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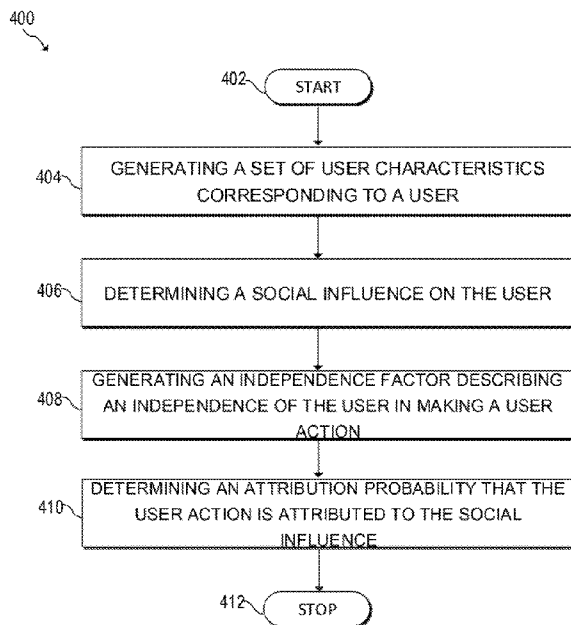


FIG. 4

(57) Abstract: A method for social influence determination includes generating a set of user characteristics corresponding to a user(404). The method includes determining a social influence on the user(406) and generating an independence factor describing an independence of the user in making a user action(408). The method includes determining an attribution probability that the user action is attributed to the social influence(410). The attribution probability is based on the set of user characteristics, the social influence and the independence factor.

SOCIAL INFLUENCE DETERMINATION

BACKGROUND

[0001] The advent of social networking sites on the Internet has led an unprecedented number of users registered with social networking sites to engage in interesting user activities such as commenting on, liking, and re-sharing content as well as interacting with each other to share thoughts. The exponential growth of information repositories and the diversity of users on these social networking sites provide great challenges for analyzing and understanding user actions and user-user relationships.

BRIEF DESCRIPTION OF THE DRAWINGS

[0002] The following detailed description references the drawings, wherein:

[0003] FIG. 1 is a block diagram of an example computing environment in which social influence determination may be useful;

[0004] FIG. 2 is a graphical representation of an example model of a joint activity and relation framework;

[0005] FIG. 3 is a flowchart of an example method for social influence and topic determination;

[0006] FIG. 4 is a flowchart of an example method for social influence determination;

[0007] FIG. 5 is a flowchart of an example method for social influence determination;

[0008] FIG. 6 is a block diagram of an example system for social influence determination; and

[0009] FIG. 7 is a block diagram of an example system for social influence determination.

DETAILED DESCRIPTION

[0010] Techniques for social analysis typically consider influence by heuristics for coarse and limited measurement. Such techniques do not measure social influence to take into account core factors for prediction tasks. Thus, the effect of social influence on prediction tasks is unclear and largely unexplored. Behavioral evidences may be leveraged to infer social relations and at the same time exploit relations to predict user behaviors in a unified framework. Moreover, social influence may be determined quantitatively to capture interactions for joint and enhanced user activity prediction and user-user relationship discovery.

[0011] The widespread social phenomenon of homophily suggests that socially acquainted users tend to behave similarly. The homophily social effect is also called the theory of “birds of a feather flock together” – people tend to follow the behaviors of their friends, and people tend to create relationships with other people who are already similar to them. This phenomenon illustrates a high correlation and mutual interactions between users’ activities and user-user relations. Bidirectional mutual interactions (BMI) can be explained through an illustrative example involving two users of an example online social network. The behavior of first user, Kate, (such as “liking” a particular phone model) can be influenced by the opinion of a second user, Kate’s friend Bob. Since Kate and Bob are friends, it is likely that they have the same behavior. On the other hand, Kate’s behavior could in turn impact her relationships with others such as Bob. If Kate and Bob have similar behaviors, there is a likelihood that Kate and Bob will create a user-user relationship. Although the illustrative example above is discussed in terms of users on an

online social network, the social influence determination systems and methods discussed herein are not limited to users of online social networks, but may be applied to users of any platform.

[0012] The mechanism that drives the characteristics and dynamics of BMI may be expressed as the underlying social influence. Social influence refers to the phenomenon that a user follows an opinion from others, which may or may not deviate from the user's own interests. Thus, the user's activities are not solely dependent on the user's own preferences but also influenced by the tastes of other people. Similarly, the social relationship between two users depends not only on their prior impressions to each other but also their behavior agreement. Social influence may be expressed quantitatively as the probability that a user follows an opinion from others, for both the user's activities and the user's relationships to others. The influences from different users are essentially different. Furthermore, some people with different interests may be very influential to a user, while some other people with very similar interests may not contribute too much to this user.

[0013] Example social influence determination systems determine social influence quantitatively to capture BMI for joint and enhanced user activity prediction and user-user relationship discovery. Example social influence determination systems may use a unified probabilistic approach, such as a joint activity and relation (JAR), for modeling and predicting users' activities and user-user relationships simultaneously in a single coherent framework. Instead of incorporating social influence in an ad hoc manner, the example social influence determination systems may capture social influence quantitatively. Based on JAR, the example social influence determination systems determine social influence between users and users' personal preferences for both user activity prediction and user-user relation discovery through statistical inference. Example social influence determination systems may use learning algorithms based on expectation maximization (EM) to address the challenges of the introduced multiple layers of hidden variables in JAR. In this manner, the example social influence determination systems use JAR to exploits mutual interactions and benefits, by taking advantage of the learned social influence

and users' personal preferences for enhanced user activity prediction and user-user relation discovery.

[0014] For example, a user may generate content for a social network and have numerous connections to other users on the social network. Example social influence determination systems may determine the probability that a user activity corresponding to that content, such as affirming or "liking" the content is attributed to the user's personal preference as opposed to the probability that the user activity is attributed to the social influence on the user from one or more other users of the social network. Similarly, example social influence determination systems may determine the probability that a user-user relationship established by a user is attributed to the user's prior impression as opposed to the probability that the user activity is attributed to the social influence on the user from one or more other users of the social network.

[0015] An example method for determining social influence may include generating a set of user characteristics corresponding to a user. The user characteristics may include user preferences and/or prior impressions. The example method may include determining a social influence on the user. The social influence may be probability that the user will be influenced by a second user. The example method may include generating an independence factor describing an independence of the user in making a user action. Example user actions may include user activities and/or user-user relationships. The example method may include determining an attribution probability that the user action is attributed to the social influence. The attribution probability is based on the set of user characteristics, the social influence and the independence factor.

[0016] FIG. 1 is an example environment 100 in which various examples may be implemented as a social influence determination system 110. Social influence determination system 110 may comprise various components, including a user characteristic engine 112, a social influence engine 114, an independence factor engine 116, a probability engine 118, a topic engine 120, a user activity probability engine 122, a user-user relationship engine 124, and/or other components. Environment 100 may also include various components

including a server computing device 120 and a client computing device 122. The client computing device 122 may communicate requests to and/or receive responses from the server computing device 120. The server computing device 120 may receive and/or respond to requests from the client computing device 122. The client computing device 122 may be any type of computing device providing a user interface through which a user can interact with a software application. For example, the client computing device 122 may include a laptop computing device, a desktop computing device, an all-in-one computing device, a tablet computing device, a mobile phone, and/or other electronic device suitable for displaying a user interface and processing user interactions with the displayed interface. While the server computing device 120 is depicted as a single computing device, the server computing device 120 may include any number of integrated or distributed computing devices serving at least one software application for consumption by the client computing device 122.

[0017] The various components (e.g., components 120 and/or 122) depicted in FIG. 1 may be coupled to at least one other component via a network 124. Network 124 may comprise any infrastructure or combination of infrastructures that enable electronic communication between the components. For example, the network 124 may include at least one of the Internet, an intranet, a PAN (Personal Area Network), a LAN (Local Area Network), a WAN (Wide Area Network), a SAN (Storage Area Network), a MAN (Metropolitan Area Network), a wireless network, a cellular communications network, a Public Switched Telephone Network, and/or other network. According to various implementations, social influence determination system 110 and the various components described herein may be implemented in hardware and/or a combination of hardware and programming that configures hardware. Furthermore, in FIG. 1 and other Figures described herein, different numbers of components or entities than depicted may be used.

