algorithm may be evaluated to select a preferred algorithm. The method terminates at step 2810. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as

analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00217] Fig. 29 illustrates a method 2900 for replacing a bid recommendation with a revised bid recommendation for an advertising placement, in accordance with an embodiment of the invention. The method initiates at step 2902. At step 2904, in response to receiving a request to place an advertisement, a plurality of competing real-time bidding algorithms relating to a plurality of available advertisement placements to bid for advertisement placements may be deployed. At step 2908, each bid recommendation created by the competing real-time bidding algorithms may be evaluated. Further at step 2910, each bid recommendation created by the competing real-time bidding algorithms may be reevaluated to select one as a revised bid recommendation. In an embodiment, the revised bid recommendation is based at least in part on a real-time bidding algorithm using real-time event data that was not available at the time of selecting the bid recommendation. Thereafter at step 2912, the bid recommendation may be replaced with the revised bid recommendation for use in deriving a recommended bid amount for the advertising placement. In an embodiment of the invention, the replacement may occur in real-time relative to the receipt of the request to place an advertisement. The method terminates at step 2914. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00218] Fig. 30 illustrates a real-time facility 3000 for measuring the value of additional third party data 164, in accordance with an embodiment of the invention. The real-time facility 2700 may include a learning machine facility 138, a valuation algorithm facility 140, a real-time bidding machine facility 142, additional third party dataset 3002, a bid request message 3004 from a publisher facility 112, and a tracking facility 144. In an embodiment of the invention, the real-time bidding machine facility 142 may receive a bid request message 3004 from the publisher facility 112. The real-time bidding machine facility 142 may be considered a “real-time” facility

since it may reply to a bid request that is associated with time constraint. The real-time bidding machine facility 142 may perform the real-time calculation using targeting algorithms provided by the learning machine facility 138. In an embodiment of the invention, the real-time bidding machine facility 142 may deploy an economic valuation model to perform the real-time calculation.

[00219] In embodiments, the learning machine facility 138 may obtain a third party data set 3002 to refine an economic valuation model. In an embodiment of the invention, the third party dataset 2702 may include data relating to users of advertising content. In embodiment of the invention, the data relating to users of advertising content may include demographic data, transaction data, conversion data, or some other type of data. In another embodiment of the invention, the third party dataset may include contextual data 162 relating to the plurality of available placements, and/or plurality of advertisements. In embodiments of the invention, the contextual data 162 may be derived from a contextualizer service 132 that may be associated with the learning machine facility 138. In yet another embodiment of the invention, the third party dataset 3010 may include financial data relating to historical advertisement impressions. Further, in embodiments of the invention, the economic valuation model may based at least in part on real-time event data, historic event data 154, user data 158, third-party commercial data, advertiser data 152, and advertising agency data 152.

[00220] In an embodiment of the invention, the real-time bidding machine facility 142 may receive an advertising campaign dataset and may split the advertising campaign dataset into a first advertising campaign dataset and a second advertising campaign dataset. Thereafter, the real-time bidding machine facility 142 may deploy an economic valuation model that may be refined through machine learning to evaluate information relating to a plurality of available placements, and/or plurality of advertisements, to predict an economic valuation for placement of ad content from the first advertising campaign dataset. In an embodiment of the invention, the machine learning may be based at least in part on a third party dataset. The machine learning may be achieved by the learning machine facility 138. After the refinement of the evaluation model, the real-time bidding machine facility 142 may place ad content from the first and second advertising campaign datasets within the plurality of available placements, and/or plurality of advertisements. Content from the first advertising campaign may be placed based at least in part on the predicted economic

valuation, and content from the second advertising campaign dataset may be placed based on a method that does not rely on the third party dataset. The real-time bidding machine facility 142 may further receive impression data from a tracking machine facility 144 that may relate to the ad content placed from the first and second advertising campaign datasets. In an embodiment of the invention, the impression data may include data regarding user interactions with the ad content. Thereafter, the real-time bidding machine facility 142, may determine a value of the third party dataset based at least in part on a comparison of impression data relating to the ad content placed from the first and second advertising campaign datasets.

[00221] Further, in an embodiment of the invention, the real-time bidding machine facility 142 may compute a valuation of the third party dataset 3002 based at least in part on a comparison of advertising impression data relating to ad content placed from first and second advertising campaign datasets. In an embodiment of the invention, the placement of the ad content from the first advertising campaign dataset may be based at least in part on a machine learning algorithm employing the third party dataset 2710 to select optimum ad placements. Thereafter, the real-time bidding machine facility 142 may bill an advertiser 104 a portion of the valuation to place an ad content from the first advertising campaign dataset. In an embodiment of the invention, the computation of the valuation and the billing of the advertiser 104 may be automatically performed upon receipt of a request to place content from the advertiser 104. In another embodiment of the invention, the computation of the valuation may be the result of the comparison of the performance of multiple competing valuation algorithms 140. In an embodiment of the invention, the comparison of the performance of multiple competing valuation algorithms 140 may include the use of valuation algorithms 140 based at least in part on historical data. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00222] Further in an embodiment of the invention, the real-time bidding machine facility 142 may compute a valuation of a third party dataset 3010 based at least in part on a comparison of advertising impression data relating to ad content

placed from first and second advertising campaign datasets. In an embodiment of the invention, the placement of the ad content from the first advertising campaign dataset may be based at least in part on a machine learning algorithm employing the third party dataset 3010 to select optimum ad placements. Thereafter, the real-time bidding machine facility 142 may calibrate a bid amount recommendation for a publisher 112 to pay for a placement of an ad content based at least in part on the valuation. In an embodiment of the invention, the calibration may be adjusted iteratively to account for real-time event data 160 and its effect on the valuation.

[00223] Fig. 31 illustrates a method 3100 for advertising valuation that has the ability to measure the value of additional third party data in accordance with an embodiment of the invention. The method initiates at step 3102. At step 3104, an advertising campaign dataset may be split into a first advertising campaign dataset and a second advertising campaign dataset. At step 3108, an economic valuation model that may be refined through machine learning, may be deployed to evaluate information relating to a plurality of available placements, and/or plurality of advertisements to predict an economic valuation for placement of ad content from the first advertising campaign dataset. In an embodiment of the invention, the machine learning may be based at least in part on a third party dataset. At step 3110, ad content from the first and second advertising campaign datasets may be placed within the plurality of available placements, and/or plurality of advertisements. In an embodiment of the invention, content from the first advertising campaign may be placed based at least in part on the predicted economic valuation, and content from the second advertising campaign dataset may be placed based on a method that does not rely on the third party dataset. Further at step 3112, impression data from a tracking machine facility relating to the ad content placed from the first and second advertising campaign datasets may be received. In an embodiment, the impression data may include data regarding user interactions with the ad content. Thereafter, at step 3114, a value of the third party dataset based at least in part on a comparison of impression data relating to the ad content placed from the first and second advertising campaign datasets may be determined. In an embodiment of the invention, the third party dataset may include data relating to users of advertising content, contextual data relating to the plurality of available placements, and/or plurality of advertisements, or financial data relating to historical advertisement impressions. In an embodiment of the invention, data relating to users of advertising content may include demographic

data, transaction data or advertisement conversion data. In an embodiment of the invention, contextual data may be derived from a contextualizer service that is associated with the machine learning facility. In an embodiment of the invention, economic valuation model may be based at least in part on real-time event data, part on historic event data, part on user data, part on third-party commercial data, part on advertiser data or part on advertising agency data. The method terminates at step 3118.

[00224] Fig. 32 illustrates a method 3200 for computing a valuation of a third party dataset and billing an advertiser a portion of the valuation, in accordance with an embodiment of the invention. The method initiates at step 3202. At step 3204, a valuation of a third party dataset may be computed based at least in part on a comparison of advertising impression data relating to ad content placed from first and second advertising campaign datasets. In an embodiment of the invention, the placement of the ad content from the first advertising campaign dataset may be based at least in part on a machine learning algorithm employing the third party dataset to select optimum ad placements. Thereafter, at step 3208, an advertiser may be billed a portion of the valuation to place an ad content from the first advertising campaign dataset. In an embodiment of the invention, the computation of the valuation and the billing of the advertiser may be automatically performed upon receipt of a request to place content from the advertiser. In another embodiment of the invention, computation of the valuation may be the result of comparing the performance of multiple competing valuation algorithms. In an embodiment of the invention, comparison of the performance of multiple competing valuation algorithms may include the use of valuation algorithms based at least in part on historical data. The method terminates at step 3210. It will be understood that general analytic methods, statistical techniques, and tools for evaluating competing algorithms and models, such as valuation models, as well as analytic methods, statistical techniques, and tools known to a person of ordinary skill in the art are intended to be encompassed by the present invention and may be used to evaluate competing algorithms and valuation models in accordance with the methods and systems of the present invention.

[00225] Fig. 33 illustrates a method 3300 for computing a valuation of a third party dataset and calibrating a bid amount recommendation for a publisher to pay for a placement of an ad content based at least in part on the valuation, in accordance with an embodiment of the invention. The method initiates at step 3302.

At step 3304, a valuation of a third party dataset may be computed based at least in part on a comparison of advertising impression data relating to ad content placed from first and second advertising campaign datasets. In an embodiment of the invention, the placement of the ad content from the first advertising campaign dataset may be based at least in part on a machine learning algorithm employing the third party dataset to select optimum ad placements. Thereafter, at step 3308, a bid amount recommendation for a publisher to pay may be calibrated for a placement of an ad content based at least in part on the valuation. In an embodiment of the invention, calibration may be adjusted iteratively to account for real-time event data and its effect on the valuation. The method terminates at step 3310.

[00226] In embodiments, the analytic output of the analytic platform 114 may be illustrated using data visualization techniques including, but not limited to the surface charts shown in Figs. 34-38. Surface charts may illustrate places of efficiency within, for example, the performance of an advertising campaign, where the height of the surface measures a conversion value per ad impression which is indexed to average performance. In an embodiment, surface areas with a value greater than one (1) may indicate better average conversion value and areas below one (1) may indicate underperformance. A confidence test may be applied to account for lower volume cross-sections of a surface chart and its associated data. Fig. 34 depicts a data visualization embodiment presenting a summary of advertising performance by time of day versus day of the week. Fig. 35 depicts a data visualization embodiment presenting a summary of advertising performance by population density. Fig. 36 depicts a data visualization embodiment presenting a summary of advertising performance by geographic region in the United States. Fig. 37 depicts a data visualization embodiment presenting a summary of advertising performance by personal income. Fig. 38 depicts a data visualization embodiment presenting a summary of advertising performance by gender.

[00227] Fig. 39 illustrates an affinity index, by category, for an advertising campaign/brand. The methods and system of the present invention may identify characteristics of consumers that are more likely than the general population to be interested in an advertiser brand. The methods and systems may also identify characteristics of consumers that are less likely than the general population to be interested in the advertiser brand. On the left side of the chart in Fig. 39, the characteristics of consumers that are more interested are presented. The chart also

shows an index that represents how much more likely than the general population those consumers are to be engaged with the advertiser brand. The right side of the chart presents the characteristics of consumers that are less interested, and shows an index that represents how much less likely than the general population those consumers are to be engaged with the brand. Indexes, such as that presented in Fig. 39 may take into account the size of the sample, and use a formulation that incorporates sample size and uncertainty ranges.

[00228] Fig. 40 depicts a data visualization embodiment presenting a summary of page visits by the number of impressions. The methods and system of the present invention may identify the conversion rates that different cohorts of consumers present. As shown in Fig. 40, each cohort may be defined by the number of ads shown to consumer-members of the cohort. The analytic platform 114 may analyze the consumers who saw a given number of ads and compute a conversion rate. The analytic platform 114 may take into account only impressions that were shown to consumers prior to the consumer executing the action, based at least in part on data included in an impression log 148. As an example, a consumer who has seen 3 ads before performing an action desirable to the advertiser is member of cohort 3. The other 10 members of cohort 3 might have seen 3 ads, but might have not perform any action deemed beneficial to the advertiser. The conversion rate for cohort 3 is $3/10 = 0.3$ or 300,000 per million consumers. The analysis takes into account the size of the sample, and uses a formulation that incorporates sample size and uncertainty ranges. The analysis also fits a curve that most likely represents the behavior observed across all cohorts.

[00229] The ability to measure advertising campaign results is a priority of a majority of advertising systems. Measured advertising campaign results, including results that are categorized by user, user groups, and the like, may be subsequently utilized by advertisers to modify advertising campaigns to maximize the effect of the advertisement messages on intended user and/or user group targets. For example, an advertiser may modify its campaigns by reallocating budgets and prices, from lower performing ones to focus on user groups that have a history of responsiveness to the campaign, similar campaigns, or advertisements that share an attribute(s) with material contained within an advertising campaign. Additionally, a plurality of media channels may be used for communicating the advertising campaign to consumers.

[00230] For online advertising, it may be possible to measure the effect of advertisements by using consumer identifiers stored in cookies. This enables an advertiser to distinguish individuals, while keeping their identity anonymous. However, there are cases where it is not possible or desirable to distinguish individuals. In embodiments of the present invention, methods and systems are provided for an advertising measurement solution for cases where it may not be possible or desirable to identify individuals. For example, using the methods and systems of the present invention it may be possible to measure multiple characteristics that may describe a media channel to link advertising messages shown and their subsequent effect on consumers and consumer groupings. This may permit measure of campaign effectiveness, advertising success, and the like, even when the measurement of effect may not be feasible using conventional methods, as it may not be possible or desirable to identify individuals. Examples of such use cases include, but are not limited to, the measurement of advertising across different channels (e.g., TV and online media) and measurement of online advertising without the use of cookie identifiers.

[00231] In accordance with various embodiments of the present invention, several characteristics of media may be utilized to enable the creation of small segments that may contain anywhere from one or a plurality of individuals, all of whom may share one or more characteristics. Characteristics may include, but are not limited to, a time of day (e.g., the time of day that an advertisement is viewed), a geographic region, an individuals' interest in a type of content. Each characteristic, or combination of characteristics may be used to define and/or describe a set of individuals. Therefore, the characteristics (such as time of the day, day of the week, browser and operating system used, screen resolution, geographic region, and type of content/content category) may be used as targeting parameters.

[00232] Targeting parameters may vary among media channels in terms of nature of these channels. For example, channel A might have only three parameters available, while channel B may have more than 40. Moreover, the nature of these parameters may change. For example, for print media, an advertiser may consider the parameters as edition of a magazine, type or genre of the magazine, and the size of the advertisement on a physical page, such as a magazine page, or some other parameter. Similarly, for TV advertising, the parameters may be the time the advertisement was

shown, its duration, and whether it included a product shot at the end, or some other parameter.

[00233] In embodiments, it may be possible to use a combination of multiple parameters (available to a channel) to name definite sections of the channel, irrespective of the channel being chosen by the advertiser. Also, channel sections may be small in some cases and describe few individuals, but may be defined nonetheless by using as many targeting parameters as possible. Different channels may be linked based on an assumption that individuals reached by those channels behave in the same way. For example, a sports enthusiast may be assumed to watch sports on TV, and to also follow sports on the web and print media.

[00234] In embodiments of the present invention, a set of targeting parameters, defining a set of users reached through a specific channel, may be used to create a Synthetic User Identifier (SUID). The SUID may be stored on a server side system such that it, or an accumulation of them may be used to project advertisement channel segmentation in the future. For example, an ad placement or ad interaction may cause the collection and extraction of user, device, and/or contextual information from the placement, interaction or client device. A SUID may describe several individuals, but in specific cases (by adding multiple parameters) it may describe a unique individual. For example, a special combination of software loaded, the Internet Protocol (IP) address, the type of operating system and screen resolution, and content interest may describe a specific individual or a set of individuals. In another embodiment, users may be tagged by several SUIDs. For example, a user may follow sports content from 3 pm to 6 pm, and follow news content from 7 pm to 10 pm in the same geographic region. Each of the combinations (i.e., 3-6pm, sports, and 7-10pm, news) may have its own SUID. Additionally, in an embodiment of the present invention, the effect of the advertisements in a small crowd of users may be measured. For this purpose, success may be measured each time it is observed. Success may be defined as a particular action at the advertiser's website, such as an ad conversion, click-through, or some other behavior. When a user executes particular actions on the advertiser's website, for example, the actions may also reveal information relating to when the advertisement was received. Parameters such as content category (e.g., of the referral URL), geographical location, time of the day, day of the week, browser used, operating system, screen resolution, or some other data may be recorded by the advertiser's website and/or an agent working in coordination with such website. As a

consequence, using the methods and systems as described herein, it may be possible to establish a statistical link between online advertisements shown and actions achieved at the advertiser's website. Furthermore, when using media and advertisements shown off-line, it may be possible to rely on coarser metrics and distribute the positive outcome measured by the advertiser across a wider population (described by multiple SUIDs). In an example, it may not be possible to link a T.V. advertisement with a specific user's screen resolution and operating system. Nevertheless, the geographical information, the type of content, and the time and date of the T.V. advertisement may be indicators of the types of users targeted through such advertisement. Furthermore, for T.V. advertisements, the count of users receiving an advertisement, and other data may be acquired through off-line surveys. This data may be used to measure the number of members for each SUID.

[00235] In some sample scenarios, it may not be possible to link the sales result at a specific advertiser's store to either specific consumers or advertisements. However, it may be possible to link the sales result to a limited number of zip codes as revealed by the addresses of consumers buying at the store. Furthermore, it may be possible to overlay the timeline of the advertisements shown versus the timeline of the sales results. In accordance with an embodiment of the present invention, the sales result for a given week may be allocated to SUIDs that capture information regarding zip codes in proximity to the store. The proportion of sales allocated to each zip code may be driven by the data captured by the point-of-sale (POS) system, which may, for example, provide a proportion based on count of individuals, the sum of revenue driven by each zip code, or some other analytic measure. In another embodiment, a telephone order may be traced to a geographic area, representative of the area code of the caller. If additional information is captured, the result may be linked to the zip code address of the buyer, including the "zip+4" address, which may enable mapping.

[00236] The ability to identify unique users (or small groups of users), deliver advertising to them, and link the performance of such advertisements to those users may further enable a granular measurement of advertisement and advertisement campaign success and facilitate adjustment of price or amount to pay to access and invest in such media further using the methods and systems as described herein. Cross-channel attribution may be enhanced and stimulated by the use of couponing that may enable validation of inferred links between different SUIDs.

[00237] Referring to Fig. 57, in embodiments, the presently disclosed invention may provide methods and systems 5700 for creating, at a server facility, a plurality of Synthetic User Identifiers by associating an advertisement with the advertisement's impression data and at least two of user, device, and contextual information as derived from a plurality of users' interactions with the advertisement 5704. One or more databases may include a contextual database that may provide contextual data, associated with advertisers, advertiser's content publishers, publisher's content (e.g., a publisher's website), and the like. The contextual database(s) may be provided within the analytic platform 114 or associated with the analytic platform, as described herein. Contextual data, may include, but is not limited to, keywords found within the ad; an URL associated with prior placements of the ad, or some other type of contextual data, and may be stored as a categorization metadata relating to publisher's content, as described herein. In an example, such categorization metadata may record that a first publisher's website is related to music content, and a second publisher's content is predominantly automobile-related. The Synthetic User Identifiers may be stored in a database that is accessible to the server facility and separate from a client system 5708. The server facility may be provided within the analytic platform 114 or associated with the analytic platform, as described herein. The plurality of Synthetic User Identifiers may be analyzed for correlations that indicate an advertisement type may produce a predetermined conversion rate if presented to an advertisement channel 5710, and a targeted advertisement may be recommended, which is associated with the advertisement type, to be presented to the advertisement channel 5712. The analysis, may include the usage of machine learning and matrix-based techniques, as described herein. Examples of machine learning algorithms may include, but are not limited to, Naïve Bayes, Bayes Net, Support Vector Machines, Logistic Regression, Neural Networks, and Decision Trees. These algorithms may be used to produce classifiers, which are algorithms that classify whether or not an advertisement is likely to produce an action or not. In their basic form, they return a "yes" or "no" answer and a score indicated the strength of certainty of the classifier. More complicated predictors may be used. When calibration techniques are applied, they return a probability estimate of the likelihood of a prediction to be correct. Calibration techniques can also indicate which specific advertisement is most likely to produce a desired user action or which characteristics describe advertisements most likely to produce an action.

[00238] In embodiments, the step of recommending a targeted advertisement may involve recommending a bid amount for the targeted advertisement, recommending a budget allocation for the targeted advertisement, or some other type of recommendation. Recommending may involve partitioning an advertisement inventory based on the Synthetic User Identifier.

[00239] In embodiments, the plurality of users' interactions with the advertisement may derive from a plurality of advertising channels. The plurality of advertising channels may include online and offline advertising channels. Online advertising channels may include a website. Offline advertising channels may include a print medium.

[00240] In embodiments, contextual information may be a device characteristic, an operating system, an advertising medium type, a plurality of contextual information, a user demographic, or some other type of contextual information.

[00241] Referring to Fig. 58, in embodiments, the presently disclosed invention may provide methods and systems 5800 for categorizing a plurality of available advertising channels, wherein each of the available advertising channels is categorized based at least in part on contextual information 5804, impression history, advertising channel performance characteristics, or some other type of data. For example, the tracking machine facility 144, as described herein, may record the ID of an ad requestor, user, or other information that labels the user including, but not limited to, Internet Protocol (IP) address, context of an ad and/or ad placement, a user's history, geo-location information of the user, social behavior, inferred demographics, advertising impressions, user clickthroughs, action logs, or some other type of data, and use this data to categorize available advertising channels. An advertising impression log relating to prior advertising placements within the plurality of categorized available advertising channels may be analyzed, using the statistical techniques as described herein, wherein the analysis produces a quantitative association between a user and at least one of the available advertising channels, the quantitative association expressing at least in part a probability of the user recording an advertising conversion within at least one of the available advertising channels 5808. The quantitative association may be stored as a Synthetic User Identifier 5810, and an advertisement may be selected to present to the user within at least one of the available advertising channels based at least in part on the Synthetic User Identifier

5812. Further, the real-time bidding machine facility 142 may use economic valuation model to further classify each of a plurality of available advertisements. The classification may be a datum indicating a probability of each of the available advertising placements achieving an advertising impression. The real-time bidding machine facility 142 may then prioritize the available advertising placements based at least in part on the datum indicating the probability of achieving an advertising impression in addition to using the Synthetic User Identifier. Thereafter, the real-time bidding machine facility 142 may select and present to a user at least one of the plurality of available placements, and/or plurality of advertisements, based on the prioritization. Available advertising channels may also be prioritized using similar statistical methods based at least in part on the Synthetic User Identifier and bidding data or some other type of data used by the analytic platform 114, as described herein.

[00242] In embodiments, the selected advertisement may be presented to a second user that shares an attribute of the user with whom the user Synthetic User Identifier is associated.

[00243] In embodiments, a failure of the user to register a new impression following presentation of the selected advertisement is used by a learning machine facility to update the quantitative association.

[00244] In embodiments, a plurality of Synthetic User Identifiers, each bearing a quantitative association with the other, may be tagged as a consumer cohort to which advertisers may bid on the opportunity to present advertisements using a real-time bidding machine facility. The analysis may include using an economic valuation model that is further based in part on real-time bidding log data. The analysis may include using an economic valuation model that is further based in part on historical bidding data.

[00245] Referring to Fig. 59, in embodiments, the presently disclosed invention may provide methods and systems 5900 for targeting the placement of advertising within an available channel based at least in part on contextual information, the system comprising: a computer having a processor and software which is operable on the processor. The software may include an analytics platform facility that includes at least a learning machine and a valuation algorithms facility. The software may be adapted to: (i) create, at a server facility, a plurality of Synthetic User Identifiers by associating an advertisement with the advertisement's impression data and at least two of user, device, and contextual information as derived from a

plurality of users' interactions with the advertisement 5904; (ii) store the Synthetic User Identifiers in a database accessible to the server facility and separate from a client system 5908; (iii) use the Synthetic User Identifiers to target advertisements to consumers, wherein at least one of the amount, timing or duration of advertising presented to consumers is varied across available advertising channels based at least in part by use of the Synthetic User Identifiers 5910; (iv) analyze the plurality of Synthetic User Identifiers for correlations that indicate an advertisement type may produce a predetermined conversion rate if advertisements are presented through an advertisement channel and with an intensity level, wherein the intensity level is at least one of the amount, timing or duration of the advertising presented 5912; and (v) recommend, for each specific Synthetic User Identifier, an adjusted intensity of advertising associated with the advertisement type, to be presented through each advertisement channel 5914.

[00246] In an embodiment, the assignment of effect achieved by mapping advertising results (identified by different SUIDs) to the SUIDs of the advertisements may be governed by a matrix (M). This matrix may represent a probabilistic model that may disclose overlap between different SUIDs. The matrix (M) may have a column for each possible 'Effect Synthetic User ID' (EID) and rows for each Channel Synthetic User ID (CID). The sum of coefficients in each given row of matrix M will add to 1.

[00247] The coefficients for each specific cell row i , column j of matrix M may be computed by calculating the probability that a certain number of CID_i will have an effect on EID_j . These probabilities may then be normalized to 1 for each given row i column j . The normalization may be needed as CIDs may overlap (e.g., an individual who is a sports aficionado online, might also be targeted through an outdoor panel in a highway). A vector CID of attribution may be computed by multiplying the vector that expresses the effects EID times the matrix (M) through the matricial product.

[00248] Fig. 41 depicts an example of matrix operations (including M effects matrix 4102, CID vector 4104, and EID vector 4108) that may be used to map the number of impressions as expressed through the channel ID to affect the store sales may be provided.

[00249] Fig. 42 illustrates an example of parameters that may create a SUID partition of the advertisement inventory. The parameters include time of the

day in which advertisement is placed (4202), geographical region where the consumer is located (4204), content category along which an advertisement is placed (4208), size of the online advertisement (4210), and browser used to load the advertisement (4212).

[00250] Fig. 43 illustrates an example of a feedback loop for offline data and online data to advertising.

[00251] Referring to Fig. 44, a number of internal machines (including hardware and software components) and services such as a real time bidding machine facility 142, tracking machine facility 144, real time bidding logs 150, impression, click, and action logs 148, and learning machine facility 138 among others, as described herein, that may be used for managing and tracking the advertisement activities in association with SUIDs.

[00252] In embodiments, the real time bidding machine facility 142 may receive bid request messages from an Advertising Distribution Service (ADS) 122. It may be considered as a real time system since bid requests may be responded within certain time constraints. The real time bidding machine facility 142 may also calculate which advertising message to show, while the user is waiting for the system to decide. Data such as SUIDs may be used to model bidding and valuation based at least in part on historical data associated with the SUIDs, such as advertisement success, advertisement conversions, and the like. The system may perform the real time calculations such as by dynamically estimating an optimal bid value using algorithms that include SUIDs that are provided at least in part by the learning machine facility 138.

[00253] The real time bidding logs 150 may include records of bid requests received and bid responses sent by the real time bidding machine facility 142. These logs may contain data regarding the sites visited by the user. This may be further used to derive user interests, browsing habits, and to compute SUIDs. Additionally, these logs may record the rate of arrival of advertising placement opportunities from different channels.

[00254] In embodiments, the learning machine facility 138 may be used to develop targeting algorithms for the real time bidding engine, including targeting algorithms that are based at least in part on SUIDs. It may adopt patterns, including social behavior, inferred demographics, inferred SUIDs, among others, which may be used to better target online advertisements. The learning machine facility 138 may

also utilize the impression, click, and action logs 148 produced by the tracking system.

[00255] The interaction and coordination among the various machines may be described using a scenario where an advertiser A places an “order” with instructions limiting and/or describing location and time for an advertisement placement. In an embodiment, these instructions may include the selection of targeting parameter, such as SUIDs provided by the methods and systems, as described herein. The order may then be executed across multiple channels. The advertiser may specify a criterion of ‘goodness’ for the campaign to be successful. A ‘goodness’ criteria may be measured through specific metrics that may be tracked through recording of activities that the user may complete at the advertiser website, or through off-line purchases, visits or other interactions with the advertiser.

[00256] Continuing the example, as a next step, the system may divide the available channels to place advertisements (online and offline) into smaller sections, for example where each section represents a SUID. The division may be based on a combination of parameters such as time of day, day of week, type of content, user geographical location, user browser, or some other data type. In an example, the division for T.V. media can be based on geography, time of day, day of week, type of content, and the like. For magazines, the division may be based on month of the year, geography (for magazines running multiple advertising regions), and type of content. The criteria of ‘goodness’ specified by the advertiser and the distribution of positive outcomes may be codified so that a positive outcome can be assigned to one or more SUIDs. For online advertisements, the combination of parameters may result in highly granular links that identify a few users for each SUID.

[00257] In embodiments, a learning system may be used to leverage the information pertaining to which SUIDs were more successful in creating desired outcomes versus others. This learning system may develop customized targeting algorithms based on what has been successful. The algorithms may calculate an expected value of the advertisement based on the given conditions, and may seek to maximize the specified ‘goodness’ criteria.

[00258] In the case of real time bidding, algorithms may be received by the real time bidding machine facility 142, which may wait for opportunities to place the advertisement. Bid requests may be received by the real-time bidding machine. Each request may be evaluated for its value for each advertiser, using the received

algorithms (which may utilize SUIDs). Bid responses may be sent for advertisements that have an attractive value. Lower values may be bid if they are estimated appropriately. The bid response requests may then be placed at a particular price.

[00259] On the other hand, in the case of non-real time advertisement purchases, algorithms may be received by a non-real time order creation system that will decide how much budget to allocate to each advertising channel, with the degree of granularity as the advertising channel supports. For example, it may not be possible to buy T.V. spots at a specific hour, but may be in another programming time slot, such as morning, afternoon, evening, or night. For non-real time advertisement purchases, metrics about advertisements running times, reach, and other parameters may be collected through off-line methods, and the related data may be added to the system.

[00260] For online media, the tracking machine facility 144 may log advertisement impressions, user clicks, and/or user actions. The tracking machine facility 144 logs may be further sent to the learning system, which may use the ‘goodness criteria’ and decide regarding the improvement and customization of algorithms. This process may be an iterative process.

[00261] In accordance with various embodiments, the present invention facilitates grouping of users (as required) to describe them through media, consumer, and creative attributes that the users share. Each of these groups may be assigned an SUID, which describes groups as granularly as possible. In the case of online, mobile, and video over IP content, combined SUIDs may result in describing very few individuals or just one. Simultaneous tagging of users with multiple SUIDs may be possible. However, the degree of granularity for each SUID and parameters that describe each SUID may vary across channels or for other reasons. Nevertheless, identification of positive results, and linking of positive results with one or more SUIDs, may be possible for the advertiser using the methods and systems, as described herein. Further, the present invention may facilitate the creation of a feedback data process whereby data from advertisements placed under each SUID may be aligned with the results achieved, even when it may not be possible to map each advertisement and unique individual with a result. In embodiments, the present invention may enable automatic reallocation of budgets across channels.

[00262] In accordance with an embodiment of the present invention, methods and systems for global yield management for buyers and sellers of digital

and analog media that may measure and maximize the performance of advertising campaigns is provided. Examples of digital media may include, but are not limited to, display advertisements, video advertisements, mobile advertisements, search advertisements, email advertisements, IPTV, and digital billboards. Examples of analog media may include, but are not limited to, radio, outdoors panels, indoors panels, print media, or some other type of analog media.

[00263] In embodiments, the methods and systems may enable a reverse auction that may allow buyers to maximize their results. In an example, sellers of advertisements may connect with the Global Yield Manager-Buyer (GYM-B 4712) system, calling it when trying to sell one or a plurality of advertisement opportunities. Buyers may observe the offer to sell and make purchase decisions, seeking to maximize their own benefit. In any of these cases, the system may keep record, and observe rules about which advertisers are allowed for each publisher and vice versa.

[00264] In an embodiment, a buyer may call the seller asking for advertisements to be sold. In another embodiment, the system may look to the buyer as an ad server that may be called each time the seller decides to offer an opportunity to place one or more advertisements to the buyer. In a simplified example, there may be a single advertiser associated with the Global Yield Management system. In such a case, there may not be options available from the buyers' perspective (i.e., all impressions provided by the publisher may be used). In addition, the price to pay for each advertisement placement opportunity may be fixed and the advertiser may have multiple versions of the advertisement that may be used for each placement opportunity. In this case, the GYM-B 4712 may decide in only one dimension: which creative(s) to show and the optimization may seek to maximize the campaign performance, as measured by the success metric for such a campaign. Further, GYM-B 4712 may have specific performance goals for each publisher associated with the GYM-B 4712; and when those goals are not achieved, it may trigger an automated email, communicating this fact to the operator and/or publisher.

[00265] In another example, there may be a single advertiser associated with the Global Yield Management system and options may be available from the buyers' perspective (i.e., the buyer may not use an impression and may not pay for it). In addition, the price to pay for each advertisement placement opportunity may be fixed and the advertiser may have multiple versions of the advertisement that can be used for each placement opportunity. In such a scenario, the GYM-B 4712 may

decide on two dimensions: whether to take an advertisement or a plurality of advertisements, and which creative(s) to show. Further, the optimization may seek to maximize the campaign performance, as measured by the success metric for such campaign. The GYM-B 4712 may have specific performance goals for each publisher associated with the GYM-B 4712, and when those goals are not achieved, it may trigger an automated email, communicating this to the operator and/or the publisher.

[00266] In an example embodiment to illustrate the concept of optionality, an advertiser may include a publisher-advertiser deal involving a fixed budget and price. In this case, the system may keep track of the remaining publisher budget as time and purchases progress, and may decrement the budget for each advertisement placed. The negotiated deal may result in an “advertisement placement.” Further, integration may be achieved, at least in part, through standard advertisement tags. Advertisement tags may be unique by publisher deal and pool (e.g., publishers may have multiple deals within a pool).

[00267] In an embodiments, inventory optionality may be provided. Thus, the system may consume only an agreed to budget amount that is independent of call volume. In an embodiment, the system may decide which calls to accept. For unaccepted calls, the system may return a pre-assigned URL. The pre-assigned URL may be decided by publisher, advertiser, and the like. Advertisement tags may capture information such as URL of the page, user agent information (OS, browser, resolution, etc.), cookie access (for user ID, others if stored at cookie), IP address of user, ID of the pool, ID of the publisher specific advertisement tag, and other information that publishers may share (e.g. demographics from login). In addition, advertisement tags may use Javascript or an alternative coding for data capture. Fig. 45 illustrates a simplified embodiment of the chain between publisher and advertisement networks, in accordance with an embodiment of the present invention. In an embodiment, the system may evenly distribute placement budget along all days where placement may be active. Further, budget pacing may be independent of advertisement call volume. Pacing may be held periodically (e.g., daily). In example embodiments, monthly or lifetime pacing may be allowed. In other embodiments, publishers may see an aggregated even pacing, even when individual advertisers may buy more or less each day. Each publisher in the GYM-B system may be a substitute for another, even if prices are different.

[00268] In accordance with embodiments of the present invention, if a campaign objective exists, then the system may maximize the value of the placement. Mathematically, it may be represented as: *Value of placement = Sum of bids (as calculated by the Real Time System bidding machine) minus sum of inventory cost (either the fixed or variable cost agreed between the buyer and seller, and recorded in the pool database)*. Further, the system may maximize the sum of bids as inventory cost is fixed. In case there is no campaign objective, the bid may be the CPM price specified in the required fixed. A flight is understood as a subdivision of a campaign, with an assigned budget, defined targeting parameters that describe the media to use to show ads, and an specific set of advertising messages and graphics to show using such media. An advertising campaign is executed through one or more flights. . Thus, benefit may be achieved on consolidated buy and using all available data for performance measurement and optimization. The pool may rely on RTS 4502 valuation to evaluate advertisement fitness.

[00269] In another embodiment, the data structures may be linked to GYM-B 4712 such that the GYM-B 4712 system holds multiple publisher placements. The placements are to publishers, as behave like the campaign flights, are to advertisers; the placement enables a publisher to exercise some control as to how much budget to provide through each, and which advertisers can use them. There may be a plurality of GYM-B 4712 system attributes such as GYM-B 4712 system Name, Placements that belong to it, Controlling entity (the controlling agency may be an advertiser, or an ad agency or the like), Pool Budget, Flight it is linked to, Pool start and end date (inventory must be bought), or some other attribute. In embodiments, there may be a plurality of publisher placement attributes such as Placement Name, Publisher name, Pool it belongs to, Placement Budget, CPM price, call volume, Placement start and end date, Pass-back advertisement tag, Placement-specific industries, advertisers' blacklist, or some other attribute.

[00270] In accordance with various embodiments of the present invention, user interface (UI) functionality may be provided for a GYM-B 4712 system. The UI may facilitate the functionality of the GYM-B 4712 system, such as allocating budget to GYM-B 4712 system. The UI may facilitate the selection of an inventory source type, and entering new GYM-B 4712 system attributes, GYM-B 4712 system name, GYM-B 4712 system budget, advertiser name, start and end dates inherited from flight, or some other attribute. A newly created pool may appear only to the

advertiser that created the pool. Further, placements for each publisher in GYM-B 4712 system may be created. Placements may be added using the UI in a manner similar to adding flights to a campaign. For the creation of placements, variables such as placement name, publisher name, placement budget, CPM price, call volume, placement start and end date, pass-back advertisement tag, Placement-specific industries, advertisers' blacklist, and the like may be provided. The UI may provide advertisement tags to send to the publisher. Subsequently, this may be integrated with, for example, emails. The UI may also include additional screens to add placements similar to adding flights.

[00271] The UI may also provide access to reporting such as pool level reporting, placement level reporting, placement level performance, top level domain reporting, billing reporting for reconciliation, and the like.

[00272] Pool level reporting may include volume of advertisements by day and/or by creative, or some other criterion. Placement level reporting (e.g., for each publisher flight) may include volume by day and pass-back percentages. Further, placement level performance (e.g., for each publisher flight) may include valuation/performance that may be equal to the difference of the sum of bid values and sum of advertisement costs. Similarly, the top level domain reporting may include top level domains with daily and monthly cumulative volume, and daily and monthly cumulative uniques. The billing reporting for reconciliation for each publisher flight may include last six months, and month-to-date information, consumed budget, impressions acquired, calls received, percentage of pass-back, or some other information. In an embodiment, all budgets may come from single flight, with definite starts/end dates. Alternatively, multiple advertisers may start and end campaigns that use ads from a placement, within the pool start and end dates.

[00273] In another example, there may be a plurality of advertisers associated with the Global Yield Management system such that there is optionality from the buyers' perspective (i.e., the buyer may not use some impression, and may not pay for them). The price to be paid for each advertisement placement opportunity may be fixed and the advertiser may have multiple versions of the advertisement that may be used for each placement opportunity. In this case, the GYM-B 4712 may make decision on, for example, three dimensions, whether to take the advertisement(s) or not, which advertisers should take the advertisement or advertisements, and which creative(s) to show for that advertiser. The optimization

may seek to maximize the sum of a campaign's performance as measured by the success metric for each campaign. There may be some campaigns for which the goals may not be completed. This may be considered while setting priorities by the operator of the GYM-B 4712. The operator of the GYM-B 4712 may have volume goals, which may be taken into account to decide whether to take an impression or not. Further, the GYM-B 4712 may have specific performance goals for each publisher associated with the GYM-B 4712, and when those goals are not achieved, it may trigger an automated email, communicating this to the operator and/or the publisher.

[00274] In another example embodiment, there may be several advertisers associated with the Global Yield Management system. There may be optionality from the buyer's perspective (i.e., the buyer may not use some impression, and may not pay for them). The price to pay for each advertisement placement opportunity may be variable. The advertiser may have multiple versions of the advertisement that may be used for each placement opportunity. In this case, the GYM-B 4712 may decide on multiple dimensions, for example, whether to take the advertisement (s) or not, how much to pay for them, which advertisers should take the advertisement(s), and which creative(s) to be shown for that advertiser, among others. The optimization may seek to maximize the overall value of the market by reaching a maximum performance as measured by the success metric for each campaign for all campaigns linked and by paying the lowest possible price for each impression. Alternatively, the optimization may seek to pay impressions 'at value' or 'at value less margin', thereby incentivizing publishers to participate by paying high prices for selected opportunities. Publishers with high densities of good opportunities may receive overall higher prices, creating an incentive for good quality content to participate. In addition, the operator of the GYM-B 4712 may have volume goals, which may be taken into account to decide whether to take an impression or not. There may be some campaigns that may not be able to complete the goals; for them, priorities can be set by the operator of the GYM-B 4712. Further, the GYM-B 4712 may have specific performance goals for each publisher associated with the GYM-B 4712, and when those goals are not achieved, it may trigger an automated email to communicate this to the operator and/or the publisher. It may be noted that each publisher may optionally specify a 'floor price' under which it may not sell its advertisements.

