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**(54) Title:** A METHOD TO PREVENT CHURN OF CUSTOMERS

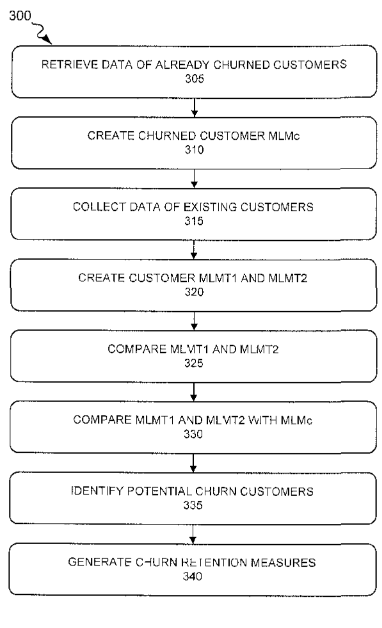


FIG. 3

300 Recuperer des donnees de clients deja perdus
310 Creer un MLMc client perdu
315 Collecter des donnees de clients existants
320 Creer un MLMTĪ et un MLMT2 client
325 Comparer MLMT1 et MLMT2
330 Comparer MLMT1 et MLMT2 avec MLMc
335 Identifier des clients perdus potentiels
340 Generer des mesures de retenue de clients perdus

**(57) Abstract:** A method to prevent churn of customers may include creating a customer model based on churned customers' behavior; creating one or more other customer models corresponding to existing customers' behavior during corresponding one or more time periods; comparing the customer model to the one or more other customer models; identifying whether the existing customers are potential churn customers based on the comparison; and generating measures to retain the existing customers when the existing customers are identified as potential churn customers.

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# A method to prevent churn of customers

## TECHNICAL FIELD

Implementations described herein relate generally to information processing. More particularly, implementations described herein relate to a machine learning scheme.

## BACKGROUND

In today's commercial industry, information gathering and information processing is increasingly becoming a centerpiece for tailoring business practices. One facet of processing information involves data mining. Data mining is a process of sorting through large amounts of data and eliciting relevant information. For example, a machine learning system may be employed to perform data mining operations.

As with most, if not all business models, minimizing cost associated with providing a product or a service is beneficial. For example, providers may have up to ten times the expenditures associated with attracting and/or obtaining a new customer than they may have in retaining an existing customer.

In a communications network, an abundance of information may be created based on a customer's activity. An operator may try to gain knowledge from this information (e.g., customer behavior) using statistics, creating reports, etc. However, at present, the detection of customer churn (i.e., customers that potentially may terminate their service) is very complicated, costly, and requires human intervention. For example, an expert needs to configure a knowledge extraction system to extract a particular type of knowledge from the communications network. This configuration process may need to be performed for each type of knowledge that the operator wishes to extract. The configuration of the knowledge extraction system requires the expert to design and input appropriate tasks (e.g., machine learning algorithms, data sets, schemas for data repositories, mathematical transformations, etc.) so that the appropriate knowledge can be discovered and utilized. In addition to cost, human intervention, etc., this approach tends to be time-consuming to the extent that the operator may lose customers before customer churn is detected and possibly prevented.

## SUMMARY

It is an object to obviate at least some of the above disadvantages and to improve the process of machine learning.

According to one aspect, a method to prevent churn of customers may include creating a customer model based on churned customers' behavior; creating one or more other customer models corresponding to existing customers' behavior during corresponding one or more time periods; comparing the customer model to the one or more other customer models; identifying whether the existing customers are potential churn customers based on the comparison; and generating measures to retain the existing customers when the existing customers are identified as potential churn customers.

According to another aspect, a device may include one or more components to collect data that includes customer activity associated with a service provided by a network; create a customer model that includes metrics corresponding to churned customers based on the collected data; create another customer model that includes metrics corresponding to existing customers based on the collected data; compare the customer model to the other customer model; and identify whether the existing customers are potential churn customers based on the comparison.

According to still another aspect, one or more computer-readable mediums may contain instructions that include one or more instructions for collecting data that includes customer activity associated with a service utilized by customers; one or more instructions for creating a customer model, based on the collected data, that corresponds to a segment of the customers classified as already churned customers; one or more instructions for creating another customer model, based on the collected data, that corresponds to a segment of the customers classified as existing customers; one or more instructions for comparing the customer model with the other customer model; one or more instructions of determining whether the existing customers are classifiable as potential churn customers based on the comparison; and one or more instructions for generating a new offer of service to minimize the churning of the potential churn customers when it is determined that the existing customers are classifiable as potential churn customers.

## BRIEF DESCRIPTION OF THE DRAWINGS

Fig. 1 is a diagram illustrating exemplary components of a machine learning system;

Fig. 2 is a diagram illustrating exemplary components of a device in which one or more of the components of Fig. 1 may be implemented;

Fig. 3 is a flow diagram illustrating an exemplary process for minimizing churn of potential churn customers;

Fig. 4 is a diagram illustrating an exemplary transformation of data to a customer model;

Figs. 5A and 5B are diagrams illustrating exemplary comparisons between customer models; and

Fig. 6 is a diagram illustrating an exemplary comparison between vectors representative of customer models to identify potential churn customers.

## DETAILED DESCRIPTION

The following detailed description refers to the accompanying drawings. The same reference numbers in different drawings may identify the same or similar elements. Also, the following description does not limit the invention.

The term "metric," as used herein, may include, for example, a system of parameters that may be measured.

The term "potential churn customers," as used herein, may include, for example, customers that are dissatisfied and/or have the potential to terminate a subscription to a service.

The term "already churned customers," as used herein, may include for example, customers that have terminated a subscription to a service.

The term "customer model," as used herein, may include, for example, a metric presenting a usage pattern of customers extracted by a machine learning system. For example, the usage pattern of customers may correspond to the usage pattern of potential churn customer(s) and already churned customer(s). A customer model may be representative of the behavior of a customer or a group of customers. A customer model may include vectors, matrices, and/or other forms of parameterizations.

The term "table," as used herein, may refer to, for example, any searchable form, arrangement of data, or data structure.

Embodiments described herein include a machine learning system that utilizes training data corresponding to the activity of churned customers before their churn to identify trends (e.g., usage patterns) in collected data associated with existing customers. The machine learning system may identify potential churn customers based on the training data and the collected data. In one implementation, the training data and the collected data may be utilized to form various customer models. Based on these various customer models, the machine learning system may provide measurements relating to how the behavior of existing customers is evolving toward the behavior of customers that exhibit potential churn. The machine learning system may further provide measurements relating to how the behavior of potential churn customers is evolving toward the behavior of already churned customers. Additionally, the machine learning system may also determine the reason for customer behavior and create appropriate counter measures to address customer behavior.