[0018] As described above, social influence determination system 110 may comprise various components, including a user characteristic engine 112, a social influence engine 114, an independence factor engine 116, a probability engine 118, a topic engine 120, a user activity probability engine 122, a

user-user relationship engine 124, and/or other components. The components of the social influence determination system 110 as described herein, may refer to a hardware or a combination of hardware and instructions that performs a designated function. As is illustrated with respect to FIG. 7, the hardware of the various components of social influence determination system 110, for example, may include one or both of a processor and a machine-readable storage medium, while the instructions are code stored on the machine-readable storage medium and executable by the processor to perform the designated function.

[0019] User characteristic engine 112 may generate a set of user characteristics corresponding to a user. The user may be a member or otherwise belong to a social network. However, online social networks are just one example of platforms with users and the social influence determination systems and methods discussed herein may be applied to and/or used with users of any platform, group, etc. The set of user characteristics may include user preferences corresponding to a user of a social network, such as topics, products, etc. The set of characteristics may also include prior impressions from a first user of a social network on a second user of the social network. For example, a first user may have influence on a second user in creating a relationship, creating content, etc. In other examples, the user characteristics may include additional and/or alternate elements associated with a user.

[0020] Social influence engine 114 may determine a social influence between one or more users. The social influence may be a probability that a first user will be influenced by the second user.

[0021] Independence factor engine 116 may generate an independence factor for a user of the social network. The independence factor may describe an independence of the user in performing a user action, such as a user activity and/or a user-user relationship. The independence factor may weight the probability of a user's own interests affecting the user's activity. The independence factor may additionally and/or alternatively weight the probability of a user's own interests affecting the likelihood of the user creating a user-user relationship. The independence factor may be a value from 0.0 to 1.0 with an incremental step of 0.1.

[0022] Probability engine 118 may determine an attribution probability that the user activity is attributed to the user influence. The attribution probability may be based on: the set of user characteristics (e.g., as discussed herein with respect to user characteristic engine 112), the social influence (e.g., as discussed herein with respect to social influence engine 114), and the independence factor (e.g., as discussed herein with respect to independence factor engine 116). The probability engine 118 may determine a first attribution probability that the user action is attributed to the social influence as well as a second probability that the user action is attributed to the user characteristics. The first and second probabilities may be compared and/or otherwise analyzed. The comparison and/or analysis may generate a third attribution probability.

[0023] The probability engine 118 may incorporate one or more models in determining the attribution probability. For example, the probability engine 118 may incorporate a joint activity and relation (JAR) model.

[0024] FIG. 2 shows a graphical representation of a model 200 of a joint activity and relation (JAR) framework. The model 200 explores several important factors, such as user preferences and social influence, contributing to user actions. User actions may include actions taken by a user on a social network, such as user activities and user-user relationships. As used herein, the term “user-user relationship” may refer to a relationship between two or more users of a social network. The model enables quantified social influence among individuals for both users’ activities and user-user relationships.

[0025] The model 200 models activity of a user u (left portion 202), activity of user v (right portion 204), and user-user relationship between user u and user v (middle portion 206). As the left portion 202 and the right portion 204 of the model 200 have a similar structure, the left portion 202 (modeling the activity of user u) is described to illustrate user activity. Example user activities may include generating content, such as a post, sharing content, affirming content, commenting, etc. The preference of user u may be captured through a set of latent topics t and the activities y of user u and corresponding tags w are correlated with user u through the set of latent topics t .

[0026] Each activity y is associated with a set of tags $w = \{w_1, w_2, \dots, w_m\} (w \in W)$ representing the content of this activity. The latent topic set $t = \{t_1, t_2, \dots, t_l\} (t \in T)$ is introduced to capture the interests and/or preferences of user u , and also to characterize user activities y and their content w . The user activity $y (y \in Y)$ (y is associated with a tag w) of user $u (u \in V)$ is subject to the preference of user u (the latent topic t) for the independent selection of user u and the social influence s from others.

[0027] Similarly, in the middle portion 206 of the model 200, user u 's relationship to user v is attributed to user u 's own prior impression to user v and the social influence s . Without loss of generality, the social influence variable s represents any user directly connected to user u in the social graph G . A connection of user u , may be another user of the social network that user u has a relationship with, via, for example, a user activity, a direct user relationship, etc. Connections may include close friends, family members, colleagues, acquaintances, etc. Let $S(u) (S(u) \subseteq V)$ be the set of three users directly connected to user u . The social influence from s in $S(u)$ to u is measured as the probability of the preferences of the social influence s that contribute to user activities of user u and/or user u 's relationship to v . In some situations user u 's independent choice and user u 's own tastes may play a more important role for a user action (such as user activity y , user u 's relationship to user v , etc.) than the social influence and preferences from $S(u)$.

[0028] Both the user activity y of user u and the relationship of user u to user v are probabilistically determined based on the interests of user u or the preferences of $s (s \in S(u))$ via social influence. The social influence dependency $P(s|u)$ is defined as the probability of user u to be influenced by user s . For user activity, once s is selected based on $P(s|u)$, a topic t may be randomly selected from the interests of user s based on the conditional probability $P(t|s)$. The topic t generates an activity y and a tag w based on activity distribution of topic $t (P(y|t))$ and the content distribution of topic $t P(w|t)$. Otherwise, a topic t may be selected for the tastes of user u based on $P(t|u)$. For a user-user relationship, once s is selected based on $P(s|u)$, the relationship probability from u to v is measured as $P(s|u)P(v|s)$. Otherwise, the relationship

probability from u to v is measured based on u 's prior impression as $P(v|u)$. Both user activities and user-user relationships are modeled in a single coherent framework via social influence to capture the BMI between them. Thus, the social influence from $S(u)$ may be measured quantitatively and efficiently and the effect of social influence for both user activities and user-user relations may be analyzed.

[0029] Referring again to FIG. 1, the probability engine 118 may also incorporate one or more algorithms, equations, etc., in conjunction with the one or more models in determining the attribution probability.

[0030] For example, the probability engine 118 may optimize the joint conditional probability $P(y, v|u)$ for most likely activity prediction and relationship discovery. $P(y, v|u)$ may be calculated as:

[0031] Equation (1):
$$P(y, v|u) = \frac{P(y, v, u)}{P(u)} \propto P(y, v, u)$$
$$\propto \sum_{s \in S(u)} \sum_{t \in T} \sum_{w \in W} P(y, w, s, t, u, v)$$

[0032] Based on the model 200 illustrated in FIG. 2, user activities y and tags w are independently conditioned on the topics t . Consequently the joint probability dependency $P(y, w, s, t, u, v)$ over all factors is decomposed as:

[0033] Equation (2):

$$P(y, w, s, t, u, v) = P(v)P(u|v)P(s|u)P(t|s)P(y|t)P(w|t)$$

[0034] As further depicted in the model 200 illustrated in FIG. 2, user u and topic t are independently conditioned on social influence s , and social influence s , user activity y and tags w are independently conditioned on topic t . Accordingly, equation (2) can be rewritten as follows:

[0035] Equation (3):

$$\begin{aligned} P(y, w, s, t, u, v) &= P(u|v)P(v)[P(s|u)P(t|s)P(y|t)P(w|t)] \\ &= P(v|u)P(u)[P(s|u)P(t|s)P(y|t)P(w|t)] \\ &= P(v|u)[P(t)P(u|s)P(s|t)P(y|t)P(w|t)] \end{aligned}$$

[0036] Social influence s and topics t are hidden variables which are unobserved in the social data. Accordingly, in order to model the probability $P(y, w, s, t, u, v)$ in terms of social influence s and t , Equation (3) may be transformed into the following equation as:

[0037] Equation (4):
$$P(s, t|u, v, y, w) = \frac{P(y, w, s, t, u, v)}{\sum_s \sum_t P(y, w, s, t, u, v)}$$

$$= \frac{P(t)P(u|s)P(s|t)P(y|t)P(w|t)}{\sum_s \sum_t P(t)P(u|s)P(s|t)P(y|t)P(w|t)}$$

[0038] According to Equation (4), several model parameters of JAR are estimated, including $P(u|s)$, $P(s|t)$, $P(y|t)$, $P(w|t)$ and $P(t)$, in order to calculate probabilities $P(y, w, s, t, u, v)$ and $P(y, v, u)$. In summary, JAR jointly incorporates several important factors for simultaneous user activity prediction and user-user relationship inference, including the distribution of social influence $P(u|s)$ from s to u ; the distribution of u 's own preference $P(t|u)$ over the latent topics t ; the distribution of s 's preference $P(s|t)$ over the latent topics t ; the distribution of activity $P(y|t)$ for each topic t ; and the distribution of generated content $P(w|t)$ for each topic t .