[00275] Moreover, the above scenario includes multiple advertisers that may participate from the same GYM-B 4712 system. The RTS 4502 may decide which advertiser and advertisements to show. The RTS 4502 may have an organic solution for deciding which advertiser and advertisements to show. Although the RTS 4502 may not solve publisher pacing, the pool may decide which advertisement call to use and which to pass-back. The embodiments of this system facilitate reduction of complexity at the RTS 4502 core and enable a transparent policy facing publishers and publisher optimizers.

[00276] The functionalities of the GYM-B 4712 system may also include receiving an advertisement call, translating and calling the RTS 4502, deciding whether to take the call or pass-back, sending the right answer (advertisement tag or pass-back address), recording these and other events processing events using its infrastructure.

[00277] Fig. 46 depicts the temporal relationship between multiple inventories and advertising campaigns with multiple starting and ending dates for available budgets. The UI functionality for the GYM-B 4712 system may enable the assignment of a name to a pool and for campaigns inside the scope of a creating entity (where the pool shows up as an available inventory source). The UI may also display the budget tab (e.g., a budget sum of budgets of associated flights). Using the UI, new flight budgets may be added at any time. In embodiments, multiple flights may provide budgets and multiple advertisers may be sourced from inventory.

[00278] In embodiments, budget options may be balanced by allowing only new flights with corresponding new inventory and matching times and budgets. A pool may be a 'meeting place for exchange' between advertisers and the pool may be balanced. In other embodiments, budget options may be balanced by restricting flights and budgets to start/end on a weekly basis to ensure that the available inventory may be sold each week. It may be assumed that flight pacing may vary (e.g., if nominal pacing is USD1K/day, actual may vary from USD0/day to USD3K/day). Further, in embodiments of the invention, publishers' placements pacing may also vary.

[00279] The UI may be designed to handle allocation issues across different pricing frameworks (i.e., fixed or variable mark up percentage) and different rates that might be paid by advertisers.

[00280] In other embodiments of the present invention, the UI may allow publishers or advertisers to self-serve. The UI may integrate reporting, other pricing modalities (variable CPM with floor), other pass-back mechanisms, and secondary premium, and the like. Pass-back may be resold as a block or impression by impression.

[00281] In embodiments, an advertisement tag may call a proxy. The call may include cookie information, agent, and other variables. Javascript, or some other method, may be used to create the call; the Javascript code may be served from CDN so that an advertisement tag may be compact and customized when required. Further, the decision to take or not take advertisement may happen at the proxy. Using a proxy simplifies the implementation as it keeps most of the already built bidding infrastructure intact. Advertisement tag information may be translated into an RTS 4502 format, for example, by adding a Faux Exchange ID. The Faux Exchange ID may be unique per advertisement tag. In an embodiment, a lookup table may be created to categorize inventory, and forward that information in an RTS 4502 call (e.g. for every impression from XXNews, Category = News and for every impression for AA, Category = Business). Moreover, advertisement flights may be targeted at a Faux Exchange ID(s).

[00282] It may be understood that for all the described scenarios herein, there may be a variant where impressions (that are not used) may be passed to a secondary buyer, who will take them without the options. This variant may require the agreement of the publisher, as their advertisement opportunity will be placed with this secondary buyer. For scenarios where there is no optionality, the variant may create one.

[00283] In embodiments, use of GYM-B 4712 may facilitate penetration of advertiser budgets. Advertisers may in turn achieve centralized reporting and optimization. Advertising agencies may improve campaign performance by impression inventory allocation. Further, content safety issues with unknown publishers may be effectively resolved. For cases, where advertisers negotiate media buy outs and inventory may be sourced from premium sites or high quality portals; and with a guaranteed budget, the system may select right advertisement to show for impression. The system may leverage campaign placements for learning, unify reporting, and provide early automated reports on publisher performance. For cases, where publishers execute negotiated media buys and advertisements are sold to

premium brands with protected prices, the system may select a suitable advertiser and page to show for an impression. The system may leverage all campaign placements for learning, unify reporting, and provide automated reports on advertiser performance. Publishers may be used to deal with ad servers and daisy chains as shown in Fig. 45. The system may further facilitate the use of an advertisement call that may send a user browser to an actual ad server to retrieve a graphic or a redirect that may send a user browser to the next level in the chain.

[00284] In another embodiment, the system may work by selecting the advertisements to sell, and the minimum price to accept for a bid, and assigning those advertisements to different buyers. A first buyer may be an advertisement biddable exchange, a second buyer may be an advertiser, and a third buyer may be a reseller. Each of the buyers may have different conditions for buying advertisements, paying premiums in some conditions, and not taking advertisements in others. One objective of the GYM-Seller (GYM-S) may be to help the seller to maximize the monetization of the advertisement inventory sold.

[00285] In one of the implementations, sellers may use the system to send offers to sell an advertisement(s).

[00286] The GYM-S 4814 system may decide which buyer will get an advertisement or advertisements, what information to attach to an advertisement or advertisements, what is the acceptable price to sell, whether to accept the bid or not, what floor price to be communicated, whether to offer optionality with the offer to sell, and at what price to do so, or some other information. The information attached with the advertisement(s) may vary, and may either include the publisher identity or may make it anonymous. The system may keep a record, and may respect rules about which advertiser(s) are allowed for each publisher and vice versa.

[00287] In an example, there may be a single seller and a single buyer associated with the Global Yield Management system. There may not be optionality from the buyers' perspective. All calls with advertisement opportunities from seller may be responded by the buyer with an advertisement bid. Similarly, there may not be optionality from the seller's perspective such that all bids sent by buyers may be accepted. The price that is bid for each advertisement placement opportunity may be fixed i.e., all bids may be at the same fixed price. The advertiser may have multiple advertisement sizes and a page may be sent to the buyer. This page may be a part of the other pages provided by the publisher, or it may belong to a specific category of

content. In this case, the GYM-S 4114 may decide in only one dimension (e.g., advertisement size) to be sent. In the case where there is no signal from the buyer to the seller indicating which inventory performs better, the optimization strategy may be to send advertisement opportunities with the lowest possible alternative monetization to the buyer. However, in the case where there is a signal that indicates what advertisements perform better, the strategy may be to maximize performance by sending the highest performing pages with the lowest possible alternative monetization.

[00288] In embodiments, the GYM-S 4114 may have specific monetization goals (revenue per thousand advertisements sold) for each publisher associated with the GYM-S 4114, and when those goals are not achieved, it may trigger an automated email, communicating the operator and/or the advertiser of this fact.

[00289] As another example, there may be a single seller and multiple buyers associated with the GYM-S 4114 system. There may not be optionality from the buyers' perspective. All calls with advertisement opportunities from seller may be responded by the buyer with an advertisement bid. Similarly, there may not be optionality from the seller's perspective such that all bids sent by buyers may be accepted. The price that may be bid for each advertisement placement opportunity may be fixed (all bids may be at the same fixed price). The advertiser may have multiple advertisement sizes and a page may be sent to the buyer. This page may be a part of other pages provided by the publisher, or it may belong to a specific category of content. In this case, the GYM-S 4114 may decide on dimensions, such as, advertisement size, a page to be send, and buyer to send it to. In the case where there is no signal from the buyer to the seller indicating which inventory performs better, the optimization strategy may be to send advertisement opportunities with the lowest possible alternative monetization to the buyer. However, in the case where there is a signal that indicates which advertisements perform better, the strategy may be to maximize performance by sending the highest performing pages, with the lowest possible alternative monetization. GYM-S 4114 may have specific monetization goals (revenue per thousand advertisements sold) for each publisher associated with the GYM-S 4114, and when those goals are not achieved, it may trigger an automated email, communicating the operator and/or the advertiser of this fact.

[00290] In other example, there may be a single seller and multiple buyers associated with the GYM-S 4114. There may not be optionality from the buyers'

perspective. All calls with advertisement opportunities from the seller may be responded to by the buyer with an advertisement bid. Further, there may be optionality from the seller's perspective (e.g., not all bids sent by buyers may be accepted). The price that is bid for each advertisement placement opportunity may be fixed (e.g., all bids may be at the same fixed price). Furthermore, the publisher may have multiple pages, each with different types of content and each with multiple ad sizes available for ads placement; the publisher can decide which specific page to send to the buyer, and within that page, which ad size to send. In this scenario, the GYM-S 4114 may decide in dimensions, such as, advertisement size and page to be sent, buyer to send it to, and whether to accept the resulting bid. In the case where there is no signal from the buyer to the seller indicating which inventory performs better, the optimization strategy may be to send advertisement opportunities with the lowest possible alternative monetization to the buyer. In the case where there is a signal that indicates what advertisements perform better, the strategy may be to maximize performance by sending the highest performing pages, with the lowest possible alternative monetization. The GYM-S 4114 may have specific monetization goals (revenue per thousand advertisements sold) for each publisher associated with the GYM-S 4114; and when those goals are not achieved, it may trigger an automated email, communicating the operator and/or the advertiser of this fact.

[00291] In another sample embodiment, there may be a single seller and multiple buyers associated with the GYM-S 4114. There may be optionality from the buyers' perspective. For example, not all calls with advertisement opportunities from a seller may be responded to by a buyer with an advertisement bid. Similarly, there may be optionality from the sellers' perspective; not all bids sent by buyers may be accepted. The price that may be bid for each advertisement placement opportunity may be fixed. Further, the advertiser may have multiple advertisement sizes and a page may be sent to the buyer. In this case, the GYM-S 4114 may decide in dimensions, such as, advertisement size and a page to be sent, the buyer to whom the page may be sent, and whether to accept the resulting bid. The system may utilize a "no bid by buyer" signal to measure the level of interest in inventory, and it may send pages with the highest likelihood of getting a bid, and with the lowest possible alternative monetization. The GYM-S 4114 may have specific monetization goals (revenue per thousand advertisements sold) for each publisher associated with the

GYM-S 4114, and when those goals are not achieved, it may trigger an automated email, communicating the operator and/or the advertiser of this fact

[00292] In another example, there may be multiple sellers and multiple buyers associated with the GYM-S 411. There may be optionality from the buyers' perspective. For example, not all calls with advertisement opportunities from a seller may be responded to by the buyer with an advertisement bid. Similarly, there may be optionality from the seller's perspective; not all bids sent by buyers may be accepted. The price that is bid for each advertisement placement opportunity may be fixed (all bids may be at the same fixed price). The advertiser may have multiple advertisement sizes and a page may be sent to the buyer. In this case, the GYM-S 4114 may decide in dimensions, such as, which seller to use, which advertisement size and page to send, which buyer to send it to, and whether to accept the resulting bid. The system may take advantage of the "no bid by buyer" signal to measure the lack of interest in inventory, and it may send pages with the highest likelihood of getting a bid, and the lowest possible alternative monetization. The GYM-S 4114 may have specific monetization goals (revenue per thousand advertisements sold) for each publisher associated with the GYM-S 4114, and when those goals are not achieved, it may trigger an automated email, communicating the operator and/or the advertiser of this fact.

[00293] In another example, there may be multiple sellers and multiple buyers associated with the GYM-S 4114. There may be optionality from the buyers' perspective. For example, not all calls with advertisement opportunities, from seller, may be responded by the buyer with an advertisement bid. There may be optionality from the seller's perspective; not all bids sent by buyers may be accepted. Further, the price that is bid for each advertisement placement opportunity may be variable. The advertiser may have multiple advertisement sizes and a page may be sent to the buyer. In this case, the GYM-S 4114 may decide in dimensions, such as, which seller to use, which advertisement size and page to send, which buyer to send it to, and whether to accept the resulting bid. The system may utilize the "no bid by buyer" signal, and the price bid signal to measure the level of interest in inventory, and it may send pages with the highest likelihood of getting a bid and with the lowest possible alternative monetization. The GYM-S 4114 may have specific monetization goals (revenue per thousand advertisements sold) for each publisher associated with the

GYM-S 4114, and when those goals are not achieved, it may trigger an automated email, communicating the operator or the advertiser of this fact.

[00294] Fig. 47 and 48 are schematic representations of an exemplary GYM for buyers and sellers using a proxy translator in real time bidding calls, in accordance with an embodiment of the present invention.

[00295] Fig. 49 depicts another schematic representation of an exemplary GYM for sellers using real time bidding system for valuation, in accordance with an embodiment of the present invention.

[00296] In accordance with various embodiments of the present invention, there may be external and internal machines (including software and hardware components) and services in the system. Examples of external machines or services may include agencies or advertisers, agency data campaign descriptor, agency data historic logs, advertiser data 152, key performance indicators, historic event data 154, user data, contextualize service, real time event data, advertising distribution services, advertising recipient, or some other type of external machine and/or service.

[00297] In embodiments, an agency data campaign descriptor may describe the channels, times, and budgets that may be allowed for diffusion of advertising messages. Agency data historic logs may describe the placement for each advertising message to a user, including, for example, one or more of a user identifier, the channel, time, price paid, advertisement message shown, and user resulting user actions. Additional logs may also record spontaneous user actions. Advertiser data 152 may include, but is not limited to, business intelligence data that may describe dynamic or static marketing objectives (e.g., the amount of overstock of a given product that the advertiser has in its warehouses.)

[00298] Key Performance Indicators (KPI) may be the set of parameters that express the ‘goodness’ for each given user action. For example, product activation may be valued at some specified price X, and a product configuration can be valued at a different price Y The KPI will be expressed as the sum of these different campaign goals (in this example: product activation, and product configuration), each with specific weights.

[00299] Historic event data 154 may be significant since the real time bidding system may attempt to correlate the time of user events with other events happening in their region. For example, response rates to certain types of advertisements may be correlated to stock market movements. Historic event data

154 may include, but is not limited to, weather data, events data, or local news data. User data block may include data provided by third parties that may contain personally linked information about advertising recipients. This information may show users preferences or other indicators that label the users. Further, a contextualizer service may identify the contextual category of a medium for advertising. For example, a contextualizer may analyze the web content to determine whether a web page contains content about sports, finance, or some other topic. This information may be used as input to the learning system, to better refine which advertisements may appear on which types of pages. Real time event data may include data similar to historic data, but is up to date (e.g., for seconds, minutes, hours, or days). For example, if the learning machine facility 138 identifies a correlation between advertisement performance and historic stock market index values, the real-time stock market index value may be used to value advertisements by the real time bidding machine facility 142. Examples of advertising distribution services may include Ad Networks, Ad Exchanges, Sell-Side Optimizers, and the like.

[00300] The advertising recipient may be a person who receives an advertising message. The content may be specifically requested (“pulled”) as part of or attached to content requested by the advertising recipient, or “pushed” over the network by the advertising distribution service. Some non-limiting examples of modes of receiving advertising may include the Internet, mobile phone display screens, radio transmissions, television transmissions, electronic bulletin boards, printed media, and cinematographic projections.

[00301] In embodiments, examples of external machines or services may include, but are not limited to, real time bidding machine facility 142, tracking machine facility 144, real time bidding logs 150, impression click and action logs 148, and leaning machine.

[00302] An operator of GYM for Buyers (GYM-B 4712) may create placements for each publisher that it may intend to associate with. Each of these placements may have several parameters. The operator or an agent may negotiate to buy media under certain conditions with a publisher. The publisher and operator may agree on a certain number of impressions, price to pay, and whether there is the opportunity of not using some impressions. In some cases, the price to pay may also be left undecided. In an embodiment, the publisher may call the GYM-B 4712 whenever an advertisement opportunity appears. The GYM-B 4712 may decide

which advertisement to use and in some cases, which advertiser should use the advertisement, whether the impression is used, and how much to pay for it. In order to decide, the GYM-B 4712 may use multiple constraints, including the value of the advertisement to each advertiser, the pacing of the publisher relative to goal, the pacing of the advertiser campaign, whether the consumer has reached its frequency limit, and whether the operator is able to use publisher media for a given advertiser. Once a decision is made, the GYM-B 4712 may send a call to an advertising distribution service to deliver the advertisement. In a case where the impression is not to be used, the GYM-B 4712 may re-sell it to a secondary market or return it to the publisher for the publisher to use.

[00303] The GYM-B 4712 may keep track of impression calls received through each publisher deal, such as the values of these opportunities, whether it was taken or not, and which advertiser and creative took it. Statistics may be created to depict which publisher deals are more valuable than others, how many times advertisement impressions were rejected/taken, and which advertisers or creative(s) are using the impressions for a given publisher. The GYM-B 4712 may also provide analytics at the page level of the significantly effective pages for each publisher, thereby providing an input to the publisher about what content is most effective. Reporting created from the GYM-B 4712 may be used to bill the advertiser about the media used, and to correlate bills received from publishers with actual media consumed by the advertisers. Moreover, statistics about performance by publisher may be used to trigger automated email messages to the operator, publisher or both when certain conditions are met.

[00304] The GYM-S 4814 may maximize benefits on behalf of publishers, in accordance with an embodiment of the present invention. The GYM-S 4814 may work on behalf of one or many publishers, and be associated with several advertisers. The operator of the GYM-S 4814 may create placements for each advertiser and publisher it may intend to associate with. An operator or an agent may negotiate to buy media under certain conditions with one or more buyers. The buyer and operator may agree on certain number of impressions, price to pay, and whether there is the opportunity of not using some impressions. In some cases, the price to pay may also be left undecided. The GYM-S 4814 may assign each advertisement opportunity to an advertiser that may maximize the monetization on behalf of the publisher. An estimation regarding this may be created by querying an instance of the real time

bidding system that may include valuation frameworks for participating advertisers. These frameworks may have been created using machine learning, including the machine learning and analytic platform depicted in Fig. 1A, that takes into account each advertiser campaign KPI. The GYM-S 4814 may decide which advertisement to use and in some cases, whether the impression may be used, which advertiser should use it, and how much to be paid for it. For this purpose, the GYM-S 4814 may use multiple constraints, including the value of the advertisement to each advertiser, the pacing of the publisher relative to goal, the pacing of the advertiser campaign, whether the consumer has reached its frequency limit, whether the operator is able to use publisher media for a given advertiser, and what the alternative realization price is for such advertisement with other advertisers. Once a decision is made, the GYM-S 4814 may send a call to the advertiser's advertisement distribution service to deliver the advertisement, or if the impression is not to be used, it may re-sell it to a secondary market or return it to the publisher for the publisher to use.

[00305] In embodiments, the GYM-S 4814 may keep track of impression calls received from each publisher and delivered to each advertiser, how much each of these opportunities was valued, whether it was taken or not, and which advertiser and creative took it. Therefore, statistics may be created to show which advertisers are more valuable than others, how many times advertisement impressions were rejected/taken, and which advertisers or creative(s) are using the impressions for a given publisher. The GYM-S 4814 may also provide analytics at the advertisement message level of the most effective advertisers for each publisher (most valuable); thereby providing an input to the publisher about what content is most effective. Reporting created from the GYM-S 4814 may be used to bill the advertiser about the media used, and to correlate bills received from publishers with actual media consumed by the advertisers. Moreover, statistics about performance by publisher may be used to trigger automated email messages to the operator, publisher, advertiser or to some or all of them, when certain conditions are met (e.g., in cases where media received is less than the requirement in a given period, media received was underperforming, media more than the requirement was sent, contract is about to finish, advertiser advertisements are underperforming, etc.)

[00306] The present invention facilitates real time optimization for online media acquired with negotiated deals and with fixed conditions. The real time optimization for online media may be sold with negotiated deals and with fixed

conditions. The present invention further facilitates managing yield of such media, across multiple advertisers and using a simple to use integration system. Similarly, the present invention facilitates managing yield of media across multiple publishers, using real time bidding system.

[00307] In an embodiment of the present invention, a real time bidding system to decide on advertisement value may be used. In another embodiment of the present invention, a dynamic pricing adjustment that may trade negotiated media and exchange media for each advertisement opportunity may be used. In yet other embodiment, a dynamic pricing that may trade publishers in real time to monetize content effectively may be used. The present invention may facilitate creation of a market across publishers' negotiated deals that may compete for the budget of all available advertisers and creation of a market across advertiser negotiated deals, which may be traded in real time for impressions available from publishers. Further, the present invention may facilitate reduction of waste, since the maximum number of advertisements per consumer may have reached for one advertiser, but another one may be able to use the impression with benefit. The present invention may be use to create an early alert system that may communicate to publishers, advertisers, operators or a combination of them when media acquired through negotiated deals or advertisements placed may be underperforming relative to goals or past performance, or when the media may be out of the pre-negotiated parameters (impressions per day, etc.).

[00308] In accordance with various embodiments of the present invention, a system for multi-channel decisions for acquiring media for placing advertising may be executed in real time (such as an acceptable time constraint, which may depend on the media channel where the media is acquired). Examples of the channels upon which the multi-channel decisions may be made may include online display advertising, mobile display advertising, online video advertising, online search advertising, email advertising, TV advertising, cable advertising, Addressable IP-TV advertising, Radio advertising, Newspaper advertising, Magazines Advertising, Outdoor advertising, and the like.

[00309] The system may use a uniform framework to decide where to place advertisements across multiple channels, including those described above. The uniform framework may assign a value to each advertisement opportunity, and may decide on the message to be presented to the consumer. The framework may provide

valuation to single advertisements and to a set of advertisements. Further, the system may automatically adjust media plans to execute campaigns by assigning a lower value to advertisements that may be less effective, which may either force the seller to lower their prices or not sell at the offered price. Sellers may make their advertisement opportunities attractive by lowering the prices. On the other hand, by not accepting to sell, they may drive a budget reallocation to other effective advertisement opportunities. In both cases, the valuation function may define the media plan, may adjust buying volumes, and reallocate budgets.

[00310] The framework of the present invention, include the learning machine and analytic platform depicted in Fig. 1A, may be used to describe multiple channels; therefore, these changes may trade off one channel against another. As the framework is constantly refreshed, the framework may constantly adjust how each channel is used and how they interact based on results. This may subsequently result in the selection and tradeoff of the best way to reach consumers across all media channels. The framework may be represented, for example, as a mathematical function or an algorithm, with multiple variables as input and one or many variables as output. The input of the mathematical function may include parameters that describe “Ad Placement Opportunities” (APO). For example, the mathematical function may receive input variables such as “time of day” for placing the advertisement 5002, “geographical region” where the consumer is located 5004, “type of content” on which advertisement may be inserted 5008, “size of the online advertisement” that may only be valid for online display advertisements 5010, “length of the TV spot” that is only valid for TV advertisements 5012, “print advertisement size” 5014, “odd or even page” that is only valid for print advertisements 5018, “channel used” that tells the mathematical function about the type of advertisement placed 5020, “consumer ID” that can be an actual consumer ID or a Virtual Global Consumer ID 5022 as shown in Fig. 50. Additionally, the input variables may be “impressions” that may describe the size of the purchase in number of messages delivered, “number of consumers” that may describe the size of the purchase in number of consumers impacted, and “budget” that may describe the size of the purchase in monetary value. The list of the input parameters is exemplary and there may be other input parameters that may be involved in a framework for an advertisement campaign with three channels such as online display, TV, and print.

[00311] Considering an example where a TV spot may be evaluated by the system, the input parameters “time of day”, “geographical region”, and “type of content” may not be provided. In this scenario, the mathematical function may be able to provide an answer in cases where parameters are not provided, assuming a typical distribution for each of the parameters. Similarly, parameters “size of online advertisement”, “odd or even page”, and “consumer ID” may not be applicable. The mathematical function may ignore the fact that these parameters may not be relevant in this context. However, parameters “length of the T.V. spot” and “channel used” may be available and may also be used. Parameters “impressions”, “number of consumers”, and “budget” illustrate the size of the decision, and at least one of them may be provided. As a consequence, each combination of parameters (variables) describes an “Ad Placement Opportunity” (APO). The combinations that may not be feasible (e.g., TV advertisement with “odd or even page” value), may not create a valid APO. The output of the mathematical function may at least be a “value” for the advertisement opportunity, either as an index, or as a monetary value. Additionally, the system may help select the message to show through one or more additional output variables that can describe the message. Examples may include concept of the advertisement to use from a list of concepts, the variation of the advertisement to use from a list of available variations, and the call to action of the advertisement to present to the consumer from a list of available CTA. Mathematically, it may be represented in one embodiment as is listed below:

$$\text{advertisement}(\text{value}, \text{concept}, \text{variation}, \text{CTA}) = f(\text{TOD}, \text{GEO}, \text{TOC}, \text{SIZE}, \text{Length}, \text{OorE}, \text{Chan}, \text{ConsID}, \text{Imp}, \text{NofCons}, \text{Budget})$$

[00312] In embodiments, the APO and message shown may impact consumers and, subsequently, influence the valuation and output message from the framework. The impact on consumers may depend on the nature of the advertisement campaign, the brand, and the advertising market. Therefore, the output of this framework may be different for each campaign and market state. As a consequence, a new framework may be created for each campaign. This may be significant since the campaign may be adjusted to impact consumers using different combinations of variables (see Fig. 51).

[00313] Further, the framework for the valuation may be created by using machine learning techniques, as describe herein and including the facilities depicted in Fig. 1A. These machine learning techniques may rely on a closed feedback loop

that may show messages through APOs to consumers, and capture data on how those users have modified their behavior as a consequence of these APOs and messages. The framework created by machine learning techniques may assign APOs and messages with higher probabilities to influence consumers in positive way versus other messages with a lower probability.

[00314] Owing to the nature of the advertising market, different channels may be expected to have different degrees of coarseness on their addressability. For example, while it is possible to buy a single APO for online display, TV APO may be sold through whole blocks that may involve multiple advertisements that may be presented to a large audience. The framework, as described above, may evaluate APO in the unit in which they are purchased, using averages and other statistics to estimate values for channels that have a coarse addressability. For example, outdoor advertising may be traced to people living or working in several zip-codes, their number, and the zip-codes to which they belong. In order to measure the results of each APO and message shown, it may be linked to an advertiser's results for each APO and the message's ability to improve them. Subsequently, the advertisers may use these measurements to modify their campaigns to maximize the effect of their advertisement messages.

[00315] In an embodiment, online advertising may use unique numbers, stored in cookies, to anonymously identify consumers and link APOs used and messages shown to consumers. However, even when these consumer's unique numbers are anonymous, there may be cases where use of these unique numbers may not be recommendable or possible. In such cases, the use of certain characteristics of the APO description may help to establish a link with consumers. For this purpose, small segments of relatively homogeneous consumers may be described by some APO variables. For example, at a certain time of day, a certain geographic region, and consumer's interest in a type of content, a set of individuals may be defined that may constitute a Synthetic User Identifier (SUID)

[00316] In another embodiment of the present invention, the effect of APOs and messages shown to these groups of consumers (described by their CID) may be linked to actual results through a probabilistic matrix M . This concept may be useful for cases where it may not be possible to address advertisements to individuals, or to follow individuals across channels (e.g., cases involving multiple channel advertising, TV advertisings, and print and online media advertising). The methodology to create

this probabilistic matrix may be based, at least in part, on the minimization of errors. Each row in the matrix may codify a linear combination of weights that may translate strength of messaging through APOs and messages into actual results that may be measured. The coefficients of the linear combination may be changed to minimize the error between what the linear combination states as result, and the actual result. Further, the framework may also consider the concept of a consumer journey, from initial awareness about a brand to an actual conversion at, for example, an advertisers' store. Consumer journey may refer to different states a consumer may pass through the process of buying. It may be the objective of every advertisement campaign to influence consumers to move along this journey, even in cases where an actual conversion at the advertiser's store occurs outside the timeline is being measured.

[00317] In an embodiment, the framework may use the measurements along the consumer's journey as input to sense the buying behavior of consumers and understand the effect of APOs and messages on changing such a state/behavior. This may be significant in case of multiple channels, as a few channels (such as TV and radio) may influence consumers effectively in the initial steps of their journey, and others may influence during the advanced states, helping to close the sale (such as display and search advertisements). The consideration of the consumer journey may result in providing a more accurate valuation of each APO. By measuring the consumer's progress in the journey, and using this data as input to the framework, it may be possible to provide a more effective valuation of APOs and messages. However, a few channels may have a relatively small effect in driving consumers through the final states, but may be significantly valuable in driving consumers in the initial states.

[00318] In embodiments of the present invention, there may be a number of internal and external machines and/or services in the system and an interaction among them may result in effective real time bidding for advertising delivery. For example, an advertiser may place an "order" with instructions limiting where and when an advertisement may be placed. The order may be received by the learning machine facility 138. Thereafter, the advertiser may specify the criteria of 'goodness' for the campaign to be successful. Such 'goodness' criteria may be measurable using the tracking machine facility 144, or through other external systems, such as surveys. In addition, the advertiser may specify channels to use, and may provide messages. Further, the advertiser may provide historic data to bootstrap the system.

[00319] Based on the available data, the learning system may develop a framework for valuation, which can be codified as a mathematical function. The function may calculate the expected value of each advertisement placement opportunity, and may also provide the concept, variation, and call to action among others, to select the message to show to consumers. The selection of value and message to show may maximize the specified ‘goodness’ criteria. Thereafter, the mathematical function may be received by the real time bidding machine facility 142. Bid requests may be received by the real time bidding machine facility 142 and may be evaluated for its value for each advertiser, using the received algorithms. Subsequently, bid responses may be sent for advertisements that may have an attractive value. The selected advertisement may then be placed at a particular price.

[00320] In an embodiment, the mathematical function may also be invoked through a manual process, specifying the value for each variable that describes the advertisement placement opportunity to evaluate. In both cases, one or many advertisements may be valued simultaneously. As a next step, a matrix may be created that may link advertisement placement opportunities and messages shown to results, either purchases or change in consumers’ buying behavior. The advertisement result linking matrix may be created and constantly adjusted for tracking the results that cannot be tracked for each consumer.

[00321] In an embodiment, advertisements may be tagged with a tracking system, such as a pixel displayed in a browser. The tracking machine facility 144 may log advertisement impressions, user clicks, and/or user actions. Also, additional external metrics that involve consumer state may be included. The results, advertisement placement opportunities, and messages may be linked through the advertisement result linking matrix. The ‘goodness criteria’ may be used by the learning system to further customize the valuation mathematical function. The system may also correlate expected values with current events in the advertisement recipient’s geo-region.

[00322] The various embodiments of the present invention facilitate allocation of budget for media and pricing. The budget may be updated in real time (e.g., in a timely way for taking a decision as the channel requires it). The present invention may enable the use of a single framework to decide on value and message across multiple media channels, thus enabling trading advertisements shown through one channel with advertisements shown through a different channel. Further, varying

degrees of coarseness in the type of decision may be involved to acquire media. Therefore, coarseness may be determined by the addressability, type of media, and the granularity that may be achieved at expressing the effect of advertisements.

[00323] The present invention may facilitate optimization of the effect of advertisements by paying the right price and ensuring advertisements are placed to the consumers and through the channels that ensure their best effect. Still further, the present invention considers the state in which the consumer is as they progress in the journey from initial awareness to purchase of a good or service. Measurement of consumers' buying behavior through surveys or panels may also be performed; this measurement is independent of the fact that whether they purchased a good or service. In addition, the present invention facilitates use of a probabilistic approach for linking different channels, and their results as a change in consumers' state and purchases of goods or services. This approach may be used in cases where there is little or no certainty to link individuals and results.

[00324] In embodiments, the present invention may provide for impression level decisioning for guaranteed buys towards audience optimization. Referring to Fig. 52, the system may apply rules in real-time to allocate impressions to best advertisement ('advert') campaign, such as based on consumer segment membership. For example, and as depicted, various context sources (e.g. CNN.com, Vanityfair.com, espn.com, vogue.com) may be presented with an opportunity to place an advert, such as to individuals in a certain demographic, individuals with a known profile, in relation to a creative (e.g. AXE, Dove, Vaseline), and the like. The use of machine learning or statistical techniques may be utilized to identify segment fitness, such as in cases where the profile of the consumer behind an impression is unknown. The regulation of the tradeoff between segment fitness and campaign pacing may be through a coefficient.

[00325] In many cases, advertisers may be interested in showing their advertisements within a specific online publisher media. In these cases, the advertiser may buy 100% of the advertisements shown within this online publisher. The selection of which advertiser to buy may be guided by the audience that predominantly browses the website. In other cases, advertisers may be interested in showing their advertisements using a combination of online and offline content channels, such as online websites, online mobile, online video, TV, IPTV, print, radio, and the like. In these cases, the minimum investment size may vary by channel, and

outlet, but it may be in most cases possible to know certain attributes for the addressed audience. For example, 60% of the consumers browsing at a sports site may be male. Advertisers, seeking to target a male audience, may show advertisements at this sports site, and consider those advertisements shown to women, to not hit their target, but still be paid for. As such, the effective cost per thousand advertisements shown in the target may be higher by a certain factor that incorporates the spill over outside the target audience. In many cases, a product may target several audiences, some of which may be primary, and others may be secondary. With more advanced technology it may now be possible to know, such as in a percentage of cases, what is the profile of a consumer, so as to know if the consumer is ‘in target’. When an advertiser seeks to advertise different products with non-overlapping audiences, the system may be able to identify users as they arrive, as part of a segment or another, and then show the most appropriate advertisement for the most appropriate product. By doing this, the system may reduce the spill over, using those impressions from the sports site that are shown to women, to show advertisements relevant to women. In embodiments, this may be limited to an individual on which there is data to identify their profile.

[00326] In some cases the ability to address specific impressions may not be available (e.g. broadcast TV, radio), and the spillover may be unavoidable. However, the system may still create an effective cost including the spillover. The system may compare the efficiency of the channel with other channels, using the analytic platform as described herein, where more granular addressability is available. In certain cases the same channel may provide diverse levels of granularity and variable price associated with each. For instance, a TV network may sell ‘daily rotation national broadcast’ advertisements at one price, ‘prime time national broadcast’ at a higher price, ‘prime-time regional broadcast’ at a different price, and ‘specific show national broadcast’ at a different price as well. The platform may evaluate each target audience, and compare them against all other available ways to reach the target audience. Moreover, the system may detect whether it needs to complement one channel with a different channel, for example, expanding the number of consumers reached with an TV broadcast offer, with individuals found online, that belong to the same target segment. In order to measure overlap between these two segments, surveys or other methodologies may be used. Further, the system can create a score for every consumer, as to whether they belong in a segment or not. This

score may be created using machine learning techniques, or other statistical techniques, the analytic platform, as described herein, and/or use information from multiple sources. One source of such information may be related to the consumer, such as past browsing history for the consumer, exhibiting the interests the consumer has, collected online or from off-line behavior matched to an online ID, demographical, geographical, behavioral or other information related to the consumer. The system may also consider the types of ‘creatives’ the consumer likes or dislikes, and which ones the consumer has interacted, such as described herein.

[00327] Another source of such information may be related to the context where the ad will be seen, and may include the type of channel used, such as online video, online mobile, online text, television, interactive television, IPTV, physical newspapers, physical magazines, radio, and the like. For any content, no matter what the channel is, it may be topically categorized (e.g., sports, news, science, entertainment), thus information about the topical content may also be used. For any content, there may be a brand for the specific content (e.g., a specific piece of news or science published on the web, a show name when broadcasting through TV). Content brand may be information that can be used as well. At the same time there may be a publisher name, and families of publishers, which groups have certain specific contents, in a hierarchical manner. For example in TV, it may be the channel name (ESPN2), and the network name (ESPN), besides the specific show name, such as when considering online sites there are specific web pages, that belong to a section of a website, that belong to a website, where such a website may in turn belong to a publisher. For every content there may also be additional qualifiers, such as whether it is paid or free, user generated content, broadcast, editorialized; whether it is public air broadcast, or cable; high definition or standard definition; stereo, multichannel or mono; color or monochrome; and the like.

[00328] Another source of such information may be the creative, which denotes the specific advertising message that is shown to a consumer. Any information that describes the creative can be used. The creative may be described by its nature as static display, animated or dynamic display, motion picture, audio, and the like. The creative may be described by its size, such as in pixels, seconds, column-inches, column-cms, and the like. The creative may be described by its intent in trying to show product features, interest consumers with a low price, engage with the consumer at an emotional level, explain to the consumer advantage over competitors,

explain to the consumer why competitors are not adequate, and the like. The creative may be described by its specific message. The creative may be described by its success, and where, when and with whom such success happened, and how was it measured. The creative may be described by the time it has been shown to consumers.

[00329] A score may exist for every consumer, and for every impression, not only for those consumers whose profile is known. The score may be higher with a higher certainty that the consumer is a member of a certain class or has certain attributes. The system may describe it as the likelihood of having a certain ‘some’-ness, an example of which may be ‘urbanicity’ (likelihood of living in a urban environment), ‘rational’-ness (likelihood of thinking like a rational thinker), ‘female’-ness (likelihood of behaving like a female), and the like. For example, the score may describe the probability of an individual being a member of a marketing segment. This score may change by the closeness of the individual to the description of the attribute. For example, someone living in a suburb has a higher ‘urbanicity’ score than someone living in a ‘deep rural’ geographical location. The score may change with additional data that further confirms the individual’s score, such as knowing only roughly the region where an individual resides, only by itself, will project a certain average ‘urbanicity’ value on that individual; knowing the specific area where the individual resides allows to further refine the value of such score, and the like. The geographic region may be just one of the parameters used to estimate someone’s ‘urbanicity’; others may be the type of content visited.

[00330] By using this score, the system may allocate consumers to the segment that best fit them, even when their profile is not known. The net result may be that every impression will be used to the best possible application. For people for whom the profile is known, the system will allocate them to a segment or segments they are members of; for people with an unknown profile, scores for every profile may be used. This score may be used in combination with another score that reflects the campaign need to deliver advertisement impressions in time. Campaigns that have delivered enough impressions may have a lower score vs. campaigns that are short of their goals. These two factors may be combined so that campaigns run within their expected impression delivery rate, and with the best possible consumer fit. Allowing campaigns to over or under deliver may allow for considering better segment fitness coefficients. Thus the weighting used to combine the coefficients in the previous row may drive the tradeoff between segment fitness and campaign pacing. A third party

system may then measure the audience that received advertisements and verify whether they were in a target audience, such as using a recruited panel methodology. For instance, such a third party system may recognize that the execution delivered the highest effective cost per thousand advertisements delivered, for a campaign, measuring effective cost per thousand, as counting only those advertisements delivered to an 'in-target audience', considering the media and data cost associated with the campaign, and the like.

[00331] By using a methodology as described herein, it may be possible to achieve a global management of the yield of the content used to show advertisements. In many cases, the buyer of content to show advertisements may be corporations with multiple divisions, associations of corporations, and the like, willing to share in a cooperative. Within a corporation its divisions may have different lines and products, and for each product and line there may be different messages, creatives, offers, and the like. By using the system described herein, it may be possible to maximize the effect of a given investment in content to show advertisements. Each advertisement may be selected as the best match to the advertising goals of the advertiser, the effect of advertising, given the constraints of using a specific investment in content to show ads, given the constraints of minimum and maximum investment levels per corporation, division, line, product, message, creative, offer, and the like. The search of such optimal allocation may incorporate the nature of the content being acquired, be it on an impression-by-impression basis or on a specific minimum addressable investment size.

[00332] In embodiments, the present invention may provide for methods and systems to maximize advertisement effectiveness based on automated incorporation of off-line results, where the system may receive real time feedback from an offline source (e.g. surveys, offline purchase patterns) and incorporates such feedback into the optimization of an advertisement campaign. The system may utilize the differential between exposed and unexposed populations, across combinations of attributes; refine the inventory of advertisements used for brand metrics oriented advertising; provide measurement of cost per newly aware person, newly favorable person, people newly considering brand for purchase; optimize an advertisement campaign towards the lowest cost per newly aware; and the like. Referring to Fig. 53, a bid request may be related to bit request valuation, bid response, real time bidding (RTB) exchanges, and optimization parameters. Fig. 54 shows an embodiment of a

process flow from an RTB branding bidding function, to a campaign, survey, responses, and valuation algorithms leading to an optimization engine. Figs. 55-56 illustrate embodiments of how exposed market increments may be adjusted as survey results tally from a campaign.