For purposes of discussion, the machine learning system will be described in connection with minimizing churn of existing customers. In this regard, one or more components of the machine learning system may be described as, for example, including a certain type of information, performing a specific function, etc., tailored toward minimizing churn of existing customers. However, it will be appreciated that depending on the problem(s) to be solved and/or goal(s) to be attained, one or more components of the machine learning system may perform a different function, utilize different information, etc. For example, if the machine learning system were to be described in connection with maximizing profits, one or more components may perform different functions, utilize different data, models, etc., than if the machine learning system were to be described in connection with minimizing churn of existing customers.

Fig. 1 is a diagram illustrating an exemplary machine learning system (MLS) 100 in which systems and methods described herein may be implemented. As illustrated, MLS 100 may include a data manager 105, data storage 110, a learning function 115, a customer model creator 120, a customer model comparer 125, an offer creator 130, and offering registry storage 135.

Data manager 105 may collect and manage data stored on data storage 110. Data manager 110 may collect data from various sources depending on the service provided. For example, in a communications network-related service, data manager 110 may receive network traffic data that pertains to the usage of services by customers. Data manager 110 may also collect data from other sources, such as, for example, customer databases.

A customer may transition from a customer to a potential churn customer. Data manager 105 may automatically collect data when one or more indications of dissatisfaction occur. These indications may include, for example, a complaining call(s) to customer support, reduced usage of service, cancelling a portion of service, changing from a higher-end service to a lower-end service (e.g., an unlimited usage of a service plan to a limited usage of a service plan), reduced payment transactions, and/or other types of customer behavior that may be indicative of customer dissatisfaction. Data manager 105 may continue to collect data with respect to a potential churn customer(s) until the potential churn customer(s) transitions to a churned customer or is considered a satisfied customer. In the event that a potential churn customer terminates his/her service, data manager 105 will have collected data leading up to this transition to a churned customer. As will be described herein, customer model creator 120 may create customer models (e.g., potential churn customer model, already churned customer model) based on this collected data.

Data manager 105 may manage the collected data. For example, data manager 105 may create various databases or other forms of data models to index and/or structure the data. In other implementations, data manager 105 may not manage the data. For example, data manager 105 may leave the collected data as raw data that may be subsequently processed by another component of MLS 100.

Data storage 110 may store data. For example, data storage 110 may include a hard disk and corresponding drive and/or some other type of computer readable medium (e.g., a compact disc (CD), a digital versatile disc (DVD), a memory, etc.). The data stored on data storage 105 may include, for example, information collected by data manager 105, information created by customer model creator 120, and other types of information (e.g., customer profiles, account information, demographic customer data, inferred data, statistical data, etc.) associated with customers, potential churn customers, and already churned customers.

Learning function 115 may include functions that allow the MLS 100 to learn. Learning function 115 may utilize one or multiple algorithms and/or machine learning techniques, such as, for example, supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, transduction, etc. Learning function 115 may obtain information from other component(s) of MLS 100 and apply, for example, various computational, statistical, data mining, predictive analytics and/or pattern recognition techniques to update and modify MLS 100.

Customer model creator 120 may create customer models associated with potential churn customers and already churned customers to be stored in data storage 110. The customer models may correspond to, for example, an individual or a group of potential churn customer(s), or an individual or a group of already churned customer(s). Customer model creator 120 may utilize various clustering techniques to provide various granularities for customer segmentation and classification.

Customer model creator 120 may create customer models based on the behavior of customers. For example, customer model creator 120 may create a representative model for potential churn customer(s) and already churned customer(s) based on indication(s) of dissatisfaction from the customer(s). Customer model creator 120 may include a knowledge discovery system to create the customer models. For example, the knowledge discovery system may process the data to derive knowledge. The knowledge discovery system may utilize various data mining techniques (e.g., classification, clustering, regression, association rule learning, etc.) to evaluate and process (e.g., parameterize, transform, etc.) the derived knowledge.

Customer model comparer 125 may compare customer models to determine whether a customer model representative of customer behavior corresponds to a potential churn customer.

Offer creator 130 may create offers to retain potential churn customers. For example, offer creator 130 may utilize combinations of customer models, behavioral models, and offerings of service that have been determined to optimally retain customers and create offers to potential churn customers corresponding to the determined best offers. Offer creator 130 may update offering registry storage 135 according to the created offers.

Offering registry storage 135 may store data. For example, offering registry storage 135 may include a hard disk and corresponding drive and/or some other type of computer readable medium (e.g., a compact disc (CD), a digital versatile disc (DVD), a memory, etc.). The data stored on offering registry storage 135 may include, for example, information related to the services, rates, etc., being offered to customers.

Although Fig. 1 illustrates an exemplary MLS 100, in other implementations, fewer, additional, and/or different components may be utilized. Additionally, or alternatively, one or more components may be combined into a single component. For example, offering registry storage 140 may be combined with data storage 110. Additionally, or alternatively, an operation or a function performed by one component, as described herein, may be performed by one or more other components.

In one implementation, MLS 100 may be implemented in a single device. In other implementations, MLS 100 may be implemented in a distributed manner (e.g., among multiple devices). For example, MLS 100 may be implemented by multiple devices communicatively coupled in a network.

Fig. 2 is a diagram illustrating exemplary components of a device in which one or more components of Fig. 1 may be implemented. For example, MLS 100 may be implemented on one more computational devices, such as, for example, one or more computers. As illustrated, a device 200 may include a bus 205, a processor 210, memory 215, storage 220, an input 225, an output 230, and a communication interface 235. The term component is intended to be broadly interpreted to include, for example, hardware, software and hardware, firmware, and/or software.

Bus 205 may permit communication among other components of device 200. For example, bus 205 may include a system bus, an address bus, a data bus, and/or a control bus. Bus 205 may also include bus drivers, bus arbiters, bus interfaces, and/or clocks.

Processor 210 may interpret and/or execute instructions and/or data. For example, processor 210 may include a general-purpose processor, a microprocessor, a data processor, a co-processor, a network processor, an application specific integrated circuit (ASIC), a controller, a programmable logic device, a chipset, and/or a field programmable gate array (FPGA), and/or some other type of logic component that may interpret and/or execute instructions and/or data. Processor 210 may control one or more other components of device 200 or one or more other components communicatively coupled to device 200.