[0039] Topic engine 120 may determine a social influence topic corresponding to an interest of the social influence and determine the effect of the social influence topic on the user action. Topic engine 120 may further determine a user topic corresponding to an interest of the user and determine the effect of the user topic on the user action. Topic engine 120 may use one or more algorithms, equations, models, etc. For example, topic engine 120 may implement a learning algorithm based on expectation maximization (EM) to determine multiple hidden variables s and t . The learning algorithm may maximize the complete log-likelihood of the social data as:

[0040] Equation (5):

$$\log P(G; \theta) = \log \sum_s \sum_t P(s, t, u, v, y, w; \theta)$$

[0041] In Equation (5), s represents social influence variables, t represents latent topic variables, and θ represents the parameters of a JAR model, such as the model 200 illustrated in FIG. 2, including $P(u|s)$, $P(s|t)$, $P(y|t)$, $P(w|t)$, and $P(t)$. Topic engine 120 may maximize the lower bound $L(\theta)$ of the log-likelihood according to Jensen's inequality as

[0042] Equation (6):

$$L(\theta) = \sum_s \sum_t \log(P)(s, t, u, v, y, w; \theta)$$

$$= \sum_s \sum_t \log[P(s, t|u, v, y, w)P(u, v, y, w)]$$

[0043] In the example EM based algorithm, the E-step includes computing the expected value of the log-likelihood objective function $L(\theta)$ with respect to the conditional distribution of latent variables s and t , under the current estimate of the model parameters. This step can be performed according to Equation (4) and Equation (6), in which s and t are computed simultaneously such that $P(s|t)$ can be estimated in the M-step. The M-step includes estimating all the parameters θ to maximize $L(\theta)$ in the E-step. $L(\theta)$ is maximized with its parameters by the Lagrangian multiplier method. For example, take the derivation of $L(\theta)$ with respect to $p(u|s)$ for the following equation:

[0044] Equation (7): $\frac{\partial}{\partial(p(u|s))} [L_{[P(u|s)]} + \lambda(1 - P(u|s))] = 0$

[0045] In Equation (7), $L_{[P(u|s)]}$ represents terms containing $P(u|s)$ in the objective function L . This can be expressed as:

[0046] Equation (8): $\lambda = \frac{\sum_{v', y', w'} \sum_{t'} P(s, t'|u, v', y', w')}{\sum_{u, v, y, w} \sum_{s, t} P(s, t|u, v, y, w)}$

[0047] The updated formula of $P(u|s)$ can be expressed as:

[0048] Equation (9): $P(u|s) = \frac{\sum_{v', y', w'} \sum_{t'} P(s, t'|u, v', y', w')}{\sum_{u, v, y, w} \sum_{s, t} P(s, t|u, v, y, w)}$

[0049] Similarly, the updated formulas of $P(s|t)$, $P(y|t)$, $P(w|t)$, and $P(t)$ can be derived as follows:

[0050] Equation (10): $P(s|t) = \frac{\sum_{u', y', w'} \sum_{v'} P(s, t|u', v', y', w')}{\sum_{u, v, y, w} \sum_{s, t} P(s, t|u, v, y, w)}$

[0051] Equation (11): $P(y|t) = \frac{\sum_{u', y', w'} \sum_{s'} P(s', t|u', v', y', w')}{\sum_{u, v, y, w} \sum_{s, t} P(s, t|u, v, y, w)}$

[0052] Equation (12): $P(w|t) = \frac{\sum_{u', v', y'} \sum_{s'} P(s', t|u', v', y', w')}{\sum_{u, v, y, w} \sum_{s, t} P(s, t|u, v, y, w)}$

[0053] Equation (13): $P(t) = \frac{\sum_{u', v', y', w'} \sum_{s'} P(s', t|u', v', y', w')}{\sum_{u, v, y, w} \sum_{s, t} P(s, t|u, v, y, w)}$

[0054] The EM-based algorithm optimizes the model parameters iteratively via E-step and M-step until converging to a local optimum. To obtain a better model fitting that generalizes well on the unseen testing social data, a generalization of the EM-based algorithm can be used, which is known as

annealing and is based on an entropic regularization term. The EM procedure in JAR could be obtained by minimizing a common objective function (also called the free energy) as follows:

[0055] Equation (14):

$$F_{\gamma} = -\gamma \sum_{s,t} \tilde{P}(s, t|u, v, y, w) \log P(u, v, y, w|s, t)P(s, t) \\ + \sum_{s,t} \tilde{P}(s, t|u, v, y, w) \log \tilde{P}(s, t|u, v, y, w)$$

[0056] In Equation (14), $\tilde{P}(s, t|u, v, y, w)$ is the variational distribution and γ is the control parameter called inverse computational temperature. In the case of $\tilde{P}(s, t|u, v, y, w) = P(s, t|u, v, y, w)$ minimizing F w.r.t. the probabilities defining $P(u, v, y, w|s, t)P(s, t)$ amounts to the standard M-step. Topic engine 120 may verify that the posteriors are obtained by minimizing F w.r.t. $\tilde{P}(s, t|u, v, y, w)$ at $\gamma = 1$. The E-step in Equation (4) may be modified as follows:

[0057] Equation (15):

$$\tilde{P}(s, t|u, v, y, w) = \frac{[P(t)P(u|s)P(s|t)P(y|t)P(w|t)]^{\gamma}}{\sum_s \sum_t [P(t)P(u|s)P(s|t)P(y|t)P(w|t)]^{\gamma}}$$

[0058] If $\gamma = 1$ Equation (15) becomes the standard E-step, while for $\gamma < 1$ the likelihood in Equation (15) is discounted. A held-out data technology may be used by first performing EM iterations and then decreasing γ until held-out performance deteriorates.

[0059] FIG. 3 is a flowchart of an example method 300 for social influence and topic determination. Method 300 summarizes the overall learning procedure of the learning algorithm based on expectation maximization (EM) to determine multiple hidden variables s and t discussed above. Method 300 may be described below as being executed or performed by a system, for example, system 110 of FIG. 1, system 600 of FIG. 6 or system 700 of FIG. 7. Other suitable systems and/or computing devices may be used as well. Method 300 may be implemented in the form of executable instructions stored on at least one machine-readable storage medium of the system and executed by at least one processor of the system. Alternatively or in addition, method 300 may be

implemented in the form of electronic circuitry (e.g., hardware). In alternate embodiments of the present disclosure, one or more steps of method 300 may be executed substantially concurrently or in a different order than shown in FIG. 3. In alternate embodiments of the present disclosure, method 300 may include more or less steps than shown in FIG. 3. In some embodiments, one or more of the steps of method 300 may, at certain times, be ongoing and/or may repeat.

[0060] Method 300 may start at step 302 and continue to step 304, where the method may set $\gamma \leftarrow 1$ and perform EM iterations with early stopping. As discussed above, γ is the control parameter called inverse computational temperature. At step 306, the method may decrease γ by $\gamma \leftarrow \eta \gamma$ with $\eta < 1$ and perform an E-Step Equation, for example, Equation (15) described above. At step 308, the method may determine if the performance on the held out data is improving. If the method determines that the performance on the held out data is not improving (NO branch of step 308), the method may return to step 306. If the method determines that the performance on the held out data is improving (YES branch of step 308) the method may go to step 310. At step 310, the method may continue to perform the E-Step Equation with the current value of γ . At step 312, the method may determine that decreasing γ does not produce further improvements. At step 314, the method may perform final iterations using both training and held-out social data. Method 300 may eventually continue to step 316, where method 300 may stop.