[00333] When placing advertisements to consumers, one of the possible goals of such advertisements is to influence consumers' awareness about a product or message, to increase favorability or ensure the product is within a consideration set. These are generally referred to as 'branding metrics'. In these cases it is desired to measure results through surveys to such consumers, in such a way that the results of showing those advertisements can be measured. In certain cases, the population of consumers would be divided in two, with one part of the population shown actual advertisements (exposed), and the other part of the population shown advertisements for a different brand, advertisements about a non-profit organization, and the like, or no advertisement at all (unexposed). Surveys to measure branding metrics are provided to both groups, exposed and unexposed. It is expected that people exposed to advertisements would respond to the survey with a higher amount of the relevant brand metric, than people unexposed. This differential is referred to as absolute brand lift, and describes the incremental in the brand metric as a result of ad exposure. Further, it may be expected that within the people in the exposed condition, those exposed to, for example, particular contents, times of the day, or from some specific regions, would exhibit an even higher absolute brand lift than others. Attributes such as these, alone or in combinations, describe areas of the advertisements inventory where the system was most effective finding a receptive audience to its advertisements. These attributes may be in the hundreds, and may vary amongst different types of advertisement. For example, attributes may belong to various classes, such as those that describe the consumer receiving the advert, those of the inventory used to deliver the advert, those relevant to the advert shown (size, concept, color), and the like.

[00334] The system may autonomously decide to be more proactive to acquire such areas of the advertisements inventory, such as through higher bids in a real time environment, through reporting that can be translated into orders to buy, and the like, in a non-real time environment. The optimization methodology may opt to seek the highest possible brand metric, to seek the highest possible differential between an exposed and an unexposed population, to achieve the most effective

incremental brand lift, and the like. Despite the highly dynamic nature of advertising, where consumers are ever changing preferences, the system may provide advice that may dynamically adjust its bidding behavior, so as to best capture the results offered by optimization, to continuously incorporate survey responses, to enable the creation and refine a model for driven brand metrics, and the like. Such an automated system may detect where it can be most effective as described herein, and decide what ad to show to each consumer, and within each context, to maximize the relevant brand metrics. Such an automated system may also work with exchange tradable media, advising how much to bid for each individual impression, such as based on the underlying value of each individual impression.

[00335] In embodiments, objectives and metrics to measure as system output may include maximum brand lift, the number of newly aware people, an estimate value for making a consumer newly aware, and the like. While surveys are one type of off-line metric that may be incorporated, other metrics such as sales of products may also be used. In this alternative use, the system may receive information about consumers buying products, creating a pattern of purchase across people exposed to ads, people unexposed to advertisements, and the like. The difference in purchase patterns between people exposed to advertisements, and people not exposed to advertisements, may be incrementally driven by the advertisements' campaign.

[00336] As in the survey case, it is expected that within the people in the exposed condition, those exposed to, for example, particular contents, times of the day, or from some specific regions, may exhibit an even higher purchase pattern than others. Attributes such as these, alone or in combinations, may describe areas of the advertisements inventory where the system was most effective finding a receptive audience to its advertisements. These attributes may be in the hundreds, and vary from type of advertisement to type of advertisement, and may belong to a number of classes that describe the consumer receiving the advertisement, such as those of the inventory used to deliver the advertisement, those relevant to the advert shown (size, concept, color), and the like. The system may autonomously decide to be more proactive to acquire such areas of the advertisements inventory, such as through higher bids in a real time environment, through reporting that can be translated into orders to buy, in a non-real time environment, and the like. Also, the system might not look for all of the tens or hundreds of different attributes as described herein (e.g.

particular contents, times of the day, from some specific regions), it may instead look to optimally allocate budgets, prices to pay, effective frequency and recency to show ads to consumers, and the like, within a few well defined segments of the population.

[00337] In embodiments, the system may define a segment as a group of consumers that share some characteristics. These segments may be demographic (e.g. women between 25 and 34 year old), have a common interest (e.g. people who like to collect stamps), be in the market for a certain product (e.g. people in market to buy a compact car), live in a certain place (e.g. people living in the vicinity of Atlanta, GA), show an affinity with a brand, and the like. These segments might also be composed through Boolean expressions of other segments.

[00338] In embodiments, there may be the need to keep a fraction of the population exposed to advertisements and another group not exposed advertisements, either by exposing them to public service advertisements, by not exposing them altogether, by exposing them to ads from a different brand or product, and the like, where a survey or an off-line metric may be used, such as purchase behavior used as a signal of goodness.

[00339] By measuring the off-line metric across the group exposed and unexposed, it may be possible to understand which segment is more receptive to the message, and what frequency, bid price, and budgets are most effective. As such, the system may automatically reallocate budgets, bids, frequencies, and the like, to acquire the advertisements inventory best suited to drive incremental awareness. Also, the system may include a mechanism to modify budget allocation to show surveys, as it may have the capability to detect lower or higher than expected survey response rates. For example, in the case were the system is expecting to show one million surveys per week, and receive 1000 answers, if it only receives 500 answers, it may automatically reallocate twice the budget to ensure 1000 answers per week are received. The same mechanism may be applied to any metric of time to ensure the right spend per unit of time is allocated, and ensure the right number of survey answers are acquired. The same mechanism may be applied to any segment or partition of the population being surveyed, so that, if there are not enough or too many answers from a certain segment or partition of the population (for example, not enough survey answers from males, 18-25 year old), the system will reallocate just enough money to increase the number of answers, using an automated mechanism, in real time.

[00340] In embodiments, the methods and systems disclosed herein may comprise pulsing advertising, which may be measured by different lengths of exposure and intensity of exposure. The method, system and/or strategy of pulsing advertising may comprise a sudden increase in advertising investment for a period of time, followed by a sudden drop, to the original advertising investment or any other desired value, which may also be kept for a period of time. The drop may comprise retiring ads from the market, or the drop may comprise replacing advertiser ads with different advertiser ads, or with a public service ad, for example in such a way that the effect on the market may be uninterrupted. In embodiments, the pulses may occur through any type of advertising channel, including online media, such as, but not limited to, web banners, social ads, search ads, online videos, mobile banners, mobile videos, SMS messages, interstitial ads, emails, and any other form of email where the individuals are reached through an interactive screen. In embodiments, the pulses may occur through any type of offline media, such as, but not limited to TV, radio, cinema, placements, outdoor billboards, print magazines, print newspapers, print of any other type, cable, street postings, and any other channel to disseminate an advertising message. In embodiments, the pulses may be deployed via the advertising distribution facility 122, advertising receiving facility 120, or advertising data distribution service facility 124, but are not limited to distributions via these facilities..

[00341] The pulse of advertising may comprise a sudden incremental increase on advertising investment. This increase may be determined by assessing numerous factors, which may comprise, but are not limited to, 1. How much is the increment in advertising investment, 2. How long the incremented investment is kept, and 3. How much time after the pulse ends will another pulse start, and the like. The pulse of advertising may be sent to the market targeting one or a plurality of targeting dimensions that are known to the art. Targeting may comprise a combination of different dimensions. In a non-limiting example, targeting dimension variables may be, but are not limited to: geographical variables (such as, but not limited to, targeting a specific household, block, neighborhood, zip code, market, city, region, country; and also groupings of the preceding targets, such as, but not limited to, a group of households, a group of blocks, a group of neighborhoods, zip codes, etc.); Demographical variables (such as, but not limited to, age, gender, income, education, ethnicity, religion, etc.; which can be individual or bracketed in ranges, such as, but

not limited to Age = 18-24, 25-34, etc.); Consumer interests (such as, but not limited to, consumers who are interested in cars, in electronics, etc.); Type of content the individual(s) consume (such as, but not limited to, readers of news, readers of entertainment, readers of science content, watchers of movies, etc.); and/or the types of channels necessary to reach the consumer (such as, but not limited to online banners, online search, online video, mobile reach, TV, radio, outdoor panels, etc.) and the like.

[00342] In embodiments, multiple pulses, and of different intensities, durations, targets, or other variables may be used. These pulses may be programmed so that a specific desired pattern may be created. A fractional factorial experiment design may be used to design the pattern of the pulses. Such patterns and all instructions relative to the execution of the pulse and patterns that arise from combinations of pulses may reside in facility 201. Referring to Fig. 60, facility 201 may send execution orders to facility 142 for execution in real time, for execution in non-real time, on an impression by impression basis, and for execution through the acquisition of a multiplicity of ads at once.

[00343] In embodiments, the pulses may be deployed to measure market responses when subject to different types of stimuli. The market responses to the stimuli may be measured through different metrics. These metrics may be measured in terms of offline or online metrics. Offline metrics may be linked to physical world measurements, such as, but not limited to, sales volume, inventory movement, surveys, automotive traffic patterns, store customer traffic, eye tracking measurements, etc.. Online metrics may be linked to internet based activities, including, but not limited to, web site activities, email opening rates, online survey responses, online sales volume, social interaction volume (both with or without mention of the product/service advertised), commentary postings in pieces of content linked in any way to the product or service advertised, etc.. These metrics may be measured in the aggregate (i.e. for all geographic locations), or, in a non-limiting example, for a specific zip code or market, for example, in instances where it may be possible to directly assign a result to a specific partition of a dimension. These aspects may be measured by an apparatus, which may deposit their recordings in facilities 152, 154, 158, 160, 164, 205, and 206.

[00344] In embodiments, the measurement of the effect of the pulse may comprise, but is not limited to: the total impact of the pulse in the metric measured

(total increment achieved from the point the pulse started, through the point in which the metric dropped to a certain percentage of the maximum value achieved by the metric; the maximum value achieved by the metric; the delay to achieve maximum value; the time it takes to drop to half the maximum value (or any other percentage of the maximum value); the residual impact, considered as the increment over the pre-pulse metric, after the drop is considered to be complete, wherein the consideration of complete drop may be defined as dropping a certain percent from the maximum; shape of the decay curve from the maximum to any convenient point; the cross-feed between neighboring, and non-neighboring pulses, such as, but not limited to showing advertising to a certain zip code may affect neighboring zip codes; and/or showing ads to a certain age group, may affect other disconnected age groups, etc., and the like.

[00345] Method for Omni-Channel Attribution. In embodiments, the methods and systems disclosed herein, may comprise a method for omni-channel attribution. It may be apparent to those skilled in the art, that an increase in intensity of pulsing advertising may not always be linked with a proportional increase in the effect on customers. In embodiments, the methods and systems disclosed herein may comprise an apparatus that may find the optimal point of operating pulses. In embodiments, a specific pattern of pulses may be created, which may present stimuli to the market, such that a causal connection between increased advertising investment and a desired specific market response may be established. In embodiments, the pulses may be analyzed in conjunction with a virtual identifier that is not necessarily linked to a specific individual, but still has a permanence during a period of time. The virtual identifier may be specialized as a market partition, so that it may be broken down by advertising markets, or some other meaningful distinction. The virtual identifier may also be construed in a more granular manner, such as, but not limited to a combination of a geographic location with a demographic component.

[00346] In embodiments, the method may comprise using a pattern that explores a large range of combination of targeting dimensions. Such type of patterns, where a metric is varied systematically with specific intensity points, is a factorial experiment. In a non-limiting example, the intensity of advertising can be explored at 0% 25%, 50%, 75%, and 100% of a certain investment increase, expecting to measure results that can be 1, 6, 9, 11, and 12. By way of example, if the first 25% of

investment creates an increment of 5 units, and the last 25% increment is only able to create a 1 unit increment, this may show a loss in efficiency.

[00347] In embodiments, the machine, methods and/or systems may rely on the concept of linking results to inventory partitions as discussed in reference to the virtual global consumer ID herein. Whereas items as described in some embodiments related to such ID may present the generic case where results may or may not be linked to specific partitions of the inventory (thus Chanel User IDs or CID), methods and systems described herein may seek to keep the link as closely to the CID as possible.

[00348] In embodiments, the method may comprise inventory partitions. In embodiments, such methods may involve limited cross contamination, which may save time and increase the certainty of the budget allocation produced by the method. In a non-limiting example, one may assume there is little cross effect between different geographical markets, as individuals may show limited mobility between markets that are separated by enough distance. Under the framework established by the methods disclosed herein, individuals who receive ads within a specific market are expected to remain there, and also are expected to show the relevant output metric (Expected Metric ID - EID), in a way that can be certainly attributed to that market.

[00349] In another non-limiting example, a partition may be assigned not only a geographic component, but also a demographic component. In this case, some cross-effect can be expected, as a demographic group (for example Women 18-24) may exert influence in another group (for example Males 18-24). In order to produce a causality model that can be replicated as desired, pulses with different degrees of intensity, across each partition may be necessary, so that the cross-effect can be adequately measured. These effects may be presented as a matrix M , assuming a linear model; however in some embodiments, the assumption may be that a non-linear model will be achieved with the characteristic of diminishing returns, that is a positive slope, but with a negative second derivative.

[00350] In another non-limiting example, another way to avoid cross-contamination may be the use of some permanent ID where it can be assured that individuals retain their identity, and results may be tracked back to that permanent ID. In embodiments, this case may also present cross-effects, yet, it may be useful for measuring the social permeability of the advertising message as it travels from individuals who received the ad message to those who were not in contact with it. By

using a pattern of pulses conveniently construed, it may be possible to neutralize or reduce the effects of seasonality, and of learning by targeted audiences. Such patterns may rely on the fact that similar partitions of the market may behave similarly, thus their effect may be averaged.

[00351] In embodiments, the length of the periods with increased advertising investment (pulse) and periods with decreased advertising investment (valley) may allow decay to be estimated. In such embodiments, it may be desirable to reduce the effect of learning, and ensure there is causality, in such a way that retiring the advertising stimuli creates a definite drop in the market response. This may be done to enable the creation of pulse patterns that don't start from the lowest investment, and also to enable the measurement of absolute increments in the results over what is believed to be a lower investment baseline. Moreover it may be necessary to separate the cross-effects between channels as enunciated below.

[00352] In embodiments, partitioning the advertising investment by channels may allow it to be possible to separate the effect of increased advertising through one channel as compared to another. A channel may be any dimension where advertising can be targeted, Examples of channels may include traditional advertising channels such as online media (web banners, social ads, search ads, online videos, mobile banners, mobile videos, SMS messages, interstitial ads, emails, and any other form of email where the individuals are reached through an interactive screen) and offline media (TV, radio, cinema, placements, outdoor billboards, print magazines, print newspapers, print of any other type, cable, street postings, and any other channel to disseminate an advertising message). The pulses may be executed through facilities 203 and 120, 122, 124, which may create a persuasion effect in consumers' minds.

[00353] In embodiments, the method may comprise assigning a channel to different advertising messaging ideas, assigning a channel to different types of content, assigning a content to different demographics, and/or assigning a channel to different vendors of ad inventory. In general any targeting dimension may be construed as a channel; and this breakdown may allow the machine or person that is looking to measure the effect of advertising in one channel vs. another. In embodiments, this measurement may be used to decide what is the best investment strategy.

[00354] While cross-contamination between different inventory partitions may be an aspect to minimize, there may be an expectation of cross-effect between

different channels. As such, it may be necessary to rely on a model that creates a pattern that explores, as completely as possible, different advertising intensities in combination. In the above mentioned non-limiting example of 0%, 25%, 50%, 75%, and 100% allocation of investment, a simple pattern execution may rely on subjecting each channel to every one of these 5 intensities, while the others remain fixed. In this non-limiting example, in a 2 channels case, channel A will remain at 0%, while channel B goes through each of the 5 investment levels, from 0% to 100% (pulses), including periods where the advertising is reduced in magnitude (valleys); then channel A will be lowered to a valley, and subsequently increased to 25%, where the same pattern may be allowed to repeat in channel B (all 5 investment levels with pulses and valleys); then channel A will be lowered to a valley and subsequently increased to 50% and so on, until the 100% level is achieved in both channels. To make the pattern a better measurement, and discard some inertia or hysteresis in the measurement, the order of the execution may not proceed from 0% to 100% for all channels but follow a different pattern, for example starting at 75%, then dropping to 25%, increasing to 100%, dropping to 50%, and finally reaching the 0% level.

[00355] These patterns may become extremely long, and for a more timely response, a pattern that does not explore every combination may be used. Cross-effects between channels may of interest to explore. For example, the slope of the curves for a given channel may change when another channel has a higher intensity. In embodiments, a multi-dimensional diminishing returns curve may be construed, and that curve may present the interesting property of allowing the scaling of investment levels at the most efficient configuration by following the mathematical gradient derivative of the curve, for example.

[00356] In embodiments, the output of the analysis may be a set of curves showing advertising investment in the horizontal axis and advertising results in the vertical axis. In embodiments, the method may comprise creation of such curves per channel and per inventory partition. Given the fact that the curves that compare advertising investment and advertising results may present “diminishing returns”, they may all have a positive first derivative, but a negative second derivative. That is the slope for those curves may be expected to be positive, but the slope may also be expected to drop towards zero. In embodiments, the determination of the optimal allocation of investment may be determined when the investment in each of the markets and inventory partitions is in such a value that the slope of the curve at that

point of investment is the same. This may imply that there is indifference between where to invest the next incremental budget, as it would create the same effect in every inventory partition and every channel. It may also imply that no amount of budget can be taken from one channel and inventory partition to invest it in another for creating a net increment, across all channels and inventory partitions. In embodiments, not all inventory partitions may provide enough predictability. As a consequence, in embodiments, a metric based on how closely the model can replicate a hold out set of data may necessary to ensure there is a valid representation of the reality and to separate those cases where the model is unable to produce a reasonable answer.

[00357] Risk Modeling for the Online Market. In embodiments, the systems and methods disclosed herein may comprise a method for risk modeling for the online market. The method may comprise creating a model that represents the cost of the risk incurred by providing a guarantee to achieve certain results via online advertising and the fair price for such guarantees. In embodiments, the method may comprise using financial tools, such as, but not limited to, a Black-Scholes modeling system to establish fair valuation for selling and buying risk of achieving a desired outcome, even in cases where that outcome is uncertain. In embodiments, various positions that may be transacted according to such models may be, but are not limited to, CPM price to acquire impressions at a certain volume, such that a comparison of spot and guaranteed markets may be achieved, eCPM to achieve an X metric (viewability, audience target, retarget, etc.) at a certain volume, pricing of the risk so that an advertiser may sell at eCPM in audience and in view to determine the prices the advertiser may sell at and deliver with minimum risk, and CPA and profit that may be achieved as a percentage of volume. The method may comprise collecting past data and create probabilistic distribution of outcomes derived from modeling positions, such as those mentioned above. The method may also comprise estimating the likelihood of incurring losses and different prices. By comparing these losses and likelihoods of the losses against other types of investments, the method may generate an estimated premium in order to incur the desired risk. By using the method, an individual or an entity may take the risk. In embodiments, if the risk is deemed non-correlated, an individual or entity may take multiple positions, and may reduce the net risk assumed. This non-limiting example may thus result in creating a profit by buying the risk. In embodiments, the method may also comprise an individual/entity

buying risk that it can resell. By doing so, a market may be created, where informed decision-makers may transact and acquire risk at a fair price, enabling liquidity in a market that sells an ability to deliver advertising results. In embodiments, the method may comprise the creation of a derivatives market where risk can be purchased and sold, under a known set of tools for fair market valuation.

[00358] Consumer Driven Attribute Classification. It may be interesting to classify opportunities to place advertisements in different slices or dimensions, which may be then used for presenting analyses or broken up into pieces to achieve the same. Typical classifications are type of content, regions where consumers receiving the ads reside, time of the day, type of consumer operating system (for online ads), cable provider (for cable based advertising) etc., and the like. In embodiments, the methods and systems disclosed may comprise a method for classifying the analysis of various dimensions. The method may offer a more insightful meaning to ordering criterion that is currently available in the art. In embodiments, methods and systems may rely on consumer behavior and analyze how results metrics changes as consumers from different slices or dimensions are measured. In a non-limiting example, if the type of dimension is content type, and the possible nominals are news, science, entertainment, and weather; then looking for the metric “conversion rate” for each type of content, we may order the content types from the one with the highest conversion rate to the one with the lowest conversion rate.

[00359] In embodiments, a single metric for the category may not elicit enough understanding of the order within that category. The average conversion rate may be roughly constant, but the conversion rate, by time of day may vary, with a pattern where, morning conversion rates are highest for weather, followed by news, then literature and entertainment. During the afternoon, the pattern may somehow be constant, and in the evening the behavior may have the highest conversion rate for entertainment, then literature, then news and finally weather. In such an example, the order in which the conversion rate changed may appear to show a logic, and also may describe a consumer behavior when facing content. Thus, the method may comprise synthesizing the new order of categories to create a synthetic metric. In embodiments, the method may comprise assessing which values are available for any given impression attribute (in general, A1,A2...An). The method may further comprise assessing whether there exists a set of metrics that are independent from each other, or projection metrics (in general B, C, D,..., Z, ...AA, AB, ... nn). The

method may comprise minimizing the sum of distances between every attribute of metric A, measured in the B...nn space, where exists the total distance in the A axis between the two extreme attributes. The method may further comprise minimizing the square error from a monotonically increasing or decreasing function for each of the B...nn metrics. The method may further comprise combining these minimizations with a set of weights so that a single metric may be minimized. The method thus may derive an order for values A1 to An such that it may create an artificial direction for attribute A that it may be sorted by consumer behavior. By using the synthetic metric, it may be possible to assign a quantity to this synthetic metric, so that each nominal value is represented now with a number. Closer numbers may represent nominals that are similar from the consumer perspective, and with respect of the chosen projection metrics. The method may result in synthetic metric that may have an actual meaning. Even in cases where it doesnot, the method may allow for better modeling of probabilities as it relies on a continuous function that represents definite consumer behavior.

[00360] Parametric ETL. In embodiments, the systems and methods disclosed herein may comprise a parametric extract, transform and load process (ETL). In embodiments, the ETL may comprise an ability to specify input parameters as key value pairs that are parsed using a supplemental dataset with metadata, with one of the key value pairs specifying the name of the metadata to use to parse. In a non-limiting example, the inputs may be: meta="VF", A=50000, B=40220, C=1000000000, D=Edimburg, E=NA, F=NA, where the VF meta-dataset would say "this is data for sales for our VF client", "must be input into table VF/Sales", A is "sales rep ID", B is "total units", C is "sales revenue total", D is "location", E, F are not used. At parsing time, the row may be read, and the corresponding metadata file is used for parsing.

[00361] Flat Table Database Schema. In embodiments, the methods and systems disclosed herein may comprise a flat table database schema. The database system disclosed may rely on simple codification, such as comma separated text files, and a separate text based file that provides metadata about the data stored to create a database system that survives in time and that may be ingested by multiple platforms. In embodiments, the database system may comprise a flat data file that has comma separated elements, and a CR at the end of the last element of the column. Blank elements may have omitted values. The name of the file may include, but is not

limited to, the table name, optionally a version, and a time/date and ordinal (likely a 5 digit number to ensure uniqueness of the time/date/ordinal combination), so that large datasets may be stored in separated files. The database system may further comprise a metadata file associated with the data file. The association may be by means of the file name. The metadata may contain the name of the columns in the order they appear in the flat data file, as well as formatting data that allows parsing of the data file. In embodiments, the database system may further comprise a dictionary where all possible entries into metadata files are named, and a brief explanation of what it means, and their format. The type of metadata stored may be, but is not limited to, the name of each column and the format of the data stored in the column. The names of columns must be unique, so that they may be stored in a dictionary.

[00362] In embodiments, the dictionary may rely on unique words. In embodiments, the system may require a central repository so that words are not repeated. Words may have longer names, so that they may be explicit to what the content of the word is. If the number of words becomes excessively long, then a suffix schema may be arranged, where a word (for example revenue) may be suffixed (for example revenue.gross, vs revenue.net). This framework may allow for long terms data storage (as it easily can be parsed by a simple ETL system, and input into any different new technology), and allows for transportability between databases. A parametric ETL may easily be used to parse and input this file into any database desired.

[00363] Quasi Static Bidding. Currently there is a demand for a method to optimize an ad inventory buy in cases where ad impressions cannot be purchased on a one by one basis. At the same time, models for creating valuation on a one by one basis may be available, and may provide an accurate mechanism to decide what is the acceptable value to pay for ad impressions. Cases where impressions cannot be purchased on a one by one basis, are those where the ability to buy ad impressions one by one has not been developed, or may be impossible. Example of such cases may be: acquiring ads placed through non-online media, such as an ad placement through linear TV, or an ad placement in a magazine. Additionally, there may be cases where it is technically possible to transact on an impression-by-impression basis, but, due to business considerations, it may be interesting to provide an aggregated value for a larger swath of inventory. In such cases, the seller of the ads may still allow for some targeting abilities. The methods and systems disclosed herein

disclose a method that breaks down the universe of available impressions into smaller slices.

[00364] In embodiments, by applying the valuation mechanism to a sample of impressions that fall within a specific slice, the method and systems may make it possible to measure the valuation in the aggregate of the slice, and thus, learn what the efficiency of that slice is. Some of these smaller slices may have a better valuation than others, and thus, may be more attractive to buy. In embodiments, the method may require an assumption that, by reducing the size of the slices, some of the slices will exhibit higher performance than when the size of the slices is larger. Therefore, it may become beneficial to use combinations of targeting parameters in order of reducing the average size of each slice. In embodiments, the slices may be overlapping, and may not need to be the same size. In embodiments, the valuation model may be used simultaneously to purchase ads on a one by one basis and on a slice basis. In embodiments, ads may not need to be online as well, and this model may then be used for optimizing media with off-line channels. The methodology may provide “on demand granularity”.

[00365] In embodiments, the methods and systems disclosed herein may comprise a method to calibrate probabilities for ad placements that may enable easy spend adjustment. When bidding on a real time ad exchange, it may be necessary to convert the attributes or “features” of the information available at bid time into a dollar bid value. These attributes include hour of day, day of week, information about the size and position of the creative, user details, the site name, and the like. In embodiments, the method may comprise a two-step process: 1. constructing a probabilistic model of the likelihood of conversion given the set of attributes, wherein such a model will give a probability between 0 and 1 of a conversion resulting from the ad placement, 2. converting this probability into a dollar value. This step is known as calibration, and many methods of calibration exist in the literature. Typically these methods may be used to convert a biased probability estimate or a model score to an unbiased probabilistic estimate based on empirical data. Two examples are Isotonic calibration (Zadrozny and Elkan (2002)) and logistic regression calibration (Platt 1999).

[00366] In embodiments, the method disclosed may be akin to the Isotonic family of methods. These methods compute probability estimates using either pre-determined or data-driven bins of the probability density function (pdf) and compute

the true probabilities for estimates that fall in these bins using cross validation examples. In embodiments, the method and systems disclosed may use pre-determined bins based on expert knowledge of the market and empirical results. In embodiments, the method may comprise computing the probabilities at the bin boundaries using samples of the market data. The calibrated value for each bin may be a bid price, and not a probability. In embodiments, the method and systems may compute this price as a multiplier of an average CPM price. In embodiments, this may give the human campaign manager one simple knob to turn to raise and lower daily spend since bids will raise or lower across the board simply by changing the CPM. In embodiments, bidding may be altered by choosing calibration profiles that are more “picky” or more “aggressive”.

[00367] In embodiments, the probabilities at bin boundaries may be computed in an offline or online fashion. In the offline version, samples of bid requests may be collected that match each flight to be calibrated according to the targeting parameters of that flight (e.g. geo region, black/whitelists). The probabilities for each sample may then be computed, outputting a probability density function.

[00368] In embodiments, in the online version, also known as “streaming calibration”, market samples may be gathered “on the fly” in the real time bidding system. In embodiments where this estimation runs in the Real Time Bidding Machine Facility, an efficient implementation may be needed. E.g. online methods described in “Greedy online histograms applied to deterministic sampling”, Vermorel and Hervé Brönnimann, 2003 or “A Streaming Parallel Decision Tree Algorithm”, Yael Ben-Haim and Elad Tom-Tov (2010). The streaming method may have the advantage that flights with tight targeting will eventually match enough bid requests to have a well sampled pdf, which may not happen in offline sampling due to the limited time and space for sampling.

[00369] In embodiments, Offline calibration may be performed in the “Learning Machine Facility 138” and creates parameterized models that plug into the “Real Time Bidding Machine Facility 142” as shown in Figure 100A. Streaming calibration may take place in the “Real Time Bidding Machine Facility 142” and may continually update models that are used to bid.

[00370] Pluggable Expert Software for Bidding System. In embodiments, the methods and systems disclosed herein may comprise a pluggable expert software

for a bidding system. Advanced bidding systems exist, which may be enabled to provide valuation for ads based on a multiplicity of targeting parameters, both in real time for a specific impression and also in batch mode for slices of inventory. These valuations may be created by expert software agents, which may take into account all available data points, and impression attributes, including consumer, context and the creative to use. However, because not every ad campaign and advertiser pursues the same objectives, the mechanisms to provide valuations may differ between campaigns. Systems and methods disclosed herein may present a platform solution to address the possibility of using different expert software agents for different situations. As such, the use of a different software agent may require a modular system, where these agents can be plugged, and unplugged easily.

[00371] In various illustrative and non-limiting embodiments, the systems and methods disclosed herein may comprise a digital consumer service that may be used for the purposes of identifying ad placement opportunities and optimizing the selection of ad and sponsored content to present to ad placement opportunities. Content includes but is not limited to ad placement opportunities, dynamic website content, digital radio, IP television content, and other forms of digital media. These methods can also be used for the purpose of creating analysis, to derive insight about consumers, the overall market, one or more advertising campaigns, or other type of communication that involves consumers, including political action.

[00372] The digital consumer service may identify consumers in real time across and within multiple devices in multiple contexts, for advertising and content-providing purposes, among others. In embodiments the digital consumer service may enable linking and recognition of aliases generated by engaging with different devices, each such device expressing and/or being dynamically, and transiently, associated with attributes such as device identifiers and the like, through online and offline content to enable anonymous and pseudonymous recognition of a shared profile between such aliases. This shared profile may be used for targeted advertising and providing both online and offline content. The profile may also be used for the analysis of the behaviors of profiles for the purposes of analytics and attribution of online/offline activities to online/offline engagement with content and advertisement.

[00373] In various illustrative and non-limiting embodiments, the digital consumer service may comprise a digital consumer profile or the creation thereof. The digital consumer profile may be dynamically, and transiently, generated, drawing

upon attribute data that is available at time of the digital consumer profile creation. In such embodiments, the digital consumer profile may further provide for dynamic and transient generations of a plurality of user profiles to fit definitions and use cases not anticipated at the outset of targeting or attribution efforts and attribute data collection. Such a consumer profile may also change based on regulatory conditions of the content context, privacy policies of advertisers and service providers, among others. Regulatory conditions, privacy policies, enterprise rules and the like may determine, at least in part, the collection and analysis of attribute data, and the merging of such data to form aliases that may be associated with consumers. Such rules, policies and rules, and manifest as rule sets that are applied to attribute and other data from a rules engine that is associated with the analytics platform facility 114. The digital consumer profile may additionally allow for auditability for why content may have been targeted to aliases that were not provided in the original content request. The digital consumer service may comprise binding expression syntax to dynamically, and transiently, identify profiles to give flexibility and extensibility beyond having a flat match table.

[00374] In various illustrative and non-limiting embodiments, and referring to Fig. 61, the digital consumer profile architecture 6100 may comprise a Master ID 6102, Aliases 6104, as well as Organization Data 6108. The Aliases may comprise individually identified Aliases 6110, such as a consumer's device ID, IP Address, personal computer fingerprint, cookies identification, among others. The Master ID may comprise organization data. In a non-limiting example, Consumer A's Master ID may comprise organization data from an organization such as a car company or advertiser. Such organization data may comprise specific data sets 6114 comprising data 6122 that may be used to target or attribute content to a consumer. Consumer A's organization data may comprise transportation data for Consumer A, such as the make and model of Consumer A's last car. The organization data may further comprise information about organization campaigns 6118 6120, and components of the organization's campaigns 6124, in order to match, target, or attribute content to a consumer. The organization data for Consumer A may comprise information about the car company's campaign for its newest vehicles, including frequency 6128 and output 6130 parameters for the targeted or attributed content.

[00375] In various illustrative and non-limiting embodiments, the digital consumer profile may comprise a Master ID. In embodiments, the Master ID may

comprise an anonymous system-generated identifier that may have consumer profile data associated with it. The Master ID may be used for the purpose of online content targeting and attribution. The Master ID may reference a data store with behavioral data associated with the Master IDs, as well as impression, frequency, and activity data attached to content. In embodiments, consumers may be dynamically, and transiently, associated with several different Master IDs, which may be grouped over time as more information becomes available. The Master ID may be used to dynamically, and transiently, cross-link various types of digital consumer identifiers available for the same consumer. The Master ID may be applied in cross-channel programmatic marketing.

[00376] In various illustrative and non-limiting embodiments, the digital consumer profile may comprise an Alias. The Alias may comprise an identifier generated by devices, browsers, algorithms, or third parties that can reference a Master ID. In embodiments, an Alias may comprise features such as, but not limited to, browser cookies from different domains, an email address, a device ID (for example an ID generated by a device manufacturer such as IDFA), IP address, or other identifying features. In embodiments, the Alias may be provided by the organization that owns the identifying feature, such as, but not limited to, Aliases provided by publishers or third parties (e.g. hashed email addresses), or client-specific aliases (e.g. encrypted store member ID). In embodiments, the Alias may be used to identify consumers who have accessed certain content in the past, e.g. visiting a web-page, and associating the same consumer with a different Alias to provide content to that same consumer on a different device via the different Alias. Such a use may allow users to ability to dynamically, and transiently, identify consumers across devices and to create cross-channel attribution methodologies. In a non-limiting example, a consumer who saw an ad on a mobile device and visited a web-page for an advertiser via her computer may still be attributed to the advertisement based on the interaction between the consumer's Aliases and her Master ID, which may be based at least in part on the Aliases. In embodiments, Aliases may act as persistent identifiers that may survive the deletion of cookies and preserve information for retargeting or attribution.

[00377] In various illustrative and non-limiting embodiments, the digital consumer profile may comprise attributes, such as Links. Links may dynamically, and transiently, establish relationships between several Aliases. Links may comprise

several attributes which may identify the Link. In embodiments, a Link may be identified by the source organization, or owner of the Link. Link source organizations may be a part of the same platform, such as the analytics platform 114. Such a Link may identify different Aliases which are on the same residential network. In embodiments, a Link source organization may be provided by clients. In a non-limiting example, the digital consumer service may be able to identify that Device ID 1 and Cookie 2 are connected via a member ID. In embodiments, the Link source organization may be provided by publishers or other third parties. In a non-limiting example, the digital consumer service may dynamically, and transiently, identify a hashed email address and device ID which are linked to the same Master ID. In embodiments, the Link may be identified by type. A Link may have different types based on the relationship of different Aliases, such as “Self,” “Household,” or “Friend,” among others. In embodiments, a Link may comprise a confidence level attribute, which may determine the confidence that different Aliases are attached to the same Master ID. Additionally, the Link may comprise a Time to Live (TTL) attribute. The TTL attribute may identify the time that the Link is valid, given the confidence level. In embodiments, the Link may comprise a Time Stamp attribute, which may identify the time of the creation of the Link. Among other uses, this may be used to expire Links within a proper time limit.

[00378] In various illustrative and non-limiting embodiments, the Master ID may be grouped into sets, called Circles. Such sets may be no-name sets, and may approximate real world targetable and attributable entities, such as, but not limited to, household members or groups of friends. In a non-limiting example, a binding expression may be used to dynamically, and transiently, create “Consumer” Circles, which may be all the possible sets of any Master IDs where a given Alias is bound by Links to other Aliases with a type of “Self.” In yet another non-limiting example, a “Household” Circle may be dynamically, and transiently, generated via a binding expression generating all possible sets of any Master IDs with Aliases bound by Links with a type of “Household” where a given Alias with type “Encrypted IP Address” has less than or equal to 5 Links to type “Encrypted Device Identifier.” In yet another non-limiting example, a binding expression may be used to dynamically, and transiently, create “Friend” circles, which may comprise all possible sets of any Master IDs with Aliases bound by of the Links of type “friend” to another Alias where the distance between the Aliases is less than 2. In embodiments, profiles of a

single Circle instance may be dynamically, and transiently, merged when being evaluated. In embodiments, a binding expression may dynamically, and transiently, define the rules for grouping Master IDs based on available Links/Aliases into Circles. Binding expressions may implement heuristics in order to group Master IDs into Circle sets. Some non-limiting examples of binding expressions may be heuristic expressions using a confidence threshold as a function of time (e.g. exponential decay). In an alternate non-limiting example, a binding expression may use ownership of Aliases or Links to group a set of Master IDs into Circles (e.g. Links established using Company A's data should only be available to Company A). In yet another alternative non-limiting example, geographical or other contextual constraints may be used to dynamically, and transiently, group Master IDs into circles (e.g. cannot use IP addresses in EU). In embodiments, binding expressions may be implemented so that Aliases can be linked to a Master ID with a link type of "Self." Such binds may comprise attributes such as "certainty of link," which may represent the probability of the Link's ability to point to a specific individual who owns the Master ID. Additionally, the bind may identify the owner of the Link, which represents the source of the data used for the linking, and may limit the Link's use or make available certain content for the Link owner. The bind may further comprise privacy feature attributes, which may be one or more attributes indicating in which conditions the Link may be used while still preserving the consumer's privacy. The bind may further comprise location information, such as geographies where the link may be exercised or not, depending on local laws. Master IDs may be linked to other Master IDs with various types of Links to create different circles. Such links may comprise a "strength of link" attribute, which represents the strength of influence between an Alias and a Master ID, when such Master ID does not belong to the Alias.

[00379] In various illustrative and non-limiting embodiments, binding expressions may be implemented at different levels of the digital consumer profile, such as the organization level, system level, and campaign levels, among others. Such binding expressions may be evaluated in conjunction with other level expressions. In a non-limiting example, when targeting or attributing with an Alias, a specific campaign level binding expression may be dynamically, and transiently, generated along with a Circle name. The organization and system level binding expressions may be applied to build the final expression that represents a Circle for targeting.

[00380] In various illustrative and non-limiting embodiments, a Circle may be dynamically, and transiently, generated by using the context of content being targeted and attributed. Context may be used by binding expressions to include or exclude Links and Aliases for evaluation. In a non-limiting example, Aliases/Links may be restricted for use only if the owner of the content has access to the content. In yet another non-limiting example, content context may depend on content geography location, where the Alias/Link may only be used in certain geography. In such cases, encrypted IP addresses may or may not be legal in some geographical locations where content is being targeted and binding expressions are evaluated, limiting a binding expression's ability to include the Alias/Link for evaluation.

[00381] Fig. 63 demonstrates a non-limiting example of a collection of links, aliases, and circles within the digital consumer service environment 6300. A single Master ID 6302 may be dynamically, and transiently, associated with an Alias/Master Link 6318 to several attribute Aliases. Such aliases may comprise device IDs 6308, Digital IDs (e.g. Encrypted IP + User Agent) 6314, platform cookie IDs 6310, the encrypted residential IP of Master IDs 6312, and advertiser provided consumer IDs 6304, among others. Each of these attribute Aliases may be associated together with different link types, such as "Household" 6320, "Self" 6314, or "Friend" 6322," among others.

[00382] In various illustrative and non-limiting embodiments, a binding expression may be evaluated according to different system level rules or preferences. Such rules or preferences may be provided according to the context of the content served, the Alias, and/or the Link. In a non-limiting example, a system level binding expression may be used to ensure all content targeting in a geographic location abides by laws of data usage in that region. Such a rule would be a system level default that could not be overridden by any organization that creates binding expressions. In embodiments, a binding expression may account for an organization's data access or private policy. As a non-limiting example, if an organization does not want to evaluate Circles using specific types of Aliases or Links, or if the organization is providing specialized Aliases or Links, such binding expressions may be evaluated according to those preferences. In embodiments, Aliases, Links, and Circles may populate a data structure in order to be evaluated. Such a data structure may be populated from internal data sources, data provided by other organizations, or data provided by third parties.