Memory 215 may store information (e.g., data, instructions, etc.). For example, memory 215 may include a random access memory (RAM), a dynamic random access memory (DRAM), a static random access memory (SRAM), a synchronous dynamic random access memory (SDRAM), a ferroelectric random access memory (FRAM), a read only memory (ROM), a programmable read only memory (PROM), an erasable programmable read only memory (EPROM), an electrically erasable programmable read only memory (EEPROM), and/or a flash memory. Memory 215 may include a storing device external to and/or removable from device 200, such as, for example, Universal Serial Bus (USB) memory stick, a memory card, etc.

Storage 220 may store information (e.g., data, applications, etc.). For example, storage 220 may include a hard disk (e.g., a magnetic disk, an optical disk, a magneto-optic disk, etc.), a compact disc (CD), a digital versatile disc (DVD), a floppy disk, a cartridge, a magnetic tape, and/or some other type of storage or computer-readable medium along with its corresponding drive. The term "computer-readable medium" is intended to be broadly interpreted to include, for example, a storing device (e.g., memory 215, storage 220) or some other form of medium (e.g., a transmission medium, a CD, a DVD, etc.). The computer-readable medium may be implemented on a single storing device or multiple storing devices. The computer-readable medium may be implemented in a distributed manner or in a centralized manner.

Input 225 may permit input to device 200. For example, input 225 may permit a user and/or a device to input information. Input 225 may include, for example, a keyboard, a keypad, a mouse, a button, a switch, a microphone, voice recognition logic, a pen, a port, etc. Output 230 may permit output from device 200. For example, output 230 may output information to a user and/or a device. Output 230 may include, for example, a display, a speaker, one or more light emitting diodes (LEDs), a port, etc.

Communication interface 235 may enable device to communicate with other devices and/or systems. For example, communication interface 235 may include an Ethernet interface, an optical interface, a coaxial interface, and/or a wireless interface.

Although Fig. 2 illustrates exemplary components of device 200, in other implementations, device 200 may include fewer, additional, and/or different components than those depicted in Fig. 2. For example, device 200 may not include a communication interface 235. It will be appreciated that one or more components of device 200 may be capable of performing one or more other operations associated with one or more other components of device 200. For example, a display may correspond to both input 225 and output 230.

Described below, in connection with Fig. 3 is exemplary operations performed by MLS 100 to minimize churn for potential churn customers. MLS 100 may derive retention measures for the potential churn customers to minimize their churn.

Fig. 3 is a flow diagram illustrating an exemplary process 300 for minimizing churn of potential churn customers. Process 300 may begin with retrieving data of already churned customers (block 305). For purposes of discussion, data manager 105 may have previously collected data associated with already churned customers and stored this data in data storage 110. For example, the data may correspond to indications exhibited by a customer(s) that already churned. These indications may include, for example, complaining call(s) to customer support, reduced usage of service, cancelling a portion of service, changing from a higher-end service to a lower-end service (e.g., an unlimited usage of a service plan to a limited usage of a service plan), reduced payment transactions, and/or other types of customer behavior that may be indicative of customer dissatisfaction. Data manager 105 may have previously collected this data during a period of time prior to the churning of a customer(s). In one implementation, data manager 105 may automatically collect data on a customer or a group of customers when one or multiple indications of dissatisfaction occur. Data manager 105 may retrieve this collected data and provide it to customer model creator 120.

A customer model may be created (block 310). Customer model creator 120 may utilize the collected stored in data storage 110 to create an already churned customer model (i.e., a machine learning model of already churned customer(s) (MLMc)). Referring to Fig. 4, customer model creator 120 may utilize collected data 405 associated with already churned customers to create MLMc. For example, customer model creator 120 may process collected data 405 to form customer table 410. Customer table 410 may include a customer field 415 and a customer vector field 420. Customer field 415 may correspond to an identifier of an already churned customer (e.g., a name, a character string). Customer vector field 420 may correspond to a mathematical transformation of collected data 405, associated with an already churned customer, in the form of a vector. In one implementation, the vector may represent a utilization of a service, by an already churned customer, during a period of time corresponding to collected data 405. An already churned customer may utilize various services and, therefore, have a corresponding number of vectors associated with him or her in customer vector field 420.

Customer model creator 120 may create the MLMc based on customer table 410. For example, customer model creator 120 may detect and identify various patterns that represent the behavior of already churned customer(s) over the course of a time period. MLMc may correspond to a function that may be utilized to classify users (e.g., classify a user(s) as a potential churn customer).

Data of existing customer(s) may be collected (block 315). Data manager 105 may collect data on existing customers. In one implementation, data manager 105 may automatically collect data on a customer or a group of customers when one or multiple indications of dissatisfaction occur (i.e., a reactive approach). Additionally, or alternatively, data manager 105 may collect data based on a proactive approach. For example, data manager 105 may periodically or non-periodically collect data.

By way of example with respect to the reactive approach, data manager 105 may collect data during a first time period (Tl) when an indication of dissatisfaction occurs. Thereafter, data manager 105 may collect data during a second time period (T2). As will be described, the collected data during time periods T1 and T2 may be utilized by MLS 100 to identify a potential churn customer(s) based on MLMc. That is, the collected data during time periods T1 and T2 may be utilized to identify whether there is a shift in behavior during T1 to T2 that corresponds to a potential churn customer(s). This shift may be identified based on the MLMc. In this way, a potential churn customer(s) may be identified and retention measures may be implemented.

Customer models MLMTl and MLMT2 may be created (block 320). Customer model creator 120 may create MLMTl and MLMT2 in correspondence to the collected data respectively associated with time periods T1 and T2. For example, customer model creator 120 may identify various patterns that represent the behavior of the existing customer(s) over the course of time periods T1 and T2. As will be described below, in some instances, MLMTl and MLMT2 may reflect behavior of a satisfied customer(s). In other instances, MLMTl and/or MLMT2 may reflect behavior of a potential churn customer(s). In one implementation, as described herein, the MLMT2 may be utilized to confirm the prediction of customer behavior associated with the MLMTl . Additionally, the MLMT2 may be utilized to identify a reason behind a shift in behavior between the MLMTl and the MLMT2, assuming a shift exists.

The MLMTl and the MLMT2 may be compared (block 325). Customer model comparer 125 may compare MLMTl and MLMT2 to identify whether a transition of customer behavior occurred during the corresponding time periods of T1 and T2. Fig. 5A is a diagram illustrating a representation of this comparison. As illustrated in Fig. 5A, the MLMTl and the MLMT2 are depicted, where the x-axis represents time and the y-axis represents customer behavior. In practice, the y-axis may correspond to multi-dimensional indicators associated with a customer's behavior (e.g., utilization of various services, complaints, etc.).