[0061] Turning again to FIG. 1, user activity probability engine 122 may determine an attribution probability that the user activity is attributed to the social influence. The attribution probability may be based on the set of user preferences, the social influence and the independence factor. In other words, the user activity of user u is probabilistically determined based on the user preferences of user u or the preferences of s via the social influence. Both the user's personal preference and social influence are relevant to accurate user action prediction. User activity probability engine 122 may determine conditional probability of user u 's activity y as follows:

[0062] Equation (16): $P(y|u) = \alpha P_{self}(y|u) + (1 - \alpha) P_{socinf}(y|u)$

[0063] In Equation (16), $P_{\text{self}}(y|u)$ is user u 's user activity based on the personal preference, and $P_{\text{socinf}}(y|u)$ is user u 's user activity based on social influence. The independence factor $\alpha(0 \leq \alpha \leq 1)$ is used to weight the probability of user u 's own tastes on user activity. An example independence factor α may be 0.8, although the independence factor may vary based on the user and/or other data. Thus the probability of social influence on user activity is measured as $1 - \alpha$. Based on user u 's personal preference, a topic t is directly drawn for u 's own tastes based on $P(t|u)$ in the JAR model. $P_{\text{self}}(y|u)$ can be calculated as:

[0064] Equation (17):

$$P_{\text{self}}(y|u) = \sum_t \sum_w P(t|u)P(y|t)P(w|t)$$

[0065] In Equation (17), $P(t|u)$, $P(y|t)$, and $P(w|t)$ can be computed efficiently from the learned model parameters. And $P_{\text{socinf}}(y|u)$ is calculated as:

[0066] Equation (18):

$$P_{\text{socinf}}(y|u) = \sum_s \sum_t \sum_w P(s|u)P(t|s)P(y|t)P(w|t)$$

[0067] User-user relationship probability engine 124 may determine an attribution probability that the user-user relationship is attributed to the social influence. The attribution probability may be based on the set of prior impressions, the social influence and the independence factor. In other words, the user-user relationship of user u is probabilistically determined based on the prior impressions of user u or the preferences of s via the social influence. Both the user's prior impressions and social influence are relevant to accurate user-user relationship prediction. User-user relationship probability engine 124 may calculate the conditional probability $P(v|u)$ of user u 's relationship to user v as:

[0068] Equation (19): $P(v|u) = \beta P_{\text{self}}(v|u) + (1 - \beta)P_{\text{socinf}}(v|u)$

[0069] In Equation (19), $P_{\text{self}}(v|u)$ measures the relationship from u to v based on u 's prior impressions to v , $P_{\text{socinf}}(v|u)$ measures the relationship from u to v based on social influence, and $\beta(0 \leq \beta \leq 1)$ is another weighting factor. An example independence factor β may be 0.7, although the

independence factor may vary based on the user and/or other data. For a given social data, $P_{\text{self}}(v|u)$ is easy to compute. And $P_{\text{socinf}}(v|u)$ can also be computed efficiently as:

[0070] Equation (20):

$$P_{\text{socinf}}(v|u) = \sum_s P(s|u)P(v|s) \propto \sum_s P(u|s)P(v|s)$$

[0071] FIG. 4 is a flowchart of an example method 400 for a determining social influence. Method 400 may be described below as being executed or performed by a system, for example, system 110 of FIG. 1, system 600 of FIG. 6 or system 700 of FIG. 7. Other suitable systems and/or computing devices may be used as well. Method 400 may be implemented in the form of executable instructions stored on at least one machine-readable storage medium of the system and executed by at least one processor of the system. Alternatively or in addition, method 400 may be implemented in the form of electronic circuitry (e.g., hardware). In alternate embodiments of the present disclosure, one or more steps of method 400 may be executed substantially concurrently or in a different order than shown in FIG. 4. In alternate embodiments of the present disclosure, method 400 may include more or less steps than shown in FIG. 4. In some embodiments, one or more of the steps of method 400 may, at certain times, be ongoing and/or may repeat.

[0072] Method 400 may start at step 402 and continue to step 404, where the method may include generating a set of user characteristics corresponding to a user. The techniques in block 404 may be performed similarly to the techniques described in relation to user characteristic engine 112 discussed above in reference to FIG. 1. The method may also include determining that the user is a member of a social network. The user characteristics may include user preferences corresponding to a user of a social network, such as topics, products, etc. The set of characteristics may also include prior impressions from a first user on a second user. For example, a first user may have influence on a second user in creating a relationship, creating content, etc. The method may include determining a user

characteristic probability that the set of user characteristics affects the user action.

[0073] At step 406, the method may include determining a social influence on the user. The techniques in block 406 may be performed similarly to the techniques described in relation to social influence engine 114 discussed above in reference to FIG. 1. The method may also include determining a social influence probability that the social influence affects the user action. Determining the social influence may include determining a probability that the user will be influenced by a second user corresponding to the social influence. The second user may be connected to the user on the social network. At step 408, the method may include generating an independence factor. The techniques in block 408 may be performed similarly to the techniques described in relation to independence factor engine 116 discussed above in reference to FIG. 1. The independence factor may describe an independence of the user in making a user action. A user action may include a user activity, a user-user relationship, etc.

[0074] At step 410, the method may include determining an attribution probability that the user action is attributed to the social influence. The techniques in block 410 may be performed similarly to the techniques described in relation to probability engine 118 discussed above in reference to FIG. 1 and may incorporate one or more formulas described in relation to probability engine 118, such as formulas (1), (2), (3) and (4). The attribution probability may be based on the set of user characteristics, the social influence and the independence factor. The attribution probability may also be based on the user characteristic probability and the social influence probability. The attribution probability may be expressed quantitatively. The method may also include determining a user activity and/or a user-user relationship that optimizes the attribution probability. Method 400 may eventually continue to step 412, where method 400 may stop.

[0075] FIG. 5 is a flowchart of an example method 500 for determining social influence. Method 500 may be described below as being executed or performed by a system, for example, system 110 of FIG. 1, system

600 of FIG. 6 or system 700 of FIG. 7. Other suitable systems and/or computing devices may be used as well. Method 500 may be implemented in the form of executable instructions stored on at least one machine-readable storage medium of the system and executed by at least one processor of the system. Alternatively or in addition, method 500 may be implemented in the form of electronic circuitry (e.g., hardware). In alternate embodiments of the present disclosure, one or more steps of method 500 may be executed substantially concurrently or in a different order than shown in FIG. 5. In alternate embodiments of the present disclosure, method 500 may include more or less steps than shown in FIG. 5. In some embodiments, one or more of the steps of method 500 may, at certain times, be ongoing and/or may repeat.

[0076] Method 500 may start at step 502 and continue to step 504, where the method may include determining a social influence topic corresponding to an interest of a social influence. The techniques in block 504 may be performed similarly to the techniques described in relation to topic engine 120 discussed above in reference to FIG. 1 and may incorporate one or more formulas described in relation to topic engine 120. At step 506, the method may include determining the effect of the social influence topic on a user action. The techniques in block 506 may be performed similarly to the techniques described in relation to topic engine 120 discussed above in reference to FIG. 1 and may incorporate one or more formulas described in relation to topic engine 120. At step 508, the method may include determining a user topic corresponding to an interest of a user. The techniques in block 508 may be performed similarly to the techniques described in relation to topic engine 120 discussed above in reference to FIG. 1 and may incorporate one or more formulas described in relation to topic engine 120. At step 510, the method may include determining the effect of the user topic on the user action. The techniques in block 510 may be performed similarly to the techniques described in relation to topic engine 120 discussed above in reference to FIG. 1 and may incorporate one or more formulas described in relation to topic engine 120. Method 500 may eventually continue to step 512, where method 500 may stop.

[0077] FIG. 6 is a block diagram of an example social influence system 600. System 600 may be similar to system 110 of FIG. 1, for example. In the embodiment of FIG. 6, system 600 includes prior impression handler 602, social influence handler 604, independence factor generator 606 and probability handler 608.

[0078] Prior impression handler 602 may determine a prior impression on a user of the social network. The prior impression may be from the user of the social network to a second user of the social network. The prior impression may also be from the second user of the social network to the user of the social network. The prior impression handler may also determine a prior impression probability that the prior impression affects the user activity. Prior impression handler 602 may be implemented in the form of executable instructions stored on at least one machine-readable storage medium of system 600 and executed by at least one processor of system 600. Alternatively or in addition, prior impression handler 602 may be implemented in the form of one or more hardware devices including electronic circuitry for implementing the functionality of prior impression handler 602.