[00383] In various illustrative and non-limiting embodiments, the digital consumer service may comprise targeting content to an Alias. In embodiments, the profiles of Master IDs contained in a circle may be dynamically, and transiently, merged in order to represent the merged profile as a single entity for the targeting of content. In a non-limiting example, if an advertiser would like to target “Households” with a frequency of 5, the advertiser may first need to define a “Household” Circle. When an Alias is evaluated by a binding expression, the profiles of all Master IDs incorporated into the Circle will aggregate the frequency for such a campaign. If the frequency is less than 5, then the campaign may be targeted to such content. Once engagement with the content is confirmed, the closest (in distance to the original Alias) Master ID’s frequency will be increased by 1, not all Master ID. In the case of a tie in distance, the oldest Master ID may be used to increment. In yet another non-limiting example if an advertiser wishes to target the “Households” Circle, all individual Master IDs within such a household are available for retargeting. The frequency may then be allocated at the Master ID level. The Master ID availability as a target may then be pre-computed at the time the signal linking the Master and the Alias is available. An Alias may be dynamically, and transiently, linked with a segment or Circle, in a situation when the individual, who owns the Master ID, visits a website for an advertiser and does so while using a device which presents the Alias. In such an embodiment, each time an opportunity to place an ad is observed (an opportunity to bid), the opportunity presents an Alias that maps to the Master ID through a binding expression, such a binding expression has a probability high enough that is acceptable to the advertiser, and the expression is allowed within regulations, then the Master ID may be attached to the opportunity to bid. Multiple Master IDs may be attached to a single opportunity to place an ad. Information about the type of Link, probabilities, and strengths may also be attached. Such information may be used by the machine deciding on the value for such opportunity to place an ad, which may be particularly useful for a real-time bidding environment.

[00384] In various illustrative and non-limiting embodiments, the digital consumer service may execute the request for finding Links between Aliases and Master IDs in real time and between multiple Master IDs. In such embodiments, it may be necessary to implement a multi-step request of key-value pairs. Such requests may be dynamically, and transiently, executed in real time with adequate sharing of data across multiple machines. This multi-step request allows storing information in a

compact form, as Aliases may point to Master IDs, which may in turn point back to Aliases. Master IDs may also point to other Master IDs. Such a multi-step request architecture may result in a complex set of connections roughly proportional to the number of Aliases in addition to the number of links between Master IDs. A non-limiting example of such complexity may be exhibited in Fig. 62. In embodiments, the digital consumer service 6200 may find links between different consumer Master IDs 6202. For example, the link between Consumer 1's Master ID and Consumer 2's Master ID is that Consumer 1 lives with 6214 Consumer 2. Similarly, Consumer 2 may have a "Works With" link 6220 with Consumer 3 and a "Friends via Social Network" link 6218 with Consumer 4. Consumer 4 may also have a "Lives With" link with Consumer 5. Each consumer may have access to various devices whose inputs may be used to target or attribute content, such as mobile phones or personal computers, among others. Such devices may comprise aliases 6204 as well as device alias links 6212 to associate the device aliases with the different consumer Master IDs. Such devices may in turn comprise various attributes aliases 6208 which may further be used to target or attribute content, such as an IP address, cookies, or device fingerprint, among others. These attribute aliases may be dynamically, and transiently, linked 6210 to device aliases, to establish a connection between different attribute aliases and different Consumer Master IDs. For example, Consumer 1, who lives with Consumer 2, may use the same iPad at home with Consumer 2. Similarly, Consumer 1 may have her favorite news website cookies preserved on both her personal computer and the iPad which she shares with Consumer 2. In embodiments, the digital consumer service may comprise multiple jumps within key value pairs to store these complex Alias/Master ID network maps in a compact form.

[00385] In various illustrative and non-limiting embodiments, the digital consumer service may dynamically, and transiently, attribute content to an Alias. In such embodiments, a given Alias of an Activity may or may not be related back to engagement with content when a binding expression is evaluated and returns a positive signal along with the content context of an instance where the Alias engaged with the content. Additionally, in embodiments, an organization may audit binding expressions as well as the state of the platform architecture in order to prove compliance with any rules or regulations that an organization is bound to follow for the purposes of targeting and attributing content and activities.

[00386] In various illustrative and non-limiting embodiments, the digital consumer service may target an attribute for multiple aliases. In embodiments, Aliases may be identifiers generated by devices, browsers, algorithms, or third parties that may be passed to the platform via requests and be made available during the bidding process. Aliases may comprise a statistical Household ID or Statistical User identifier. The Alias may also provide information about the Alias owner, and whether the Alias is “pay per use.” The statistical household ID may be derived from the IP address of the consumer once passed through a filter that determines whether the IP is a household. The statistical User ID may be derived from a combination of the consumer agent and IP address of the consumer. In embodiments, platform users may be able to add Alias type to segment creation. Aliases may therefore be used to configure segment membership criteria. Additionally, platform users may select multiple aliases to be included in the attribution model for performance to be optimized. In embodiments, new aliases may be instantiated via API, where only internal platform users may be able to access such aliases. Alias data may be ingested via platform servers, which additionally may have URL parameters appended to specify aliases that must be passed in via URL parameters.

[00387] In embodiments, the systems and methods, such as the analytic platform facility 114 and bidding system described herein may allow advertisers access to a multiplicity of expert buying agents, for trying different options expecting that some options would work better than others. In embodiments, the systems and methods may create a marketplace where software agents may be published, shared, sold, and bought. In embodiments, systems and methods may comprise a platform with clear API interfaces into what type of data is available as inputs, what type of computing resources are available (memory, CPU cycles, time to respond), and what type of format the output would provide, and the like. In embodiments, the system may comprise user exposed levers that allow a user to switch buying agents without relying on a modification of the source code. In embodiments, the capability to simultaneously use different buying agents, and apply them to certain slices of inventory, or certain partitions such as geographical location, may create an environment for comparison testing of different methodologies for buying opportunities to place ads.

[00388] The methods and systems described herein may be deployed in part or in whole through a machine that executes computer software, program codes,

and/or instructions on a processor. The processor may be part of a server, client, network infrastructure, mobile computing platform, stationary computing platform, or other computing platform. A processor may be any kind of computational or processing device capable of executing program instructions, codes, binary instructions and the like. The processor may be or include a signal processor, digital processor, embedded processor, microprocessor or any variant such as a co-processor (math co-processor, graphic co-processor, communication co-processor and the like) and the like that may directly or indirectly facilitate execution of program code or program instructions stored thereon. In addition, the processor may enable execution of multiple programs, threads, and codes. The threads may be executed simultaneously to enhance the performance of the processor and to facilitate simultaneous operations of the application. By way of implementation, methods, program codes, program instructions and the like described herein may be implemented in one or more thread. The thread may spawn other threads that may have assigned priorities associated with them; the processor may execute these threads based on priority or any other order based on instructions provided in the program code. The processor may include memory that stores methods, codes, instructions and programs as described herein and elsewhere. The processor may access a storage medium through an interface that may store methods, codes, and instructions as described herein and elsewhere. The storage medium associated with the processor for storing methods, programs, codes, program instructions or other type of instructions capable of being executed by the computing or processing device may include but may not be limited to one or more of a CD-ROM, DVD, memory, hard disk, flash drive, RAM, ROM, cache and the like.

[00389] A processor may include one or more cores that may enhance speed and performance of a multiprocessor. In embodiments, the process may be a dual core processor, quad core processors, other chip-level multiprocessor and the like that combine two or more independent cores (called a die).

[00390] The methods and systems described herein may be deployed in part or in whole through a machine that executes computer software on a server, client, firewall, gateway, hub, router, or other such computer and/or networking hardware. The software program may be associated with a server that may include a file server, print server, domain server, internet server, intranet server and other variants such as secondary server, host server, distributed server and the like. The server may include

one or more of memories, processors, computer readable media, storage media, ports (physical and virtual), communication devices, and interfaces capable of accessing other servers, clients, machines, and devices through a wired or a wireless medium, and the like. The methods, programs or codes as described herein and elsewhere may be executed by the server. In addition, other devices required for execution of methods as described in this application may be considered as a part of the infrastructure associated with the server.

[00391] The server may provide an interface to other devices including, without limitation, clients, other servers, printers, database servers, print servers, file servers, communication servers, distributed servers and the like. Additionally, this coupling and/or connection may facilitate remote execution of program across the network. The networking of some or all of these devices may facilitate parallel processing of a program or method at one or more location without deviating from the scope of the invention. In addition, any of the devices attached to the server through an interface may include at least one storage medium capable of storing methods, programs, code and/or instructions. A central repository may provide program instructions to be executed on different devices. In this implementation, the remote repository may act as a storage medium for program code, instructions, and programs.

[00392] The software program may be associated with a client that may include a file client, print client, domain client, internet client, intranet client and other variants such as secondary client, host client, distributed client and the like. The client may include one or more of memories, processors, computer readable media, storage media, ports (physical and virtual), communication devices, and interfaces capable of accessing other clients, servers, machines, and devices through a wired or a wireless medium, and the like. The methods, programs or codes as described herein and elsewhere may be executed by the client. In addition, other devices required for execution of methods as described in this application may be considered as a part of the infrastructure associated with the client.

[00393] The client may provide an interface to other devices including, without limitation, servers, other clients, printers, database servers, print servers, file servers, communication servers, distributed servers and the like. Additionally, this coupling and/or connection may facilitate remote execution of program across the network. The networking of some or all of these devices may facilitate parallel processing of a program or method at one or more location without deviating from the

scope of the invention. In addition, any of the devices attached to the client through an interface may include at least one storage medium capable of storing methods, programs, applications, code and/or instructions. A central repository may provide program instructions to be executed on different devices. In this implementation, the remote repository may act as a storage medium for program code, instructions, and programs.

[00394] The methods and systems described herein may be deployed in part or in whole through network infrastructures. The network infrastructure may include elements such as computing devices, servers, routers, hubs, firewalls, clients, personal computers, communication devices, routing devices and other active and passive devices, modules and/or components as known in the art. The computing and/or non-computing device(s) associated with the network infrastructure may include, apart from other components, a storage medium such as flash memory, buffer, stack, RAM, ROM and the like. The processes, methods, program codes, instructions described herein and elsewhere may be executed by one or more of the network infrastructural elements.

[00395] The methods, program codes, and instructions described herein and elsewhere may be implemented on a cellular network having multiple cells. The cellular network may either be frequency division multiple access (FDMA) network or code division multiple access (CDMA) network. The cellular network may include mobile devices, cell sites, base stations, repeaters, antennas, towers, and the like. The cell network may be a GSM, GPRS, 3G, EVDO, mesh, or other networks types.

[00396] The methods, programs codes, and instructions described herein and elsewhere may be implemented on or through mobile devices. The mobile devices may include navigation devices, cell phones, mobile phones, mobile personal digital assistants, laptops, palmtops, netbooks, pagers, electronic books readers, music players and the like. These devices may include, apart from other components, a storage medium such as a flash memory, buffer, RAM, ROM and one or more computing devices. The computing devices associated with mobile devices may be enabled to execute program codes, methods, and instructions stored thereon. Alternatively, the mobile devices may be configured to execute instructions in collaboration with other devices. The mobile devices may communicate with base stations interfaced with servers and configured to execute program codes. The mobile devices may communicate on a peer to peer network, mesh network, or other

communications network. The program code may be stored on the storage medium associated with the server and executed by a computing device embedded within the server. The base station may include a computing device and a storage medium. The storage device may store program codes and instructions executed by the computing devices associated with the base station.

[00397] The computer software, program codes, and/or instructions may be stored and/or accessed on machine readable media that may include: computer components, devices, and recording media that retain digital data used for computing for some interval of time; semiconductor storage known as random access memory (RAM); mass storage typically for more permanent storage, such as optical discs, forms of magnetic storage like hard disks, tapes, drums, cards and other types; processor registers, cache memory, volatile memory, non-volatile memory; optical storage such as CD, DVD; removable media such as flash memory (e.g. USB sticks or keys), floppy disks, magnetic tape, paper tape, punch cards, standalone RAM disks, Zip drives, removable mass storage, off-line, and the like; other computer memory such as dynamic memory, static memory, read/write storage, mutable storage, read only, random access, sequential access, location addressable, file addressable, content addressable, network attached storage, storage area network, bar codes, magnetic ink, and the like.

[00398] The methods and systems described herein may transform physical and/or or intangible items from one state to another. The methods and systems described herein may also transform data representing physical and/or intangible items from one state to another.

[00399] The elements described and depicted herein, including in flow charts and block diagrams throughout the figures, imply logical boundaries between the elements. However, according to software or hardware engineering practices, the depicted elements and the functions thereof may be implemented on machines through computer executable media having a processor capable of executing program instructions stored thereon as a monolithic software structure, as standalone software modules, or as modules that employ external routines, code, services, and so forth, or any combination of these, and all such implementations may be within the scope of the present disclosure. Examples of such machines may include, but may not be limited to, personal digital assistants, laptops, personal computers, mobile phones, other handheld computing devices, medical equipment, wired or wireless

communication devices, transducers, chips, calculators, satellites, tablet PCs, electronic books, gadgets, electronic devices, devices having artificial intelligence, computing devices, networking equipments, servers, routers and the like. Furthermore, the elements depicted in the flow chart and block diagrams or any other logical component may be implemented on a machine capable of executing program instructions. Thus, while the foregoing drawings and descriptions set forth functional aspects of the disclosed systems, no particular arrangement of software for implementing these functional aspects should be inferred from these descriptions unless explicitly stated or otherwise clear from the context. Similarly, it will be appreciated that the various steps identified and described above may be varied, and that the order of steps may be adapted to particular applications of the techniques disclosed herein. All such variations and modifications are intended to fall within the scope of this disclosure. As such, the depiction and/or description of an order for various steps should not be understood to require a particular order of execution for those steps, unless required by a particular application, or explicitly stated or otherwise clear from the context.

[00400] The methods and/or processes described above, and steps thereof, may be realized in hardware, software or any combination of hardware and software suitable for a particular application. The hardware may include a general purpose computer and/or dedicated computing device or specific computing device or particular aspect or component of a specific computing device. The processes may be realized in one or more microprocessors, microcontrollers, embedded microcontrollers, programmable digital signal processors or other programmable device, along with internal and/or external memory. The processes may also, or instead, be embodied in an application specific integrated circuit, a programmable gate array, programmable array logic, or any other device or combination of devices that may be configured to process electronic signals. It will further be appreciated that one or more of the processes may be realized as a computer executable code capable of being executed on a machine readable medium.

[00401] The computer executable code may be created using a structured programming language such as C, an object oriented programming language such as C++, or any other high-level or low-level programming language (including assembly languages, hardware description languages, and database programming languages and technologies) that may be stored, compiled or interpreted to run on one of the above

devices, as well as heterogeneous combinations of processors, processor architectures, or combinations of different hardware and software, or any other machine capable of executing program instructions.

[00402] Thus, in one aspect, each method described above and combinations thereof may be embodied in computer executable code that, when executing on one or more computing devices, performs the steps thereof. In another aspect, the methods may be embodied in systems that perform the steps thereof, and may be distributed across devices in a number of ways, or all of the functionality may be integrated into a dedicated, standalone device or other hardware. In another aspect, the means for performing the steps associated with the processes described above may include any of the hardware and/or software described above. All such permutations and combinations are intended to fall within the scope of the present disclosure.

[00403] While the invention has been disclosed in connection with the preferred embodiments shown and described in detail, various modifications and improvements thereon will become readily apparent to those skilled in the art. Accordingly, the spirit and scope of the present invention is not to be limited by the foregoing examples, but is to be understood in the broadest sense allowable by law.

[00404] All documents referenced herein are hereby incorporated by reference.

[00405] Throughout this specification and claims which follow, unless the context requires otherwise, the word "comprise", and variations such as "comprises" and "comprising", will be understood to imply the inclusion of a stated integer or step or group of integers or steps but not the exclusion of any other integer or step or group of integers or steps.

[00406] The reference in this specification to any prior publication (or information derived from it), or to any matter which is known, is not, and should not be taken as an acknowledgment or admission or any form of suggestion that that prior publication (or information derived from it) or known matter forms part of the common general knowledge in the field of endeavour to which this specification relates.

THE CLAIMS DEFINING THE INVENTION ARE AS FOLLOWS:

1. A computer program product embodied in a non-transitory computer readable medium that, when executing on one or more computers, performs the steps of:

acquiring a first alias, wherein the first alias is comprised of a first plurality of attributes, wherein each of the first plurality of attributes is comprised of at least one of a first device identifier datum, a first behavioral datum, and a first demographic datum;

acquiring a second alias, wherein the second alias is comprised of a second plurality of attributes, wherein each of the second plurality of attributes is comprised of at least one of a second device identifier datum, a second behavioral datum, and a second demographic datum;

dynamically and transiently linking the first alias and the second alias to form a Master ID, wherein the dynamic linking of the first and second aliases is based at least in part on analysis of the first and the second pluralities of attributes using a binding expression that expresses a statistical confidence threshold required for grouping aliases; and

targeting advertising to a consumer device based at least in part on the Master ID.

2. The computer program product of claim 1, wherein the computer program product further performs the alias acquiring and dynamically linking steps iteratively over a plurality of aliases so that a plurality of attributes are merged into a single Master ID.

3. The computer program product of claim 1, wherein the computer program product further performs a step of analyzing at least one of an advertising campaign targeted to the Master ID, consumer behavior associated with the Master ID, and consumer traits associated with the Master ID.

4. The computer program product of claim 1, wherein at least one of the first alias and the second alias is acquired from at least one of a consumer database of an organization and a third party database.
5. The computer program product of claim 1, wherein at least one of the first device identifier datum and the second device identifier datum comprises at least one of an IP address and a device ID.
6. The computer program product of claim 1, wherein dynamic linking of aliases is further based at least in part on a rules engine.
7. The computer program product of claim 6, wherein the rules engine includes rules for dynamic linking of aliases based at least in part on at least one of a regulatory constraint, a business agreement, a privacy policy, and a consumer preference.
8. The computer program product of claim 7, wherein dynamic linking of aliases prohibits linking aliases based on an identification of an IP address in certain predetermined geographical locations.
9. The computer program product of claim 1, wherein dynamic linking of aliases is performed based on a link type including at least one of self, household, and friend.
10. The computer program product of claim 1, wherein the first and the second aliases are linked only for a predetermined time period.
11. The computer program product of claim 1, wherein the aliases are stored in memory and include additional attributes time.
12. The computer program product of claim 1, wherein advertising is targeted to a plurality of linked consumer computing devices based on the Master ID.
13. The computer program product of claim 1, wherein the statistical confidence threshold varies depending on the alias attributes that are linked.

14. A computer program product embodied in a non-transitory computer readable medium that, when executing on one or more computers, performs the steps of:

acquiring a first alias, wherein the first alias is comprised of a first plurality of attributes, wherein each of the first plurality of attributes is comprised of at least one of a first device identifier datum, a first consumer datum, a first behavioral datum, and a first demographic datum;

acquiring a second alias, wherein the second alias is comprised of a second plurality of attributes, wherein each of the second plurality of attributes is comprised of at least one of a second device identifier datum, a second consumer datum, a second behavioral datum, and a second demographic datum;

dynamically and transiently linking the first alias and the second alias to form a Master ID, wherein the dynamic linking of the first and second aliases is based at least in part on analysis of the first and the second pluralities of attributes using a binding expression that expresses a statistical confidence threshold required for grouping aliases,

wherein the alias acquiring and dynamically linking steps are performed iteratively over a plurality of aliases so that a plurality of attributes are merged into a single Master ID;

targeting an advertising campaign to a consumer device based at least in part on the Master ID; and

analyzing results of the advertising campaign targeted to the Master ID.

15. The computer program product of claim 14, wherein at least one of the first alias and the second alias is acquired from at least one of a consumer database of an organization and a third party database.

16. The computer program product of claim 1, wherein dynamic linking is achieved by matching attributes of aliases including at least one of an IP address, a device ID, an e-mail address, and cookie tracking information.

17. The computer program product of claim 16, wherein dynamic linking of alias is based on a rules engine and the rules engine includes rules for dynamic linking of

aliases based at least in part on at least one of a regulatory constraint, a business agreement, a privacy policy, and a consumer preference.

18. The computer program product of claim 17, wherein the rules engine includes different rules for different geographic locations.

19. A computer program product embodied in a non-transitory computer readable medium that, when executing on one or more computers, performs the steps of:

acquiring a first alias, wherein the first alias is comprised of a first plurality of attributes, wherein each of the first plurality of attributes is comprised of at least one of a first device identifier datum, a first consumer datum, a first behavioral datum, and a first demographic datum;

acquiring a second alias, wherein the second alias is comprised of a second plurality of attributes, wherein each of the second plurality of attributes is comprised of at least one of a second device identifier datum, a second consumer datum, a second behavioral datum, and a second demographic datum;

dynamically and transiently linking the first alias and the second alias to form a first Master ID, wherein the dynamic linking of the first and second aliases is based at least in part on analysis of the first and the second pluralities of attributes using a first binding expression that expresses a statistical confidence threshold required for grouping aliases;

acquiring a third alias, wherein the third alias is comprised of a third plurality of attributes, wherein each of the third plurality of attributes is comprised of at least one of a third device identifier datum, a third consumer datum, a third behavioral datum, and a third demographic datum;

acquiring a fourth alias, wherein the fourth alias is comprised of a fourth plurality of attributes, wherein each of the fourth plurality of attributes is comprised of at least one of a fourth device identifier datum, a fourth consumer datum, a fourth behavioral datum, and a fourth demographic datum;

dynamically and transiently linking the third alias and the fourth alias to form a second Master ID, wherein the dynamic linking of the third and fourth aliases is based at least in part on analysis of the first and the second pluralities of attributes using a second binding expression that expresses a statistical confidence threshold required for grouping aliases;

merging the first Master ID and the second Master ID to form a circle set, the merging based on a recognition that the Master IDs are related to each other by one of a type of self, household, and friend; and

targeting an advertising campaign to multiple consumer devices based at least in part on the circle set.

20. The computer program product of claim 19, wherein dynamic linking is achieved by matching attributes of aliases including at least one of an IP address, a device ID, an e-mail address, and cookie tracking information.

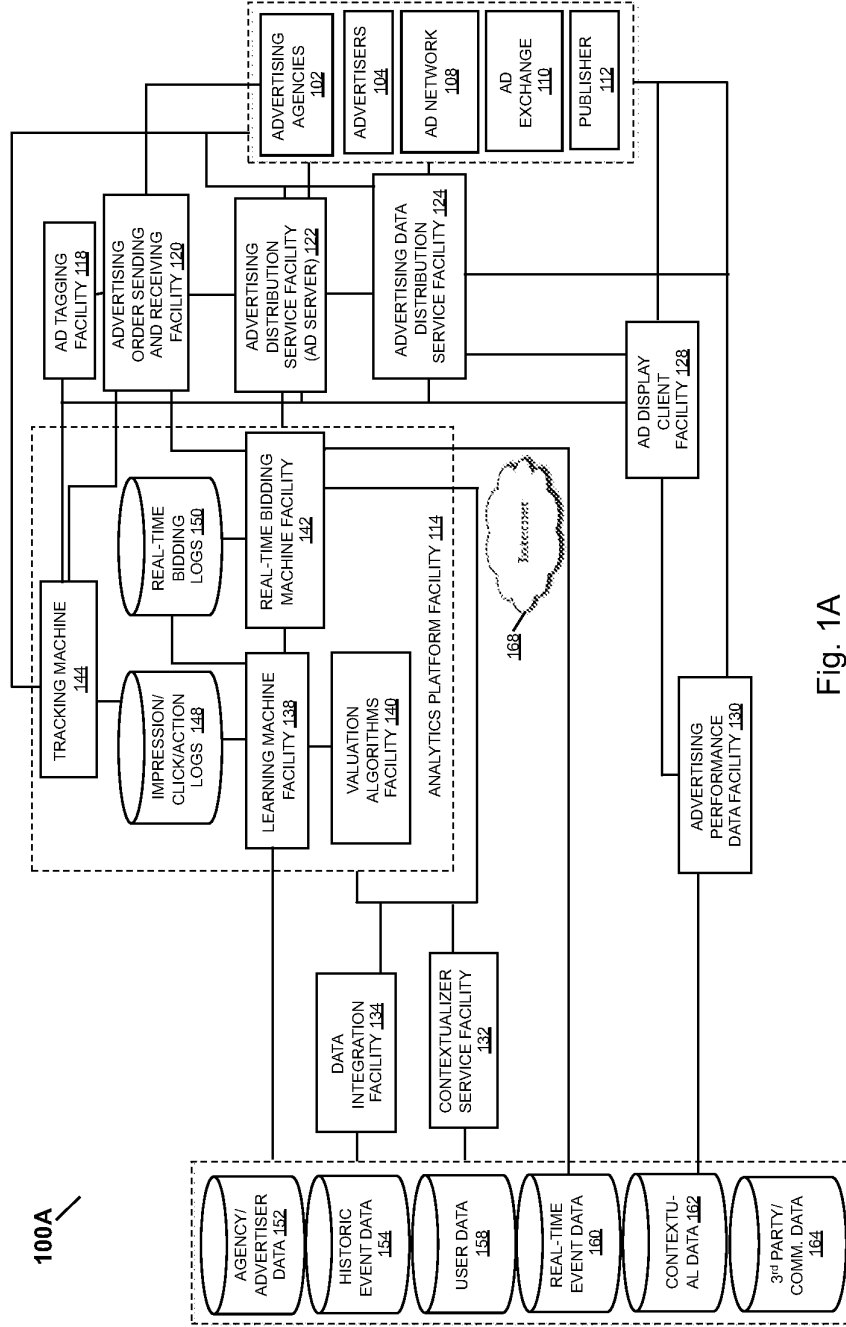


Fig. 1A

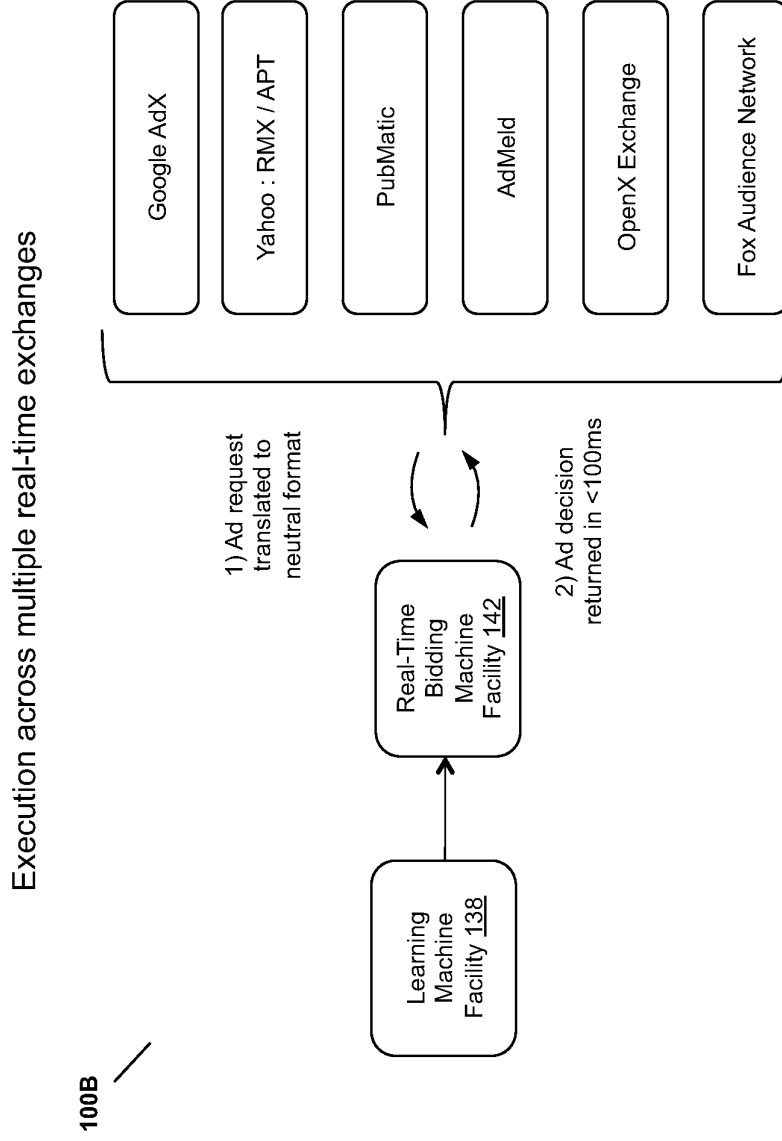


Fig. 1B

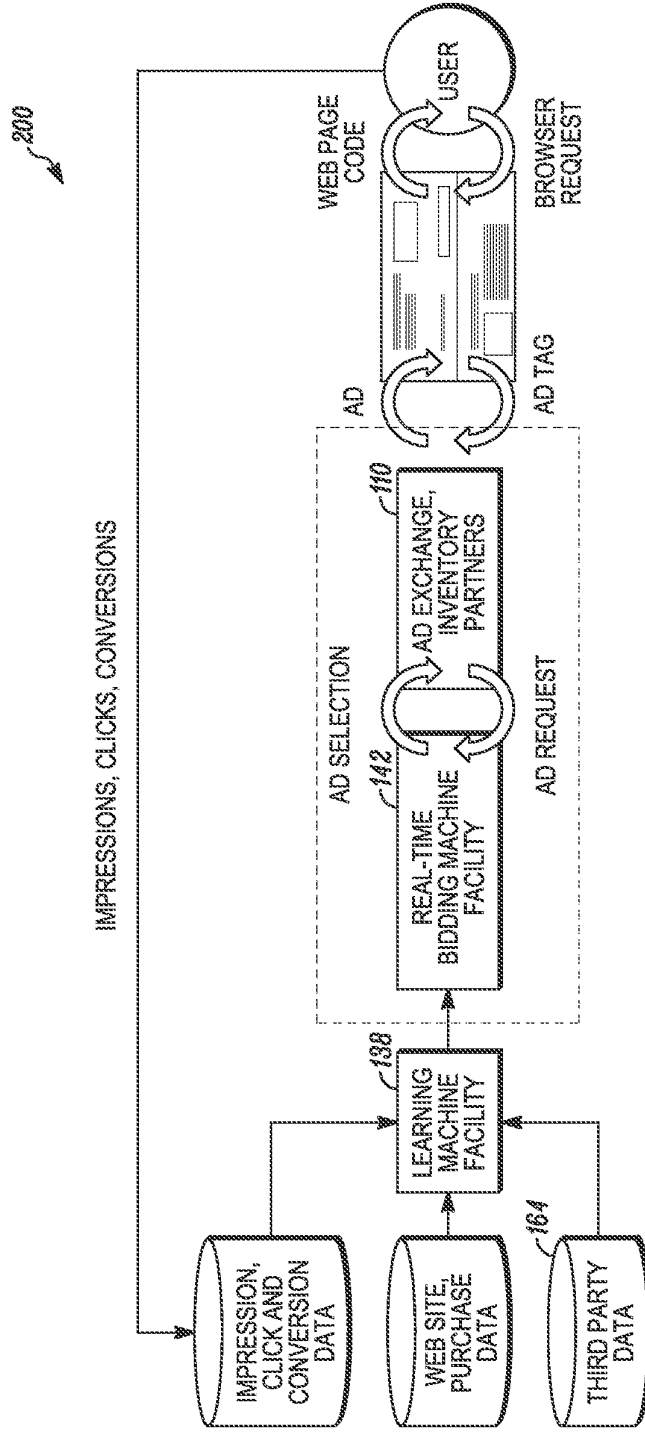


FIG. 2

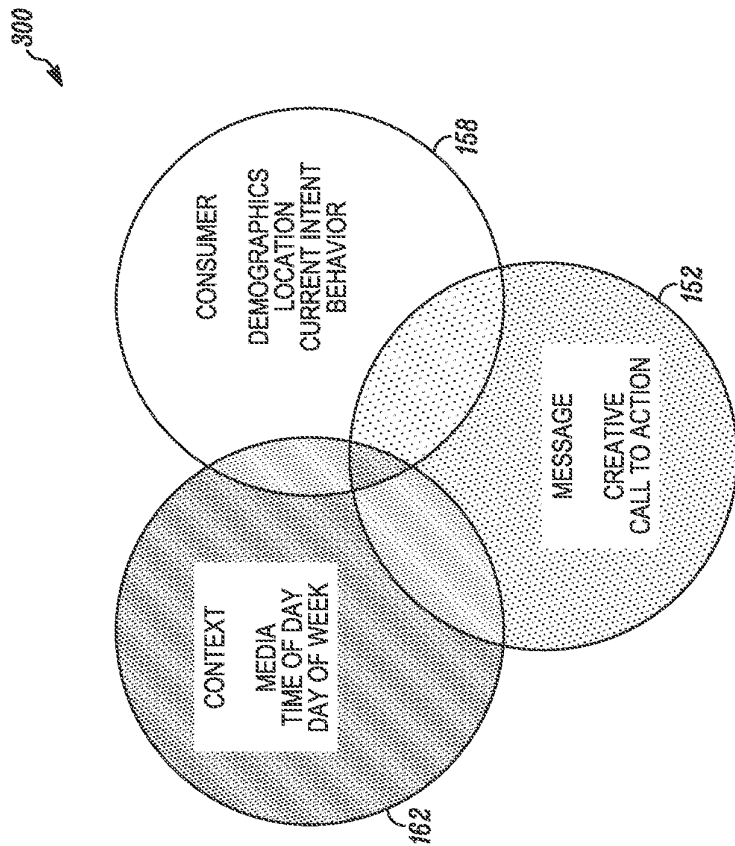


FIG. 3

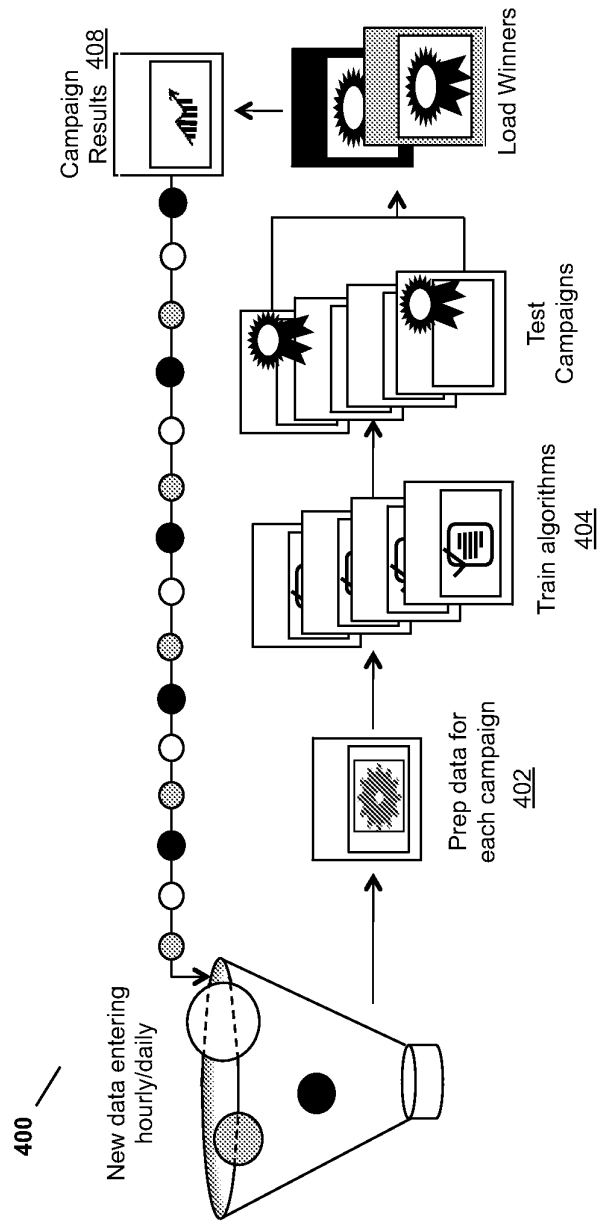


Fig. 4

Bidding value for each micro-segment (\$/CPM)

