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(54) **ADAPTIVE RECOMMENDATION
EXPLANATIONS**

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None
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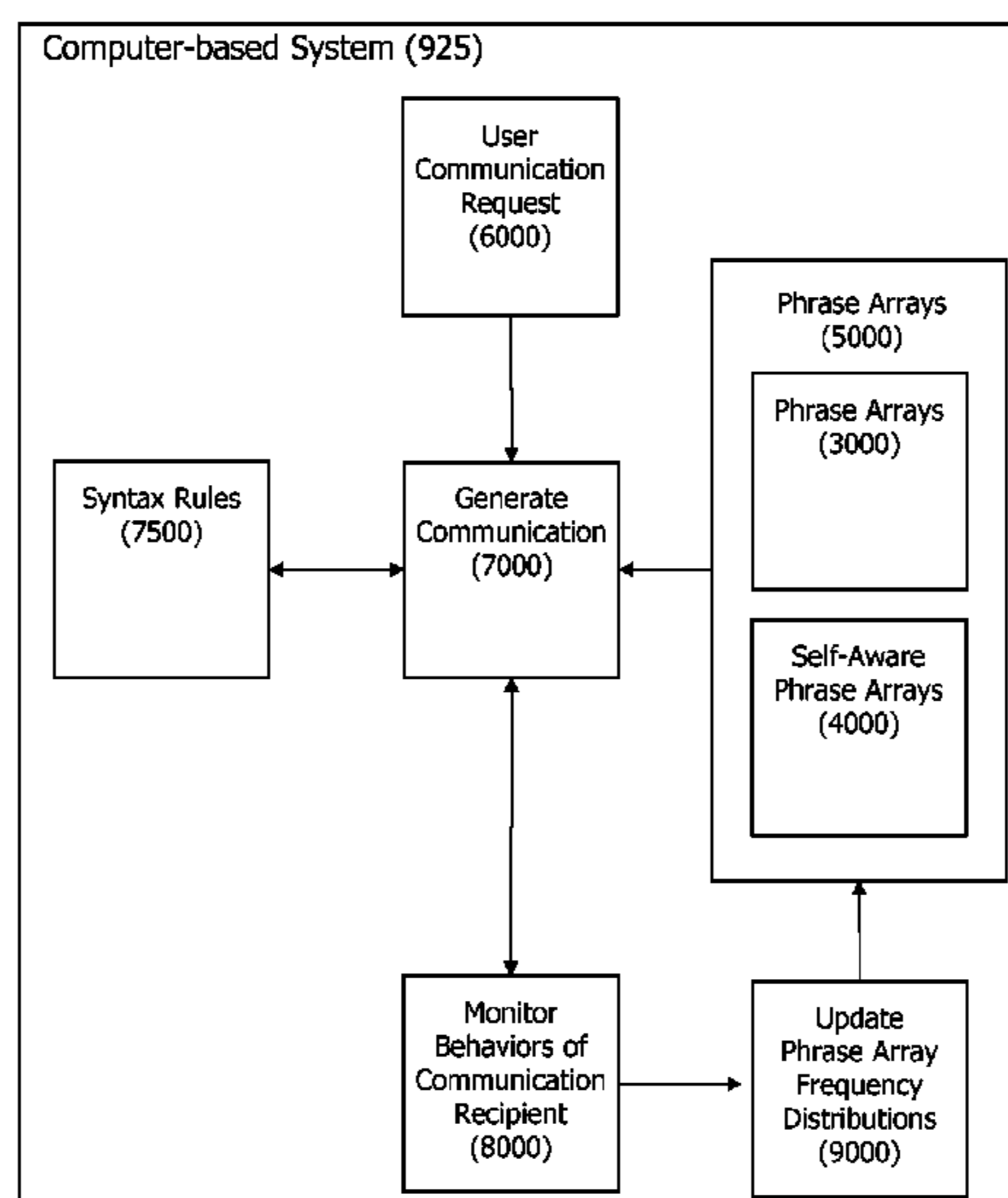
(57) **ABSTRACT**

A method and system for generating adaptive explanations
for associated recommendations is disclosed. The adaptive
explanations comprise a syntactical structure and associated
phrases that are selected in accordance with usage behaviors
and/or inferences associated with usage behaviors. The
phrases included in an adaptive explanation may be selected
through application of a non-deterministic process. The adap-
tive explanations may be beneficially applied to recommen-
dations that are associated with content, products, and people,
including recommendations that comprise advertisements.