As previously mentioned, in some instances, the comparison between the MLMTl and the MLMT2 may indicate that no transition in behavior has taken place. In other instances, the comparison between the MLMTl and the MLMT2 may indicate that a transition has taken place. In one implementation, customer model comparer 125 may generate a vector to represent the transition of customer behavior. For example, customer model comparer 125 may generate mean points 505 and 510, which may correspond to the average of all points in the MLM. Customer model comparer 125 may generate a vector 515 based on mean points 505 and 510. Vector 515 may include, among other characteristics, a magnitude and a direction. Additionally, or alternatively, other points may be generated (e.g., an edge point associated with the MLM, a random point within the MLM, etc.). Additionally, or alternatively, other vectors may be generated based on these other points.

The MLMTl and the MLMT2 may be compared with the MLMc (block 330). Customer model comparer 125 may compare MLMTl and MLMT2 with MLMc to determine whether the behavior of customer(s) represented by the MLMTl and the MLMT2 is indicative of a potential churn customer represented by the MLMc. Fig. 5B is a diagram illustrating a representation of this comparison. As illustrated in Fig. 5B, mean points 505 and 510 and vector 515 associated with the MLMTl, and the MLMc and mean point 520 (where the mean points may correspond to the average of all points in the MLM, such as a centroid) are depicted, where the x-axis represents distance and the y-axis represents customer behavior. In practice, the y-axis may correspond to multi-dimensional indicators associated with a customer's behavior (e.g., utilization of various services, complaints, etc.). In one implementation, customer model comparer 125 may compare a distance 525 between means points 505 and 520 and/or mean points 510 and 520 to determine whether the customer(s) associated with MLMTl and MLMT2 is considered or may be classified as a potential churn customer. Depending on the length of the distance 525 compared to an accuracy measurement decided by a cost function, a determination may be made whether the customer(s) are considered potential churn customer. For example, the shorter the distance, the more likely the customer(s) are moving towards a churn behavior. In one implementation, the accuracy measurement may correspond to a threshold value. The cost function may decide the value(s) associated with the accuracy measurement. The accuracy measurement may reduce a prediction error associated with identifying a customer as a potential churn customer. Additionally, or alternatively, the accuracy measurement may regulate one or more metrics associated with how MLMs are formed. For example, the accuracy measurement may impact the clustering and classification of customers. By way of example, the accuracy measurement may provide that customers belonging to a cluster must satisfy the clustering and/or classifying criteria by 95%. Depending on the value(s) of the accuracy measurement, which may be any value, the accuracy of predicting a customer(s) as a potential churn customer may be impacted.

Additionally, or alternatively, in another implementation, a vector may be generated by customer model creator 120 or customer model comparer 125 representative of the MLMc. In such an instance, the vector associated with the MLMc may be compared with vector 515. Fig. 6 is a diagram illustrating a representation of this comparison. As illustrated in Fig. 6, a vector 605 associated with the MLMc may be compared with vector 515. Based on a comparison between vector 515 and vector 605, customer model comparer 125 may generate an angle 610. Depending on the size of angle 610 compared to an accuracy measurement decided by a cost function, a determination may be made whether the customer(s) are considered potential churn customer(s). For example, the smaller the angle, the more likely the customer(s) are moving towards a churn behavior, and the length of vector 515 may be indicative of the amount or degree of such movement towards the churn behavior. Additionally, or alternatively, in other implementations, customer model comparer 125 may generate another form of a difference (e.g., magnitude, direction, etc.) between the vectors associated with the MLMc and other MLM(s).

Potential churn customers may be identified (block 335). Depending on a result of the comparison between the MLMTl and the MLMT2 with the MLMc, the existing customer(s) associated with the MLMTl and the MLMT2 may be identified as a potential churn customer(s). For purposes of discussion, process 300 will be described as if the existing customer(s) have been identified as potential churn customer(s).

Churn retention measures may be generated (block 340). Offer creator 130 may formulate new offers based on the behavioral transition between the MLMTl and the MLMT2. For example, in instances when the transition between the MLMTl to the MLMT2 reflects potential churn customer behavior, offer creator 130 may project vector 515 onto the vector space associated with the MLMT2. In this way, a customer vector 420 may be created that constitutes the reason (e.g., a service may be tied to or indicative of a dissatisfaction) associated with the customer's behavior. Offer creator 130 may reference offering registry storage 135 to obtain information relating to the services, rates, etc., currently being offered to the potential churn customer(s). Offer creator 130 may create a new offer(s) that adjusts (e.g., the rate, the amount of allowed usage, etc.) of the service that is tied to the reason. Offer creator 130 may generate a new offer(s) and store them in offering registry storage 135. The new offer(s) may be personalized toward retaining the potential churn customer(s).

Although, Fig. 3 illustrates an exemplary process 300, in other implementations, exemplary process 300 may include additional, different, and/or fewer operations than those described in connection with Fig. 3. Although not described, exemplary process 300 may include learning function 115 updating customer model creator 120, customer model comparer 125, offer creator 130, and/or other components of MLS 100 based on the accuracy of prediction of potential churn customer(s), retention success, collected data, etc. Additionally, or alternatively, although process 300 has been described in creating MLMTl and MLMT2, in other implementations, process 300 may create only a single MLM which may be compared to MLMc.

As described herein, a MLS may generate customer models to identify potential churn customers. For example, the MLS may utilize a customer model representative of already churned customers to identify potential churn customers as a customer segment. The MLS may provide measurements relating to how the behavior of potential churn customers is evolving toward the behavior of already churned customers. Additionally, the machine learning system may also determine the reason for customer behavior and create appropriate counter measures to address this adverse customer behavior. For example, the MLS may create active measures (e.g., new offers of service) to prevent customers from churning.

The foregoing description of implementations provides illustration, but is not intended to be exhaustive or to limit the implementations to the precise form disclosed. Modifications and variations are possible in light of the above teachings or may be acquired from practice of the teachings.

In addition, while a series of blocks has been described with regard to the process illustrated in Fig. 3, the order of the blocks may be modified in other implementations. Further, non-dependent blocks may be performed in parallel. It will be appreciated that the process described herein may be implemented as a computer program. The computer program may be stored on a computer-readable medium or represented in some other type of medium (e.g., a transmission medium).

It will be apparent that aspects described herein may be implemented in many different forms of software, firmware, and hardware in the implementations illustrated in the figures. The actual software code or specialized control hardware used to implement aspects does not limit the invention. Thus, the operation and behavior of the aspects were described without reference to the specific software code - it being understood that software and control hardware can be designed to implement the aspects based on the description herein.

Even though particular combinations of features are recited in the claims and/or disclosed in the specification, these combinations are not intended to limit the invention. In fact, many of these features may be combined in ways not specifically recited in the claims and/or disclosed in the specification. Although each dependent claim listed below may directly depend on only one other claim, the disclosure of the invention includes each dependent claim in combination with every other claim in the claim set.