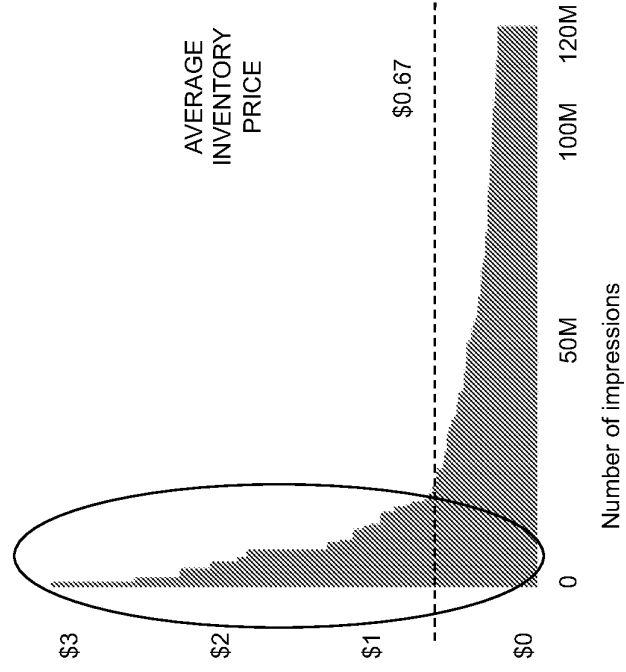


Fig. 5A

500

EXAMPLE: INSIGHT REPORTS

502

MICROSEGMENTATION ANALYSIS, CAMPAIGN TO DATE

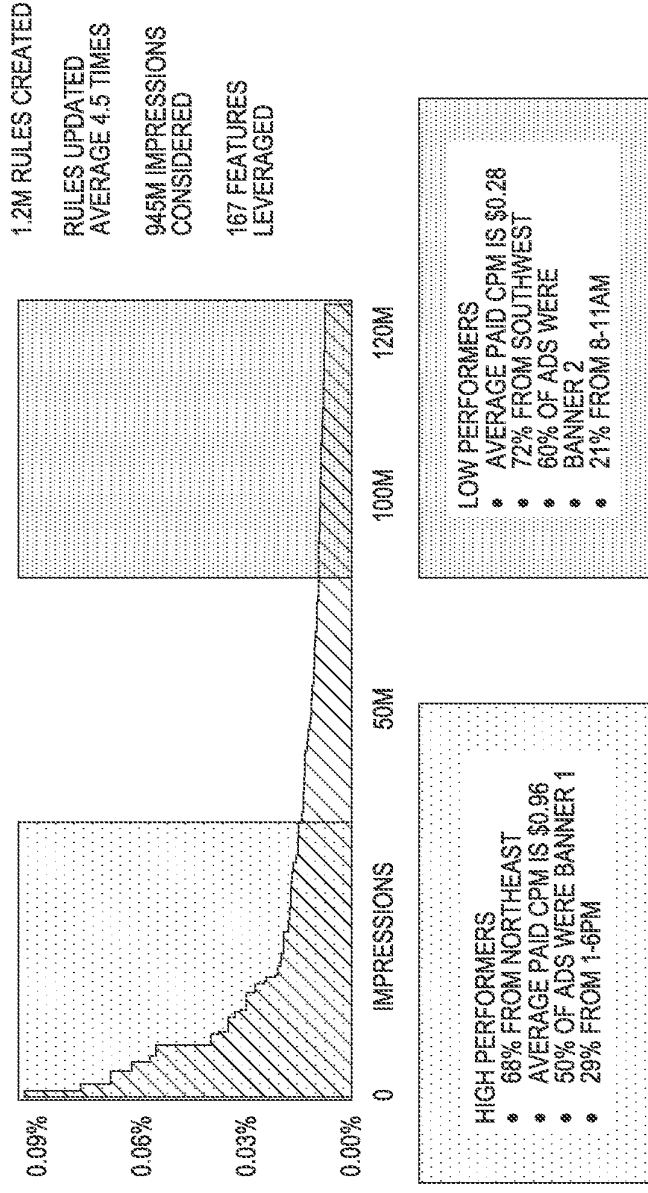


FIG. 5B

504

PRICING IS OPTIMIZED THROUGH FREQUENCY ANALYSIS

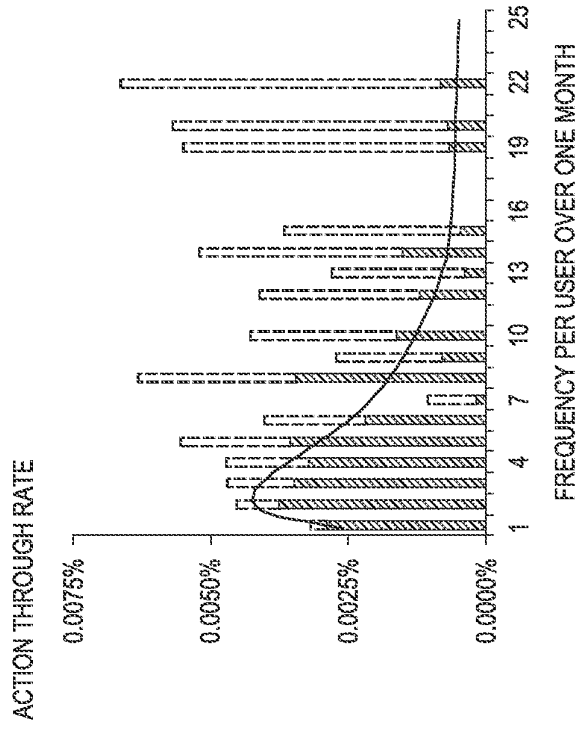


FIG. 5C

508

PACING IS OPTIMIZED THROUGH REGENCY ANALYSIS

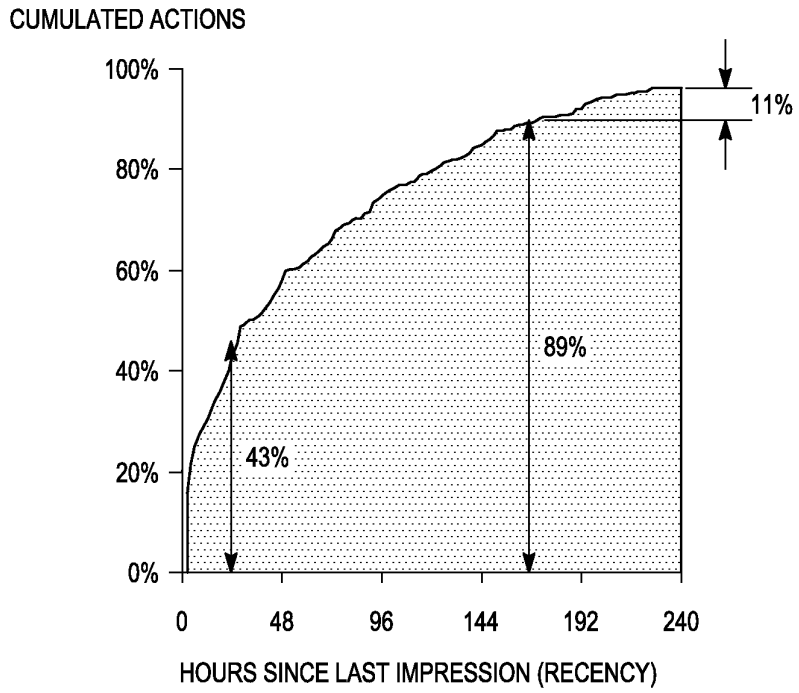


FIG. 5D

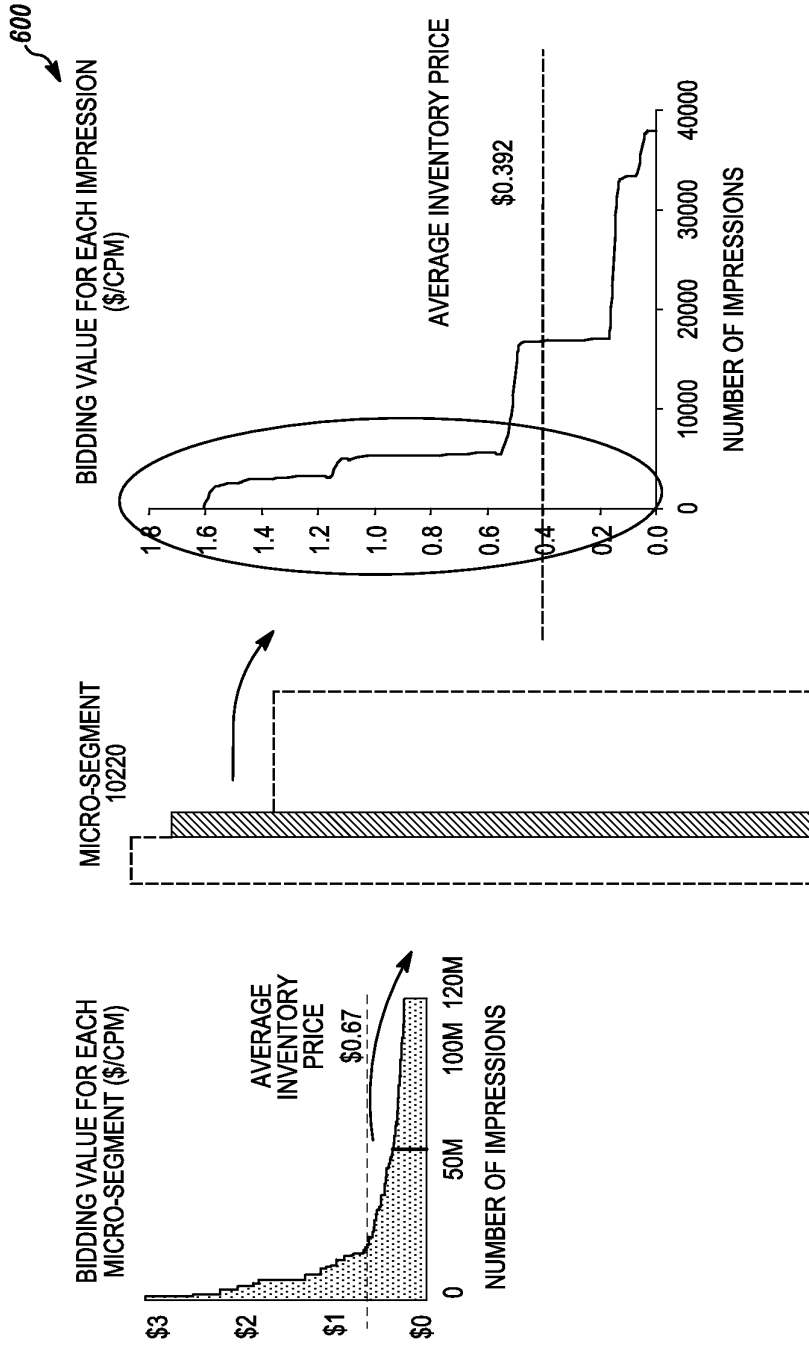


FIG. 6

700 —

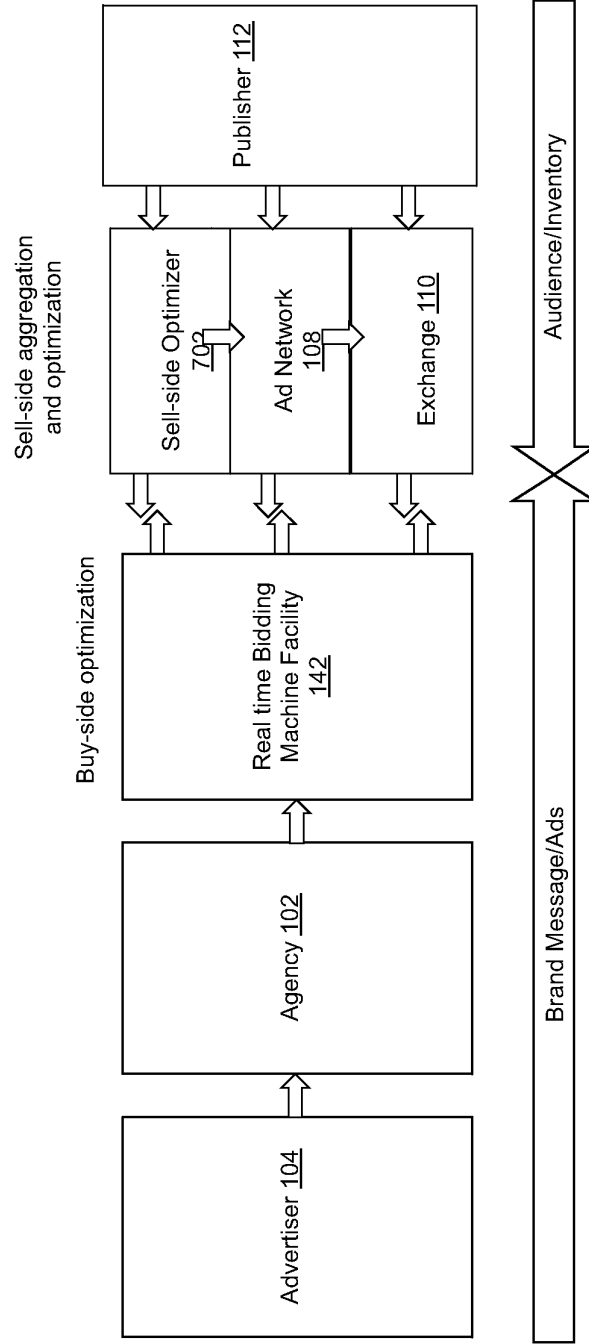


Fig. 7

800

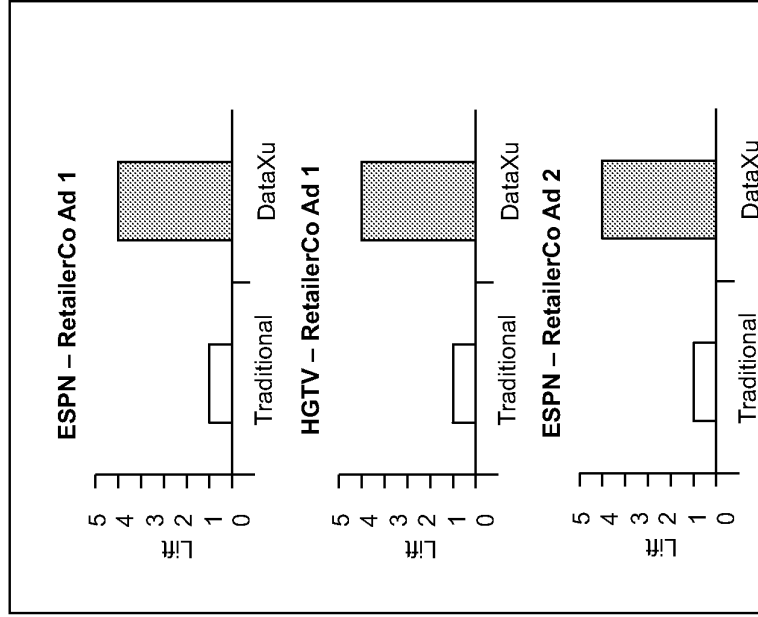


Fig. 8A

Example Results: Two campaigns from a US "big box" department store

802

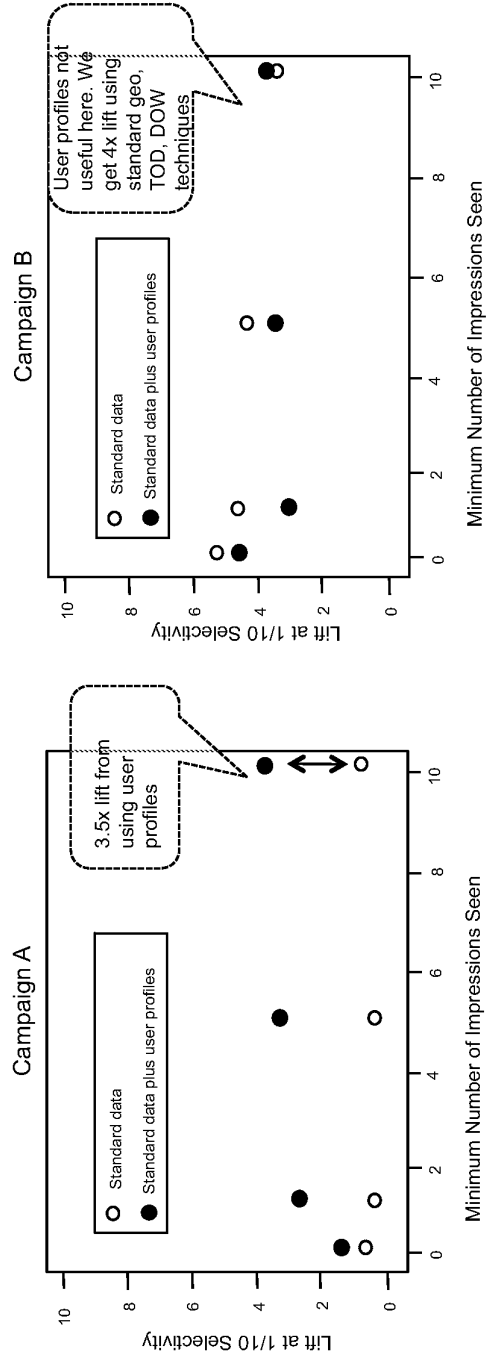


Fig. 8B

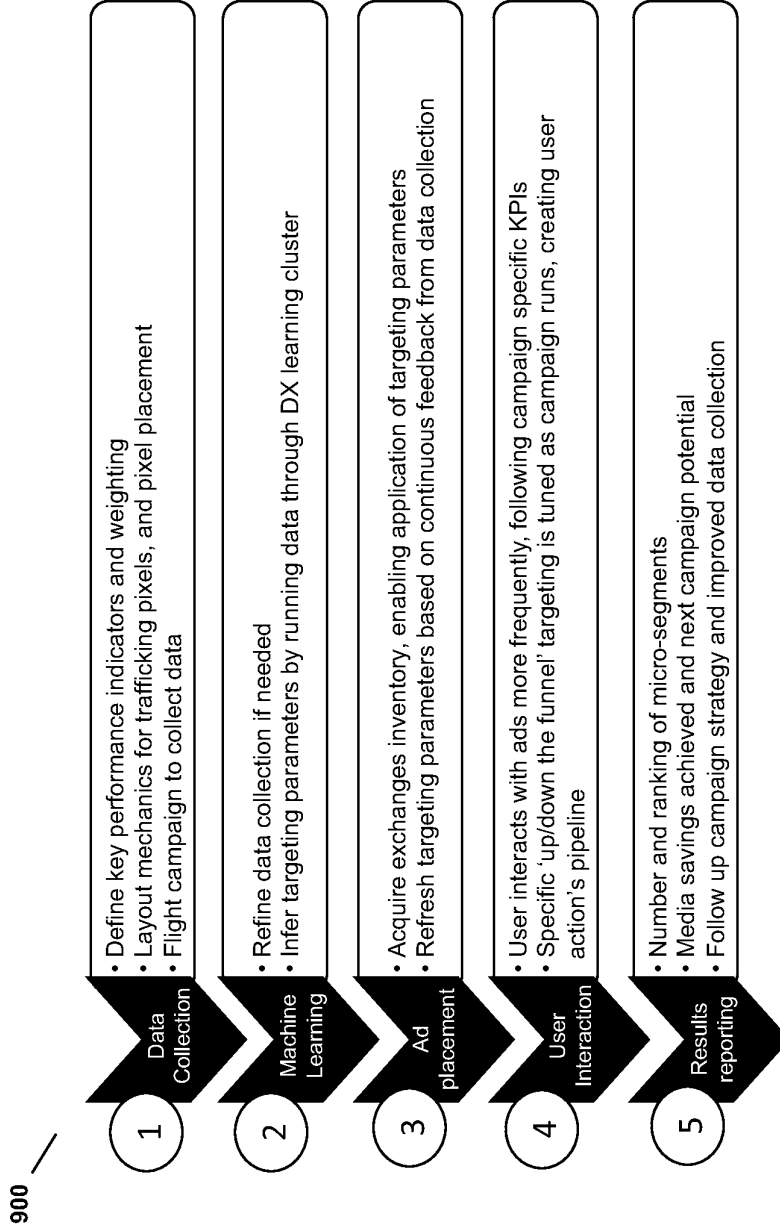


Fig. 9

1000

• PIXEL PROVISIONING SERVICE PROVIDES EASY GENERATION OF HTML OR JAVASCRIPT TAGS

DATA XU REPORTING ENGINE: DAILY... HTTP://DXPPS.U.../COM/WEBSITES/3

ADMIN LINKS: PPS USERS | FEEDBACK | LOGGED IN AS ADMIN@DATA XU.COM | ACCOUNT | LOGOUT

DATA XU
PIXEL PROVISIONING SYSTEM

AD PIXELS | WEBSITE PIXELS

[WEBSITES > BRITNEYCIRCUS.COM\(EDIT\)](#)

CHOOSE A PIXEL TYPE BELOW TO GATHER PERFORMANCE-ENHANCING DATA FROM ADVERTISER WEBSITES. REMEMBER TO ONLY ADD ONE PIXEL PER PAGE

PAGE SPECIFIC PIXEL MARKUP

PAGE-SPECIFIC PIXELS ALLOW YOU TO GATHER MORE ACCURATE INFORMATION BY IDENTIFYING EACH PAGE TYPE. FIRST SELECT THE PAGE TYPE, AND THEN SET THE VALUES FOR THE RELEVANT FIELDS. PAGE DESIGNERS OR CODERS MAY FILL IN DATA SUCH AS SEARCH TERMS FOLLOWING THE INSTRUCTIONS BELOW

WHAT TYPE OF PAGE?

PRODUCT SEARCH SEARCH RESULT HOME MARKETING CHECKOUT

SAVED PIXEL MARKUP

8)GENERIC PRODUCT PIXEL(DELETE)

`<IMG SRC="HTTP://W55C.NET/RS?ID=F9A8FAF465EC47CC8217C0707666FB26&T=PRODUCT&PRODUCT_TYPE=${PRODUCT_TYPE}&PRODUCT_SUBTYPE=${PRODUCT`

ALL SAVED PIXELS (USE TO BULK COPY AND PASTE)

FIG. 10

1100 Prepare - Impression Level Data

Impressions	Click	Activity or Site visit
Time stamp	Time stamp	Time stamp
Page URL	Page URL	Page URL
Referral URL	Referral URL	Referral URL
	Search terms (if applicable)	
Content category	Content category	Content category
User ID	User ID	User ID
Geography by DMA	Geography by DMA	Geography by DMA
Agent information (OS and Browser)	Agent information (OS and Browser)	Agent information (OS and Browser)
IP address	IP address	IP address
		Activity ID
		Other activity data (SKU, basket value)
Flight ID	Flight ID	
Campaign ID	Campaign ID	
Creative ID		
Creative format and type		
Creative position in page		

Fig. 11

TOTAL SPEND TO DATE	\$774,550
PROJECTED SPEND TO DATE	\$746,250
% OF BUDGET SPENT OVERALL	51%
ACTIONS TO DATE	33,420
PROJECTED ACTIONS TO DATE	29,850
% OF ACTION GOAL REACHED	55%
COST PER ACTION	\$23
PROJECTED COST PER ACTION	\$25