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Figure 1

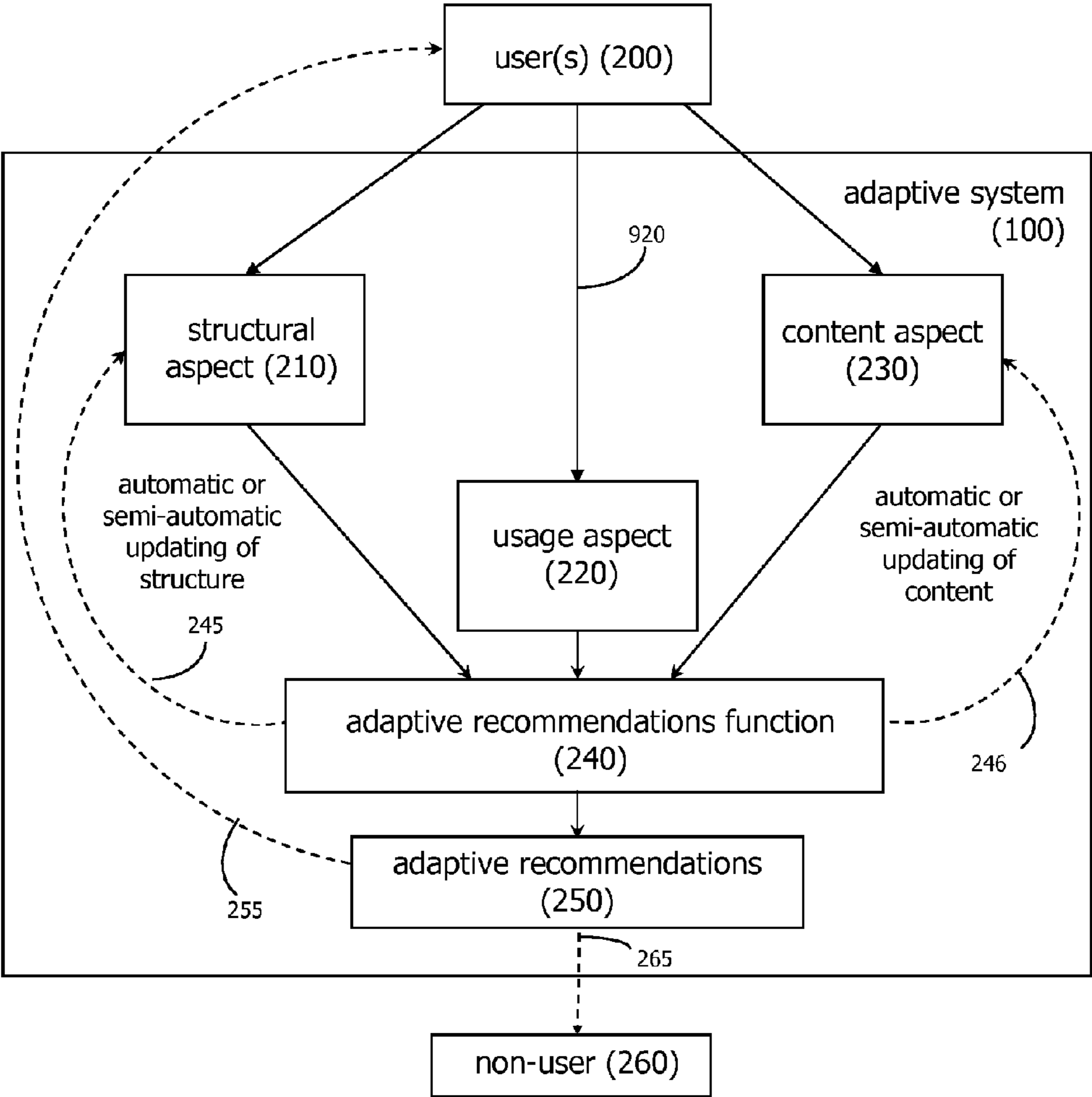


Figure 2A

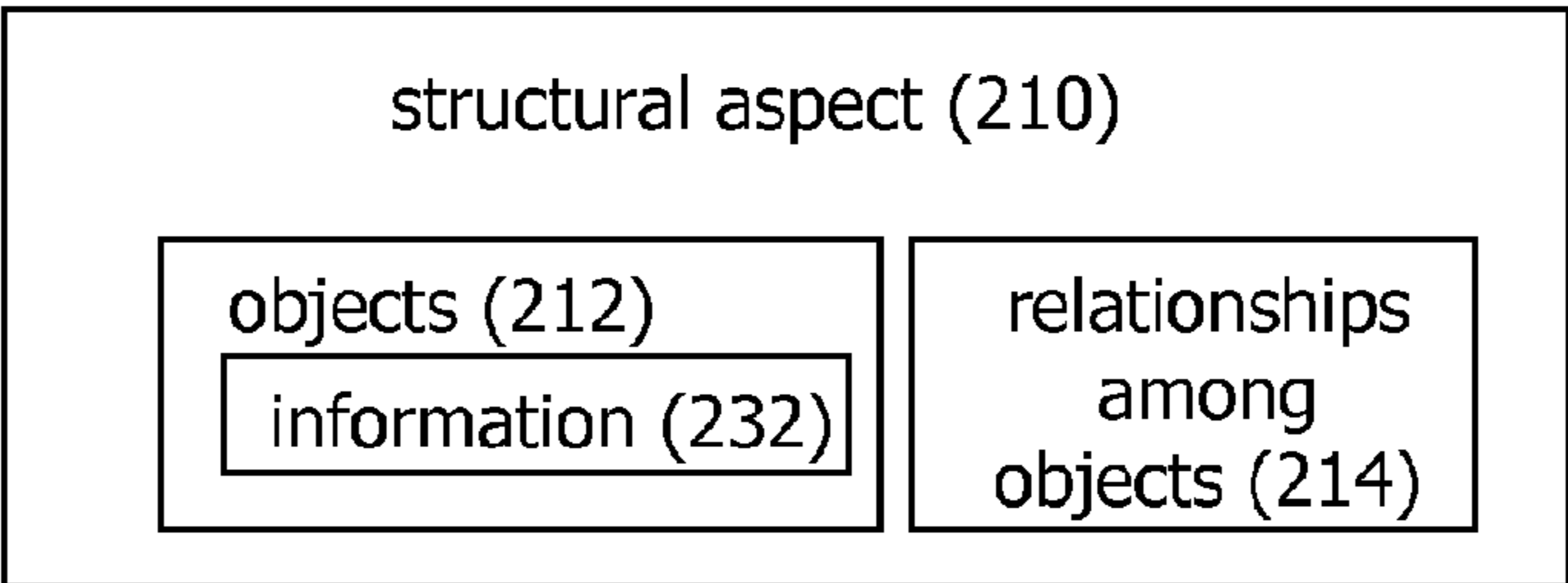


Figure 2B

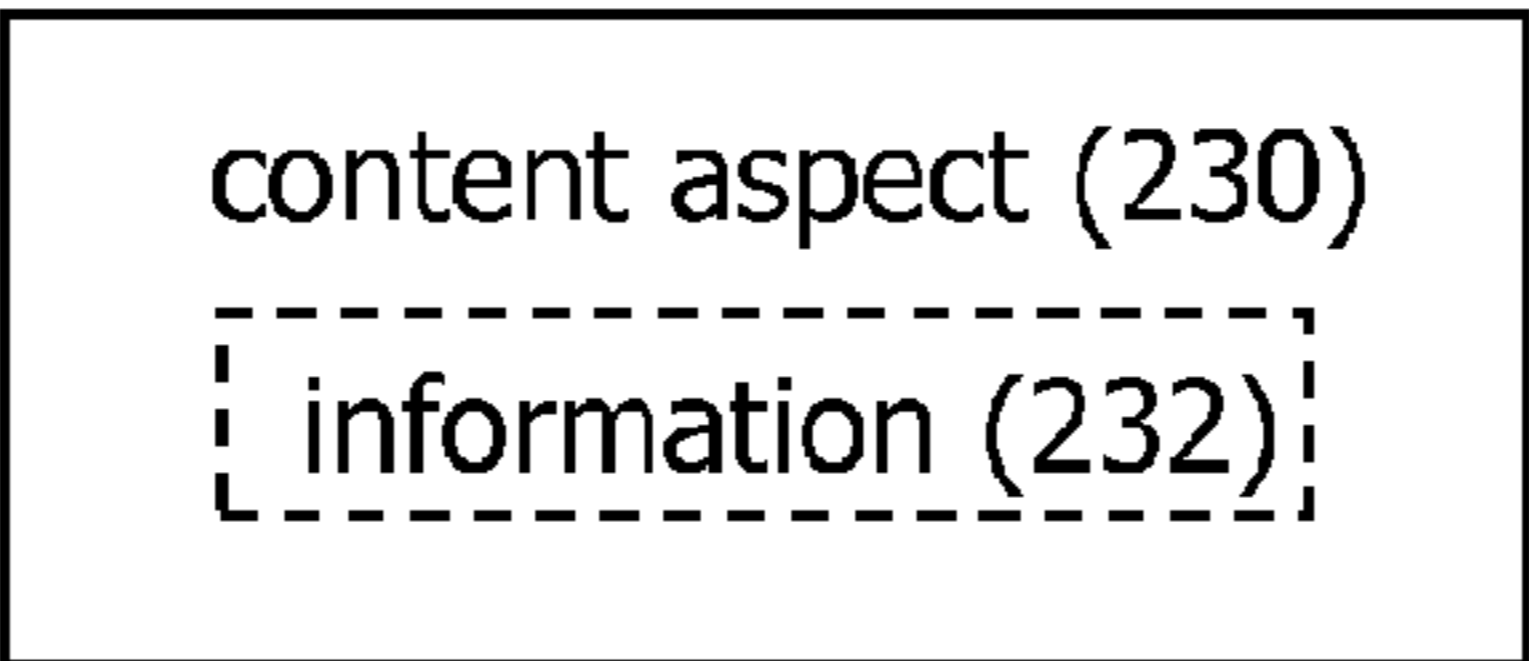


Figure 2C

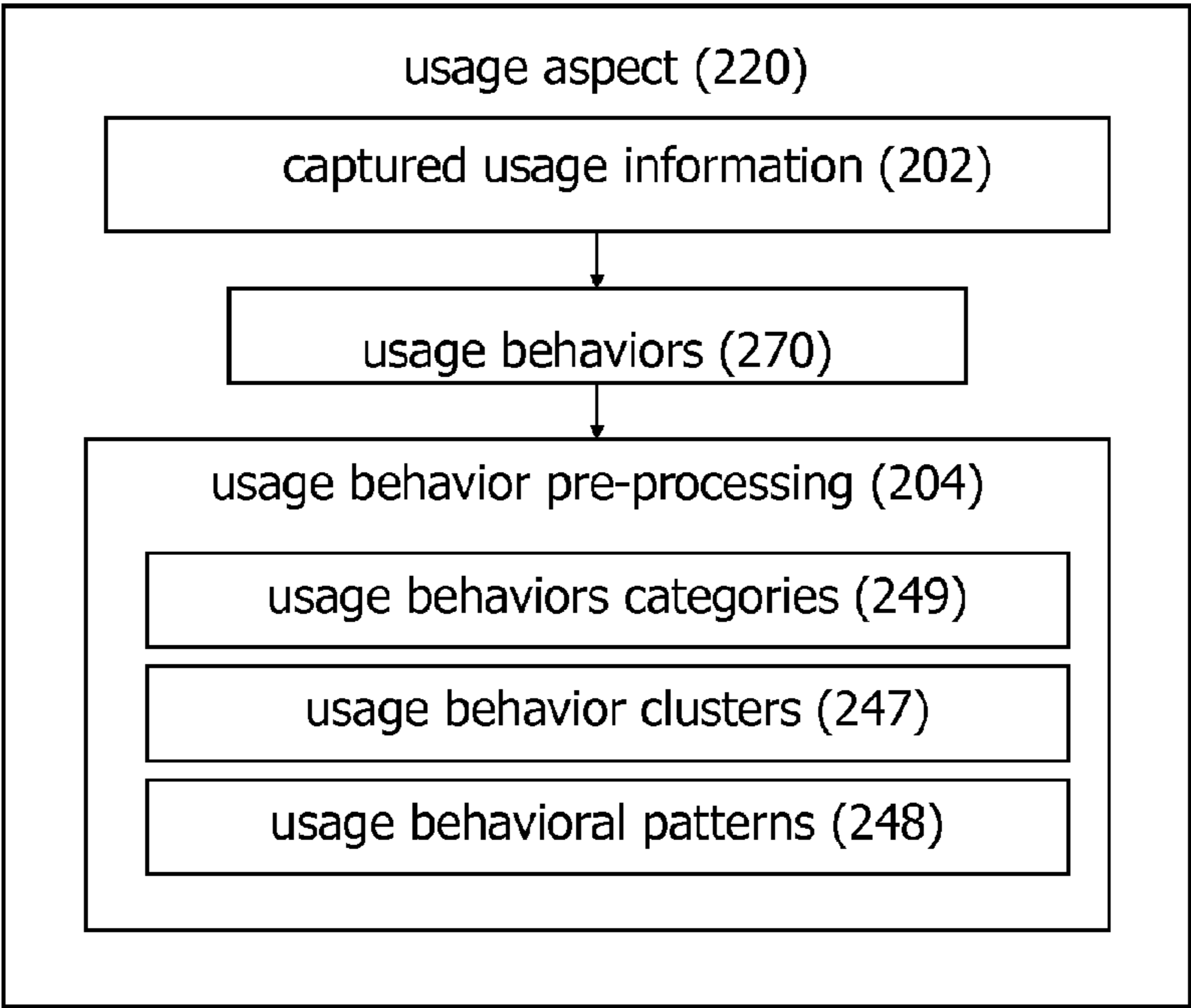


Figure 3

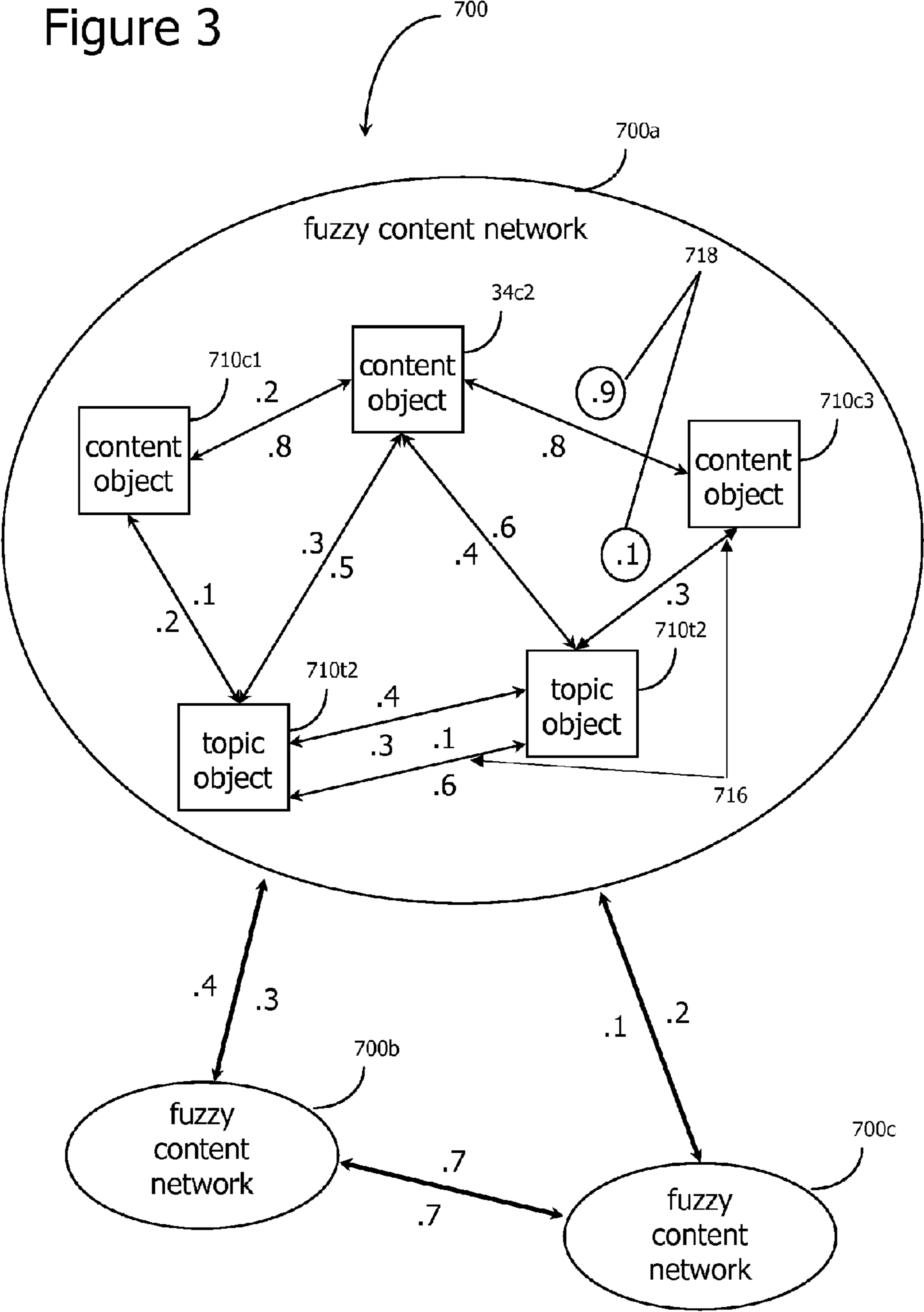


Figure 4A

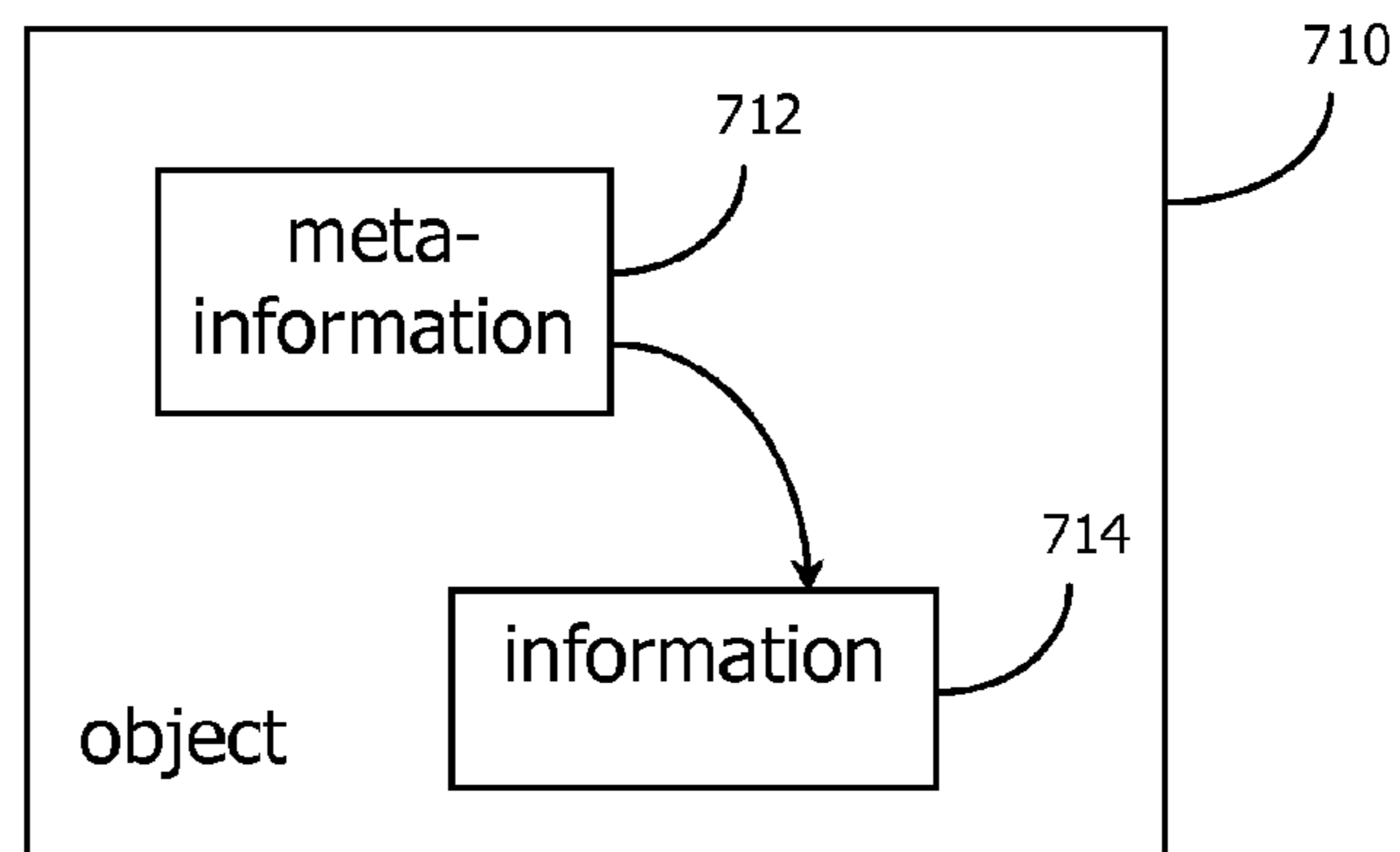


Figure 4B

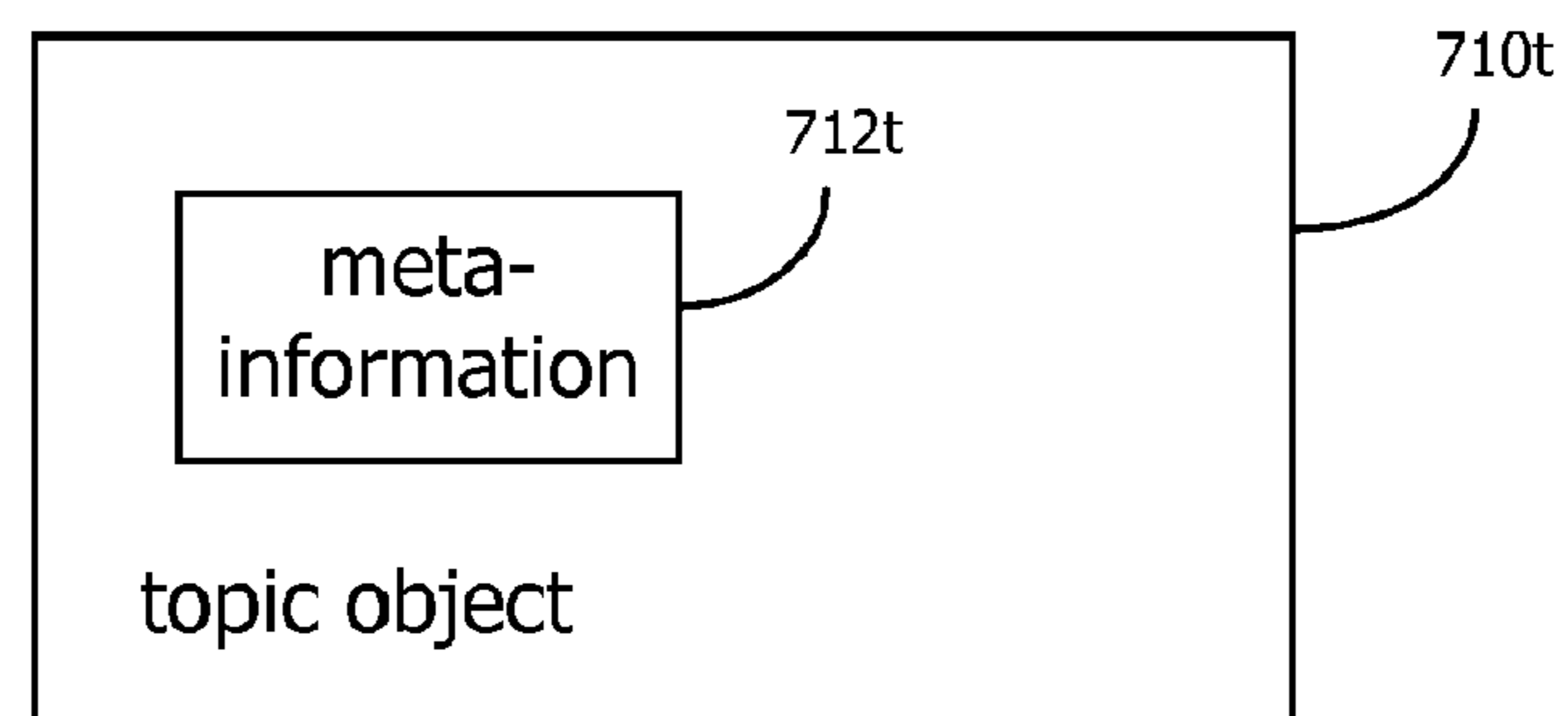


Figure 4C

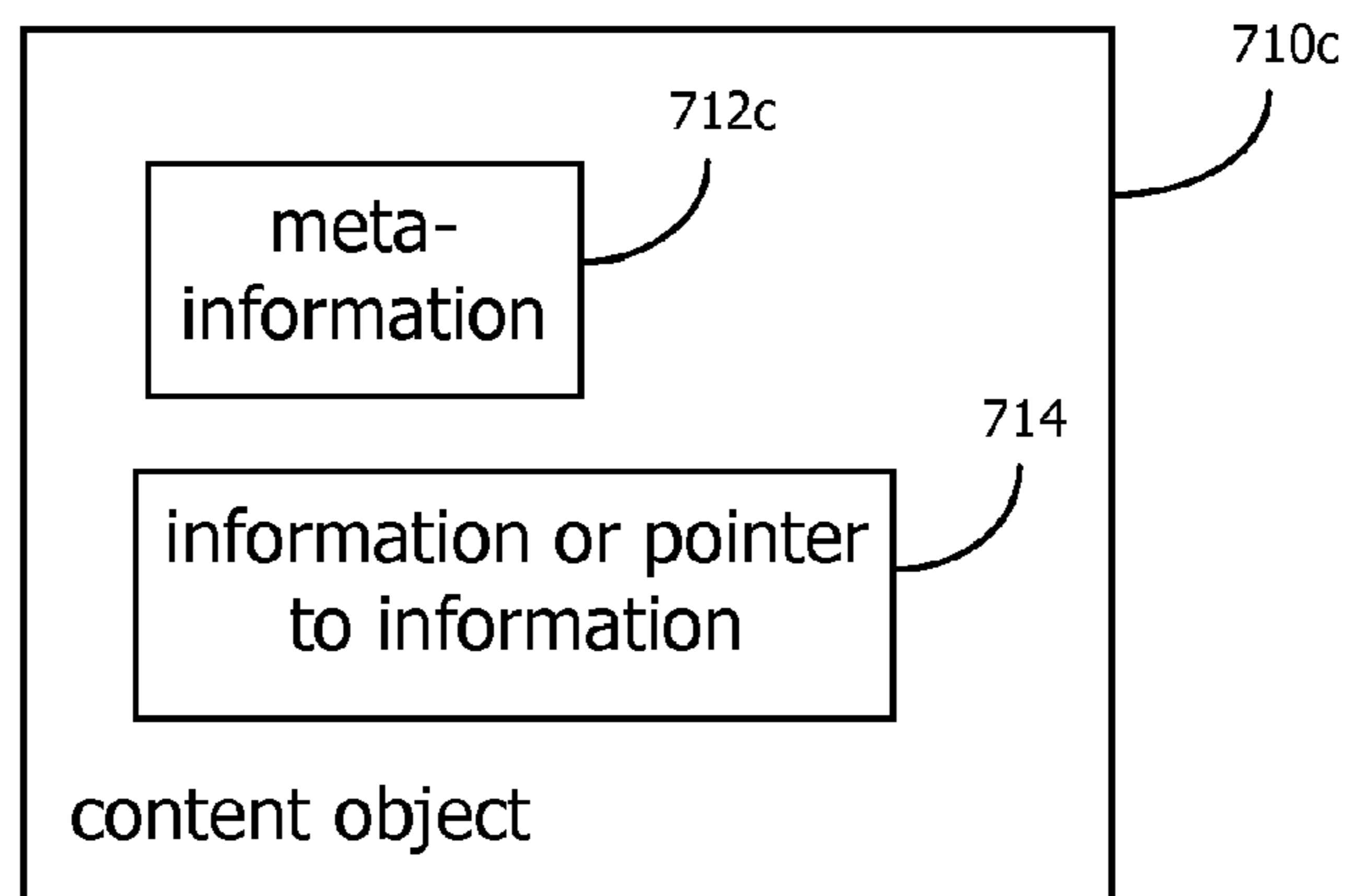


Figure 5

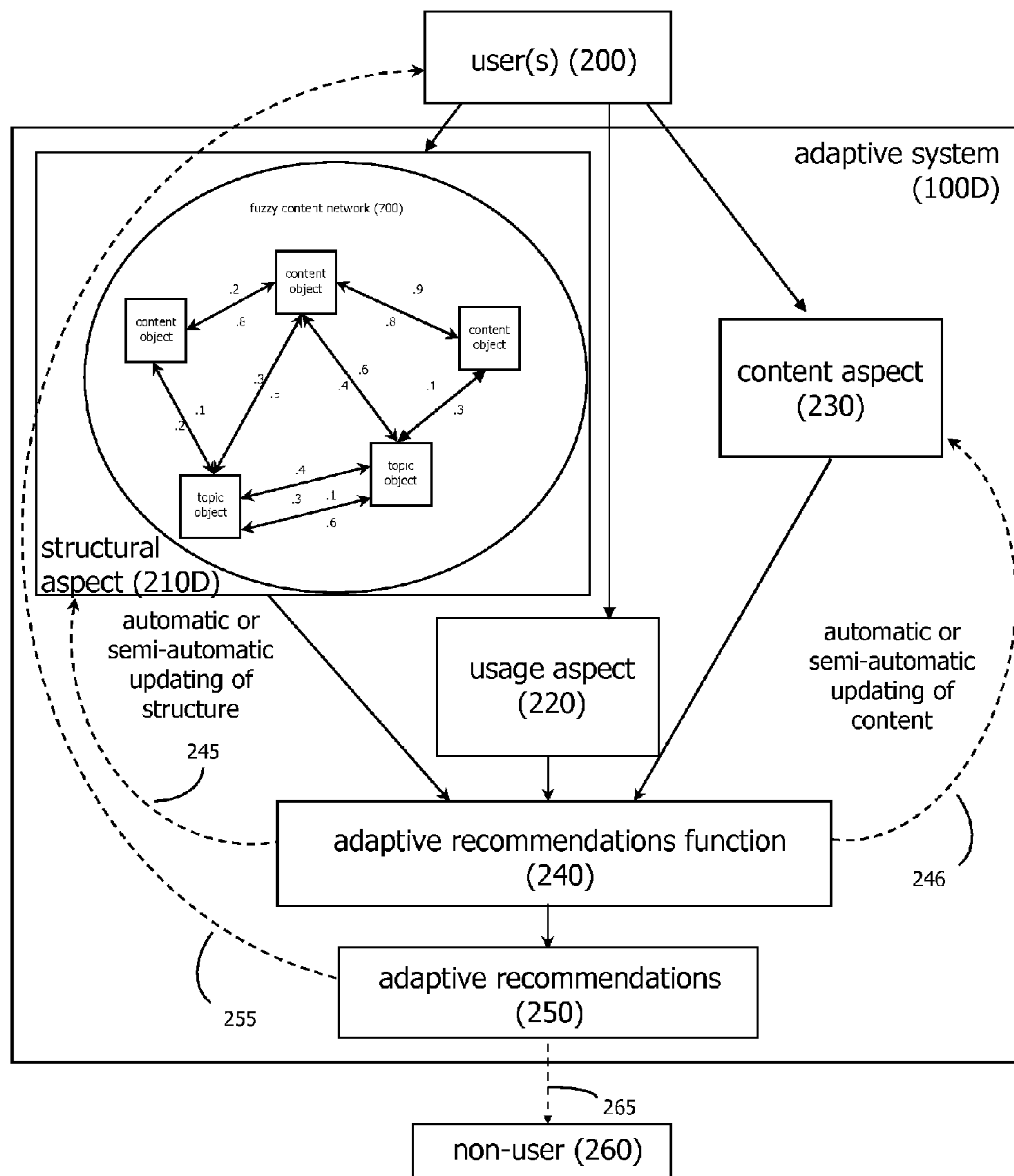


Figure 6

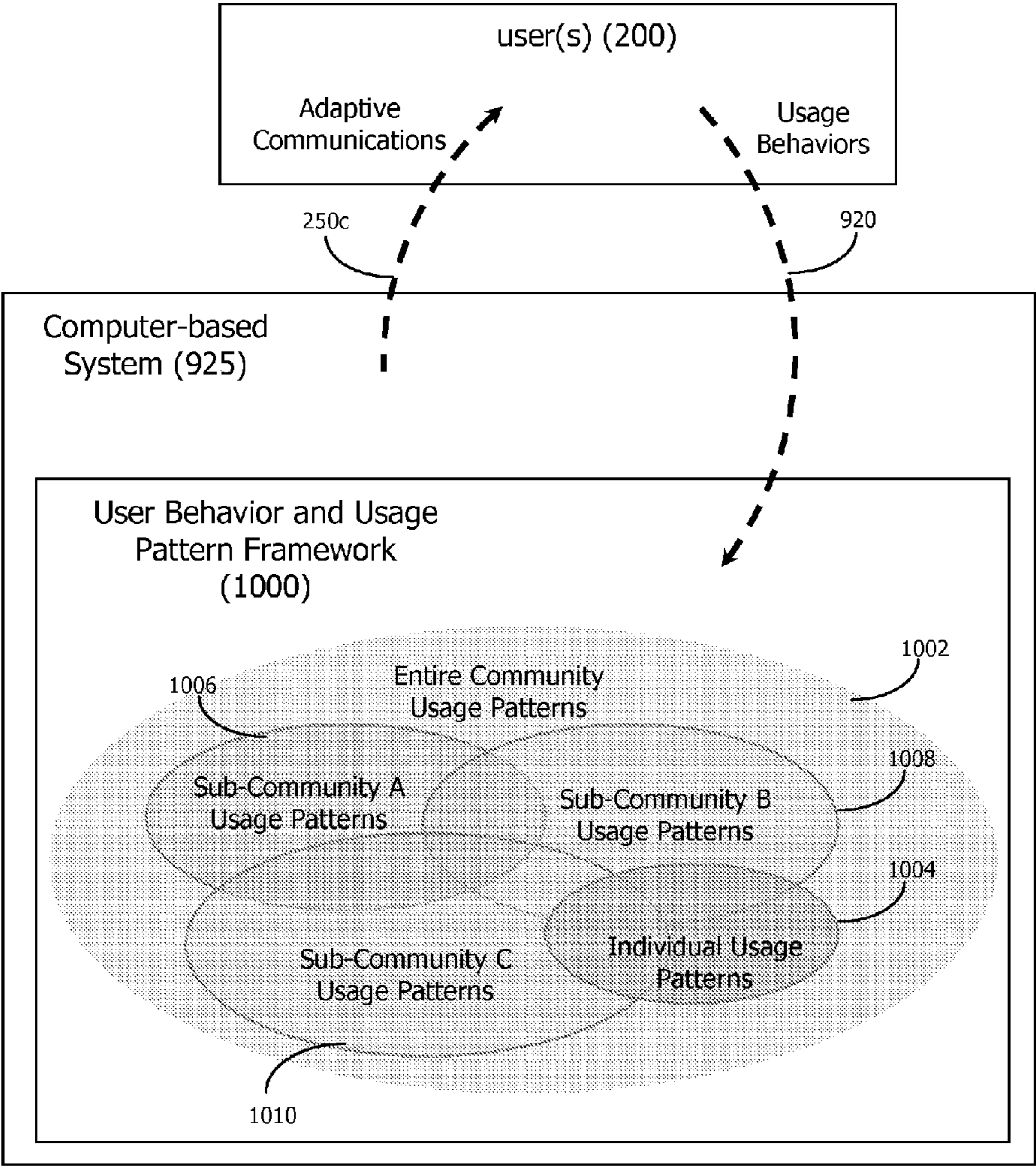


Figure 7