It should be emphasized that the term "comprises" or "comprising" when used in the specification is taken to specify the presence of stated features, integers, steps, or components but does not preclude the presence or addition of one or more other features, integers, steps, components, or groups thereof.

No element, act, or instruction used in the present application should be construed as critical or essential to the implementations described herein unless explicitly described as such.

The term "may" is used throughout this application and is intended to be interpreted, for example, as "having the potential to," configured to," or "capable of," and not in a mandatory sense (e.g., as "must"). The terms "a" and "an" are intended to be interpreted to include, for example, one or more items. Where only one item is intended, the term "one" or similar language is used. Further, the phrase "based on" is intended to be interpreted to mean, for example, "based, at least in part, on," unless explicitly stated otherwise. The term "and/or" is intended to be interpreted to include any and all combinations of one or more of the associated list items.

WHAT IS CLAIMED IS:

1. A method to prevent churn of customers characterized by:

creating (310) a customer model based on churned customers' behavior;

creating (315) one or more other customer models corresponding to existing customers' behavior during corresponding one or more time periods;

comparing (330) the customer model to the one or more other customer models;

identifying (335) whether the existing customers are potential churn customers based on the comparison; and

generating (340) measures to retain the existing customers when the existing customers are identified as potential churn customers.

2. The method of claim 1, further comprising:

identifying a reason for the existing customers becoming potential churn customers based on the comparison.

3. The method of claim 1, further comprising:

automatically collecting data associated with potential churn customers, where the collected data includes utilization of a service in a network; and where the creating the customer model comprises creating the customer model based on the collected data.

4. The method of claim 1, where the generating measures comprises:

generating new offers of service to retain the existing customers identified as potential churn customers.

5. The method of claim 1, where when more than one other customer models are created, the method further comprises:

comparing the more than one other customer models to each other; and

identifying whether a shift in the existing customers' behavior exists over the time periods, and if so, whether the shift corresponds to a shift associated with potential churn customer behavior.

6. The method of claim 1, where the churned customers' behavior includes information associated with usage of a service within a period of time prior to churning.

7. The method of claim 1, where the comparing the customer model to the one or more other customer models comprises:

creating a vector based on the customer model;

creating a vector based on the one or more other customer models; and

determining a difference in the vector associated with the customer model and the vector associated with the one or more other customer models.

8. The method of claim 1, where the comparing the customer model to the one or more other customer models comprises:

creating an average for the customer model;

creating an average for the one or more other customer models; and

comparing the average associated with the customer model with the average associated with the one or more other customer models.

9. A device (100) characterized by:

one or more components to:

collect (105) data that includes customer activity associated with a service provided by a network;

create (120) a customer model that includes metrics corresponding to churned customers based on the collected data;

create (120) another customer model that includes metrics corresponding to existing customers based on the collected data;

compare (125) the customer model to the other customer model; and

identify (125) whether the existing customers are potential churn customers based on the comparison.

10. The device of claim 9, where the device includes a machine learning system.

11. The device of claim 9, where the one or more components are further configured to:

identify a reason for the existing customers becoming potential churn customers based on the comparison.

12. The device of claim 11, where the one or more components are further configured to:

generate a offer of service to the potential churn customers based on the reason.

13. The device of claim 9, where, when comparing the customer model to the other customer model, the one or more components are configured to:

create a vector based on the customer model;

create a vector based on the other customer model; and

determine a difference in the vector associated with the customer model and the vector associated with the other customer model.

14. The device of claim 13, where, when identifying whether the existing customers are potential churn customers, the one or more components are configured to:

identify the existing customers as potential churn customers based on the determined difference.

15. The device of claim 14, where, when identifying, the one or more components are further configured to:

create a threshold value based on a cost function, where the threshold value indicates an accuracy measurement for correctly predicting potential churn customers; and

compare the difference to the threshold value.

16. One or more computer-readable mediums containing instructions, the one or more computer-readable mediums characterized by:

one or more instructions for collecting data (305) that includes customer activity associated with a service utilized by customers;

one or more instructions for creating (310) a customer model, based on the collected data, that corresponds to a segment of the customers classified as already churned customers;

one or more instructions for creating (320) another customer model, based on the collected data, that corresponds to a segment of the customers classified as existing customers;

one or more instructions for comparing (330) the customer model with the other customer model;

one or more instructions of determining (335) whether the existing customers are classifiable as potential churn customers based on the comparison; and

one or more instructions for generating (340) a new offer of service to minimize the churning of the potential churn customers when it is determined that the existing customers are classifiable as potential churn customers.

17. The one or more computer readable mediums of claim 16, further comprising:

one or more instructions for determining a service that provides a basis for the existing customers being classified as potential churn customers, and where the new offer of service includes an adjustment of the service.