1200 ↗

PERFORMANCE AND DELIVERY
TRENDING
CAMPAIGN TO DATE

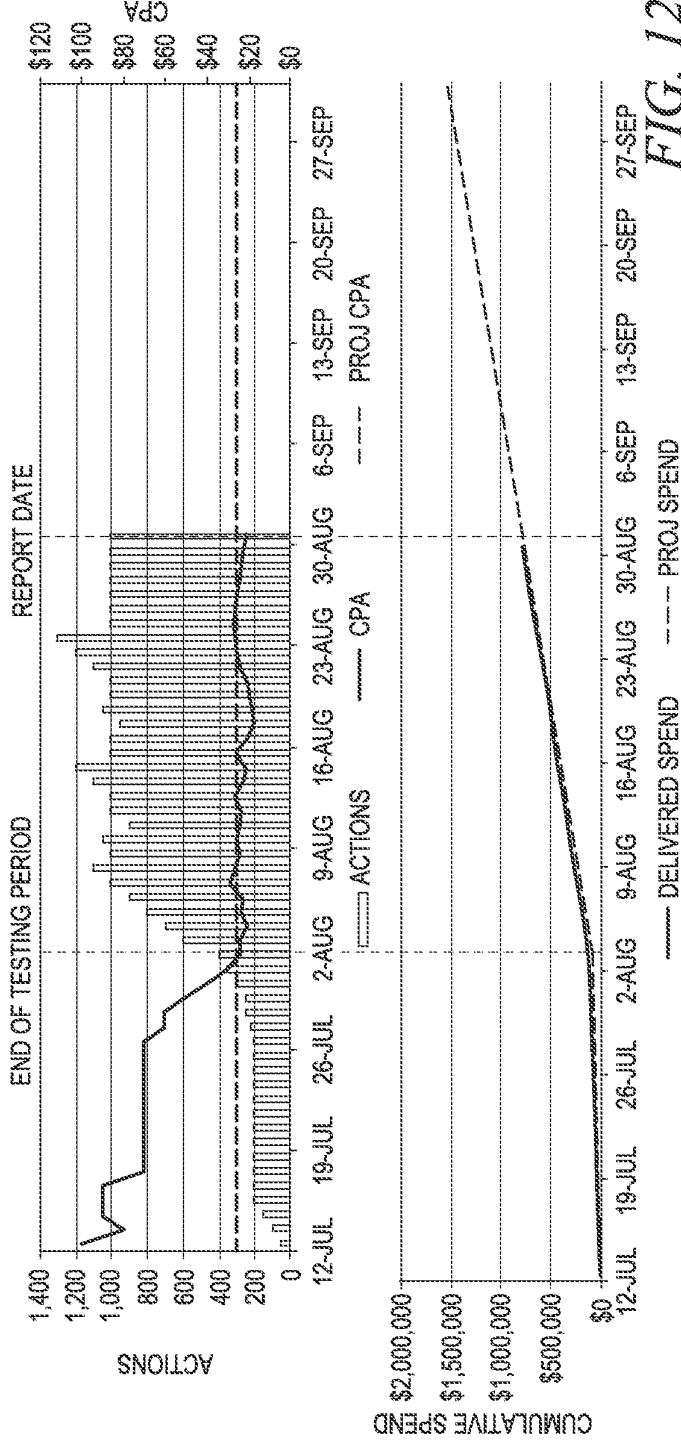


FIG. 12

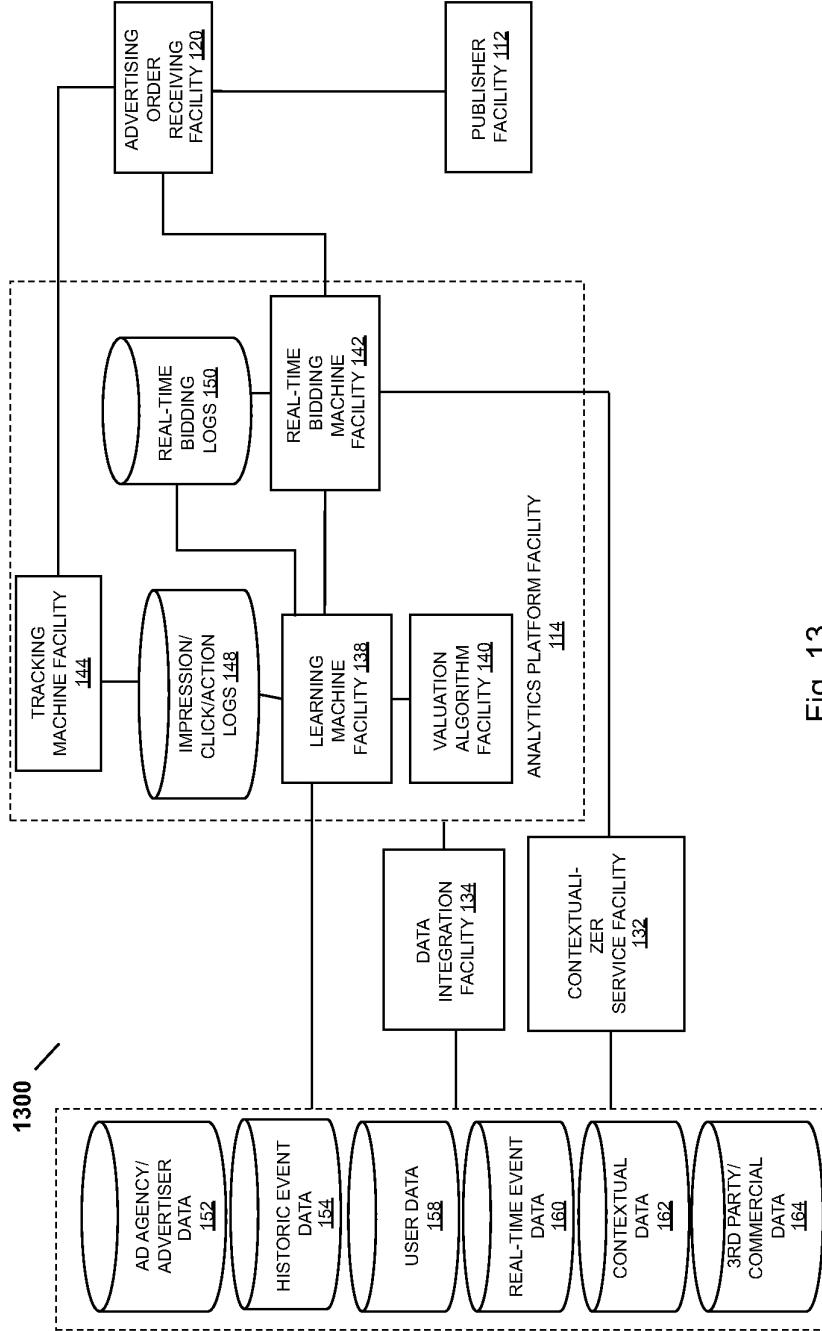


Fig. 13

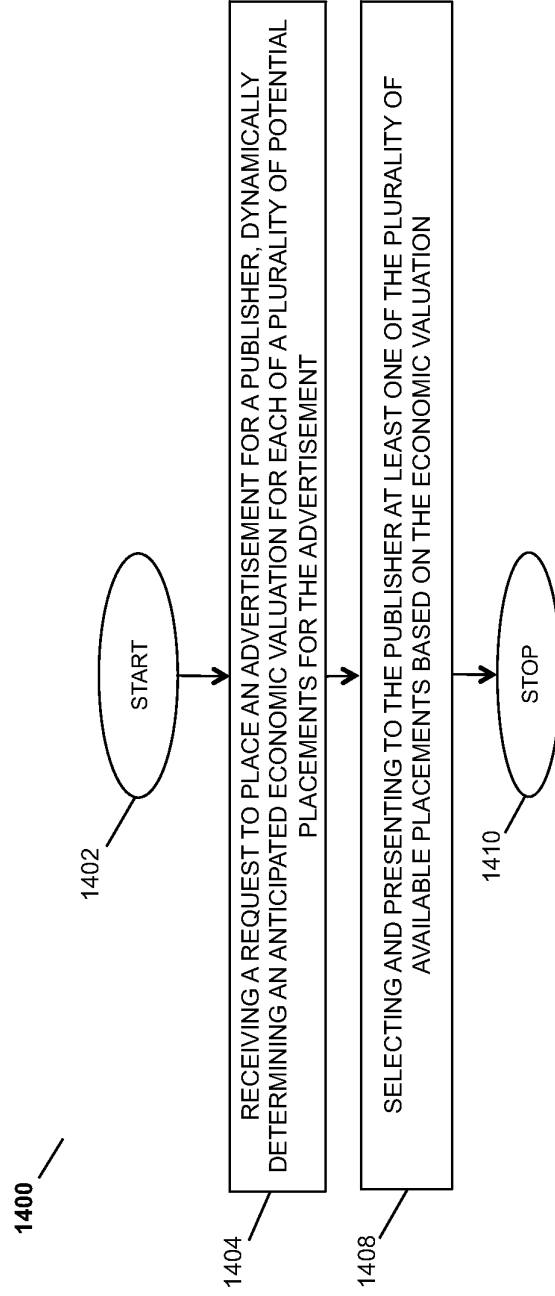


Fig. 14

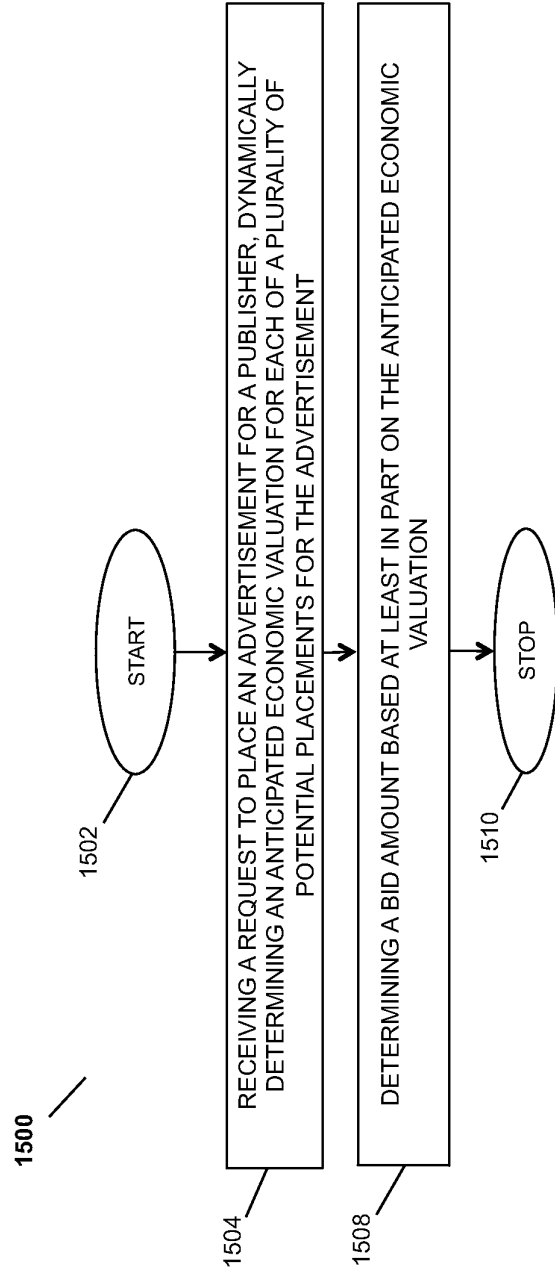


Fig. 15

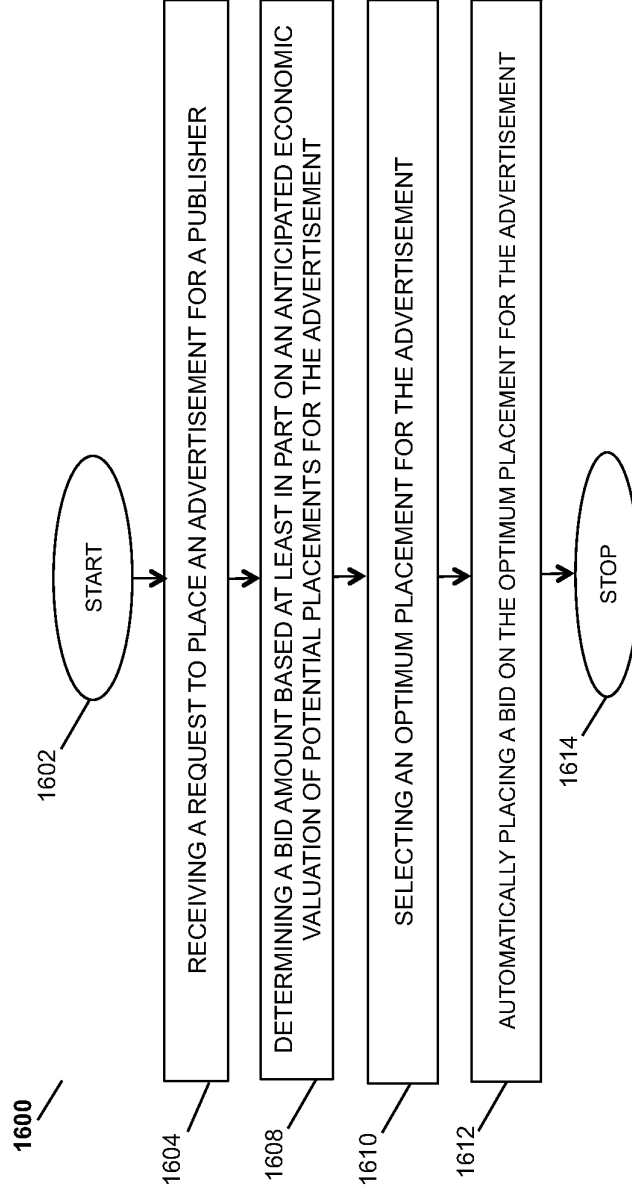


Fig. 16

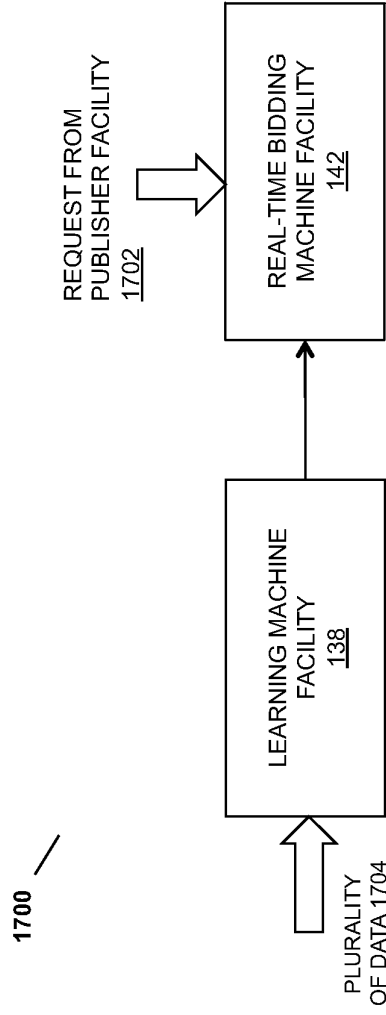


Fig. 17

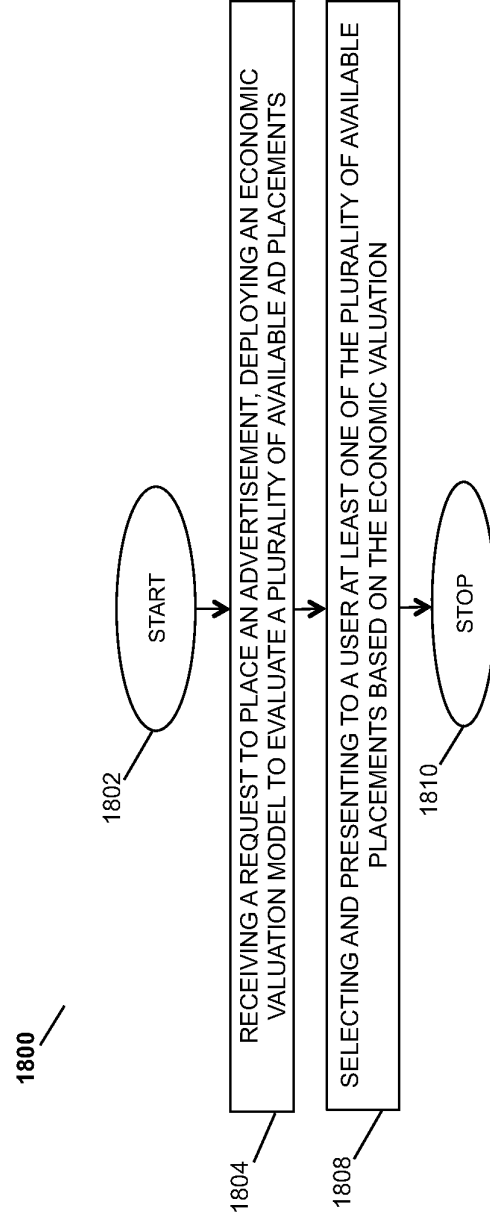


Fig. 18

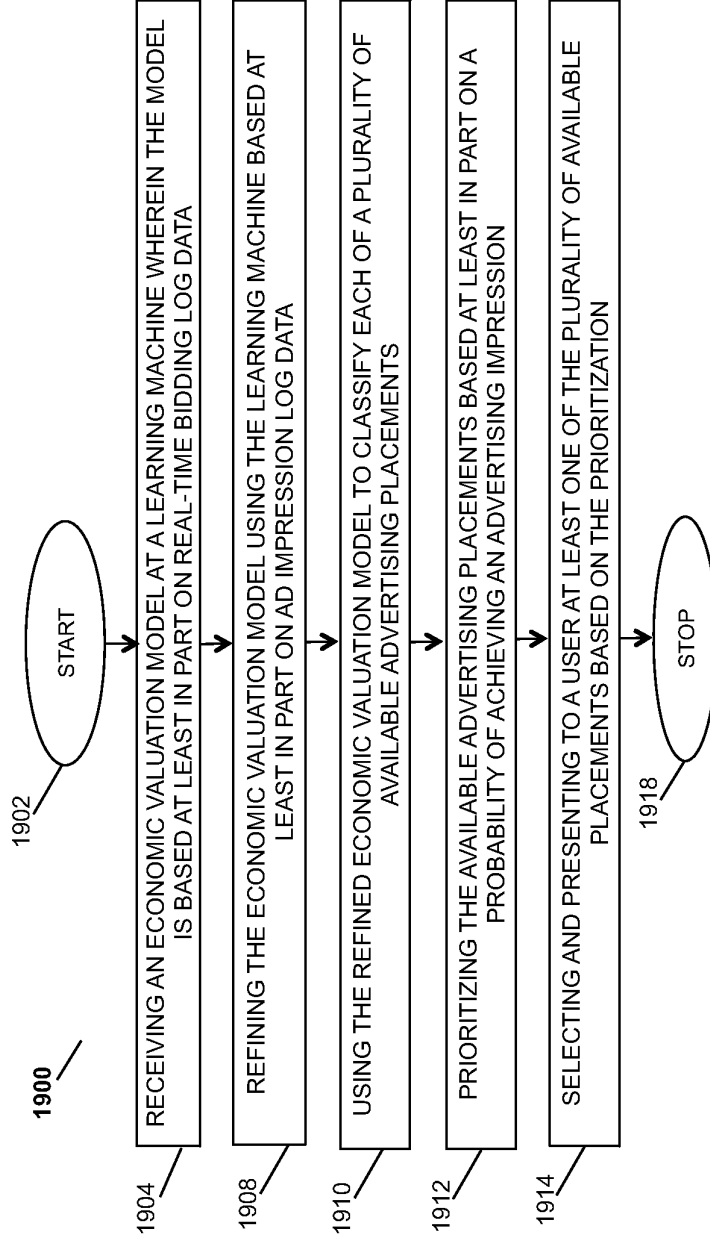


Fig. 19

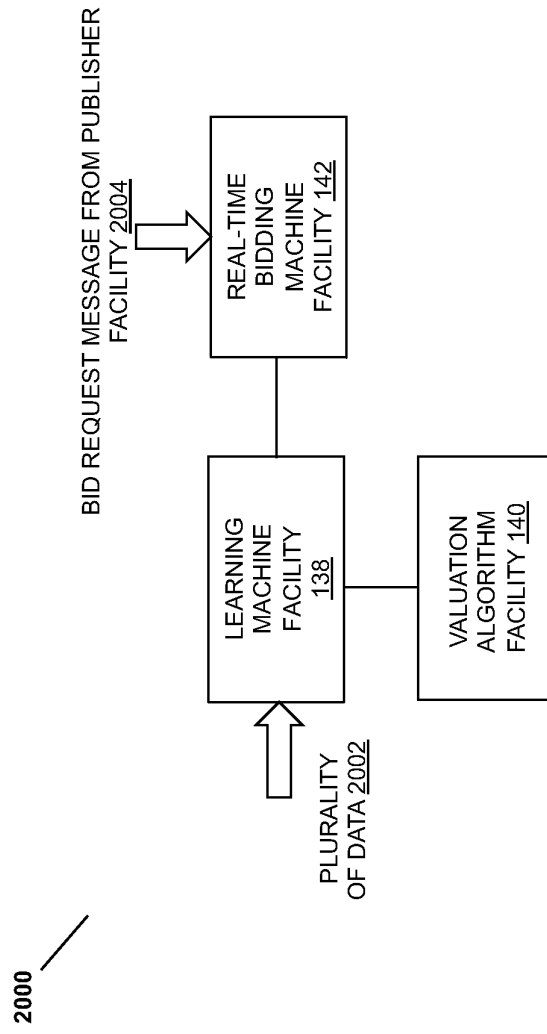


Fig. 20

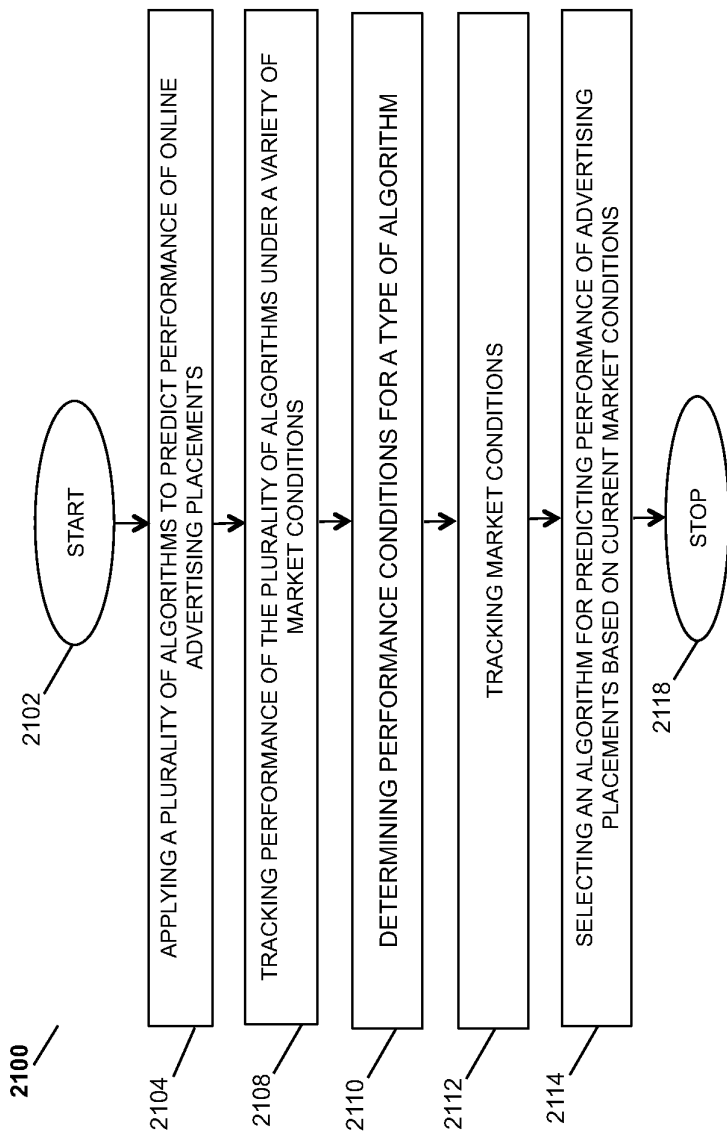


Fig. 21

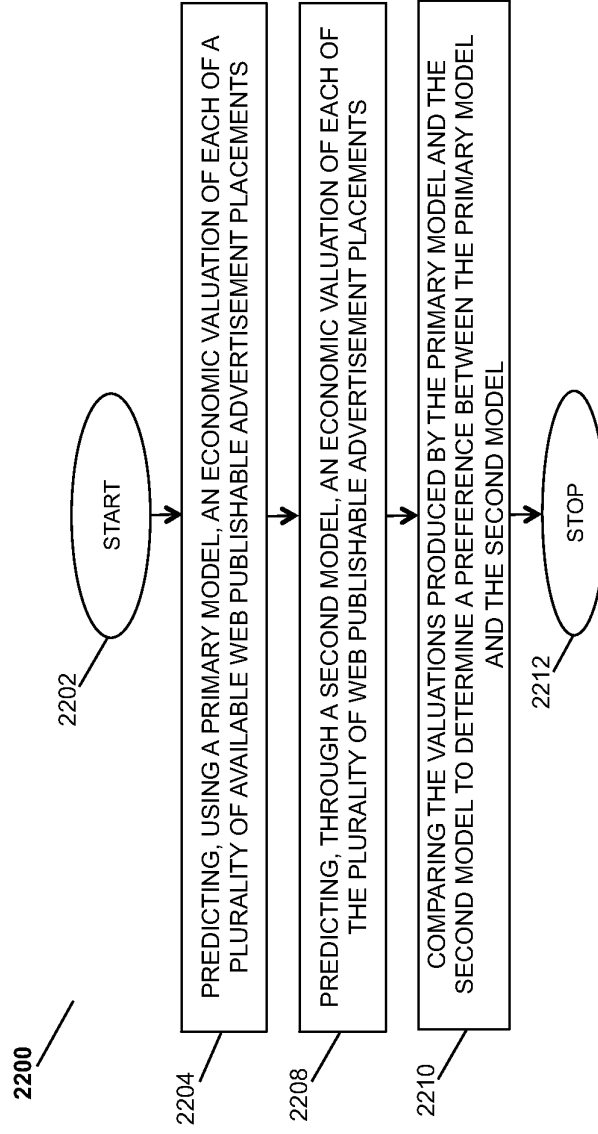


Fig. 22

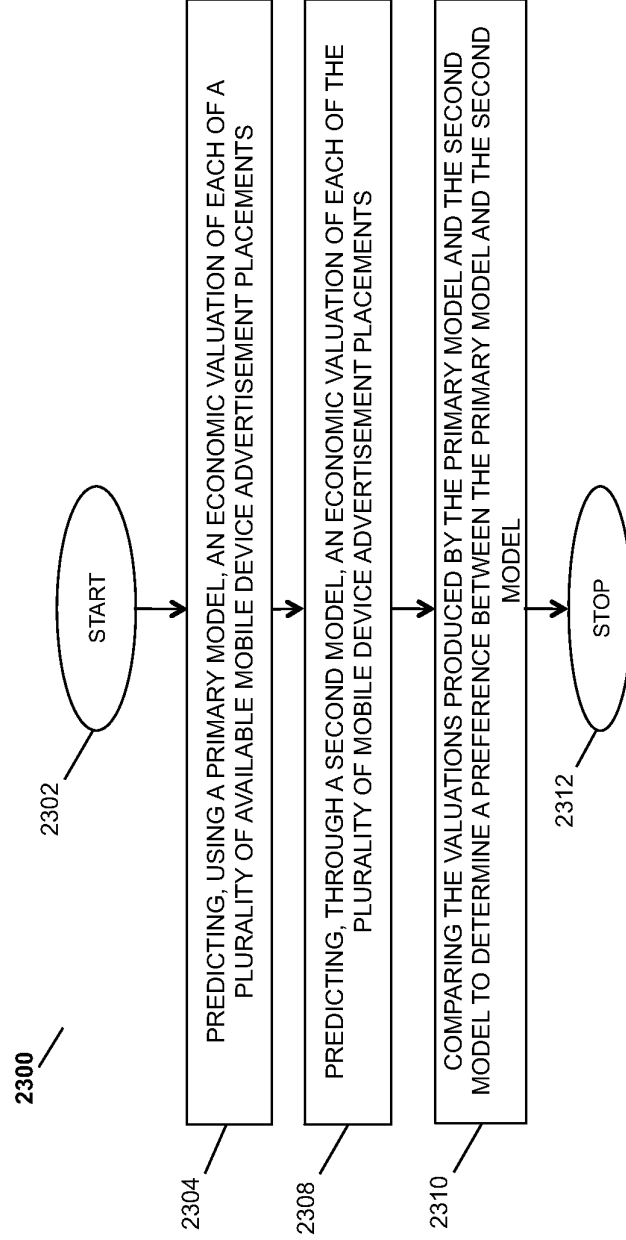


Fig. 23

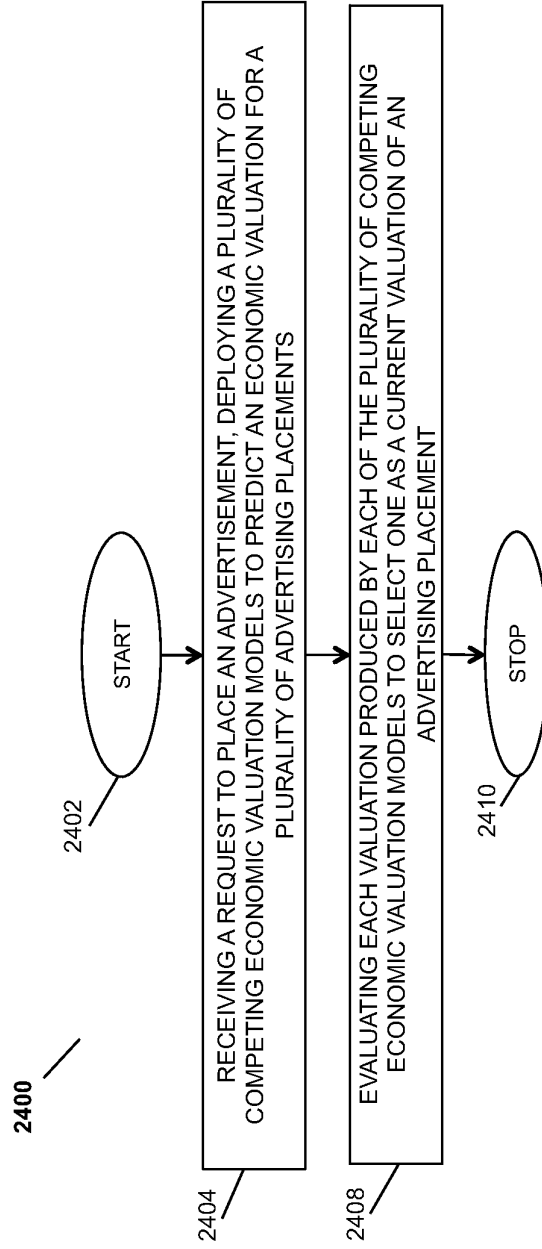


Fig. 24

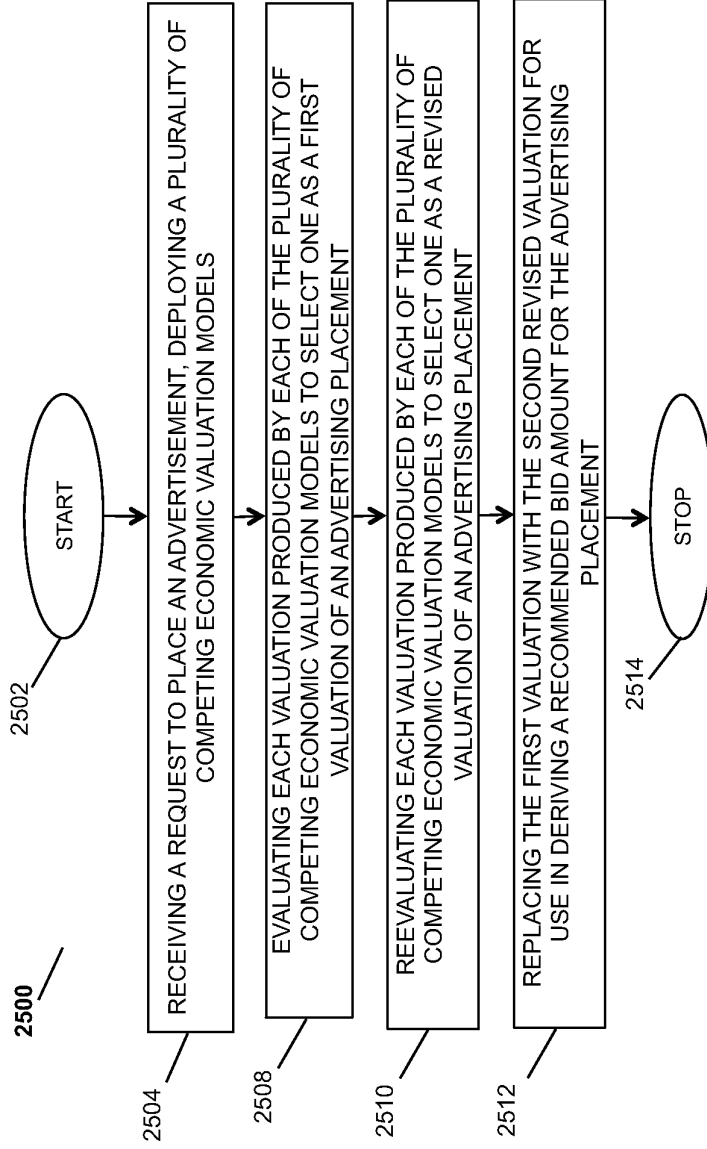


Fig. 25

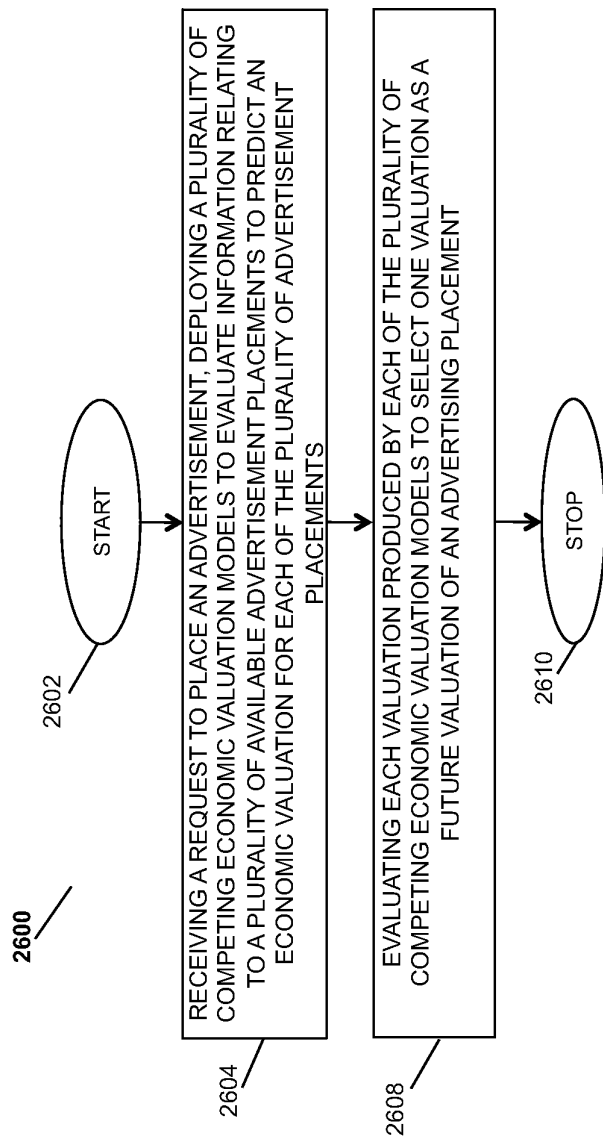


Fig. 26

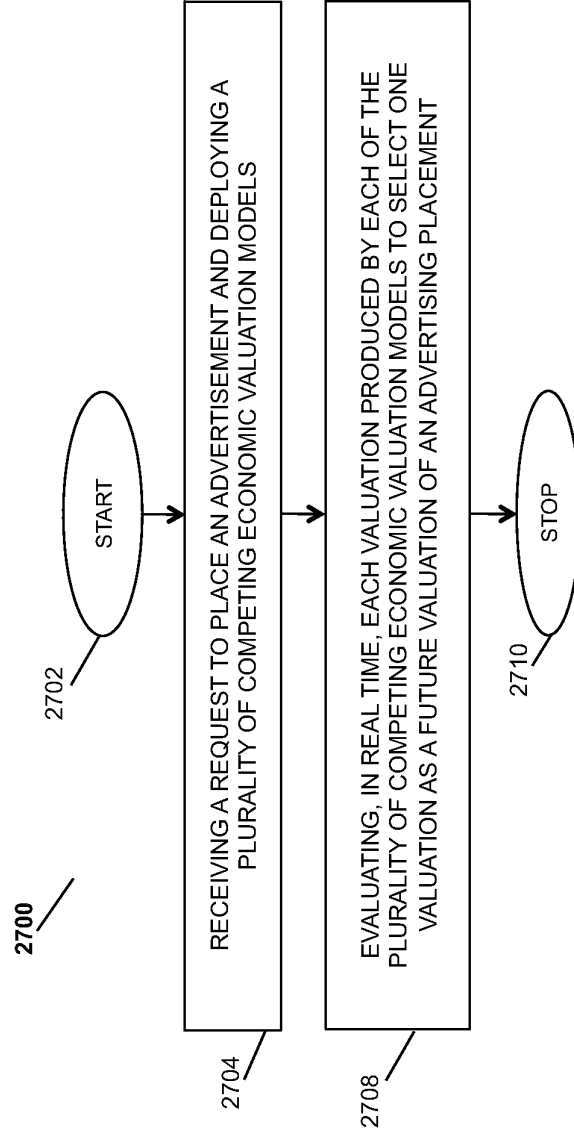


Fig. 27

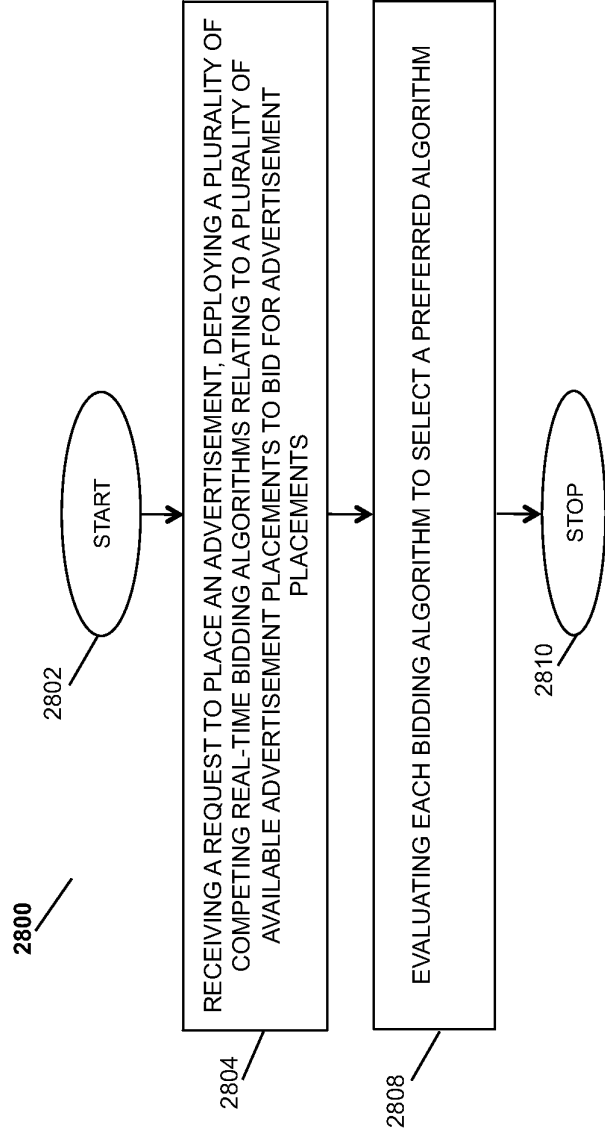


Fig. 28

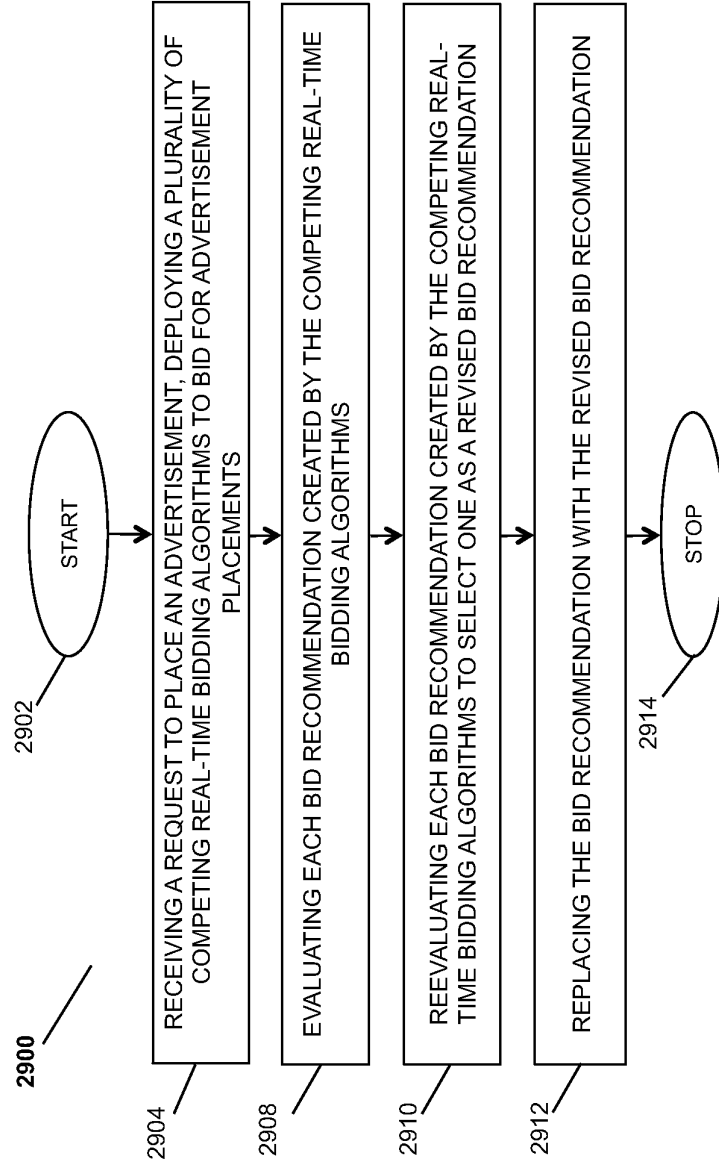


Fig. 29

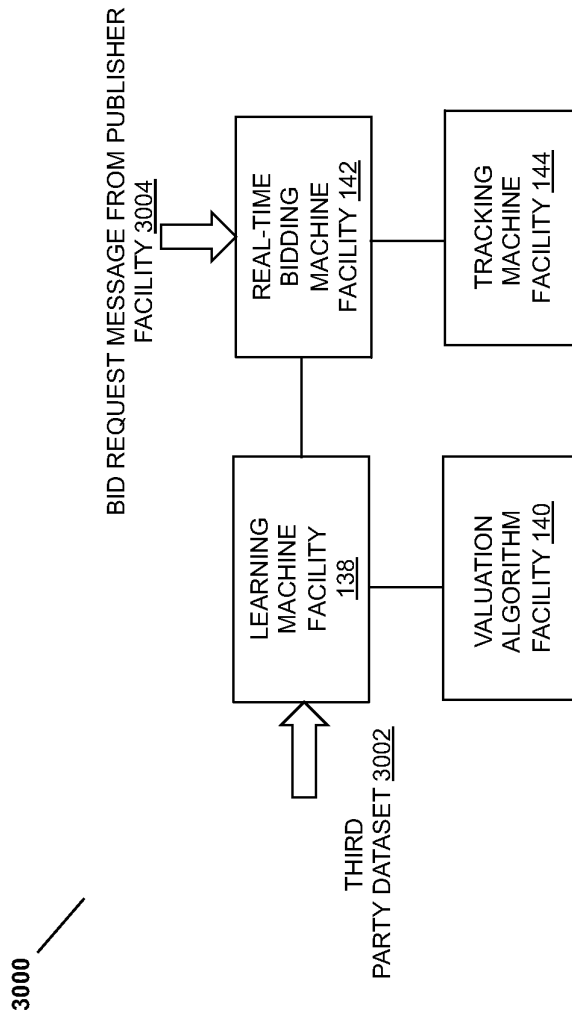


Fig. 30

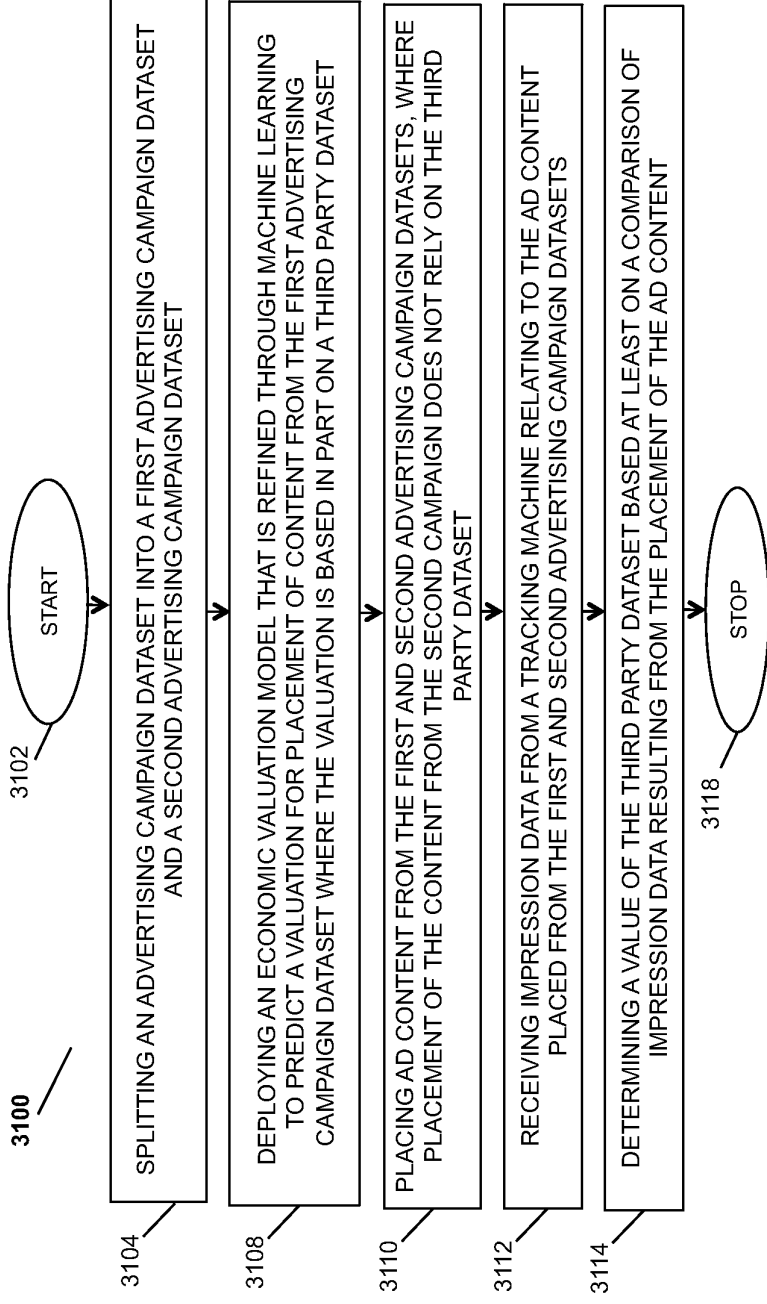


Fig. 31

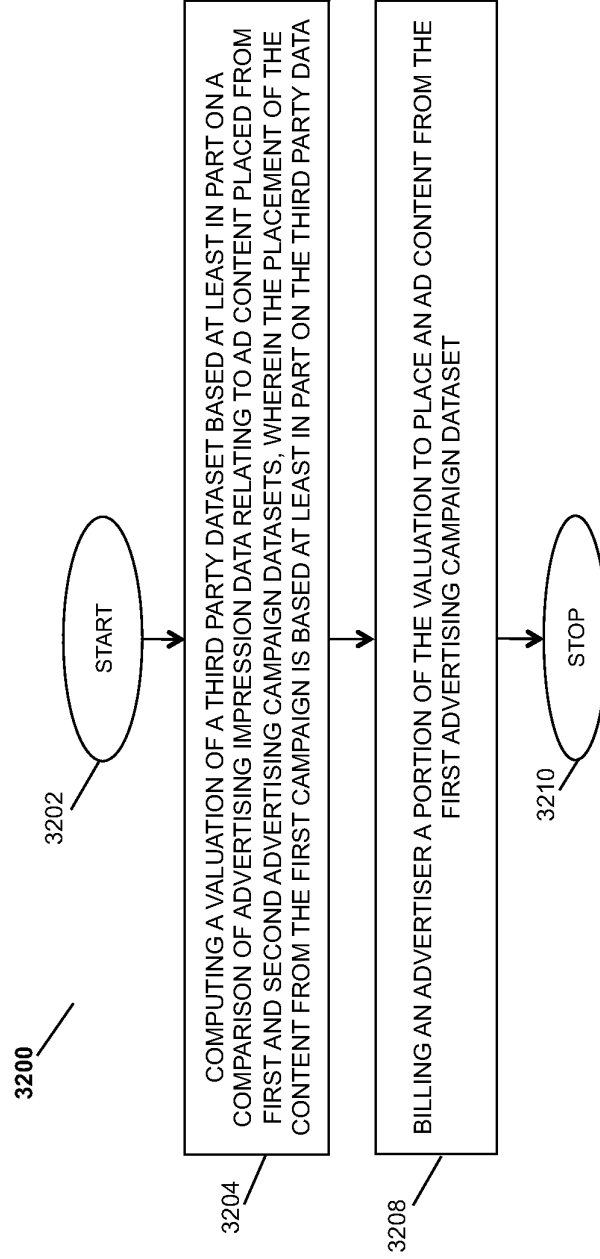


Fig. 32

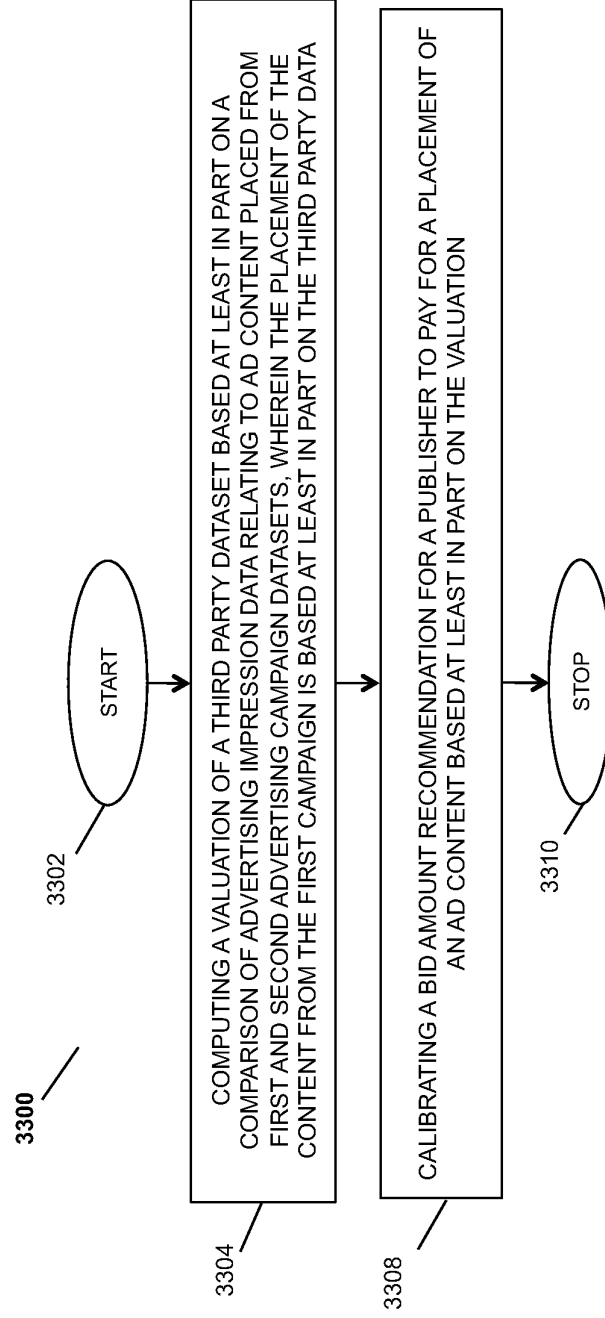


Fig. 33

- 3400 CAMPAIGN ALSO SAW STRONG PERFORMANCE ON THURSDAY EVENINGS
 - SYSTEM SAW OPPORTUNITY TO ADVERTISE IMMEDIATELY AFTER WEEKENDS
- PERFORMANCE INDEX BY TIME OF DAY VS. DAY OF WEEK INDEXED TO 1

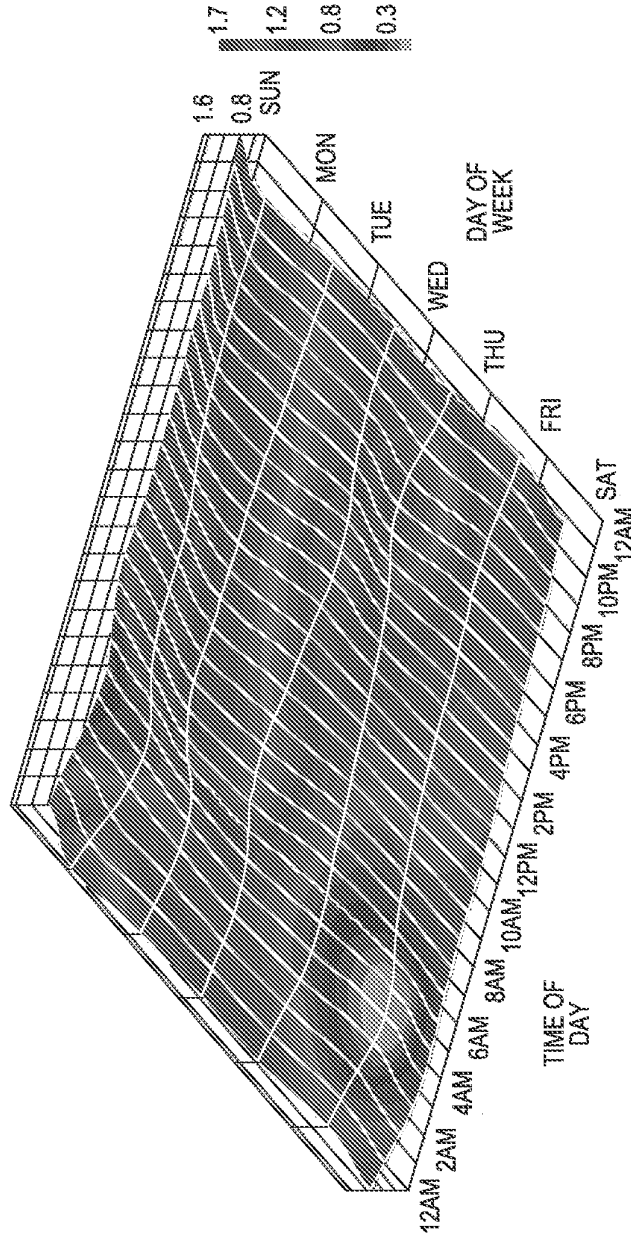


FIG. 34

- 3500
 - CAMPAIGN PERFORMED BEST IN URBAN AREAS
 - SPORTY SEDAN WAS ESPECIALLY STRONG FOR HIGHLY URBAN AREAS
- PERFORMANCE INDEX BY POPULATION DENSITY VS. CREATIVE INDEXED TO 1

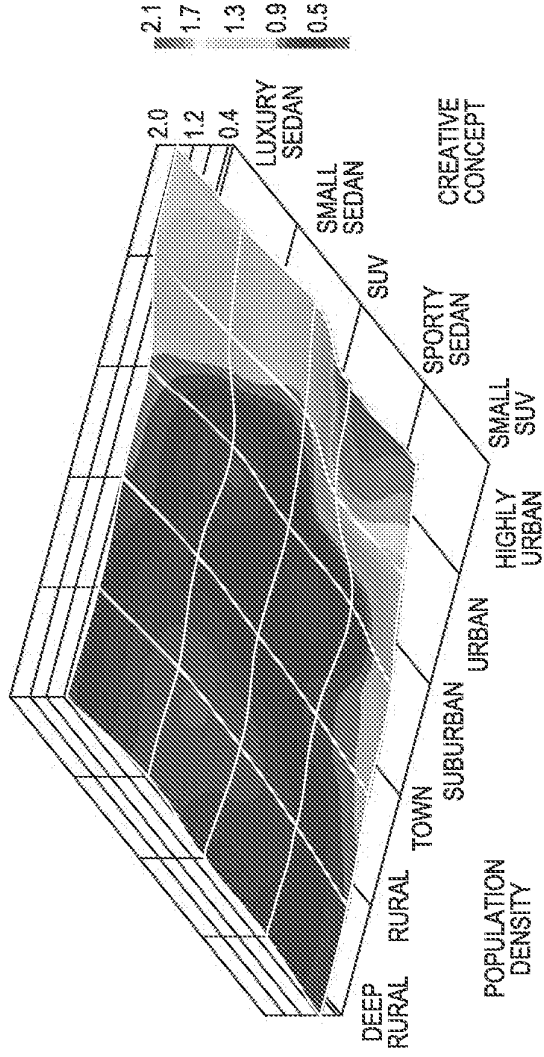


FIG. 35

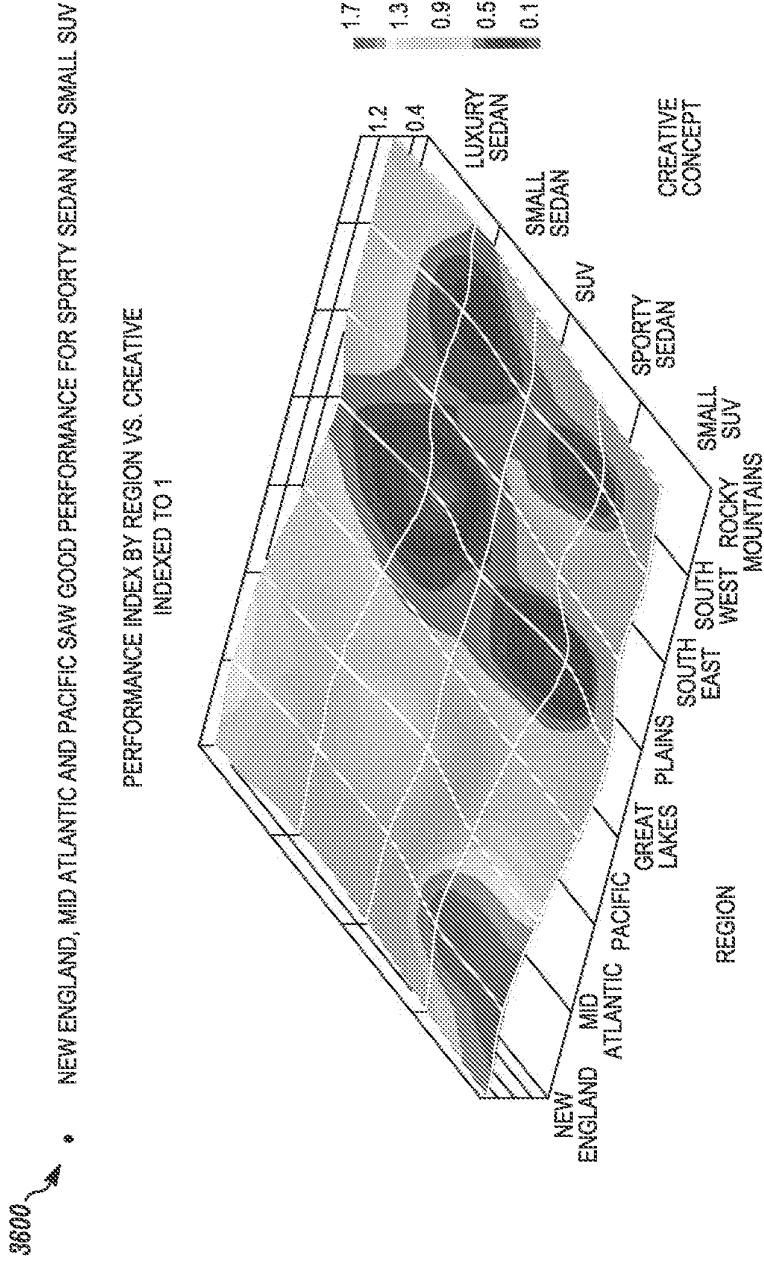


FIG. 36

3700 • MID INCOME (\$50-\$75K) SEGMENTS WERE COMPELLED BY SMALL AND SPORTY SEDANS

PERFORMANCE INDEX BY INCOME VS. CREATIVE INDEXED TO 1

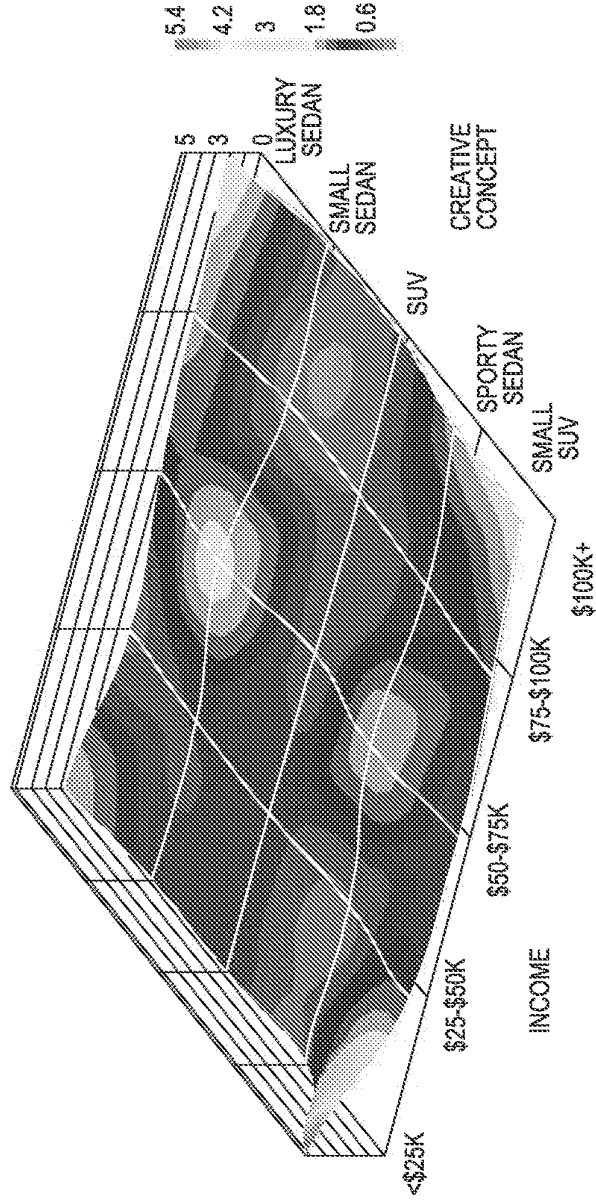


FIG. 37

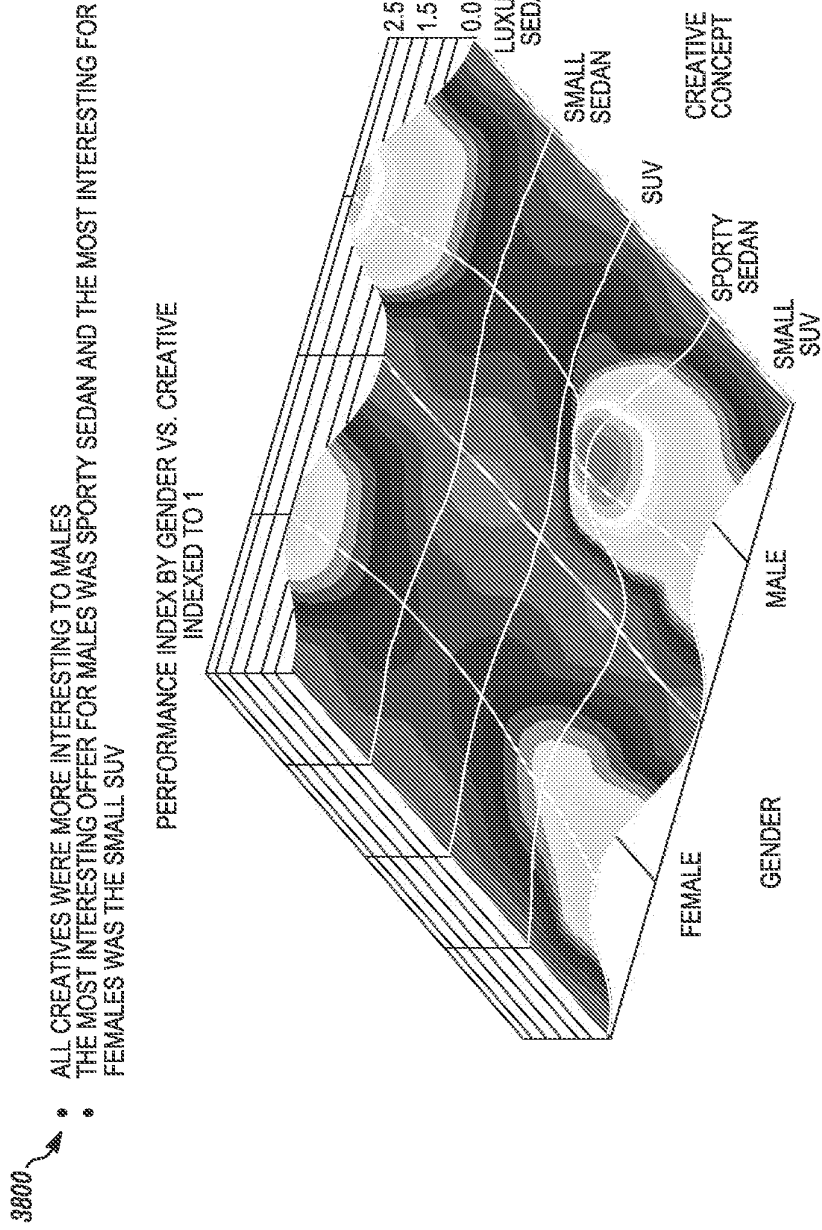


FIG. 38

TOP AND BOTTOM INTEREST CATEGORIES FOR CAMPAIGN
 AFFINITY INDEXED TO 1 ³⁹⁰⁰

TOP INTEREST CATEGORIES	AFFINITY INDEX	BOTTOM INTEREST CATEGORIES	AFFINITY INDEX
NEWS > ONLINE NEWS	3.0x	MUSIC>URBAN & HIP-HOP	0.5x
LIFESTYLES>CHARITABLE	2.2x	SPORTS>BASEBALL	0.5x
SHOPPING>ONLINE SHOPPING	2.1x	FOOD & DRINK>PIZZA	0.6x
ENTERTAINMENT>MUSIC	1.7x	GAMES>VIDEO GAMES	0.6x
ENTERTAINMENT>TV	1.5x	ENTERTAINMENT>ANIMATED	0.7x
INTERNET>PHOTO SHARING	1.5x	ENTERTAINMENT>MOVIES	0.7x
INTEREST>COOKING	1.4x	SPORTS>BASKETBALL	0.7x