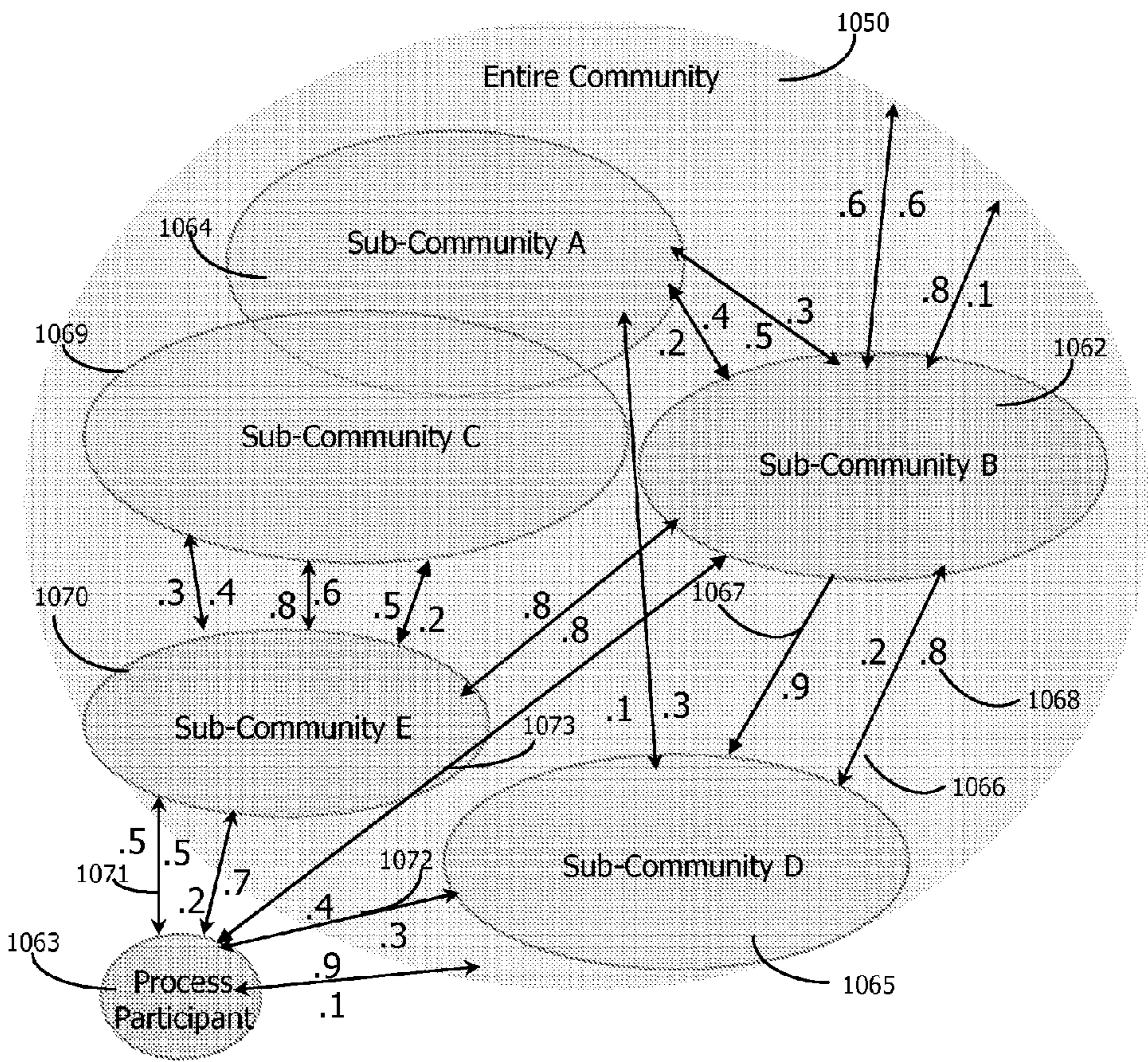


Figure 8

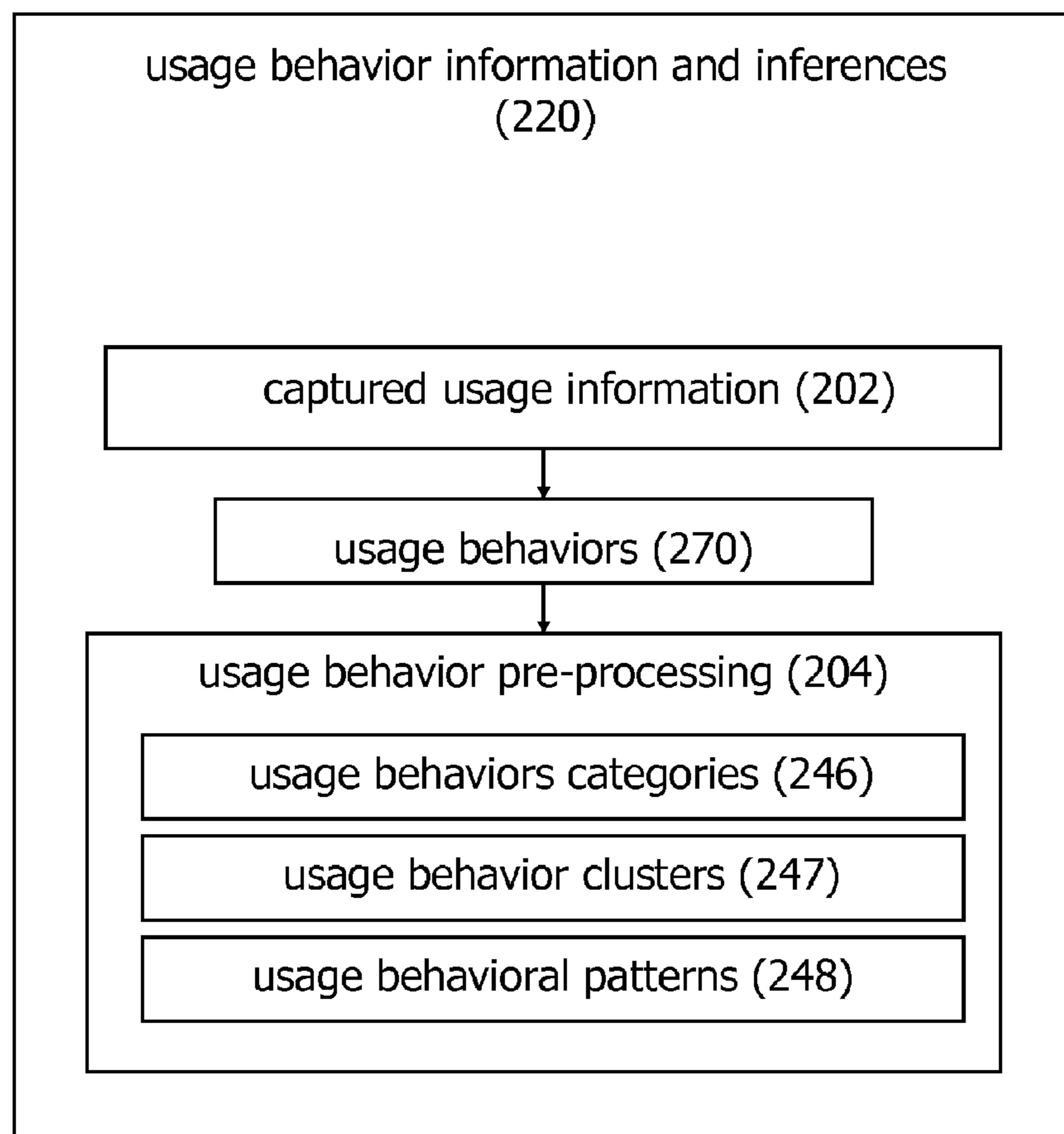


Figure 9

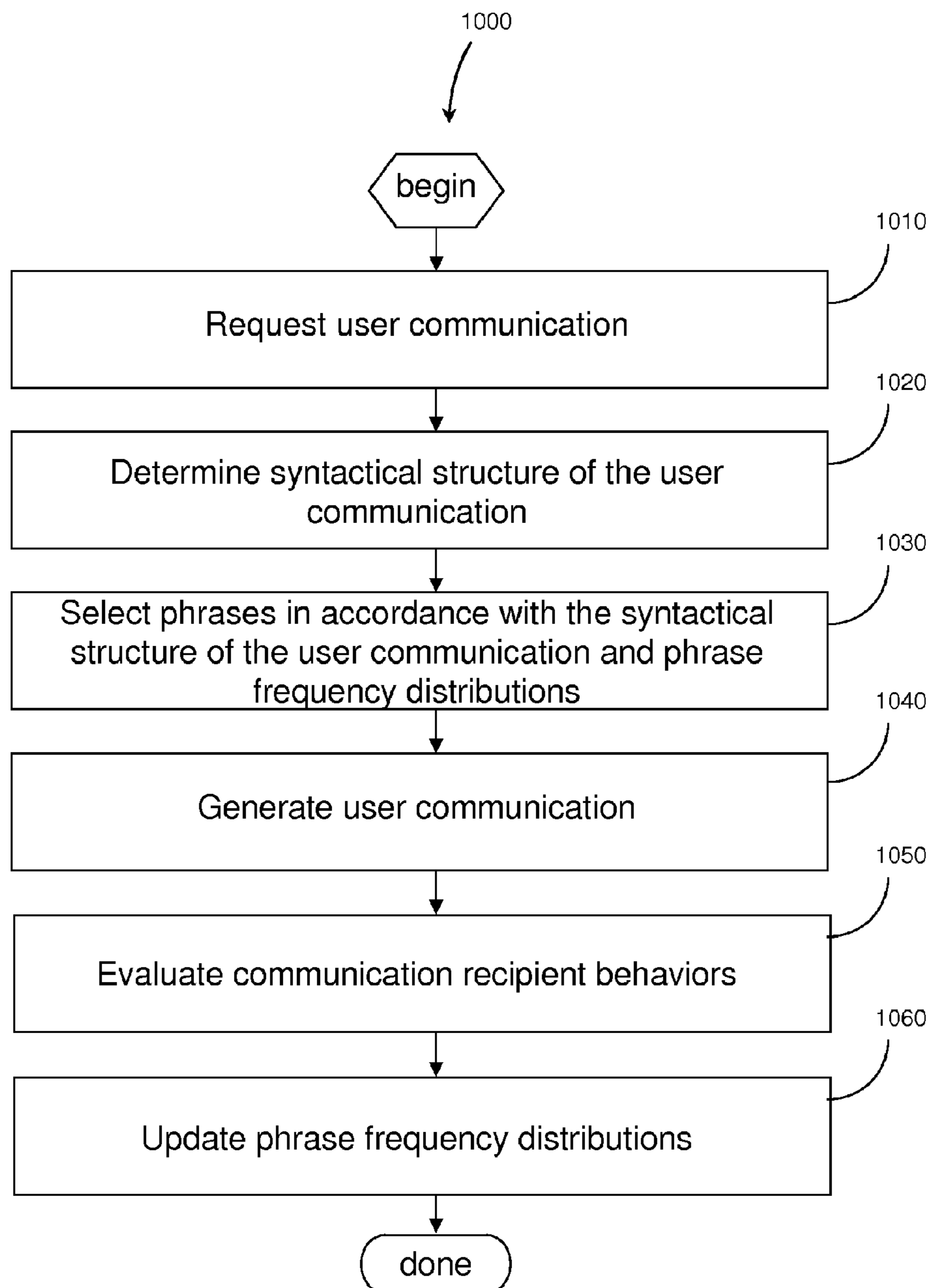


Figure 10

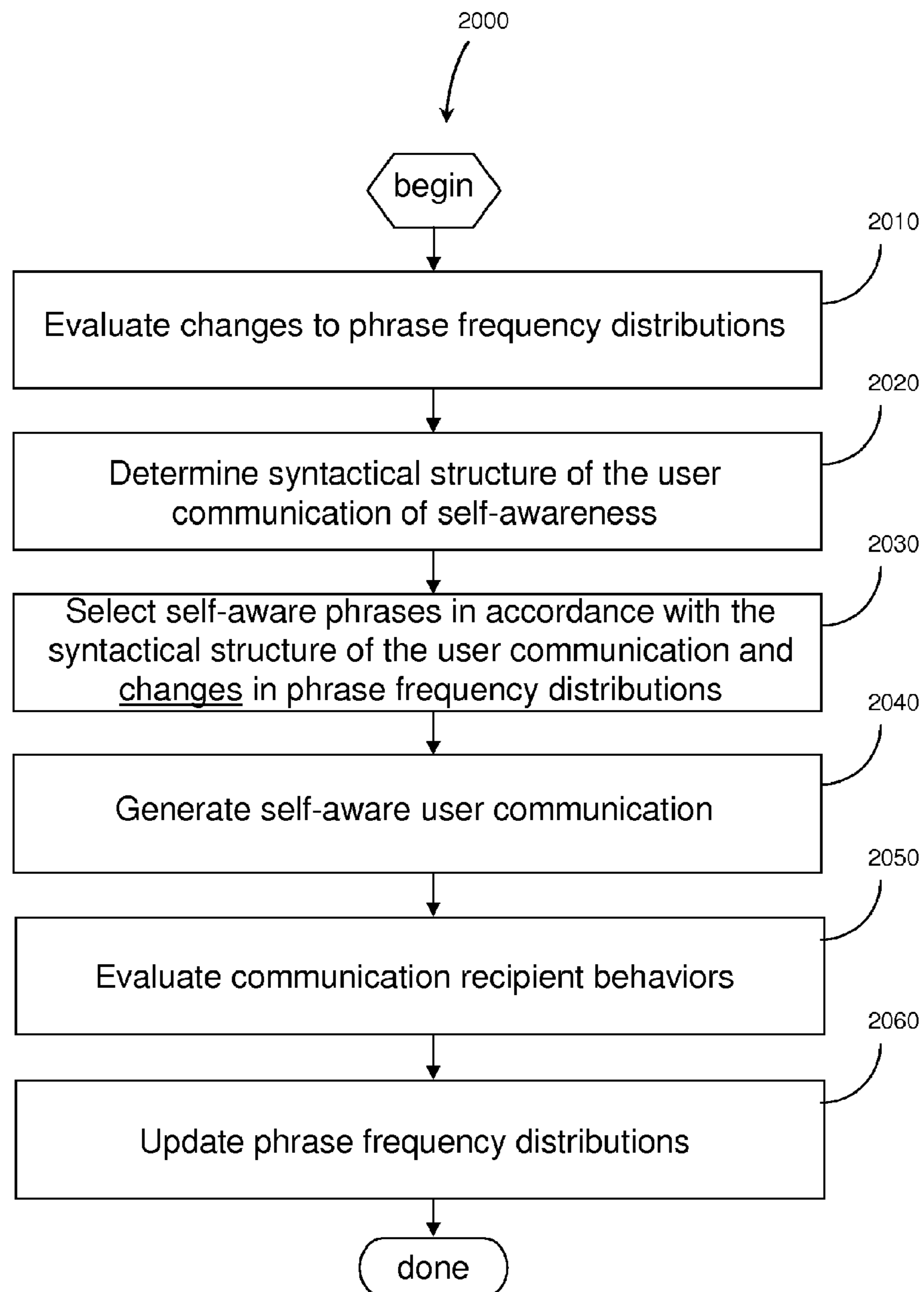


Figure 11

3000

3010 Phrase Array	3020 Phrase ID	3030 Relative Frequency	3040 Phrase	3050 Phrase Attribute 1	3060 Phrase Attribute 2
Array 1	1	1	I've noticed you've been spending a lot of time with your profile lately ;-)	Sarcastic	User-attentive
Array 1	2	3	It seems to me that you recently have been more interested in areas such as {1}	Business-like	User-attentive