[0079] Social influence handler 604 may determine a social influence between the user and the second user. The social influence may be a probability that the user will be influence by the second user. Social influence handler 604 may also determine a social influence probability that the social influence affects the user activity. Social influence handler 604 may be implemented in the form of executable instructions stored on at least one machine-readable storage medium of system 600 and executed by at least one processor of system 600. Alternatively or in addition, social influence handler 604 may be implemented in the form of one or more hardware devices including electronic circuitry for implementing the functionality of social influence handler 604.

[0080] Independence factor generator 606 may generate an independence factor describing an independence of the user in making a user-user relation. Independence factor generator 606 may be implemented in the form of executable instructions stored on at least one machine-readable storage

medium of system 600 and executed by at least one processor of system 600. Alternatively or in addition, independence factor generator 606 may be implemented in the form of one or more hardware devices including electronic circuitry for implementing the functionality of independence factor generator 606.

[0081] Probability handler 608 may determine an attribution probability that the user-user relation is attributed to the social influence of the second user. The attribution probability may be based on the prior impression, the social influence and the independence factor. The attribution probability may also be based on the prior impression probability and the social influence probability. Probability handler 608 may be implemented in the form of executable instructions stored on at least one machine-readable storage medium of system 600 and executed by at least one processor of system 600. Alternatively or in addition, probability handler 608 may be implemented in the form of one or more hardware devices including electronic circuitry for implementing the functionality of probability handler 608.

[0082] FIG. 7 is a block diagram of an example system 700 for social influence determination. System 700 may be similar to system 110 of FIG. 1, for example. In the embodiment of FIG. 7, system 700 includes a processor 702 and a machine-readable storage medium 704. Although the following descriptions refer to a single processor and a single machine-readable storage medium, the descriptions may also apply to a system with multiple processors and multiple machine-readable storage mediums. In such examples, the instructions may be distributed (e.g., stored) across multiple machine-readable storage mediums and the instructions may be distributed (e.g., executed by) across multiple processors.

[0083] Processor 702 may be one or more central processing units (CPUs), microprocessors, and/or other hardware devices suitable for retrieval and execution of instructions stored in machine-readable storage medium 704. In the particular embodiment shown in FIG. 7, processor 702 may fetch, decode, and execute instructions 706, 708, 710 and 712 to perform social influence determination. As an alternative or in addition to retrieving and executing instructions, processor 702 may include one or more electronic circuits comprising

a number of electronic components for performing the functionality of one or more of the instructions in machine-readable storage medium 704. With respect to the executable instruction representations (e.g., boxes) described and shown herein, it should be understood that part or all of the executable instructions and/or electronic circuits included within one box may, in alternate embodiments, be included in a different box shown in the figures or in a different box not shown.

[0084] Machine-readable storage medium 704 may be any electronic, magnetic, optical, or other physical storage device that stores executable instructions. Thus, machine-readable storage medium 704 may be, for example, Random Access Memory (RAM), an Electrically-Erasable Programmable Read-Only Memory (EEPROM), a storage drive, an optical disc, and the like. Machine-readable storage medium 704 may be disposed within system 700, as shown in FIG. 7. In this situation, the executable instructions may be “installed” on the system 700. Alternatively, machine-readable storage medium 704 may be a portable, external or remote storage medium, for example, that allows system 700 to download the instructions from the portable/external/remote storage medium. In this situation, the executable instructions may be part of an “installation package”. As described herein, machine-readable storage medium 704 may be encoded with executable instructions for a web technology responsive to mixtures of emotions.

[0085] Referring to FIG. 7, user preference instructions 706, when executed by a processor (e.g., 702), may cause system 700 to determine a set of user preferences corresponding to a user. The user may be a member of a social network. User preference instructions 706, when executed by a processor (e.g., 702) may also cause system 700 to determine a user preference probability that the set of user preferences affects the user activity. User preference instructions 706, when executed by a processor (e.g., 702) may also cause system 700 to determine a topic categorizing the user activity, instructions to determine a content generated by the user activity and determine a distribution of the content for the topic.

[0086] Social influence instructions 708, when executed by a processor (e.g., 702), may cause system 700 to determine a social influence on

the user, wherein the social influence is a probability that the user will be influenced by a second user. Social influence instructions 708, when executed by a processor (e.g., 702), may also cause system 700 to determine a social influence probability that the social influence affects the user activity.

[0087] Independence factor instructions 710, when executed by a processor (e.g., 702), may cause system 700 to generate an independence factor describing an independence of the user in performing a user activity. The independence factor is used to weight the probability of the user's own interests affecting the user activity. Attribution probability instructions 712, when executed by a processor (e.g., 702), may cause system 700 to determine, based on the set of user preferences, the social influence and the independence factor, an attribution probability that the user activity is influenced by the second user. The attribution probability may also be based on the user preference probability and the social influence probability.

[0088] The foregoing disclosure describes a number of examples for social influence determination. The disclosed examples may include systems, devices, computer-readable storage media, and methods for social influence determination. For purposes of explanation, certain examples are described with reference to the components illustrated in FIGS. 1-7. The functionality of the illustrated components may overlap, however, and may be present in a fewer or greater number of elements and components. Further, all or part of the functionality of illustrated elements may co-exist or be distributed among several geographically dispersed locations. Further, the disclosed examples may be implemented in various environments and are not limited to the illustrated examples.

[0089] Further, the sequence of operations described in connection with FIGS. 1-7 are examples and are not intended to be limiting. Additional or fewer operations or combinations of operations may be used or may vary without departing from the scope of the disclosed examples. Furthermore, implementations consistent with the disclosed examples need not perform the sequence of operations in any particular order. Thus, the present disclosure

merely sets forth possible examples of implementations, and many variations and modifications may be made to the described examples.

CLAIMS

1. A method for determining social influence, the method comprising:
generating, by a processor, a set of user characteristics corresponding to a user;
determining, by the processor, a social influence on the user;
generating, by the processor, an independence factor describing an independence of the user in making a user action; and
determining, by the processor, an attribution probability that the user action is attributed to the social influence, wherein the attribution probability is based on the set of user characteristics, the social influence and the independence factor.

2. The method of claim 1 further comprising:
determining, by the processor, a user characteristic probability that the set of user characteristics affects the user action;
determining, by the processor, a social influence probability that the social influence affects the user action; and
determining, by the processor, the attribution probability based on the user characteristic probability and the social influence probability.

3. The method of claim 1 further comprising:
determining, by the processor, that the user is a member of a social network;
determining, by the processor, a probability that the user will be influenced by a second user corresponding to the social influence, wherein the second user is connected to the user on the social network.

4. The method of claim 1 further comprising:
expressing, by the processor, the attribution probability quantitatively.

5. The method of claim 1 further comprising:

determining, by the processor, a prior impression on the user corresponding to the social influence.

6. The method of claim 1 further comprising:

determining, by the processor, a social influence topic corresponding to an interest of the social influence; and

determining, by the processor, an effect of the social influence topic on the user action.

7. The method of claim 1 further comprising:

determining, by the processor, a user topic; and

determining, by the processor, an effect of the user topic on the user action.

8. The method of claim 1, wherein the user action is a user activity, the method further comprising:

determining, by the processor, the user activity that optimizes the attribution probability.

9. The method of claim 1, wherein the user action is a user-user relationship, further comprising:

determining, by the processor, the user-user relationship that optimizes the attribution probability.

10. A system for determining social influence, the system comprising:

a prior impression handler to determine a prior impression on a user of the social network;

a social influence handler to determine a social influence between the user and a second user;

an independence factor generator to generate an independence factor describing an independence of the user in making a user-user relation; and

a probability handler to determine an attribution probability that the user-user relation is attributed to the social influence of the second user, wherein the

attribution probability is based on the prior impression, the social influence and the independence factor.

11. The system of claim 10 wherein:

the prior impression handler further determines a prior impression probability that the prior impression affects the user activity;

the social influence handler further determines a social influence probability that the social influence affects the user activity; and

the probability handler further determines the attribution probability based on the prior impression probability and the social influence probability.

12. The system of claim 10, wherein the social influence is a probability that the first user will be influenced by the second user.