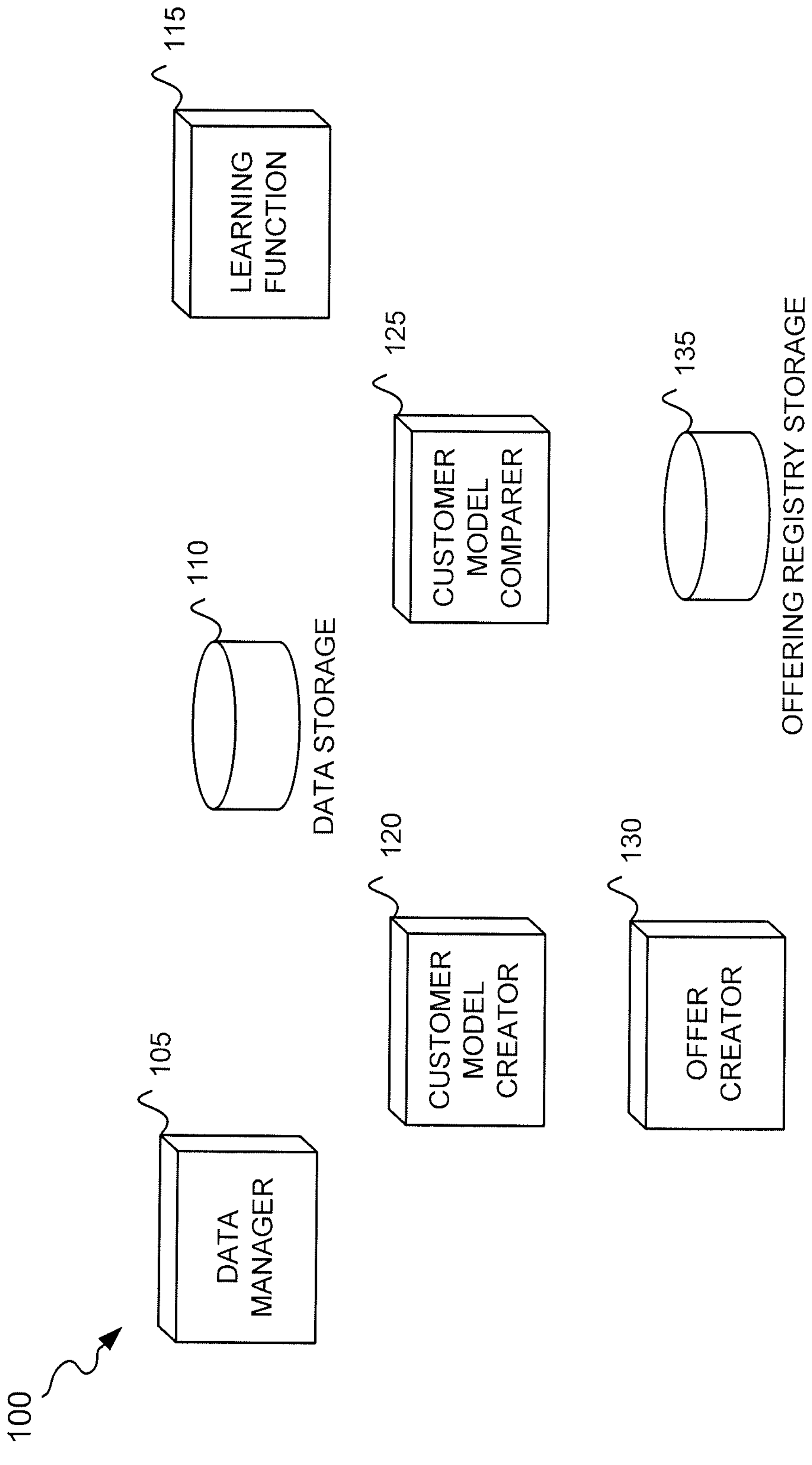
18. The one or more computer-readable mediums of claim 16, where the one or more instructions for comparing comprises:

one or more instructions for creating a vector that corresponds to the customer model;

one or more instructions for creating another vector that corresponds to the other customer model;

one or more instructions for comparing the vector with the other vector; and

one or more instructions for generating a difference between the vector and the other vector.



115
LEARNING FUNCTION
110
DATA STORAGE
125
CUSTOMER MODEL COMPARER
135
OFFERING REGISTRY STORAGE
105
DATA MANAGER
120
CUSTOMER MODEL CREATOR
130
OFFER CREATOR
100