Array 1	3	1	I've noticed your colleagues have been very interested recently in {1}-related topics	Business-like	Socially-attentive
Array 1	4	5	Null	Null	Null
Array 2	1	2	I know this is probably silly of me	Humorous	Introspective
Array 2	2	1	I often wonder why you	Inquisitive	User-attentive

4000

3010 Phrase Array	3020 Phrase ID	3030 Relative Frequency	3040 Phrase	3060 Phrase Attribute 2	3070 Phrase Attribute 3
Array 3	1	1	You know, I sense that I have become a lot more fun loving since I met you	Introspective	Humorous
Array 3	2	2	I feel like I take myself a lot less seriously when I'm around you	Introspective	Humorous
Array 3	3	10	Null	Null	Null
Array 4	1	1	I keep wondering why I've become increasingly self-absorbed of late	Introspective	Introspective
Array 4	2	1	Null	Null	Null

Figure 12

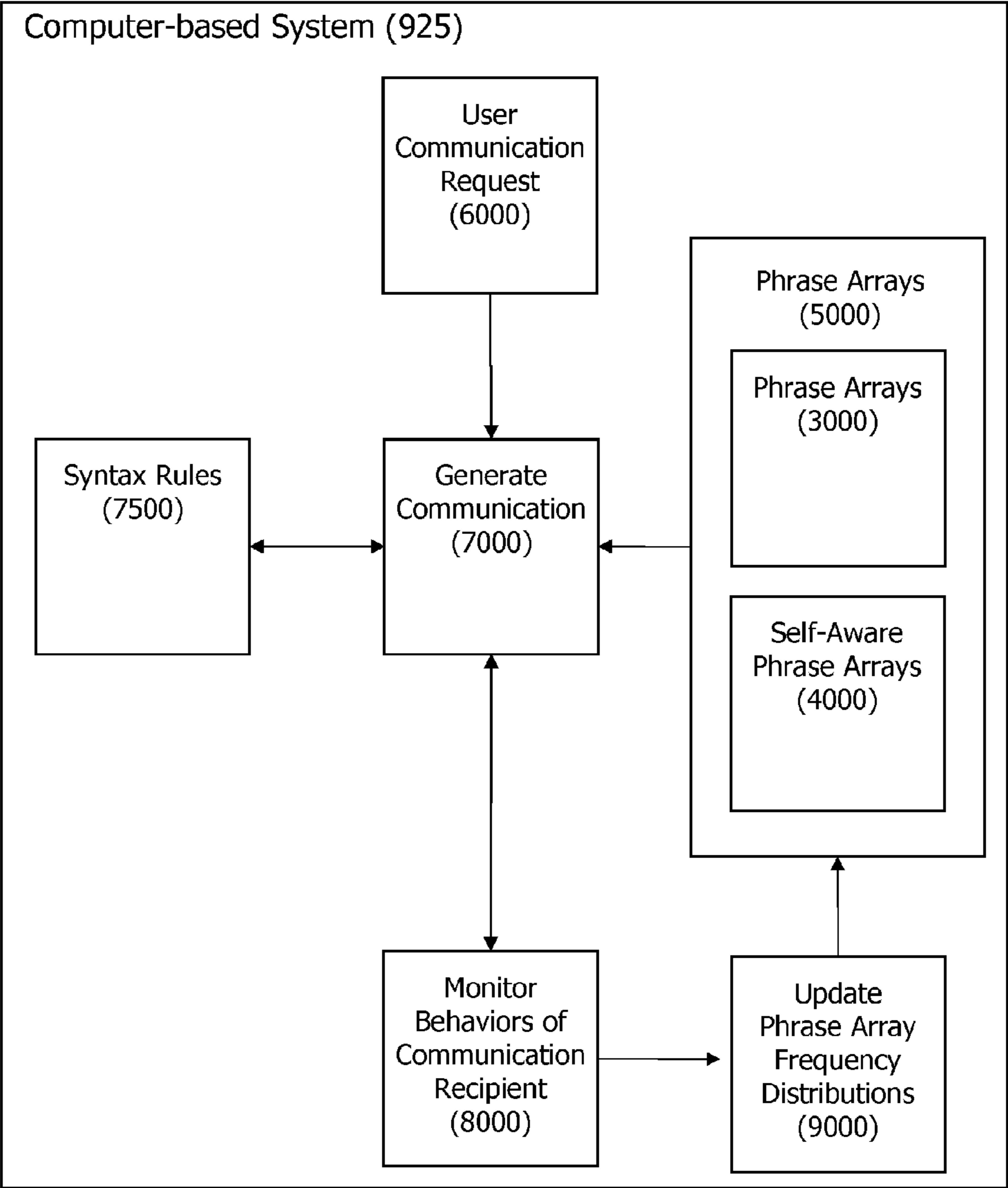
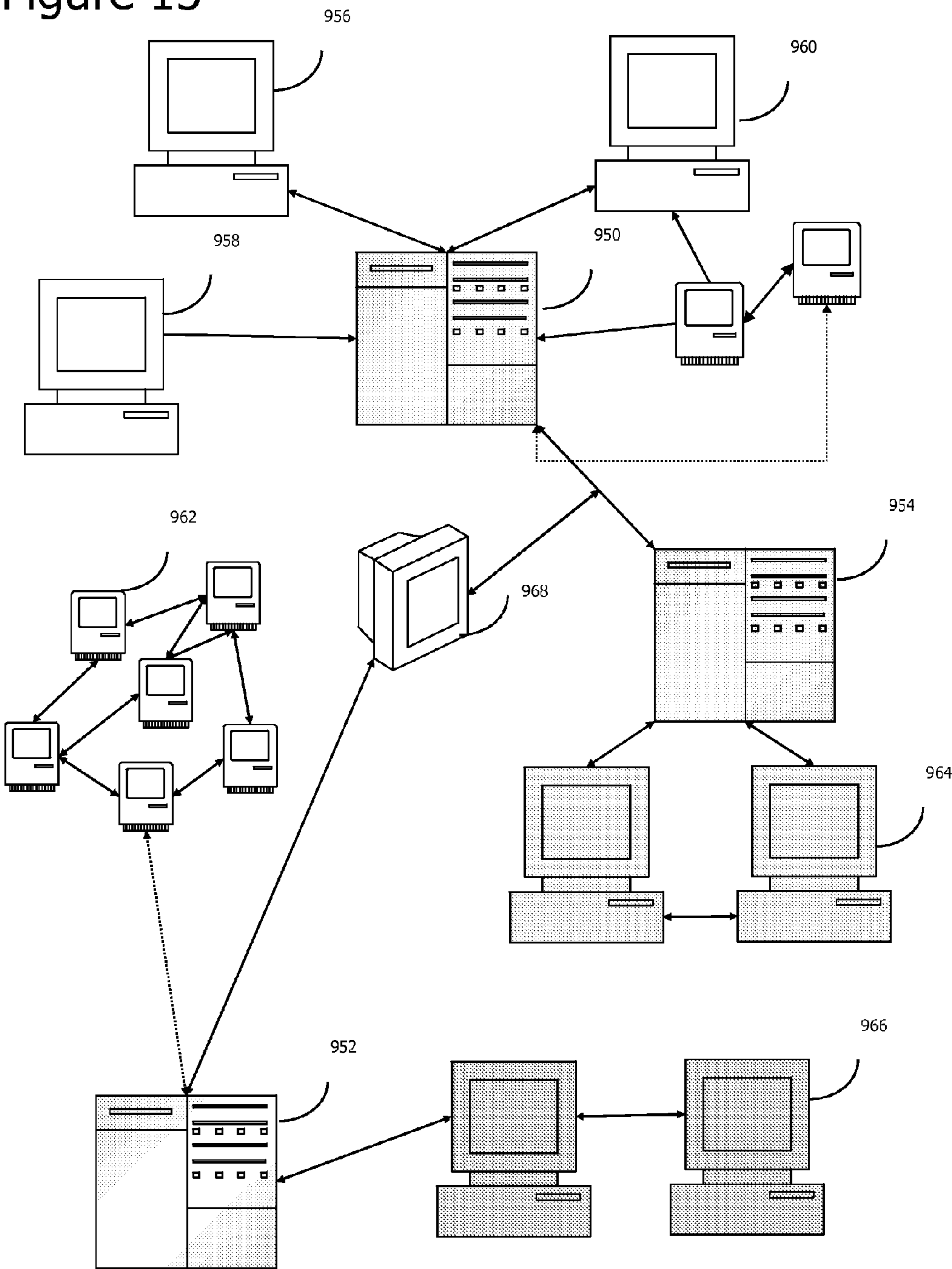


Figure 13



ADAPTIVE RECOMMENDATION EXPLANATIONS

Matter enclosed in heavy brackets [] appears in the original patent but forms no part of this reissue specification; matter printed in italics indicates the additions made by reissue; a claim printed with strikethrough indicates that the claim was canceled, disclaimed, or held invalid by a prior post-patent action or proceeding.