FIG. 39

4000 ↘

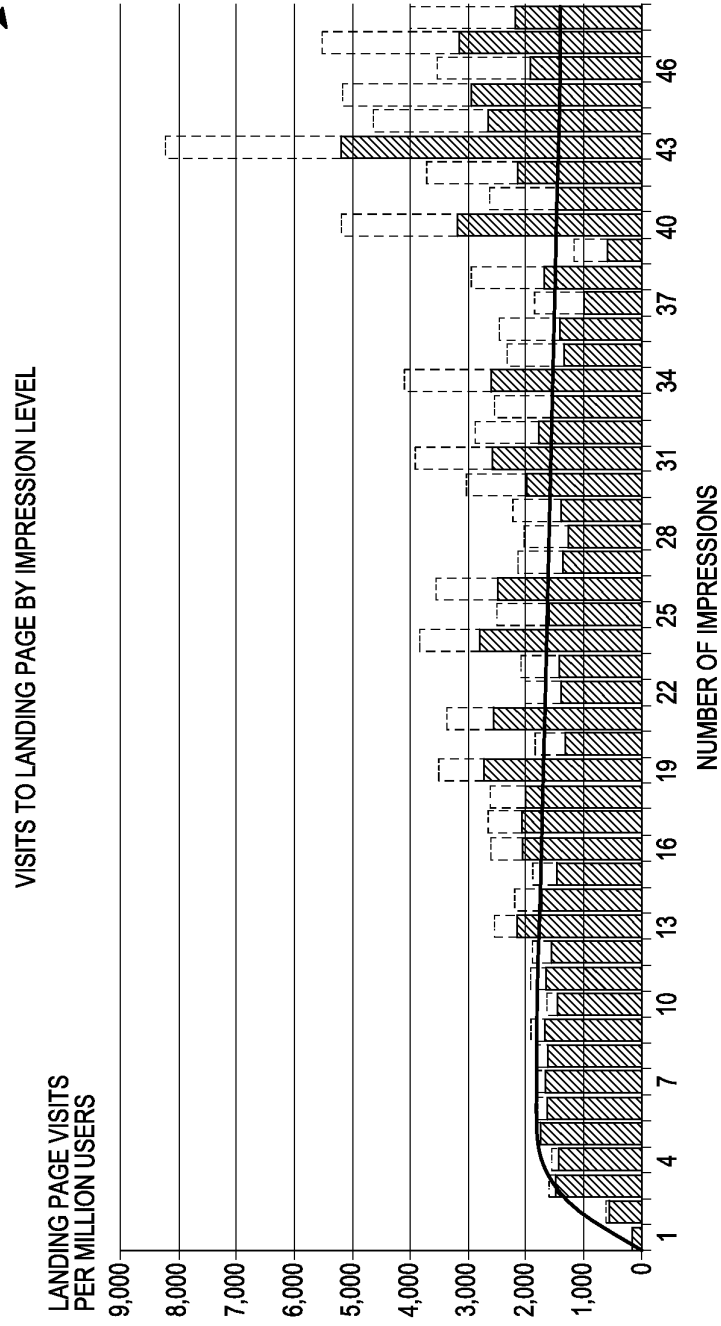


FIG. 40

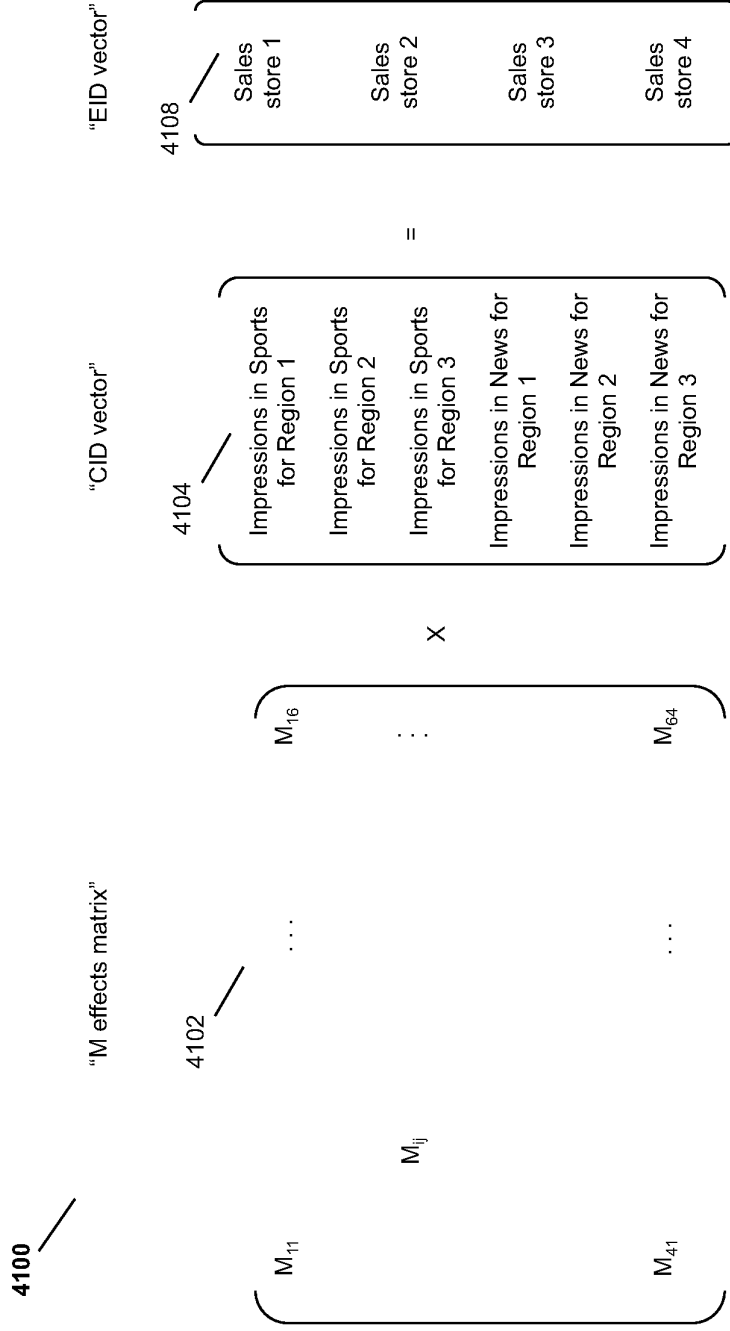


Fig. 41

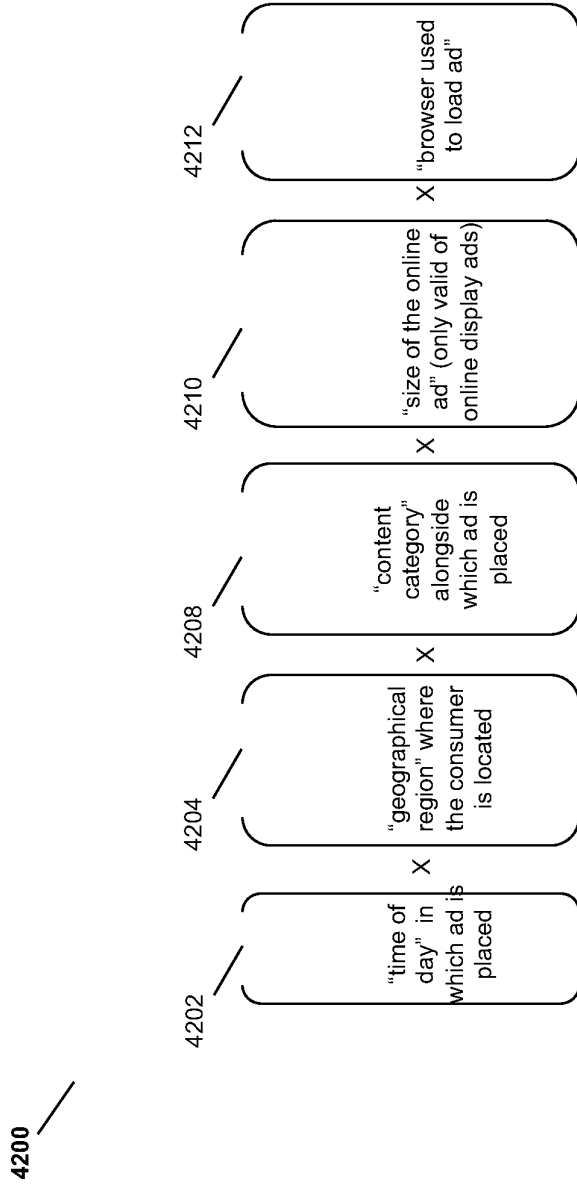


Fig. 42

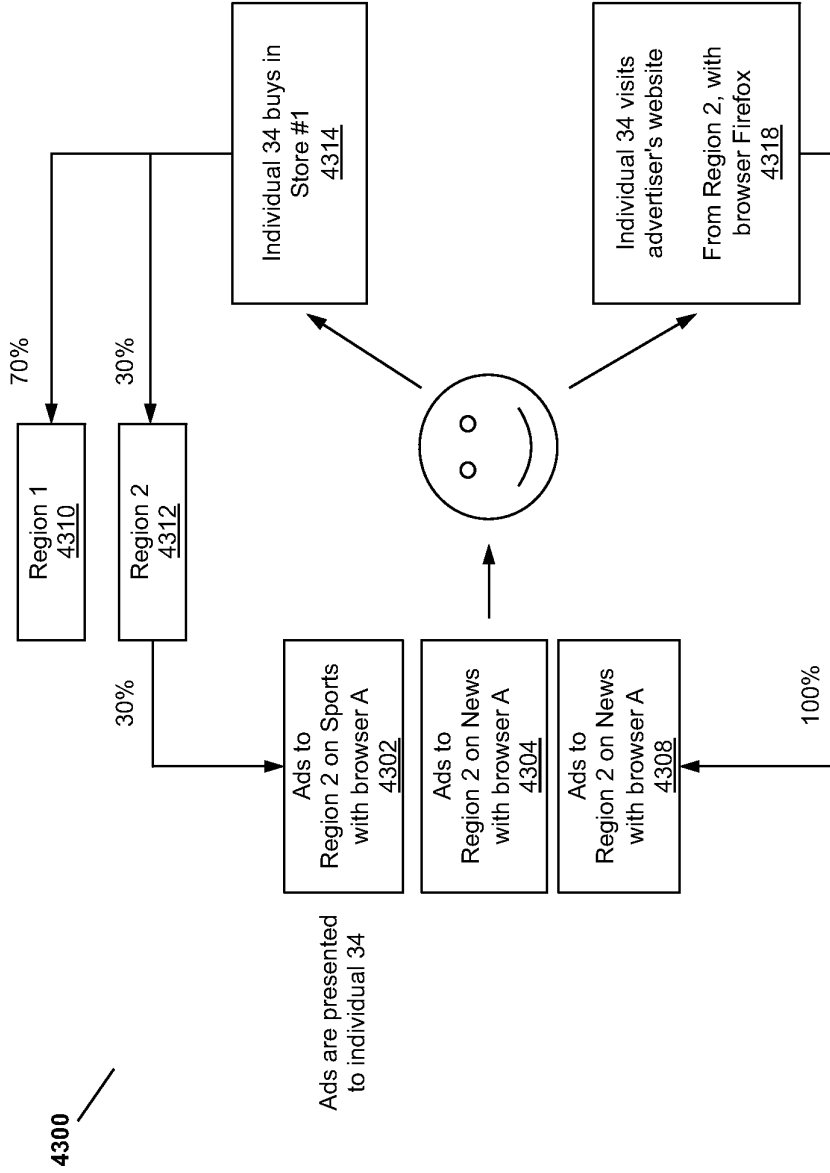


Fig. 43

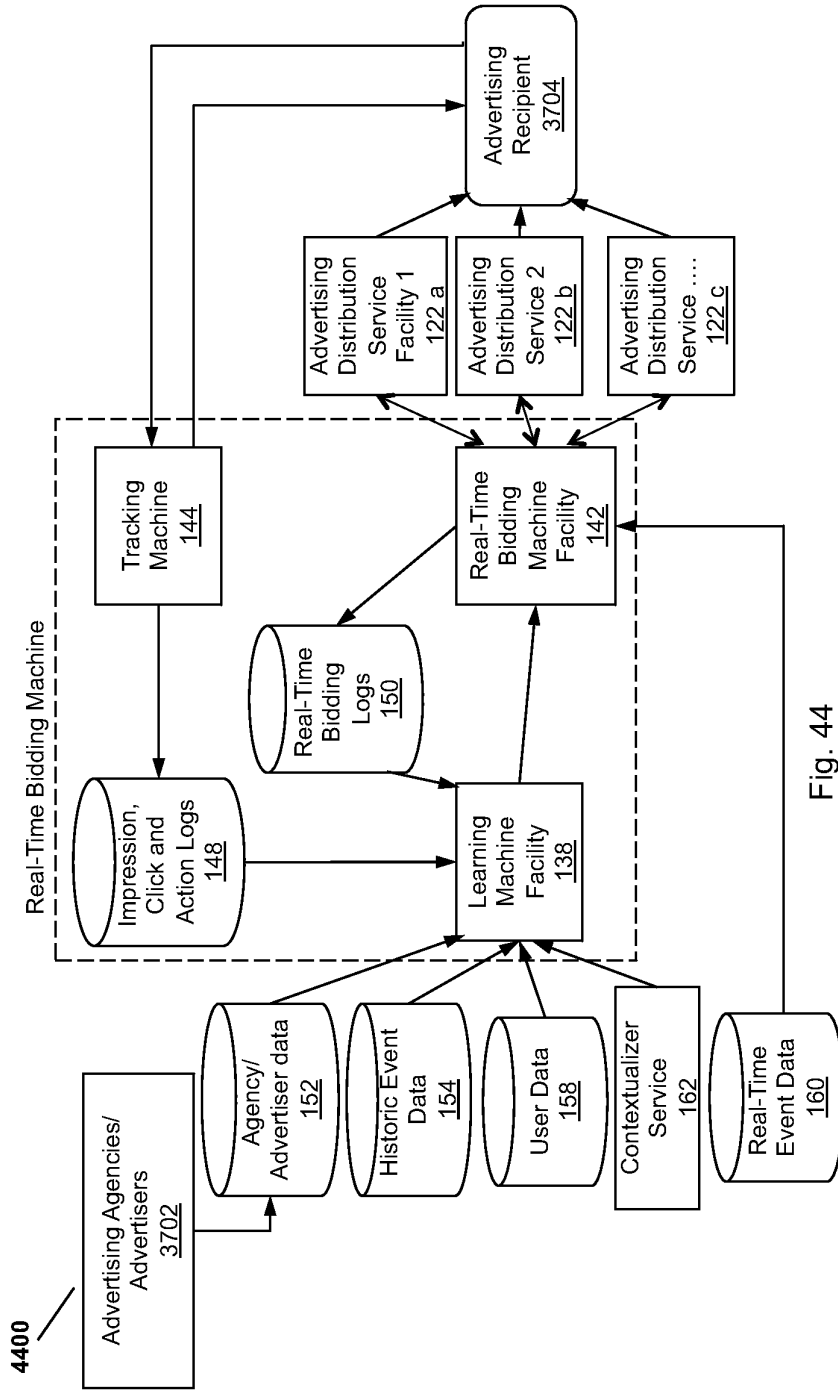
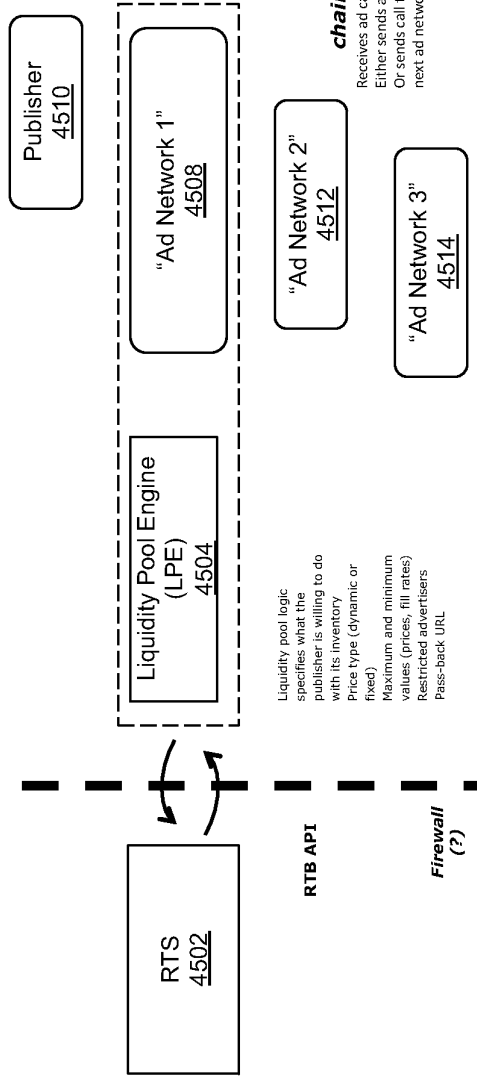


Fig. 44

4500

Liquidity Pool Engine (LPE)



Liquidity pool logic specifies what the publisher is willing to do with its inventory

- Price type (dynamic or fixed)
- Maximum and minimum values (prices, fill rates)
- Restricted advertisers
- Pass-back URL