FIG. 1

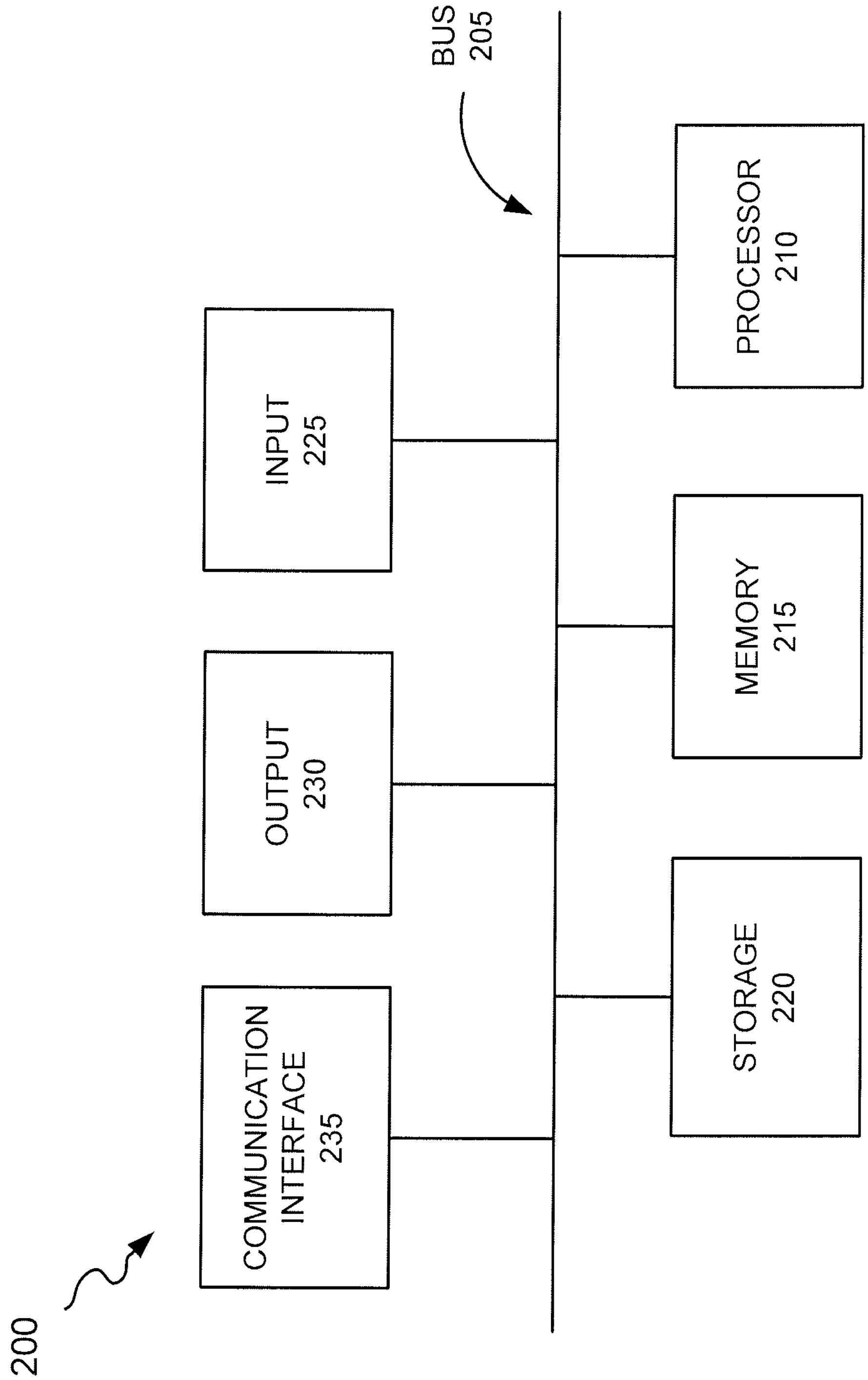

BUS 205
PROCESSOR 210
MEMORY 215
STORAGE 220
INPUT 225
OUTPUT 230
COMMUNICATION INTERFACE 235
200

FIG. 2

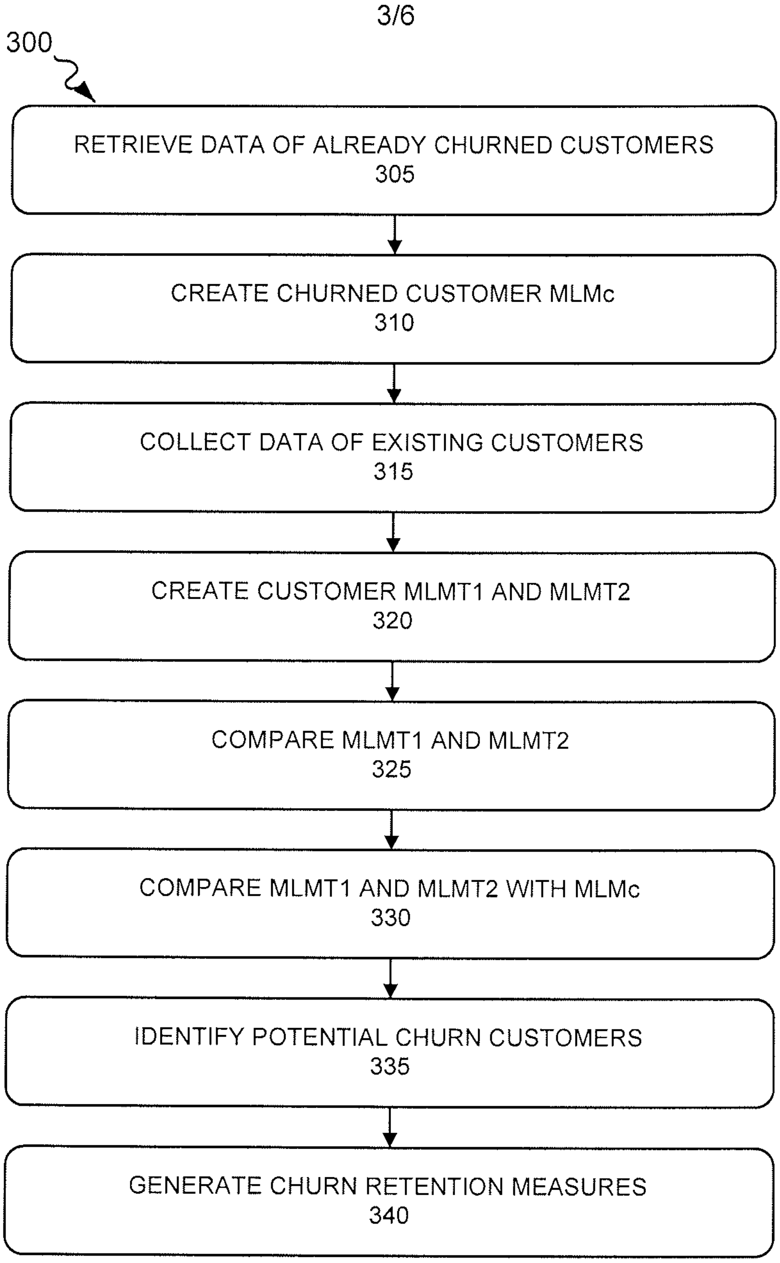

300
RETRIEVE DATA OF ALREADY CHURNED CUSTOMERS
305
CREATE CHURNED CUSTOMER MLMc
310
COLLECT DATA OF EXISTING CUSTOMERS
315
CREATE CUSTOMER MLMT1 AND MLMT2
320
COMPARE MLMT1 AND MLMT2
325
COMPARE MLMT1 AND MLMT2 WITH MLMc
330
IDENTIFY POTENTIAL CHURN CUSTOMERS
335
GENERATE CHURN RETENTION MEASURES
340