CROSS-REFERENCE TO RELATED APPLICATIONS

[The present application claims priority under 35 U.S.C. §119(e) to U.S. Provisional Patent Application Ser. No. 60/944,516, entitled "Affinity-based Adaptive Recommendation Generation," filed Jun. 17, 2007 and to U.S. Provisional Patent Application Ser. No. 61/054,141, entitled "Adaptive Computer-based Personalities," filed May 17, 2008 and is a continuation-in-part of U.S. patent application Ser. No. 11/419,554 entitled "Adaptive Self-Modifying and Recombinant Systems" filed on May 22, 2006, which claimed priority under 35 U.S.C. §119 to PCT International Application No. PCT/US2004/037176, which claimed priority under 35 U.S.C. §119(e) to U.S. Provisional Patent Application Ser. No. 60/525,120, entitled "A Method and System for Adaptive Fuzzy Networks," filed Nov. 28, 2003.] *The present application is a reissue of U.S. patent application Ser. No. 12/139,486, filed Jun. 15, 2008, now U.S. Pat. No. 7,860,811, issued Dec. 28, 2010, entitled ADAPTIVE RECOMMENDATION EXPLANATIONS, which claims priority to U.S. Provisional Patent Application Ser. No. 60/944,516, filed Jun. 17, 2007, entitled AFFINITY-BASED ADAPTIVE RECOMMENDATION GENERATION and U.S. Provisional Patent Application Ser. No. 61/054,141, filed May 17, 2008, entitled ADAPTIVE COMPUTER-BASED PERSONALITIES and which is a continuation-in-part of U.S. patent application Ser. No. 11/419,554, filed May 22, 2006, now U.S. Pat. No. 7,539,652, issued May 26, 2009, which is a continuation of PCT International Application No. PCT/US2004/037176, filed Nov. 4, 2004 entitled ADAPTIVE RECOMBINANT SYSTEMS, which claims priority to U.S. Provisional Patent Application Ser. No. 60/525,120, filed Nov. 28, 2003, entitled A METHOD AND SYSTEM FOR ADAPTIVE FUZZY NETWORKS.*

FIELD OF THE INVENTION

This invention relates to methods and systems for computer-based generation and adaptation of communications to users over time based on usage behaviors.

BACKGROUND OF THE INVENTION

Computer-based applications in which the user interface includes communications to the user in a natural language (e.g., English) format have traditionally been non-adaptive—that is, the perceived "personality" of the computer-based application as represented by its communications to the user does not automatically adapt itself to the user over time, based on the user's interactions with the computer-based application. The inability of a computer-based personality to adapt over time also forecloses the possibility of the computer-based personality exhibiting the capability of communicating to a user a sense of introspection and self-awareness with regard to changes in its personality over time, and also limits the effectiveness in conveying a sense of awareness to a user

of changes in the behaviors of a user over time. Such static personality approaches of the prior art therefore significantly limit how engaging a computer-based application's user interface can be. Thus there is a need for computer-based personalities that can adapt to one or more users over time and thereby provide users with the experience of receiving more intelligent and even human-like communications from the system.

SUMMARY OF THE INVENTION

In accordance with the embodiments described herein, a method and system for adaptive computer-based personalities, including adaptive explanations associated with computer-generated recommendations, is disclosed that addresses the shortcomings of prior art approaches. The present invention may apply features of adaptive recombinant systems as described in U.S. patent application Ser. No. 11/419,554 entitled "Adaptive Self-Modifying and Recombinant Systems" on May 22, 2006, which is incorporated herein by reference in its entirety.

Other features and embodiments will become apparent from the following description, from the drawings, and from the claims.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. 1 is a block diagram of an adaptive system, according to some embodiments;

FIGS. 2A, 2B, and 2C are block diagrams of the structural aspect, the content aspect, and the usage aspect of the adaptive system of FIG. 1, according to some embodiments;

FIG. 3 is a block diagram of a fuzzy content network-based system, according to some embodiments;

FIGS. 4A, 4B, and 4C are block diagrams of an object, a topic object, and a content object, according to some embodiments;

FIG. 5 is a block diagram of a fuzzy content network-based adaptive system, according to some embodiments;

FIG. 6 is a block diagram of a computer-based system that enables adaptive communications, according to some embodiments;

FIG. 7 is a diagram illustrating user communities and associated relationships, according to some embodiments;

FIG. 8 is a block diagram of usage behavior processing functions of the computer-based system of FIG. 6, according to some embodiments;

FIG. 9 is a flow diagram of an adaptive personality process, according to some embodiments;

FIG. 10 is a flow diagram of a self-aware personality process, according to some embodiments;

FIG. 11 is a diagram of exemplary data structures associated with the adaptive personality process and the self-aware personality process of FIGS. 9 and 10, according to some embodiments;

FIG. 12 is a block diagram of major functions of an adaptive personality and self-aware personality system, according to some embodiments; and

FIG. 13 is a diagram of various computing device topologies, according to some embodiments.

DETAILED DESCRIPTION

In the following description, numerous details are set forth to provide an understanding of the present invention. However, it will be understood by those skilled in the art that the present invention may be practiced without these details and

that numerous variations or modifications from the described embodiments may be possible.

A method and system for adapting computer-based personalities, including adaptive explanations associated with recommendations, as manifested through textual or audio communications, is disclosed. In some embodiments, a computer-based adaptive communication comprises one or more phrases that are automatically selected by a computer-based system, at least in part, through non-deterministic means. The frequency distribution of the plurality of potential phrases for selection in a potential adaptive communication is updated based on behaviors of the one or more recipients of a previous communication. Thus, the probabilistic selection of phrases included in the adaptive communications, and hence the “personality” of the computer-based system, is influenced by prior usage behaviors. In some embodiments, the computer-based personality may also exhibit “self-awareness” by monitoring changes in phrase frequency distributions over time, and including in its adaptive communications appropriate self-aware phraseology based on an evaluation of the changes in phrase frequency distributions. Awareness phrases associated with changes in user behavior over time may also be expressed in the adaptive communications in some embodiments.

Adaptive System

In some embodiments, the present invention may apply the methods and systems of an adaptive system as depicted by FIG. 1. FIG. 1 is a generalized depiction of an adaptive system 100, according to some embodiments. The adaptive system 100 includes three aspects: 1) a structural aspect 210, a usage aspect 220, and a content aspect 230. One or more users 200 interact with the adaptive system 100. An adaptive recommendations function 240 may produce adaptive recommendations 250, based upon the user interactions that are either delivered to the user 200 or applied to the adaptive system 100.

As used herein, one or more users 200 may be a single user or multiple users. As shown in FIG. 1, the one or more users 200 may receive the adaptive recommendations 250. Non-users 260 of the adaptive system 100 may also receive adaptive recommendations 250 from the adaptive system 100.

A user 200 may be a human entity, a computer system, or a second adaptive system (distinct from the adaptive system 100) that interacts with, or otherwise uses the adaptive system. The one or more users 200 may include non-human users of the adaptive system 100. In particular, one or more other adaptive systems may serve as virtual system “users.” These other adaptive systems may operate in accordance with the architecture of the adaptive system 100. Thus, multiple adaptive systems may be mutual users for one another.

It should be understood that the structural aspect 210, the content aspect 230, the usage aspect 220, and the recommendations function 240 of the adaptive system 100, and elements of each, may be contained within one computer, or distributed among multiple computers. Furthermore, one or more non-adaptive systems may be modified to become one or more adaptive systems 100 by integrating the usage aspect 220 and the recommendations function 240 with the one or more non-adaptive systems.

The term “computer system” or the term “system,” without further qualification, as used herein, will be understood to mean either a non-adaptive or an adaptive system. Likewise, the terms “system structure” or “system content,” as used herein, will be understood to refer to the structural aspect 210 and the content aspect 230, respectively, whether associated with a non-adaptive system or the adaptive system 100. The term “system structural subset” or “structural subset,” as used

herein, will be understood to mean a portion or subset of the structural aspect 210 of a system.

Structural Aspect

The structural aspect 210 of the adaptive system 100 is depicted in the block diagram of FIG. 2A. The structural aspect 210 comprises a collection of system objects 212 that are part of the adaptive system 100, as well as the relationships among the objects 214. The relationships among objects 214 may be persistent across user sessions, or may be transient in nature. The objects 212 may include or reference items of content, such as text, graphics, audio, video, interactive content, or embody any other type or item of information. The objects 212 may also include references to content, such as pointers. Computer applications, executable code, or references to computer applications may also be stored as objects 212 in the adaptive system 100. The content of the objects 212 is known herein as information 232. The information 232, though part of the object 214, is also considered part of the content aspect 230, as depicted in FIG. 2B, and described below.

The objects 212 may be managed in a relational database, or may be maintained in structures such as flat files, linked lists, inverted lists, hypertext networks, or object-oriented databases. The objects 212 may include meta-information 234 associated with the information 232 contained within, or referenced by the objects 212.

As an example, in some embodiments, the World-wide Web could be considered a structural aspect, where web pages constitute the objects of the structural aspect and links between web pages constitute the relationships among the objects. Alternatively, or in addition, in some embodiments, the structural aspect could be comprised of objects associated with an object-oriented programming language, and the relationships between the objects associated with the protocols and methods associated with interaction and communication among the objects in accordance with the object-oriented programming language.

The one or more users 200 of the adaptive system 100 may be explicitly represented as objects 212 within the system 100, therefore becoming directly incorporated within the structural aspect 210. The relationships among objects 214 may be arranged in a hierarchical structure, a relational structure (e.g. according to a relational database structure), or according to a network structure.

Content Aspect

The content aspect 230 of the adaptive system 100 is depicted in the block diagram of FIG. 2B. The content aspect 230 comprises the information 232 contained in, or referenced by the objects 212 that are part of the structural aspect 210. The content aspect 230 of the objects 212 may include text, graphics, audio, video, and interactive forms of content, such as applets, tutorials, courses, demonstrations, modules, or sections of executable code or computer programs. The one or more users 200 interact with the content aspect 230.

The content aspect 230 may be updated based on the usage aspect 220, as well as associated metrics. To achieve this, the adaptive system 100 may employ the usage aspect of other systems. Such systems may include, but are not limited to, other computer systems, other networks, such as the World Wide Web, multiple computers within an organization, other adaptive systems, or other adaptive recombinant systems. In this manner, the content aspect 230 benefits from usage occurring in other environments.

Usage Aspect

The usage aspect 220 of the adaptive system 100 is depicted in the block diagram of FIG. 2C, although it should be understood that the usage aspect 220 may also exist inde-

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pendently of adaptive system 100 in some embodiments. The usage aspect 220 denotes captured usage information 202, further identified as usage behaviors 270, and usage behavior pre-processing 204. The usage aspect 220 thus reflects the tracking, storing, categorization, and clustering of the use and associated usage behaviors of the one or more users 200 interacting with the adaptive system 100.

The captured usage information 202, known also as system usage or system use 202, includes any user behavior 920 exhibited by the one or more users 200 while using the system. The adaptive system 100 tracks and stores user key strokes and mouse clicks, for example, as well as the time period in which these interactions occurred (e.g., timestamps), as captured usage information 202. From this captured usage information 202, the adaptive system 100 identifies usage behaviors 270 of the one or more users 200 (e.g., web page access or email transmission). Finally, the usage aspect 220 includes usage-behavior pre-processing, in which usage behavior categories 249, usage behavior clusters 247, and usage behavioral patterns 248 are formulated for subsequent processing of the usage behaviors 270 by the adaptive system 100. Some usage behaviors 270 identified by the adaptive system 100, as well as usage behavior categories 249 designated by the adaptive system 100, are listed in Table 1, and described in more detail, below.

The usage behavior categories 249, usage behaviors clusters 247, and usage behavior patterns 248 may be interpreted with respect to a single user 200, or to multiple users 200, in which the multiple users may be described herein as a community, an affinity group, or a user segment. These terms are used interchangeably herein. A community is a collection of one or more users, and may include what is commonly referred to as a “community of interest.” A sub-community is also a collection of one or more users, in which members of the sub-community include a portion of the users in a previously defined community. Communities, affinity groups, and user segments are described in more detail, below.