Fig. 45

4600

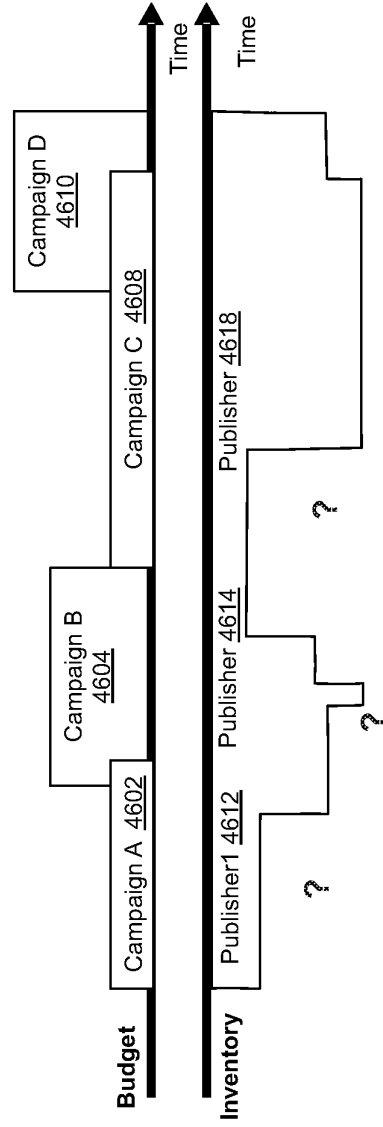


Fig. 46

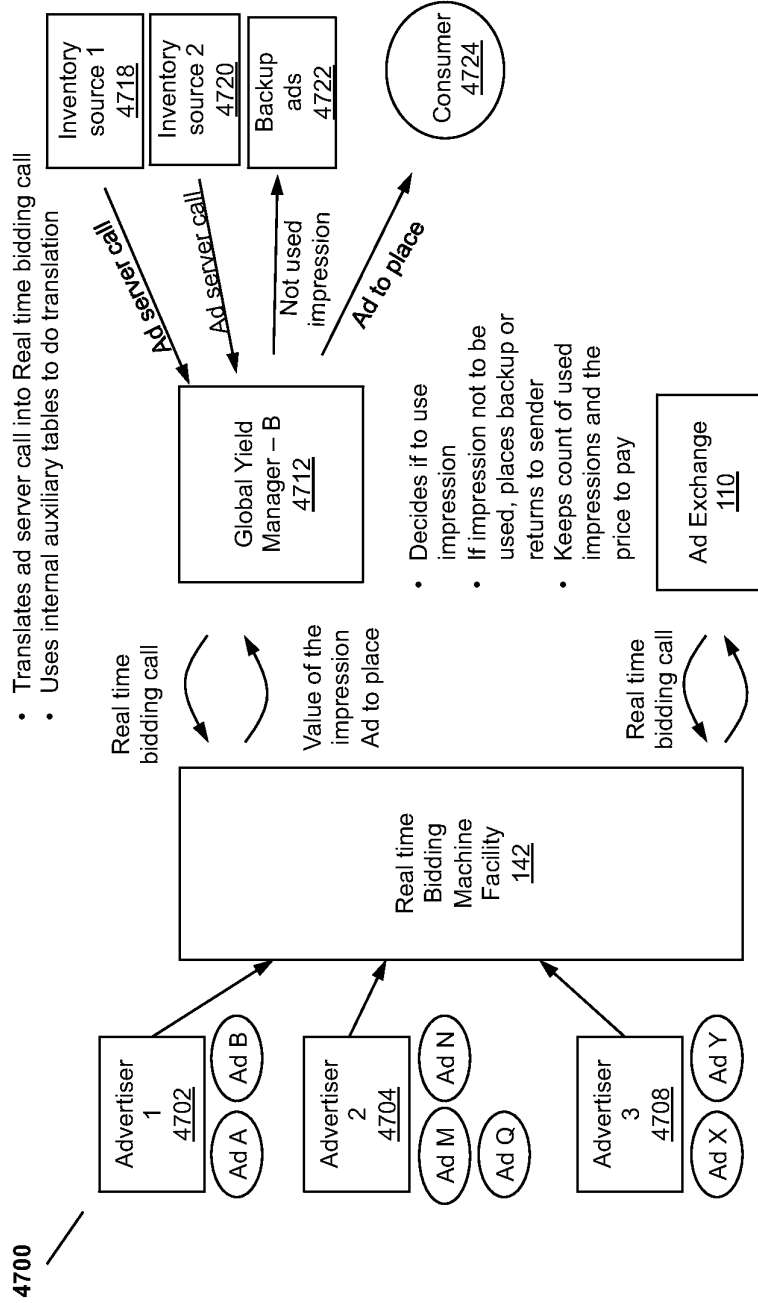


Fig. 47

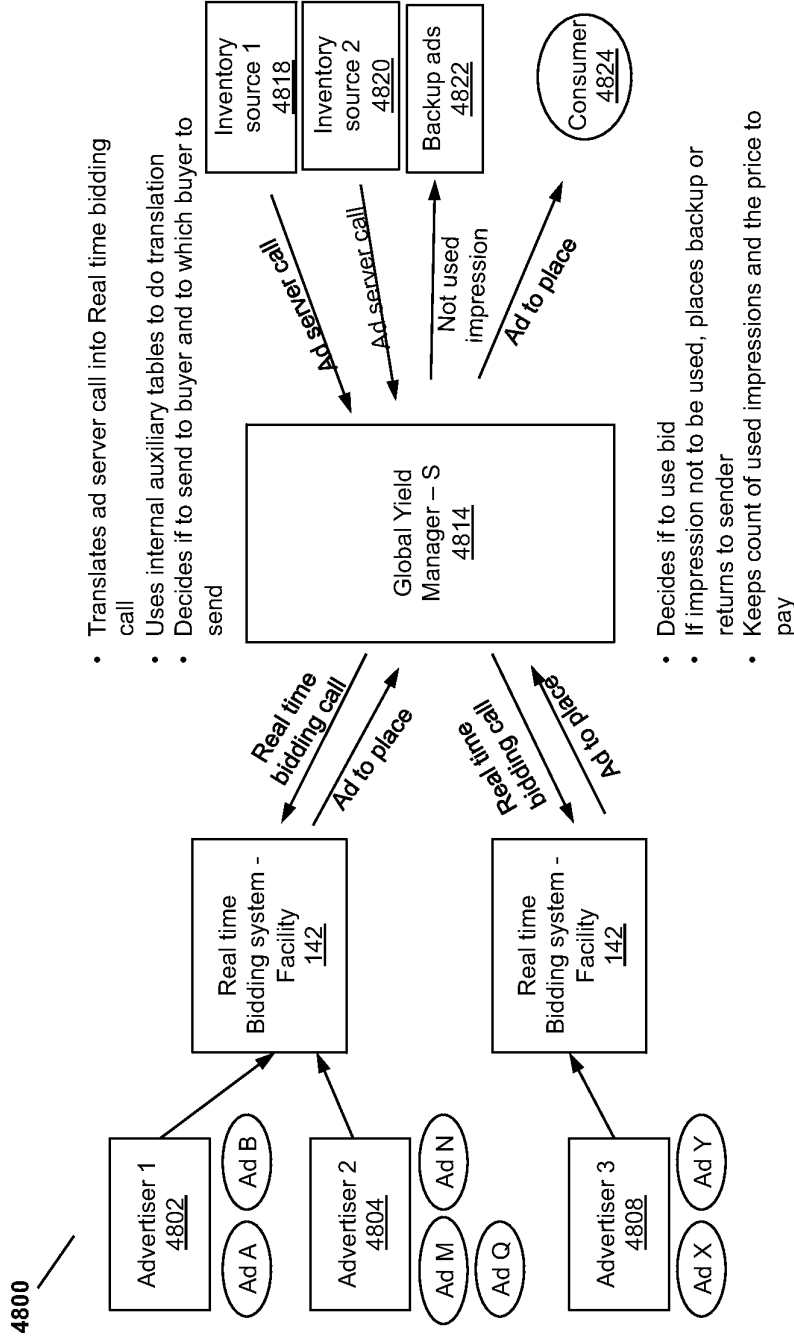


Fig. 48

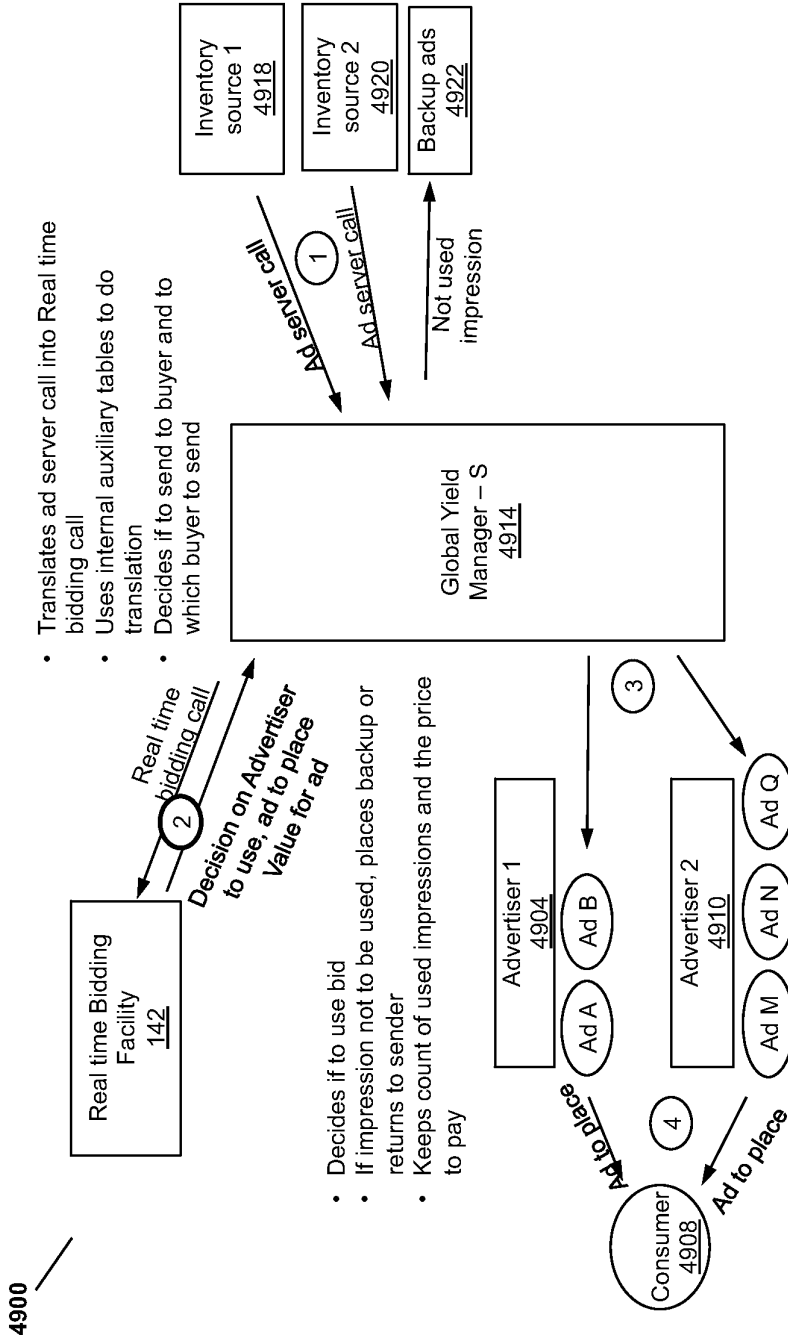


Fig. 49

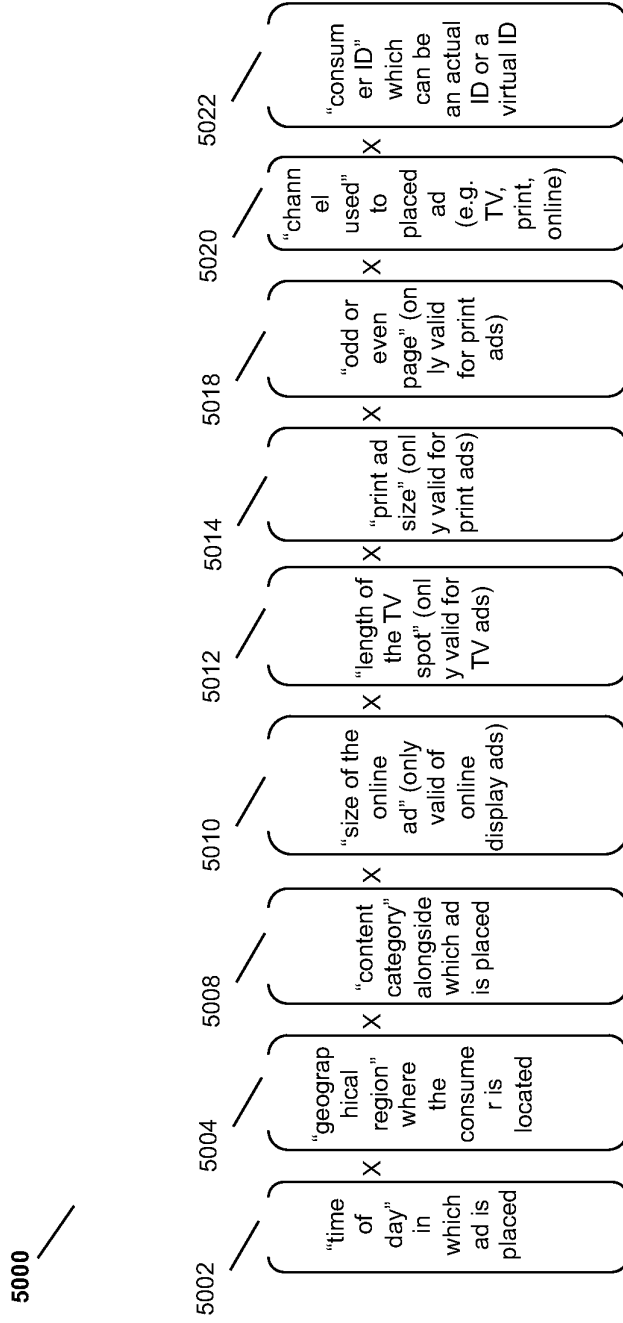


Fig. 50

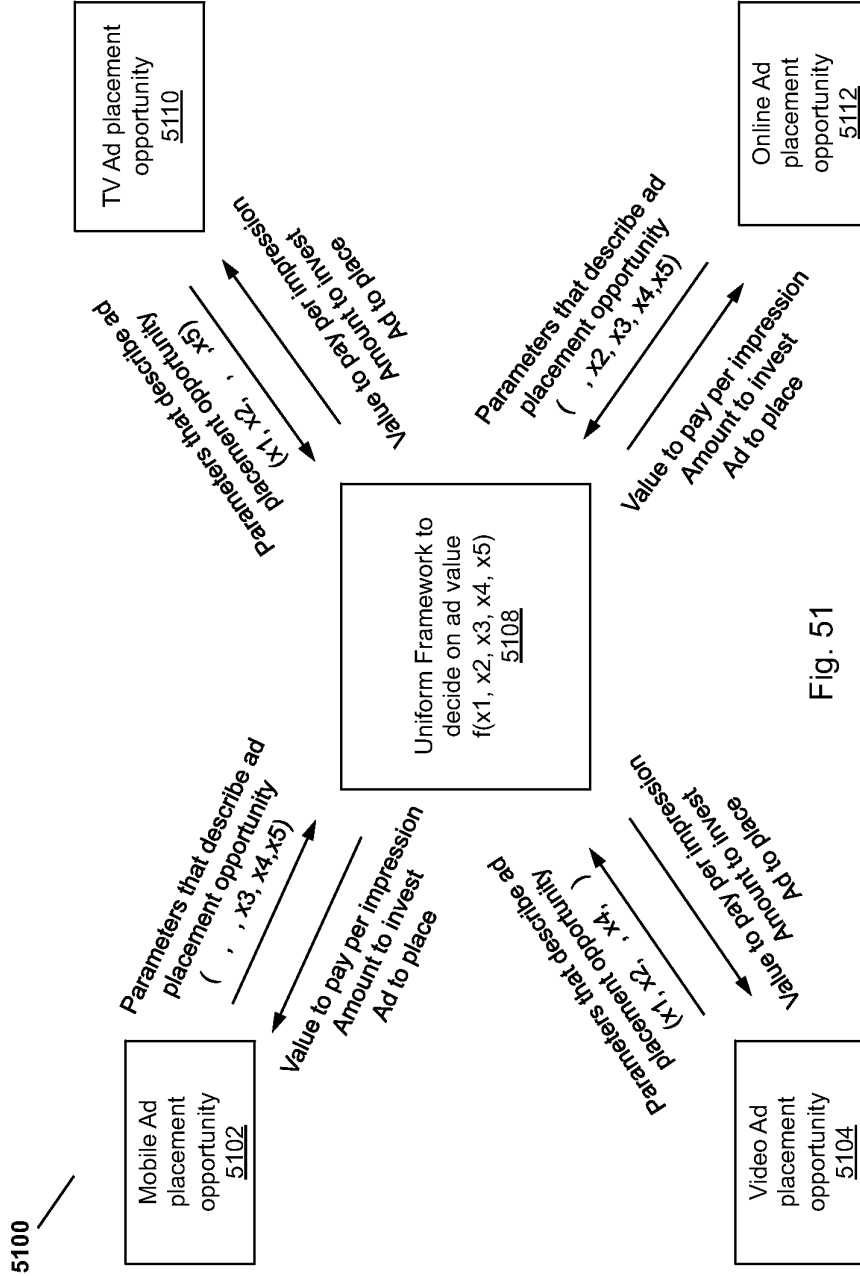


Fig. 51

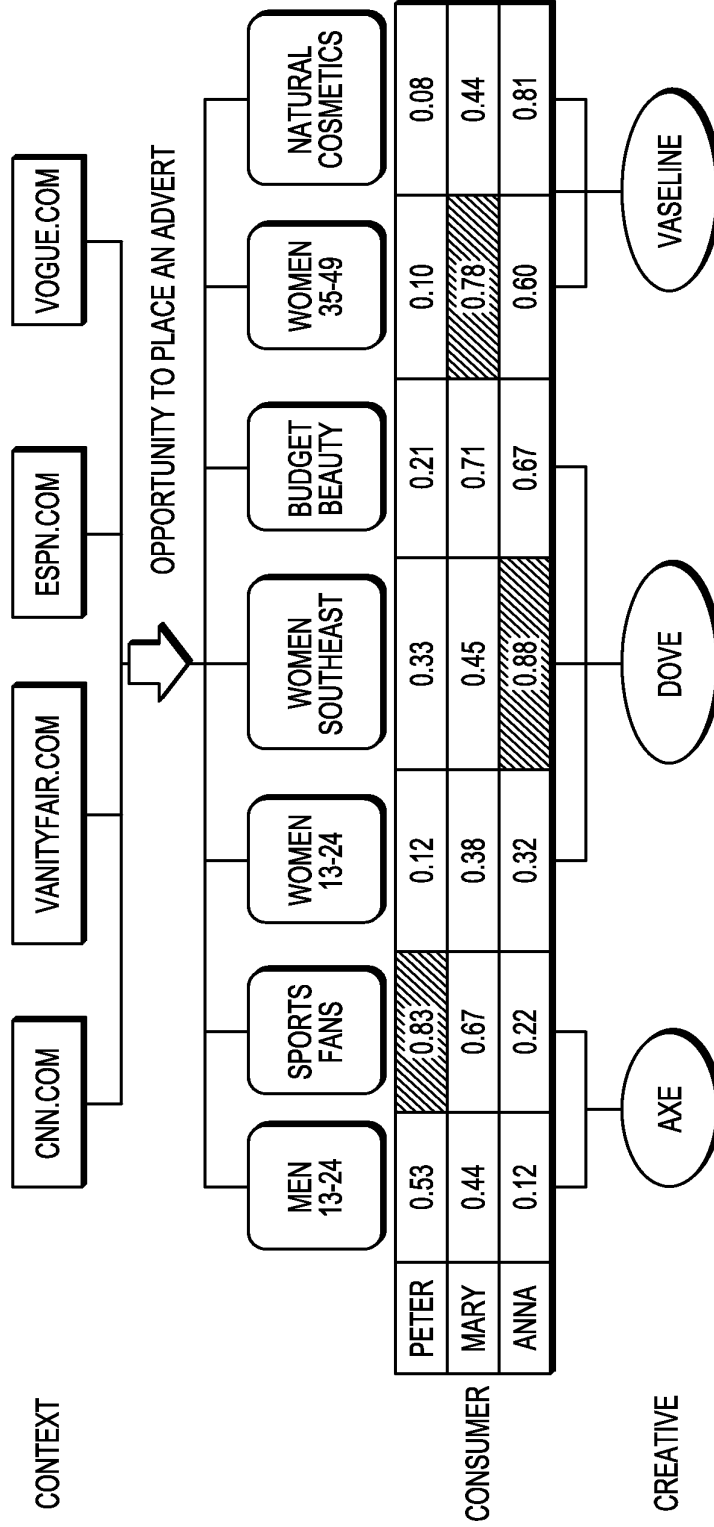


FIG. 52

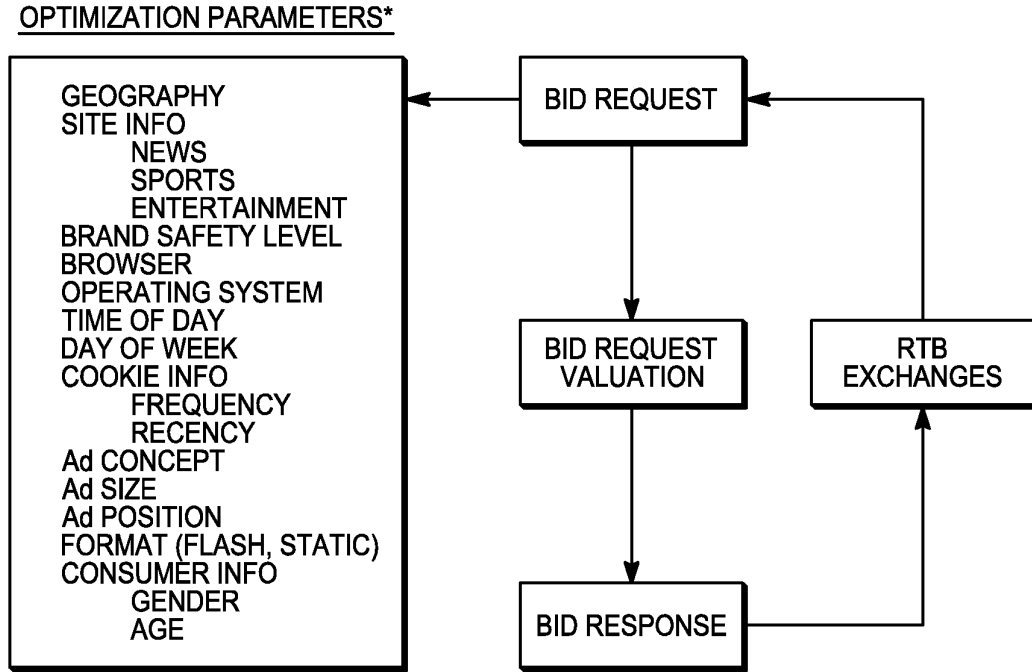


FIG. 53

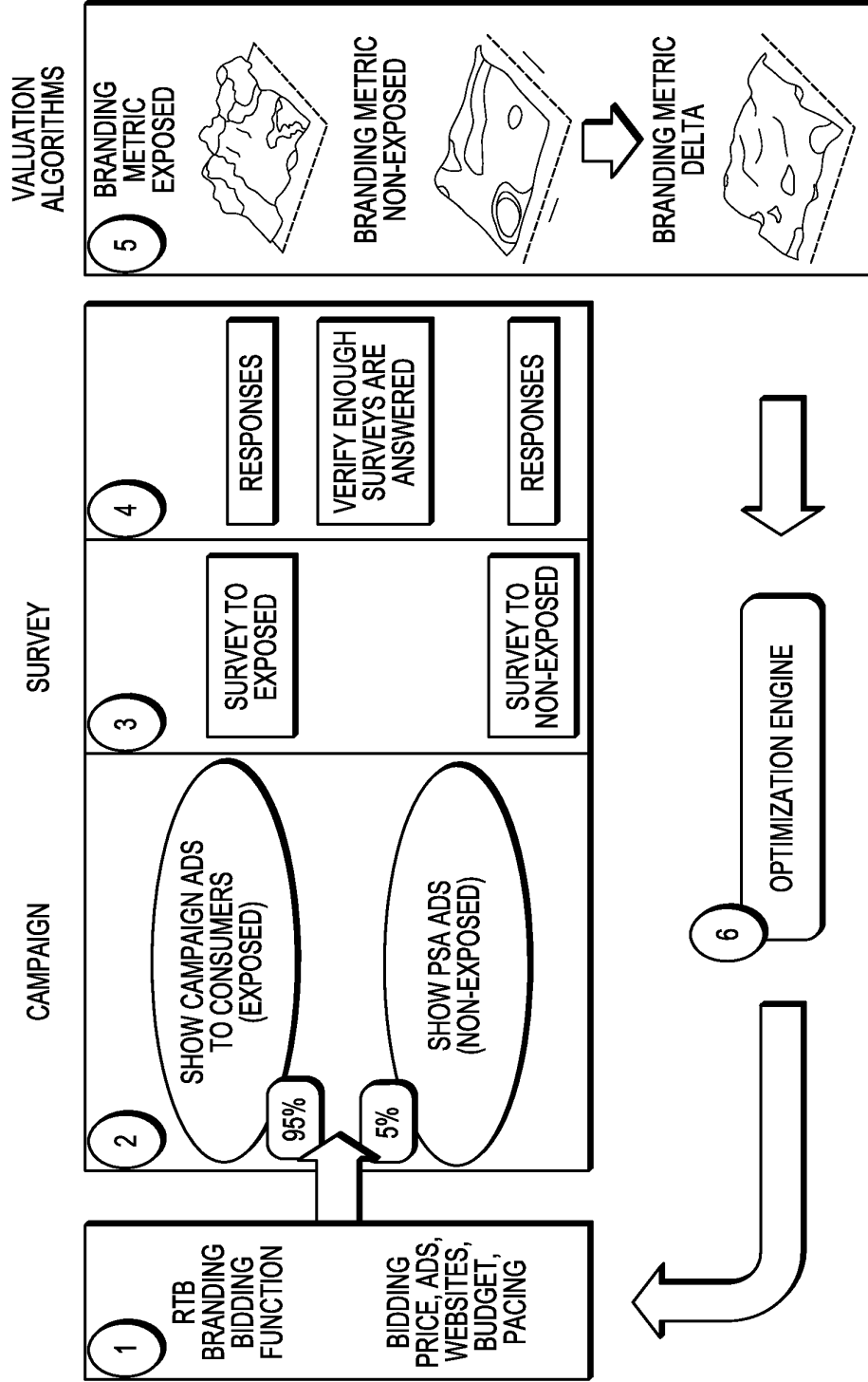


FIG. 54

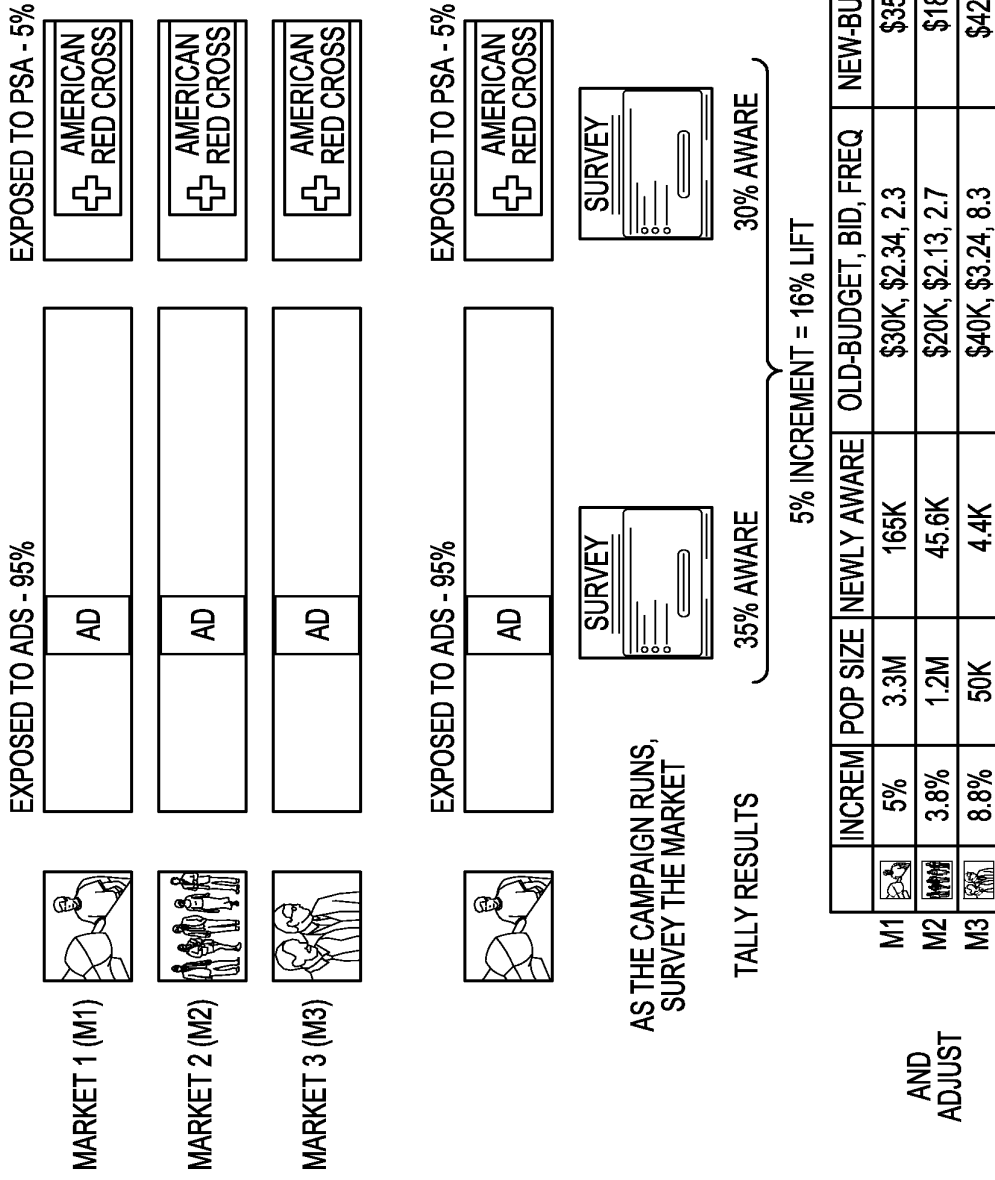


FIG. 55

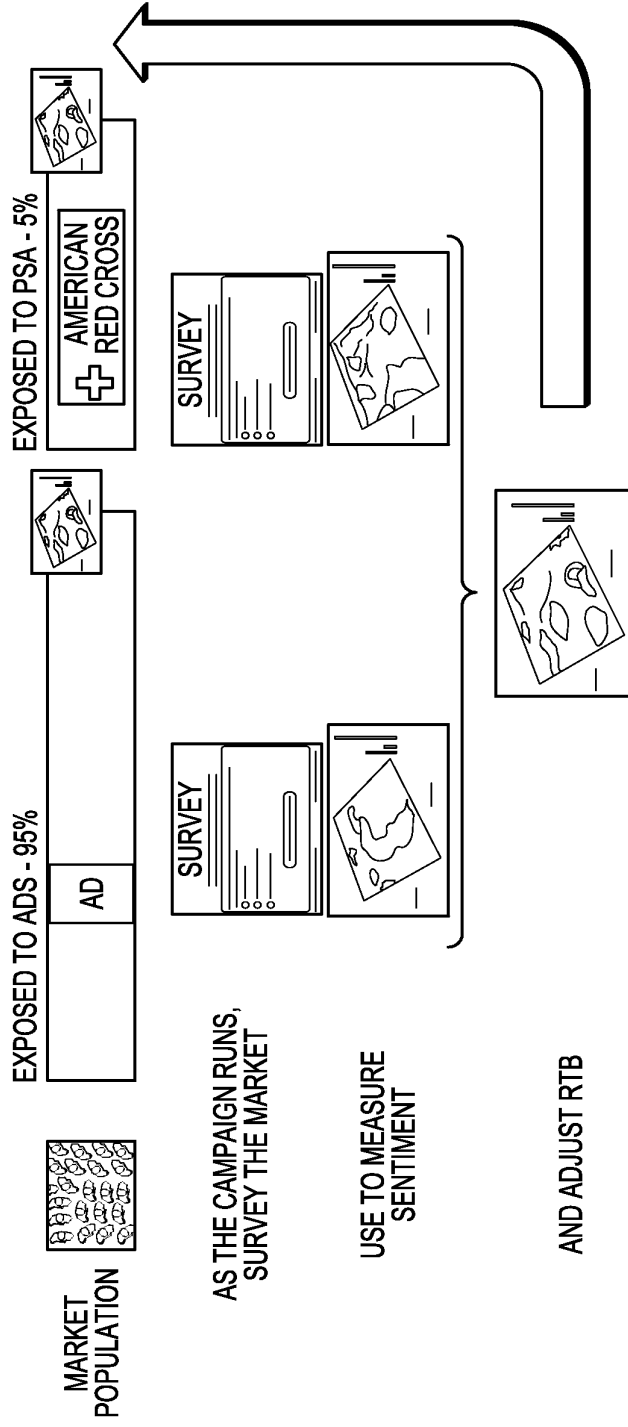


FIG. 56

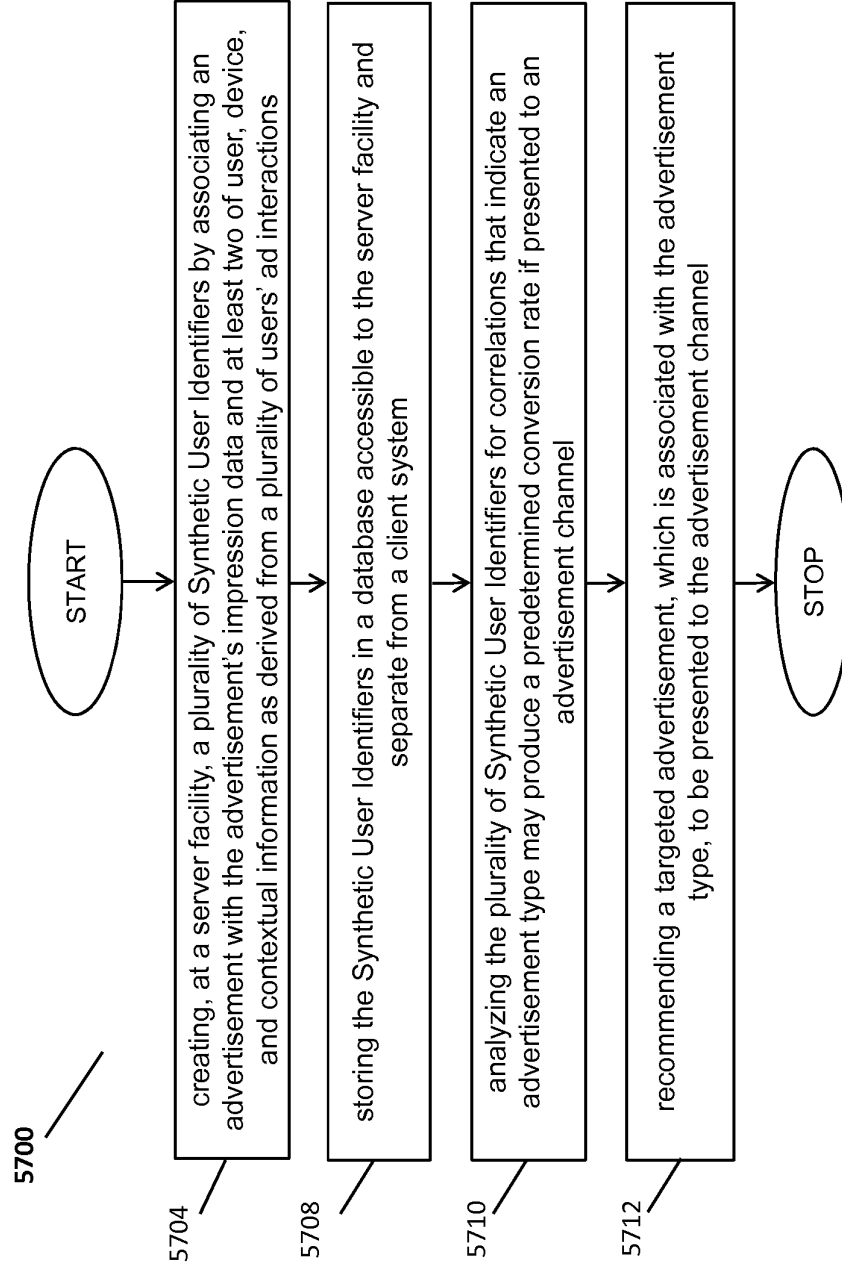


Fig. 57

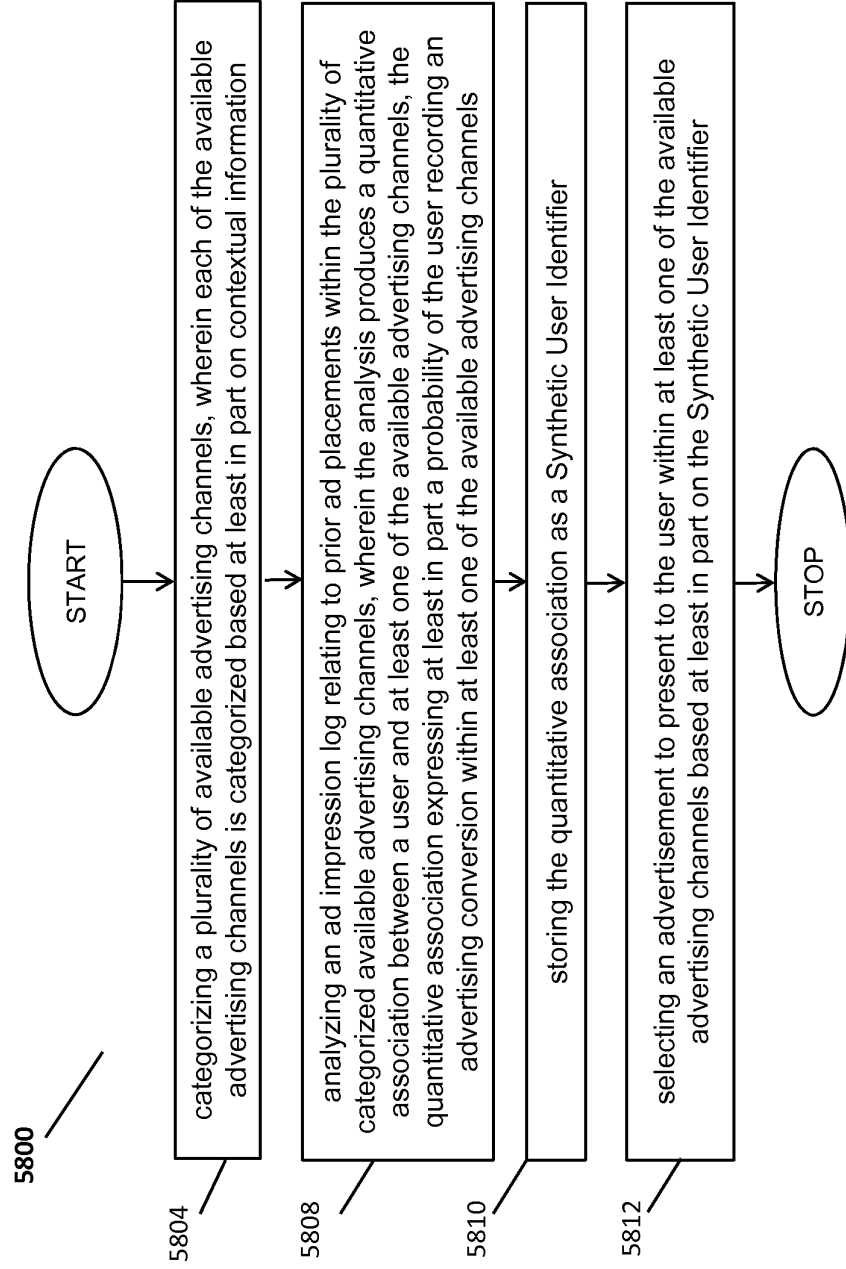


Fig. 58

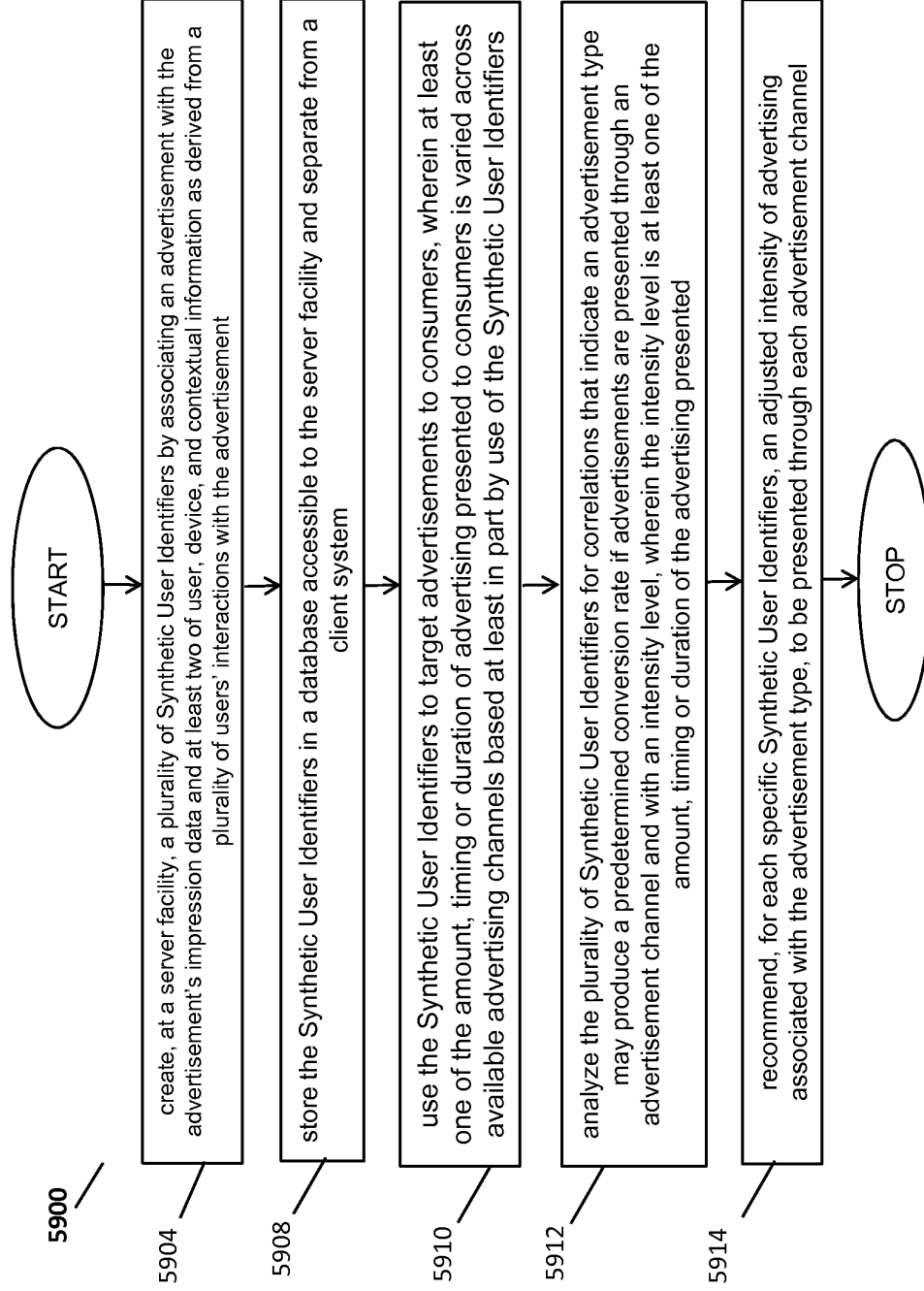


Fig. 59

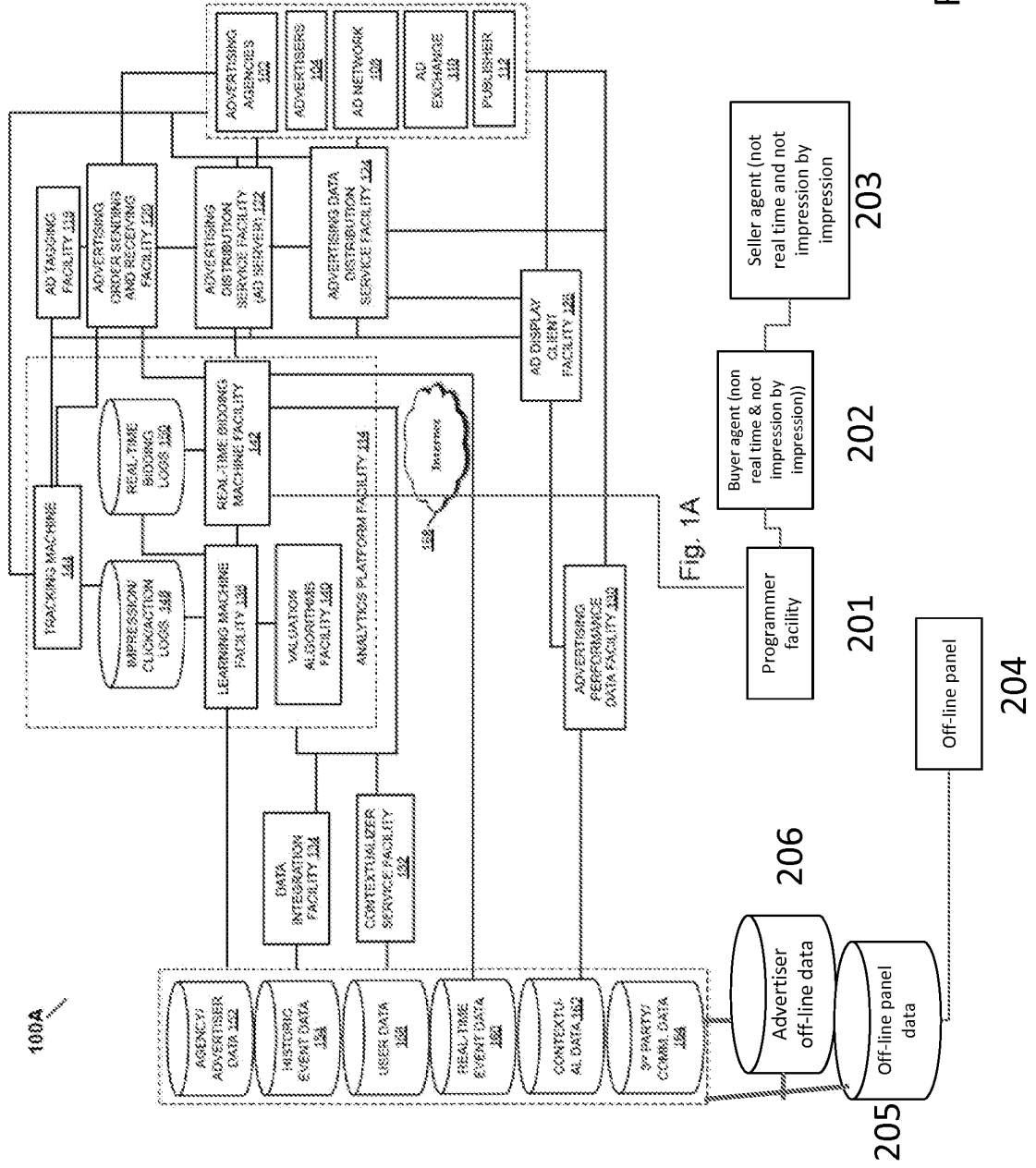


Fig. 60

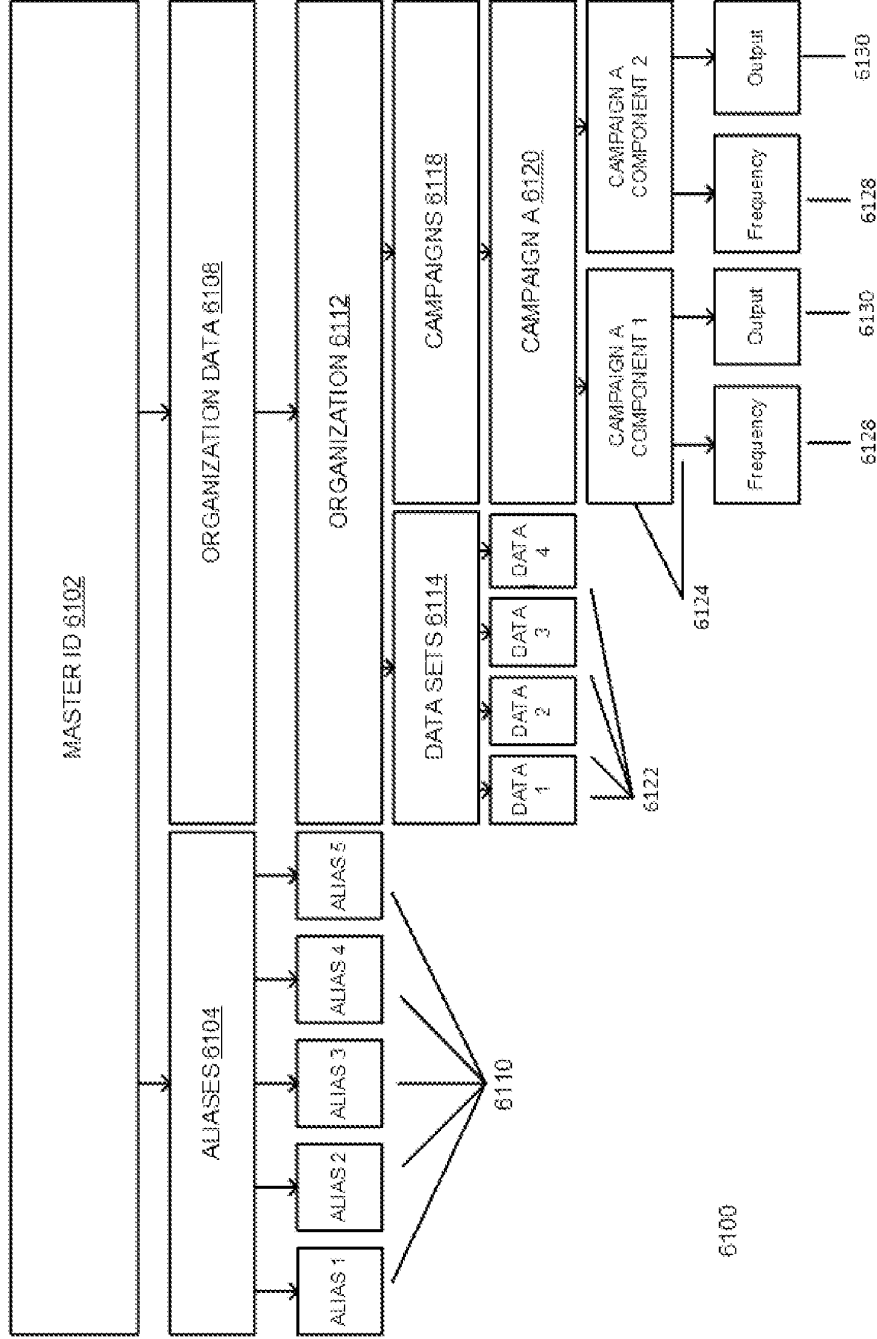


Fig. 61

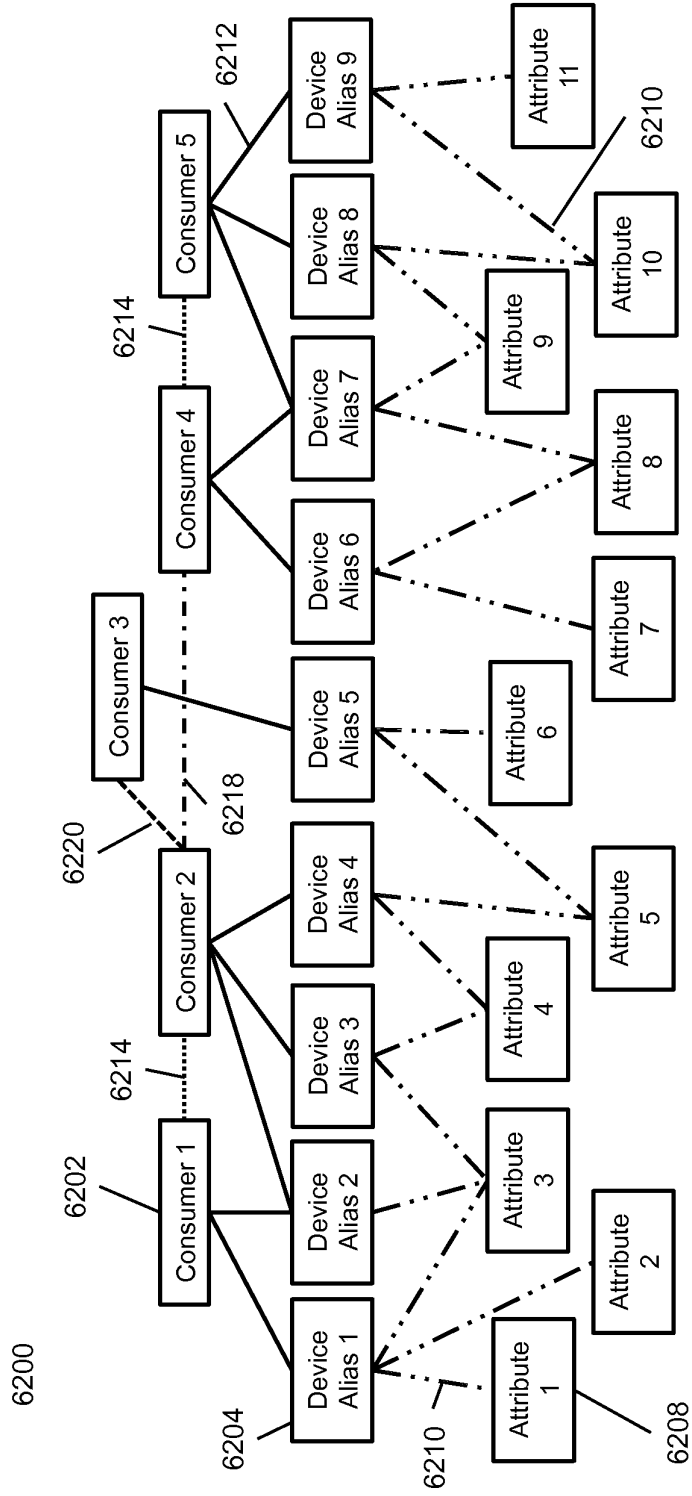


Fig. 62

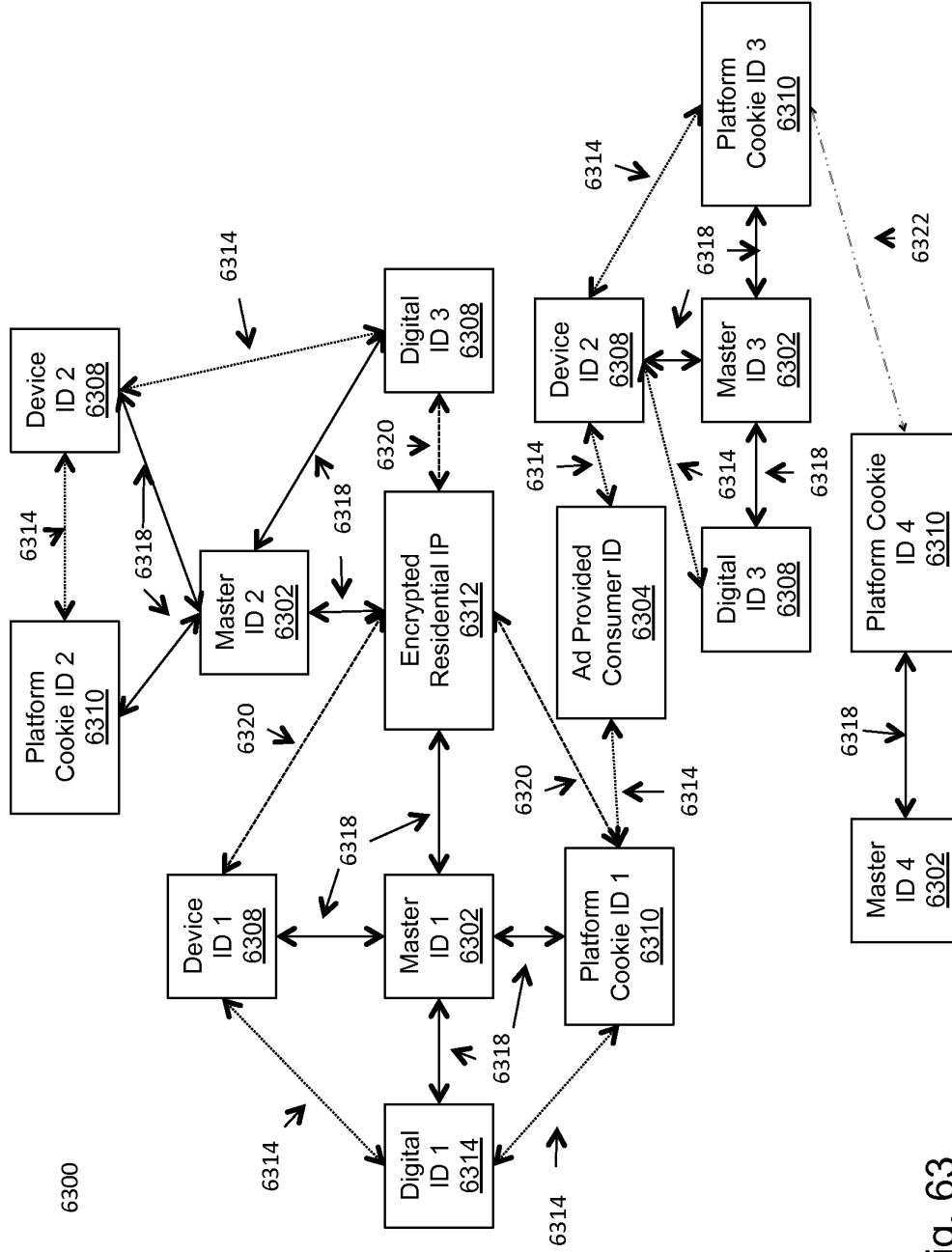


Fig. 63