FIG. 3

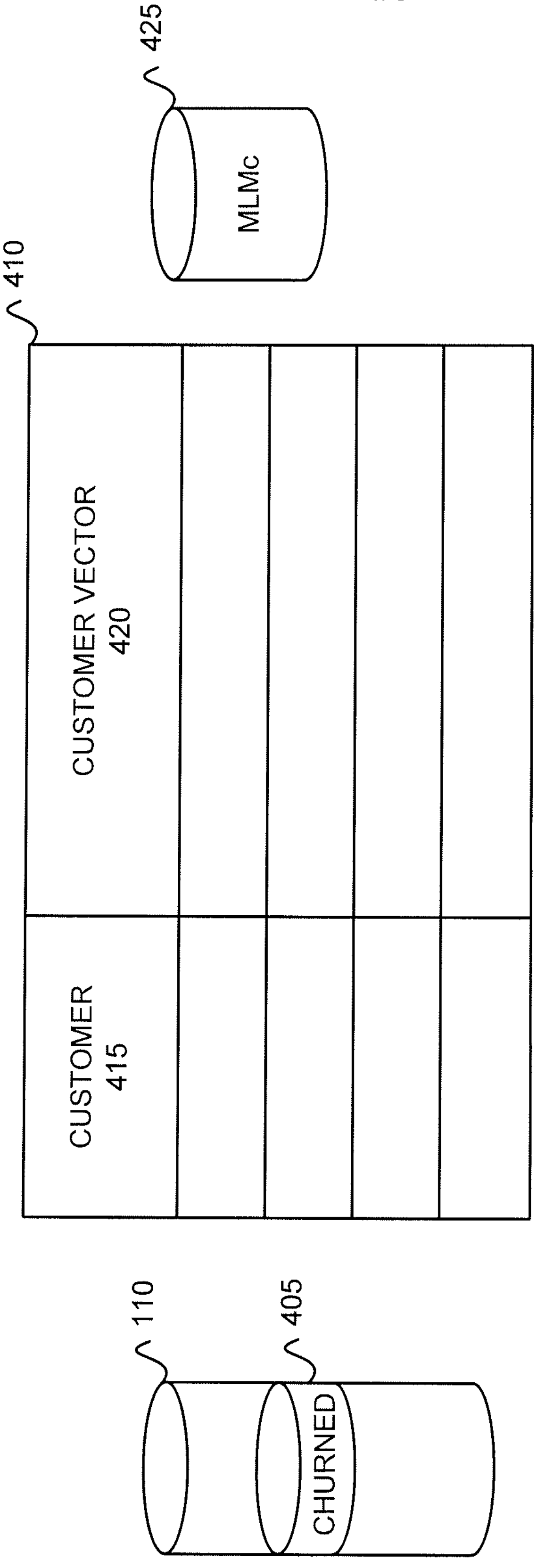

425
MLMc
410
CUSTOMER VECTOR
420
CUSTOMER
415
110
405
CHURNED

FIG. 4

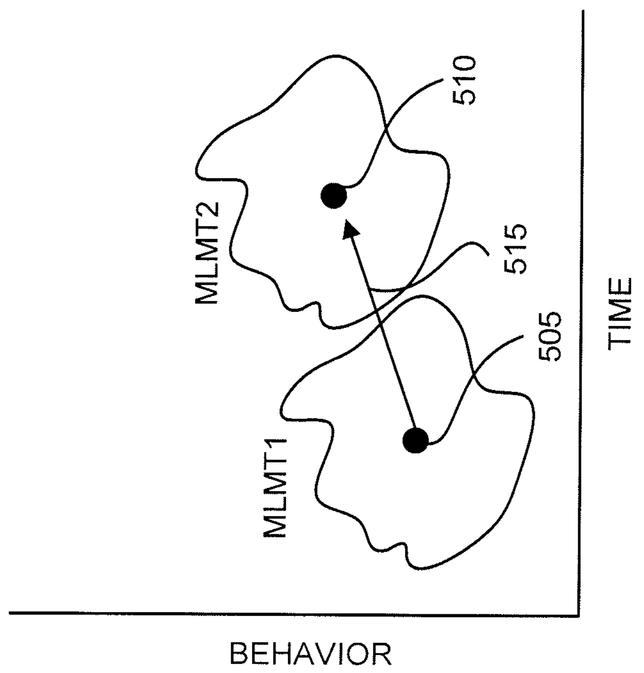

BEHAVIOR
TIME
MLMT1
MLMT2
505
510
515

FIG. 5A

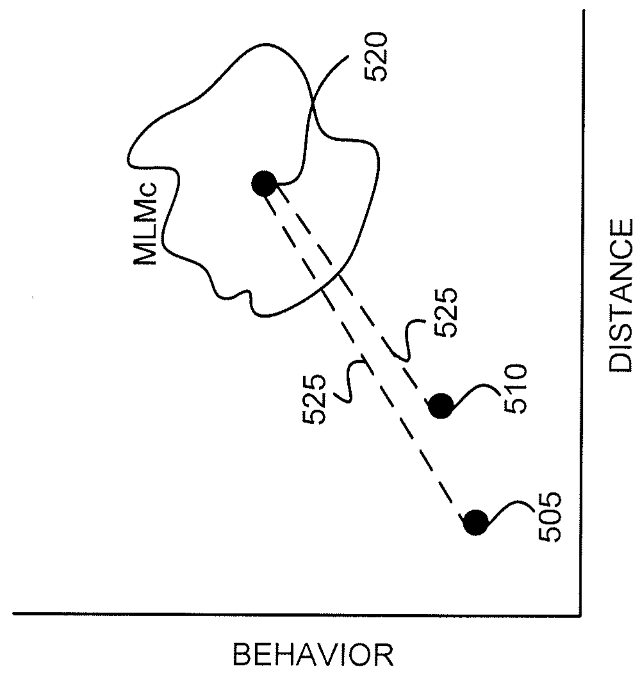

BEHAVIOR
DISTANCE
MLMc
505
510
520
525
525

FIG. 5B

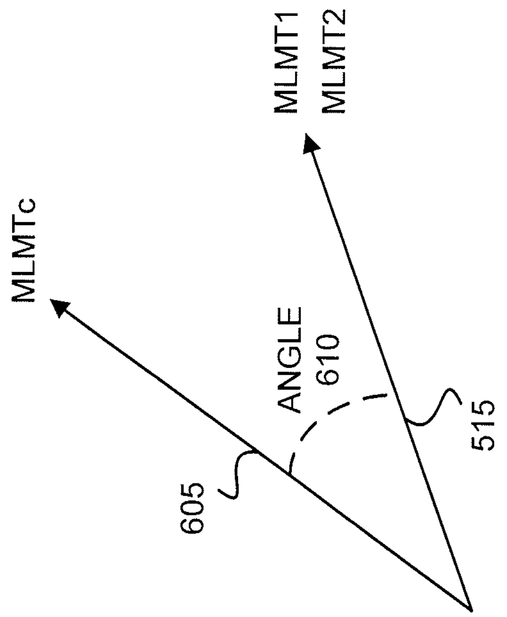



FIG. 6

# INTERNATIONAL SEARCH REPORT

International application No.
PCT/SE2009/050050

A. CLASSIFICATION OF SUBJECT MATTER

**IPC: see extra sheet**

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)

**IPC: G06Q, G06F**

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

**SE, DK, FI, NO classes as above**

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

**EPO-INTERNAL, WPI DATA, PAJ**

C. DOCUMENTS CONSIDERED TO BE RELEVANT

| Category* | Citation of document, with indication, where appropriate, of the relevant passages | Relevant to claim No. |
|---|---|---|
| X | US 20040073520 Al (ESKANDARI, RAMINE), 15 April 2004 (15.04.2004), figure 2, claims 1, 14, abstract, paragraphs [0003]-[0014], [0026]-[0037] -- | 1-18 |
| X | EP 1811446 Al (ACCENTURE GLOBAL SERVICES GMBH), 25 July 2007 (25.07.2007), figure 2, claims 1-41, abstract, paragraphs [0007]-[0013] -- | 1-18 |
| X | US 20030200135 Al (WRIGHT, CHRISTINE ELLEN), 23 October 2003 (23.10.2003), claims 1, 13, abstract -- | 1-18 |

[X] Further documents are listed in the continuation of Box C. [X] See patent family annex.

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"&" document member of the same patent family

| Date of the actual completion of the international search | Date of mailing of the international search report |
|---|---|
| 21 August 2009 | 25 -08- 2ùü9 |

| Name and mailing address of the ISA/ | Authorized officer |
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International application No.
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C (Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

| Category* | Citation of document, with indication, where appropriate, of the relevant passages | Relevant to claim No. |
|---|---|---|
| X | US 20040039593 Al (ESKANDARI, RAMINE), 26 February 2004 (26.02.2004), claims 1,21,27, abstract | 1-18 |

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**INTERNATIONAL SEARCH REPORT**

International application No.
PCT/SE2009/050050

**International patent classification (IPC)**
***G06Q 30/00*** (2006.01)

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Cited literature, if any, will be enclosed in paper form.

# INTERNATIONAL SEARCH REPORT
Information on patent family members

International application No.
PCT/SE2009/050050

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|---|---|---|---|---|
| US | 20040073520 | A1 | 15/04/2004 | NONE |
| EP | 1811446 | A1 | 25/07/2007 | NONE |
| US | 20030200135 | A1 | 23/10/2003 | NONE |
| US | 20040039593 | A1 | 26/02/2004 | NONE |