Usage behavior categories 249 include types of usage behaviors 270, such as accesses, referrals to other users, collaboration with other users, and so on. These categories and more are included in Table 1, below. Usage behavior clusters 247 are groupings of one or more usage behaviors 270, either within a particular usage behavior category 249 or across two or more usage categories. The usage behavior pre-processing 204 may also determine new “clusterings” of user behaviors 270 in previously undefined usage behavior categories 249, across categories, or among new communities. Usage behavior patterns 248, also known as “usage behavioral patterns” or “behavioral patterns,” are also groupings of usage behaviors 270 across usage behavior categories 249. Usage behavior patterns 248 are generated from one or more filtered clusters of captured usage information 202.

The usage behavior patterns 248 may also capture and organize captured usage information 202 to retain temporal information associated with usage behaviors 270. Such temporal information may include the duration or timing of the usage behaviors 270, such as those associated with reading or writing of written or graphical material, oral communications, including listening and talking, or physical location of the user 200. The usage behavioral patterns 248 may include segmentations and categorizations of usage behaviors 270 corresponding to a single user of the one or more users 200 or according to multiple users 200 (e.g., communities or affinity groups). The communities or affinity groups may be previously established, or may be generated during usage behavior pre-processing 204 based on inferred usage behavior affinities or clustering. Usage behaviors 270 may also be derived

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from the use or explicit preferences 252 associated with other adaptive or non-adaptive systems.

Adaptive Recommendations

As shown in FIG. 1, the adaptive system 100 generates adaptive recommendations 250 using the adaptive recommendations function 240. The adaptive recommendations 250, or suggestions, enable users to more effectively use and navigate through the adaptive system 100.

The adaptive recommendations 250 are presented as structural subsets of the structural aspect 210. The adaptive recommendations 250 may be in the context of a currently conducted activity of the system 100, a currently accessed object 232, or a communication with another user 200. The adaptive recommendations 250 may also be in the context of a historical path of executed system activities, accessed objects 212, or communications during a specific user session or across user sessions. The adaptive recommendations 250 may be without context of a current activity, currently accessed object 212, current session path, or historical session paths. Adaptive recommendations 250 may also be generated in response to direct user requests or queries, including search requests. Such user requests may be in the context of a current system navigation, access or activity, or may be outside of any such context. The adaptive recommendations 250 may comprise advertising content.

Fuzzy Content Network

In some embodiments, the structural aspect 210 of the adaptive system 100, comprises a fuzzy content network. A fuzzy content network 700 is depicted in FIG. 3.

The fuzzy content network 700, including content sub-networks 700a, 700b, and 700c. The content network 700 includes “content,” “data,” or “information,” packaged in modules known as objects 710.

The content network 700 discretizes information as “objects.” In contrast to typical procedural computer programming structures, objects are defined at a higher level of abstraction. This level of abstraction allows for powerful, yet simple, software architectures.

One benefit to organizing information as objects is known as encapsulation. An object is encapsulated when only essential elements of interaction with other objects are revealed. Details about how the object works internally may be hidden. In FIG. 4A, for example, the object 710 includes meta-information 712 and information 714. The object 710 thus encapsulates information 714.

Another benefit to organizing information as objects is known as inheritance. The encapsulation of FIG. 4A, for example, may form discrete object classes, with particular characteristics ascribed to each object class. A newly defined object class may inherit some of the characteristics of a parent class. Both encapsulation and inheritance enable a rich set of relationships between objects that may be effectively managed as the number of individual objects and associated object classes grows.

In the content network 700, the objects 710 may be either topic objects 710t or content objects 710c, as depicted in FIGS. 4B and 4C, respectively. Topic objects 710t are encapsulations that contain meta-information 712t and relationships to other objects (not shown), but do not contain an embedded pointer to reference associated information. The topic object 710t thus essentially operates as a “label” to a class of information. The topic object 710 therefore just refers to “itself” and the network of relationships it has with other objects 710.

Content objects 710c, as shown in FIG. 4C, are encapsulations that contain meta-information 36c and relationships to other objects 710 (not shown). Additionally, content objects

710c may include either an embedded pointer to information or the information 714 itself (hereinafter, “information 714”).

The referenced information 714 may include files, text, documents, articles, images, audio, video, multi-media, software applications and electronic or magnetic media or signals. Where the content object 714c supplies a pointer to information, the pointer may be a memory address. Where the content network 700 encapsulates information on the Internet, the pointer may be a Uniform Resource Locator (URL).

The meta-information 712 supplies a summary or abstract of the object 710. So, for example, the meta-information 712t for the topic object 710t may include a high-level description of the topic being managed. Examples of meta-information 712t include a title, a sub-title, one or more descriptions of the topic provided at different levels of detail, the publisher of the topic meta-information, the date the topic object 710t was created, and subjective attributes such as the quality, and attributes based on user feedback associated with the referenced information. Meta-information may also include a pointer to referenced information, such as a uniform resource locator (URL), in one embodiment.

The meta-information 712c for the content object 710c may include relevant keywords associated with the information 714, a summary of the information 714, and so on. The meta-information 712c may supply a “first look” at the objects 710c. The meta-information 712c may include a title, a sub-title, a description of the information 714, the author of the information 714, the publisher of the information 714, the publisher of the meta-information 712c, and the date the content object 710c was created, as examples. As with the topic object 710t, meta-information for the content object 710c may also include a pointer.

In FIG. 3, the content sub-network 700a is expanded, such that both content objects 710c and topic objects 710t are visible. The various objects 34 of the content network 700 are interrelated by degrees, using relationships 716 (unidirectional and bidirectional arrows) and relationship indicators 718 (values). Each object 710 may be related to any other object 710, and may be related by a relationship indicator 718, as shown. Thus, while information 714 is encapsulated in the objects 710, the information 714 is also interrelated to other information 714 by a degree manifested by the relationship indicators 718.

The relationship indicator 718 is a numerical indicator of the relationship between objects 710. Thus, for example, the relationship indicator 718 may be normalized to between 0 and 1, inclusive, where 0 indicates no relationship, and 1 indicates a subset relationship. Or, the relationship indicators 718 may be expressed using subjective descriptors that depict the “quality” of the relationship. For example, subjective descriptors “high,” “medium,” and “low” may indicate a relationship between two objects 710.

The relationship 716 between objects 710 may be bidirectional, as indicated by the double-pointing arrows. Each double-pointing arrow includes two relationship indicators 718, one for each “direction” of the relationships between the objects 710.

As FIG. 3 indicates, the relationships 716 between any two objects 710 need not be symmetrical. That is, topic object 710t1 has a relationship of “0.3” with content object 710c2, while content object 710c2 has a relationship of “0.5” with topic object 710t1. Furthermore, the relationships 716 need not be bi-directional—they may be in one direction only. This could be designated by a directed arrow, or by simply setting one relationship indicator 718 of a bi-directional arrow to “0,” the null relationship value.

The content networks 700A, 700B, 700C may be related to one another using relationships of multiple types and associated relationship indicators 718. For example, in FIG. 3, content sub-network 700a is related to content sub-network 700b and content sub-network 700c, using relationships of multiple types and associated relationship indicators 718. Likewise, content sub-network 700b is related to content sub-network 700a and content sub-network 700c using relationships of multiple types and associated relationship indicators 718.

Individual content and topic objects 710 within a selected content sub-network 700a may be related to individual content and topic objects 710 in another content sub-network 700b. Further, multiple sets of relationships of multiple types and associated relationship indicators 718 may be defined between two objects 710.

For example, a first set of relationships 716 and associated relationship indicators 718 may be used for a first purpose or be available to a first set of users while a second set of relationships 716 and associated relationship indicators 718 may be used for a second purpose or available to a second set of users. For example, in FIG. 3, topic object 710t1 is bi-directionally related to topic object 710t2, not once, but twice, as indicated by the two double arrows. An indefinite number of relationships 716 and associated relationship indicators 718 may therefore exist between any two objects 710 in the fuzzy content network 700. The multiple relationships 716 may correspond to distinct relationship types. For example, a relationship type might be the degree an object 710 supports the thesis of a second object 710, while another relationship type might be the degree an object 710 disconfirms the thesis of a second object 710. The content network 700 may thus be customized for various purposes and accessible to different user groups in distinct ways simultaneously.

The relationships among objects 710 in the content network 700, as well as the relationships between content networks 700a and 700b, may be modeled after fuzzy set theory. Each object 710, for example, may be considered a fuzzy set with respect to all other objects 710, which are also considered fuzzy sets. The relationships among objects 710 are the degrees to which each object 710 belongs to the fuzzy set represented by any other object 710. Although not essential, every object 710 in the content network 700 may conceivably have a relationship with every other object 710.

The topic objects 710t encompass, and are labels for, very broad fuzzy sets of the content network 700. The topic objects 710t thus may be labels for the fuzzy set, and the fuzzy set may include relationships to other topic objects 710t as well as related content objects 710c. Content objects 710c, in contrast, typically refer to a narrower domain of information in the content network 700.

The adaptive system 100 of FIG. 1 may operate in a fuzzy content network environment, such as the one depicted in FIG. 3. In FIG. 5, an adaptive system 100D includes a structural aspect 210D that is a fuzzy content network. Thus, adaptive recommendations 250 generated by the adaptive system 100D are also structural subsets that are themselves fuzzy content networks.

User Behavior and Usage Framework

FIG. 6 depicts a usage framework 1000 for performing preference and/or intention inferencing of tracked or monitored usage behaviors 920 by one or more computer-based systems 925. The one or more computer-based systems 925 may comprise an adaptive system 100. The usage framework 1000 summarizes the manner in which usage patterns are managed within the one or more computer-based systems 925. Usage behavioral patterns associated with an entire com-

munity, affinity group, or segment of users **1002** are captured by the one or more computer-based systems **925**. In another case, usage patterns specific to an individual are captured by the one or more computer-based systems **925**. Various sub-communities of usage associated with users may also be defined, as for example “sub-community A” usage patterns **1006**, “sub-community B” usage patterns **1008**, and “sub-community C” usage patterns **1010**.

Memberships in the communities are not necessarily mutually exclusive, as depicted by the overlaps of the sub-community A usage patterns **1006**, sub-community B usage patterns **1008**, and sub-community C usage patterns **1010** (as well as and the individual usage patterns **1004**) in the usage framework **1000**. Recall that a community may include a single user or multiple users. Sub-communities may likewise include one or more users. Thus, the individual usage patterns **1004** in FIG. 6 may also be described as representing the usage patterns of a community or a sub-community. For the one or more computer-based systems **925**, usage behavior patterns may be segmented among communities and individuals so as to effectively enable adaptive communications **250c** delivery for each sub-community or individual.

The communities identified by the one or more computer-based systems **925** may be determined through self-selection, through explicit designation by other users or external administrators (e.g., designation of certain users as “experts”), or through automatic determination by the one or more computer-based systems **925**. The communities themselves may have relationships between each other, of multiple types and values. In addition, a community may be composed not of human users, or solely of human users, but instead may include one or more other computer-based systems, which may have reason to interact with the one or more computer-based systems **925**. Or, such computer-based systems may provide an input into the one or more computer-based systems **925**, such as by being the output from a search engine. The interacting computer-based system may be another instance of the one or more computer-based systems **925**.

The usage behaviors **920** included in Table 1 may be categorized by the one or more computer-based systems **925** according to the usage framework **1000** of FIG. 6. For example, categories of usage behavior may be captured and categorized according to the entire community usage patterns **1002**, sub-community usage patterns **1006**, and individual usage patterns **1004**. The corresponding usage behavior information may be used to infer preferences and/or intentions and interests at each of the user levels.

Multiple usage behavior categories shown in Table 1 may be used by the one or more computer-based systems **925** to make reliable inferences of the preferences and/or intentions and/or intentions of a user with regard to elements, objects, or items of content associated with the one or more computer-based systems **925**. There are likely to be different preference inferencing results for different users.

As shown in FIG. 6, the one or more computer-based systems **925** delivers adaptive communications to the user **200**. These adaptive communications **250c** may include adaptive recommendations **250** or associated explanations for the recommendations, or may be other types of communications to the user **200**, including advertising. In some embodiments the adaptive communications **250c** comprise one or more phrases, where phrases comprise one or more words. The adaptive communications **250c** may be delivered to the user **200** in a written form, an audio form, or a combination of these forms.

By introducing different or additional behavioral characteristics, such as the duration of access of an item of content

a more adaptive communication **250c** is enabled. For example, duration of access will generally be much less correlated with navigational proximity than access sequences will be, and therefore provide a better indicator of true user preferences and/or intentions and/or intentions. Therefore, combining access sequences and access duration will generally provide better inferences and associated system structural updates than using either usage behavior alone. Effectively utilizing additional usage behaviors as described above will generally enable increasingly effective system structural updating. In addition, the one or more computer-based systems **925** may employ user affinity groups to enable even more effective system structural updating than are available merely by applying either individual (personal) usage behaviors or entire community usage behaviors.