13. A non-transitory machine-readable storage medium comprising instructions executable by a processor of a computing device for determining social influence, the machine-readable storage medium comprising:

instructions to determine a set of user preferences corresponding to a user;

instructions to determine a social influence on the user, wherein the social influence is a probability that the user will be influenced by a second user;

instructions to generate an independence factor describing an independence of the user in performing a user activity, wherein the independence factor is used to weight the probability of the user's own interests affecting the user activity; and

instructions to determine, based on the set of user preferences, the social influence and the independence factor, an attribution probability that the user activity is influenced by the second user.

14. The non-transitory machine-readable storage medium of claim 13 further comprising:

instructions to determine a user preference probability that the set of user preferences affects the user activity;

instructions to determine a social influence probability that the social influence affects the user activity; and

instructions to determine the attribution probability based on the user preference probability and the social influence probability.

15. The non-transitory machine-readable storage medium of claim 13, further comprising:

instructions to determine a topic categorizing the user activity;

instructions to determine a content generated by the user activity; and

instructions to determine a distribution of the content for the topic.

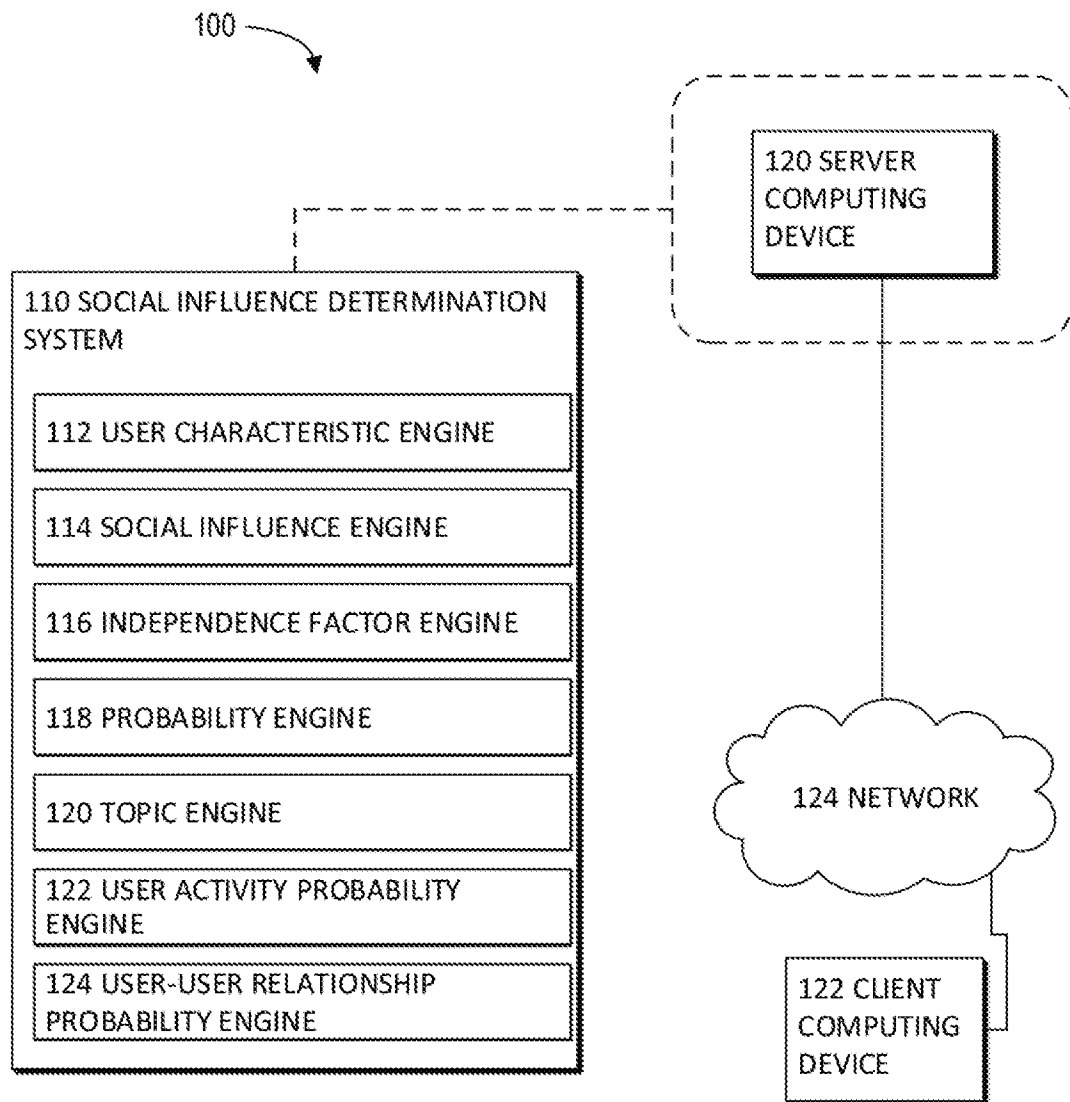


FIG. 1

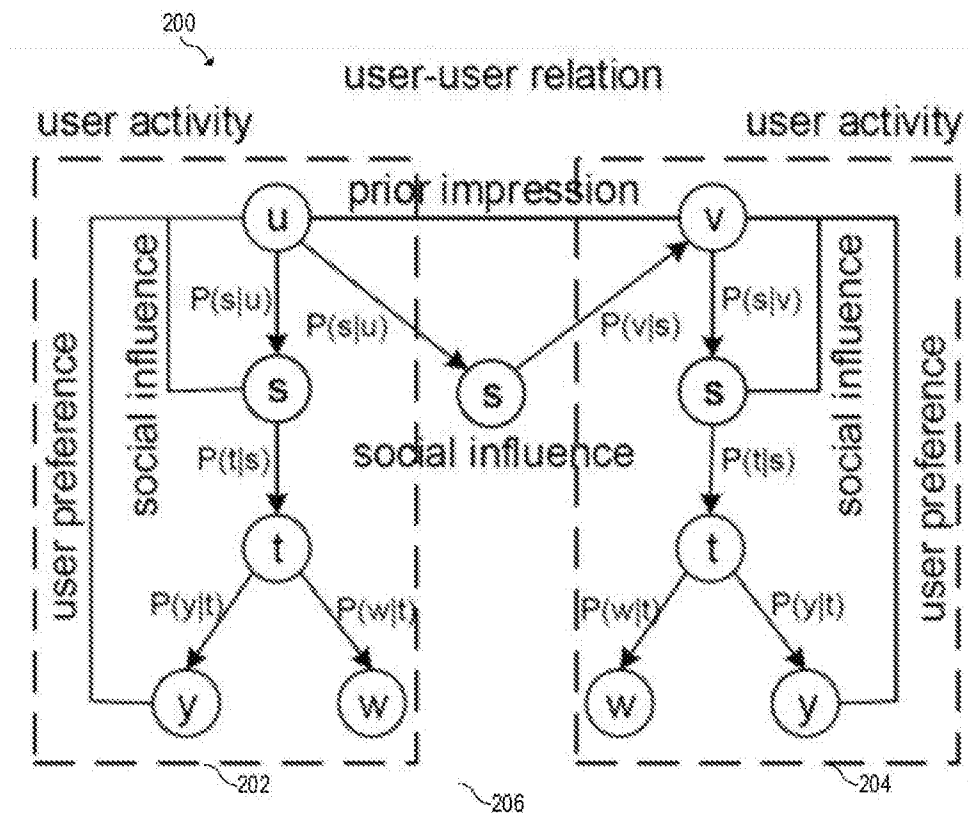


FIG. 2

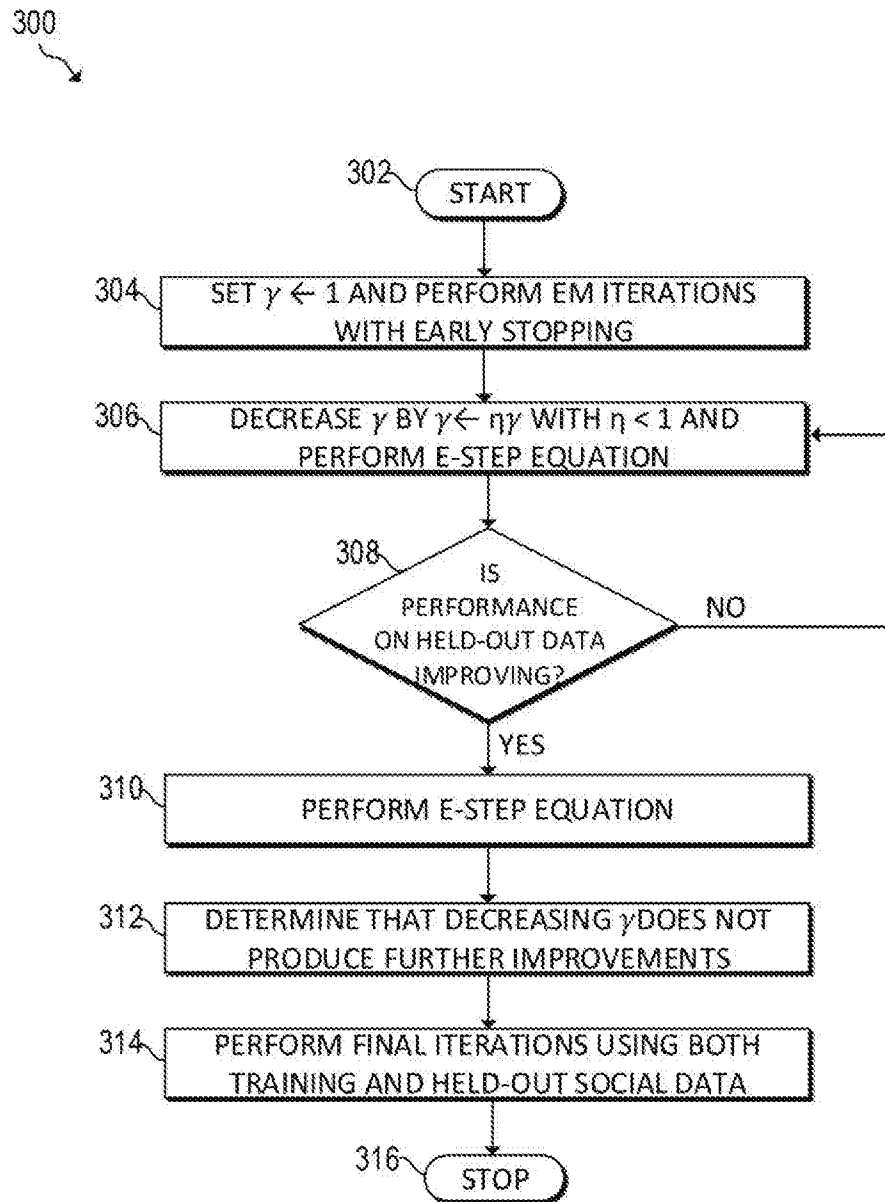


FIG. 3

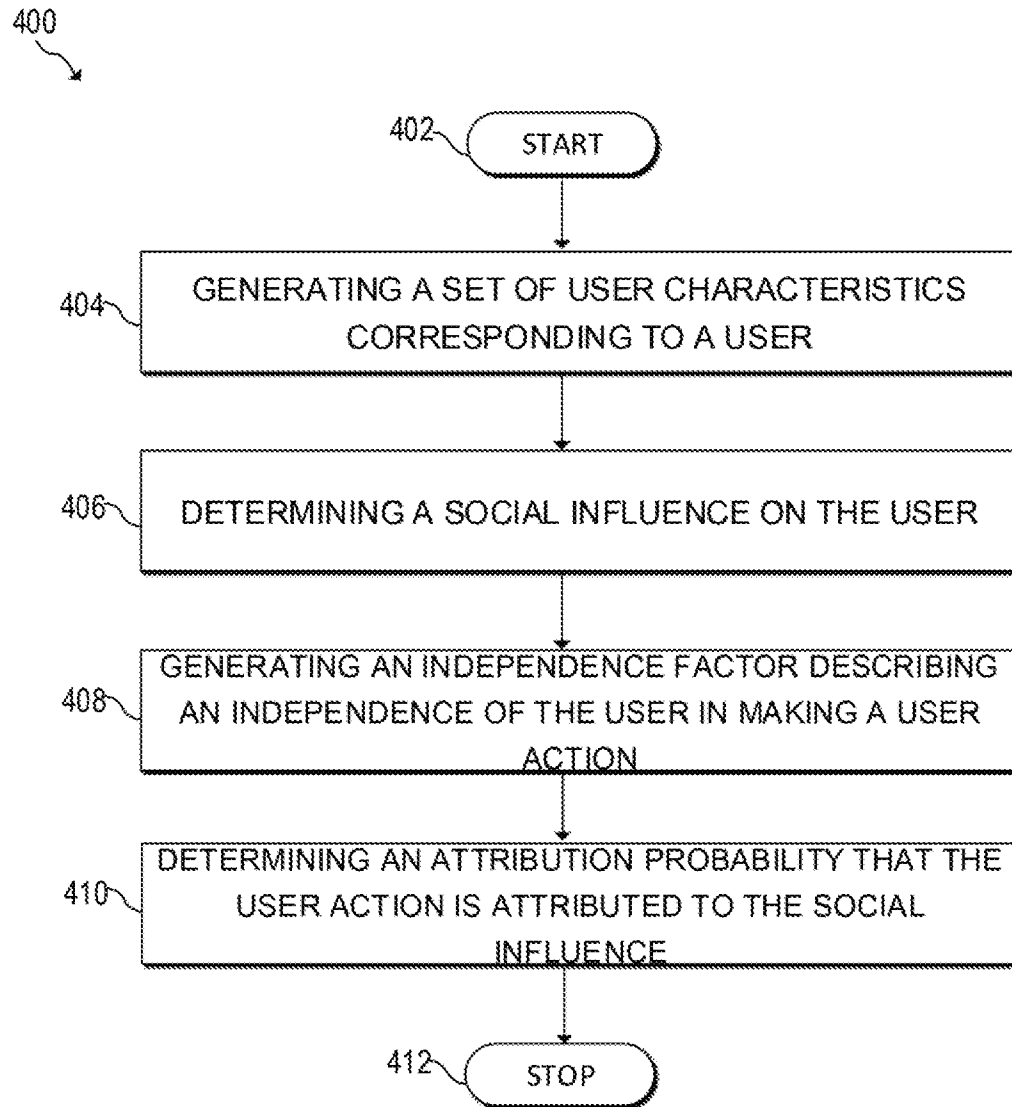


FIG. 4

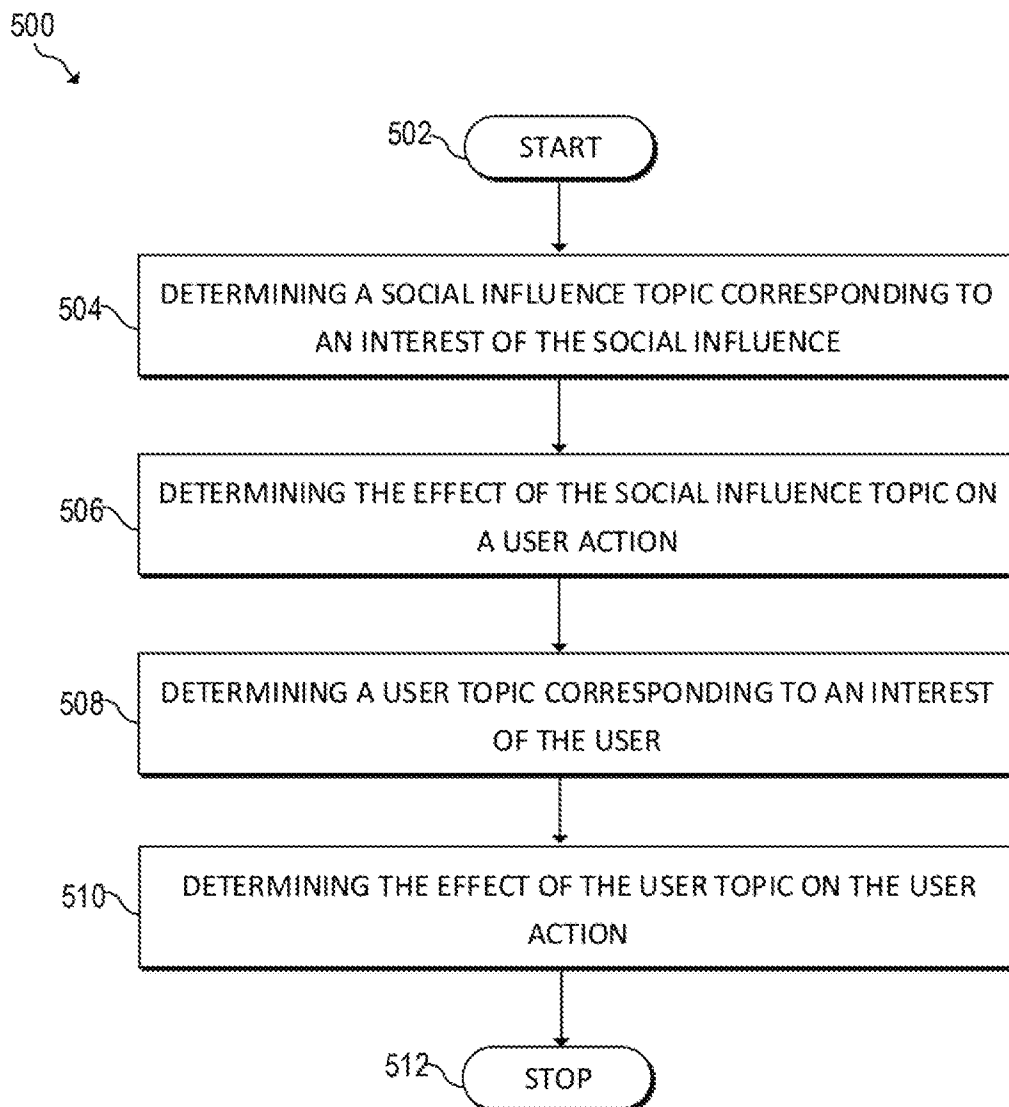


FIG. 5

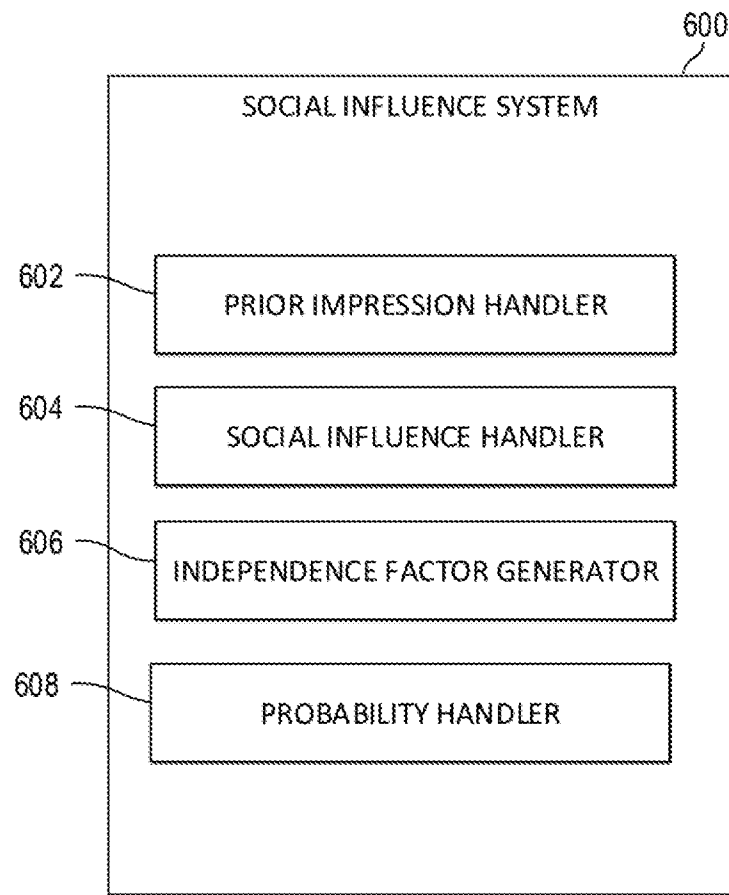


FIG. 6

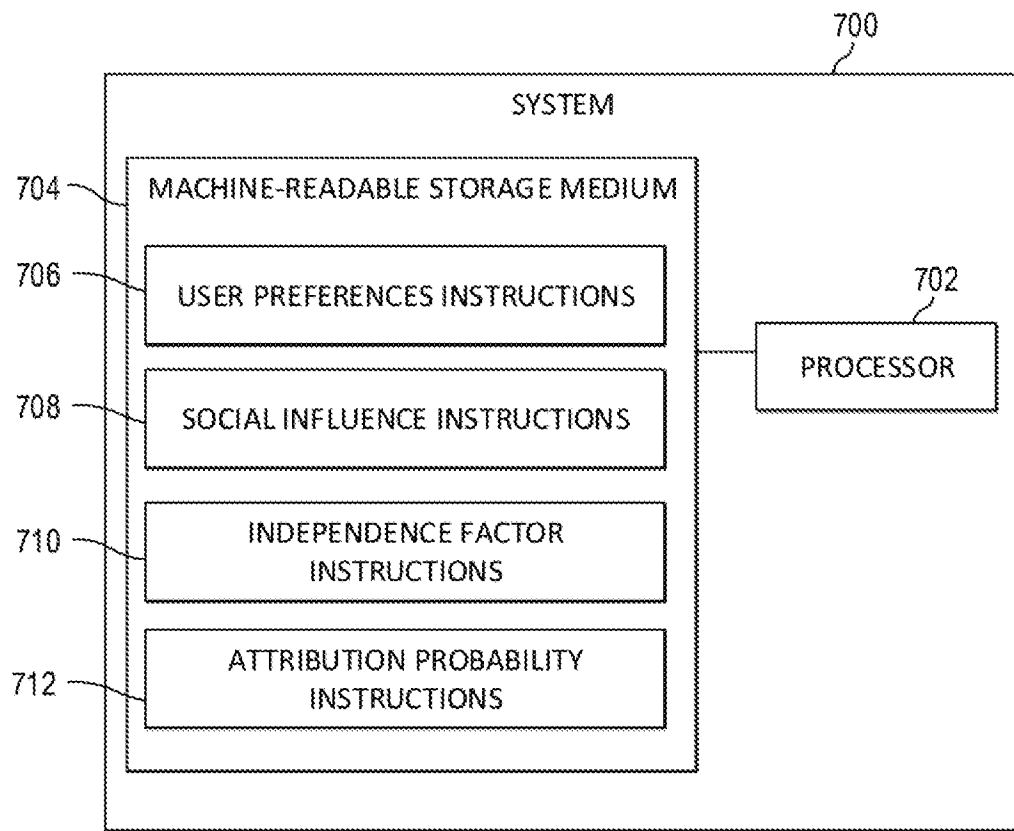


FIG. 7

INTERNATIONAL SEARCH REPORT

International application No.

PCT/CN2015/082504**A. CLASSIFICATION OF SUBJECT MATTER**

G06F 19/00(2011.01)i

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)

G06F

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

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

CNKI, CNPAT, WPI, EPODOC, IEEE: social, influence, network, characteristic, user, taste, interest, preference, profile, log, probability

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	CN 103745105 A (INSTITUTE OF COMPUTER TECHNOLOGY CHINESE ACADEMY OF SCIENCES) 23 April 2014 (2014-04-23) description, paragraphs [0059]-[0119] and figure 1	1-15
A	US 2008301118 A1 (CHIEN, SHU-YAO ET AL.) 04 December 2008 (2008-12-04) the whole document	1-15
A	US 2013159325 A1 (GARTNER, INC.) 20 June 2013 (2013-06-20) the whole document	1-15
A	CN 102880691 A (UNIVERSITY BEIHANG SHENZHEN RESEARCH INSTITUTE) 16 January 2013 (2013-01-16) the whole document	1-15



Further documents are listed in the continuation of Box C.



See patent family annex.

* Special categories of cited documents:

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“Y” document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

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Date of the actual completion of the international search

04 January 2016

Date of mailing of the international search report

27 January 2016

Name and mailing address of the ISA/CN

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INTERNATIONAL SEARCH REPORT
Information on patent family members

International application No.

PCT/CN2015/082504

Patent document cited in search report			Publication date (day/month/year)	Patent family member(s)			Publication date (day/month/year)
CN	103745105	A	23 April 2014	None			
US	2008301118	A1	04 December 2008	None			
US	2013159325	A1	20 June 2013	US	201119131	A1	04 August 2011
CN	102880691	A	16 January 2013	None			