Furthermore, relying on only one or a limited set of usage behavioral cues and signals may more easily enable potential “spoofing” or “gaming” of the one or more computer-based systems **925**. “Spoofing” or “gaming” the one or more computer-based systems **925** refers to conducting consciously insincere or otherwise intentional usage behaviors **920**, so as to influence the costs of advertisements **910** of the one or more computer-based systems **925**. Utilizing broader sets of system usage behavioral cues and signals may lessen the effects of spoofing or gaming. One or more algorithms may be employed by the one or more computer-based systems **925** to detect such contrived usage behaviors, and when detected, such behaviors may be compensated for by the preference and interest inferencing algorithms of the one or more computer-based systems **925**.

In some embodiments, the one or more computer-based systems **925** may provide users **200** with a means to limit the tracking, storing, or application of their usage behaviors **920**. A variety of limitation variables may be selected by the user **200**. For example, a user **200** may be able to limit usage behavior tracking, storing, or application by usage behavior category described in Table 1. Alternatively, or in addition, the selected limitation may be specified to apply only to particular user communities or individual users **200**. For example, a user **200** may restrict the application of the full set of her usage behaviors **920** to preference or interest inferences by one or more computer-based systems **925** for application to only herself, and make a subset of process behaviors **920** available for application to users only within her workgroup, but allow none of her process usage behaviors to be applied by the one or more computer-based systems **925** in making inferences of preferences and/or intentions and/or intentions or interests for other users.

User Communities

As described above, a user associated with one or more systems **925** may be a member of one or more communities of interest, or affinity groups, with a potentially varying degree of affinity associated with the respective communities. These affinities may change over time as interests of the user **200** and communities evolve over time. The affinities or relationships among users and communities may be categorized into specific types. An identified user **200** may be considered a member of a special sub-community containing only one member, the member being the identified user. A user can therefore be thought of as just a specific case of the more general notion of user or user segments, communities, or affinity groups.

FIG. 7 illustrates the affinities among user communities and how these affinities may automatically or semi-automatically be updated by the one or more computer-based systems **925** based on user preferences and/or intentions which are derived from user behaviors **920**. An entire community **1050**

is depicted in FIG. 7. The community may extend across organizational, functional, or process boundaries. The entire community **1050** includes sub-community A **1064**, sub-community B **1062**, sub-community C **1069**, sub-community D **1065**, and sub-community E **1070**. A user **1063** who is not part of the entire community **1050** is also featured in FIG. 7.

Sub-community B **1062** is a community that has many relationships or affinities to other communities. These relationships may be of different types and differing degrees of relevance or affinity. For example, a first relationship **1066** between sub-community B **1062** and sub-community D **1065** may be of one type, and a second relationship **1067** may be of a second type. (In FIG. 7, the first relationship **1066** is depicted using a double-pointing arrow, while the second relationship **1067** is depicted using a unidirectional arrow.)

The relationships **1066** and **1067** may be directionally distinct, and may have an indicator of relationship or affinity associated with each distinct direction of affinity or relationship. For example, the first relationship **1066** has a numerical value **1068**, or relationship value, of "0.8." The relationship value **1068** thus describes the first relationship **1066** between sub-community B **1062** and sub-community D **1065** as having a value of 0.8.

The relationship value may be scaled as in FIG. 7 (e.g., between 0 and 1), or may be scaled according to another interval. The relationship values may also be bounded or unbounded, or they may be symbolically represented (e.g., high, medium, low).

The user **1063**, which could be considered a user community including a single member, may also have a number of relationships to other communities, where these relationships are of different types, directions and relevance. From the perspective of the user **1063**, these relationship types may take many different forms. Some relationships may be automatically formed by the one or more computer-based systems **925**, for example, based on interests or geographic location or similar traffic/usage patterns. Thus, for example the entire community **1050** may include users in a particular city. Some relationships may be context-relative. For example, a community to which the user **1063** has a relationship could be associated with a certain process, and another community could be related to another process. Thus, sub-community E **1070** may be the users associated with a product development business to which the user **1063** has a relationship **1071**; sub-community B **1062** may be the members of a cross-business innovation process to which the user **1063** has a relationship **1073**; sub-community D **1065** may be experts in a specific domain of product development to which the user **1063** has a relationship **1072**. The generation of new communities which include the user **1063** may be based on the inferred interests of the user **1063** or other users within the entire community **1050**.

Membership of communities may overlap, as indicated by sub-communities A **1064** and C **1069**. The overlap may result when one community is wholly a subset of another community, such as between the entire community **1050** and sub-community B **1062**. More generally, a community overlap will occur whenever two or more communities contain at least one user or user in common. Such community subsets may be formed automatically by the one or more systems **925**, based on preference inferencing from user behaviors **920**. For example, a subset of a community may be formed based on an inference of increased interest or demand of particular content or expertise of an associated community. The one or more computer-based systems **925** is also capable of inferring that

a new community is appropriate. The one or more computer-based systems **925** will thus create the new community automatically.

For each user, whether residing within, say, sub-community A **1064**, or residing outside the community **1050**, such as the user **1063**, the relationships (such as arrows **1066** or **1067**), affinities, or "relationship values" (such as numerical indicator **1068**), and directions (of arrows) are unique. Accordingly, some relationships (and specific types of relationships) between communities may be unique to each user. Other relationships, affinities, values, and directions may have more general aspects or references that are shared among many users, or among all users of the one or more computer-based systems **925**. A distinct and unique mapping of relationships between users, such as is illustrated in FIG. 7, could thus be produced for each user by the one or more computer-based systems **925**.

The one or more computer-based systems **925** may automatically generate communities, or affinity groups, based on user behaviors **920** and associated preference inferences. In addition, communities may be identified by users, such as administrators of the process or sub-process instance **930**. Thus, the one or more computer-based systems **925** utilizes automatically generated and manually generated communities.

The communities, affinity groups, or user segments aid the one or more computer-based systems **925** in matching interests optimally, developing learning groups, prototyping process designs before adaptation, and many other uses. For example, some users that use or interact with the one or more computer-based systems **925** may receive a preview of a new adaptation of a process for testing and fine-tuning, prior to other users receiving this change.

The users or communities may be explicitly represented as elements or objects within the one or more computer-based systems **925**.

Preference and/or Intention Inferences

The usage behavior information and inferences function **220** of the one or more computer-based systems **925** is depicted in the block diagram of FIG. 8. In embodiments where computer-based systems **925** is an adaptive system **100**, then usage behavior information and inferences function **220** is equivalent to the usage aspect **220** of FIG. 1. The usage behavior information and inferences function **220** denotes captured usage information **202**, further identified as usage behaviors **270**, and usage behavior pre-processing **204**. The usage behavior information and inferences function **220** thus reflects the tracking, storing, classification, categorization, and clustering of the use and associated usage behaviors **920** of the one or more users or users **200** interacting with the one or more computer-based systems **925**.

The captured usage information **202**, known also as system usage or system use **202**, includes any interaction by the one or more users or users **200** with the system, or monitored behavior by the one or more users **200**. The one or more computer-based systems **925** may track and store user key strokes and mouse clicks, for example, as well as the time period in which these interactions occurred (e.g., timestamps), as captured usage information **202**. From this captured usage information **202**, the one or more computer-based systems **925** identifies usage behaviors **270** of the one or more users **200** (e.g., web page access or physical location changes of the user). Finally, the usage behavior information and inferences function **220** includes usage-behavior pre-processing, in which usage behavior categories **246**, usage behavior clusters **247**, and usage behavioral patterns **248** are formulated for subsequent processing of the usage behaviors

270 by the one or more computer-based systems 925. Some usage behaviors 270 identified by the one or more computer-based systems 925, as well as usage behavior categories 246 designated by the one or more computer-based systems 925, are listed in Table 1, and are described in more detail below.

The usage behavior categories 246, usage behaviors clusters 247, and usage behavior patterns 248 may be interpreted with respect to a single user 200, or to multiple users 200, in which the multiple users may be described herein as a community, an affinity group, or a user segment. These terms are used interchangeably herein. A community is a collection of one or more users, and may include what is commonly referred to as a “community of interest.” A sub-community is also a collection of one or more users, in which members of the sub-community include a portion of the users in a previously defined community. Communities, affinity groups, and user segments are described in more detail, below.

Usage behavior categories 246 include types of usage behaviors 270, such as accesses, referrals to other users, collaboration with other users, and so on. These categories and more are included in Table 1. Usage behavior clusters 247 are groupings of one or more usage behaviors 270, either within a particular usage behavior category 246 or across two or more usage categories. The usage behavior pre-processing 204 may also determine new “clusterings” of user behaviors 270 in previously undefined usage behavior categories 246, across categories, or among new communities. Usage behavior patterns 248, also known as “usage behavioral patterns” or “behavioral patterns,” are also groupings of usage behaviors 270 across usage behavior categories 246. Usage behavior patterns 248 are generated from one or more filtered clusters of captured usage information 202.

The usage behavior patterns 248 may also capture and organize captured usage information 202 to retain temporal information associated with usage behaviors 270. Such temporal information may include the duration or timing of the usage behaviors 270, such as those associated with reading or writing of written or graphical material, oral communications, including listening and talking, or physical location of the user 200, potentially including environmental aspects of the physical location(s). The usage behavioral patterns 248 may include segmentations and categorizations of usage behaviors 270 corresponding to a single user of the one or more users 200 or according to multiple users 200 (e.g., communities or affinity groups). The communities or affinity groups may be previously established, or may be generated during usage behavior pre-processing 204 based on inferred usage behavior affinities or clustering.

User Behavior Categories

In Table 1, a variety of different user behaviors 920 are identified that may be assessed by the one or more computer-based systems 925 and categorized. The usage behaviors 920 may be associated with the entire community of users, one or more sub-communities, or with individual users or users of the one of more computer-based applications 925.

TABLE 1

Usage behavior categories and usage behaviors	
usage behavior category	usage behavior examples
navigation and access	activity, content and computer application accesses, including buying/selling paths of accesses or click streams execution of searches and/or search history

TABLE 1-continued

Usage behavior categories and usage behaviors	
usage behavior category	usage behavior examples
subscription and self-profiling	personal or community subscriptions to process topical areas interest and preference self-profiling affiliation self-profiling (e.g., job function)
collaborative	referral to others discussion forum activity
reference	direct communications (voice call, messaging) content contributions or structural alterations personal or community storage and tagging personal or community organizing of stored or tagged information
direct feedback	user ratings of activities, content, computer applications and automatic recommendations user comments
physiological responses	direction of gaze brain patterns blood pressure heart rate
environmental conditions and location	current location location over time relative location to users/object references current time current weather condition

A first category of process usage behaviors 920 is known as system navigation and access behaviors. System navigation and access behaviors include usage behaviors 920 such as accesses to, and interactions with computer-based applications and content such as documents, Web pages, images, videos, TV channels, audio, radio channels, multi-media, interactive content, interactive computer applications, e-commerce applications, or any other type of information item or system “object.” These process usage behaviors may be conducted through use of a keyboard, a mouse, oral commands, or using any other input device. Usage behaviors 920 in the system navigation and access behaviors category may include, but are not limited to, the viewing or reading of displayed information, typing written information, interacting with online objects orally, or combinations of these forms of interactions with computer-based applications. This category includes the explicit searching for information, using, for example, a search engine. The search term may be in the form of a word or phrase to be matched against documents, pictures, web-pages, or any other form of on-line content. Alternatively, the search term may be posed as a question by the user.

System navigation and access behaviors may also include executing transactions, including commercial transactions, such as the buying or selling of merchandise, services, or financial instruments. System navigation and access behaviors may include not only individual accesses and interactions, but the capture and categorization of sequences of information or system object accesses and interactions over time.

A second category of usage behaviors 920 is known as subscription and self-profiling behaviors. Subscriptions may be associated with specific topical areas or other elements of the one or more computer-based systems 925, or may be associated with any other subset of the one or more computer-based systems 925. Subscriptions may thus indicate the intensity of interest with regard to elements of the one or more computer-based systems 925. The delivery of information to fulfill subscriptions may occur online, such as through electronic mail (email), on-line newsletters, XML feeds, etc., or through physical delivery of media.

Self-profiling refers to other direct, persistent (unless explicitly changed by the user) indications explicitly designated by the one or more users regarding their preferences and/or intentions and interests, or other meaningful attributes. A user **200** may explicitly identify interests or affiliations, such as job function, profession, or organization, and preferences and/or intentions, such as representative skill level (e.g., novice, business user, advanced). Self-profiling enables the one or more computer-based systems **925** to infer explicit preferences and/or intentions of the user. For example, a self-profile may contain information on skill levels or relative proficiency in a subject area, organizational affiliation, or a position held in an organization. A user **200** that is in the role, or potential role, of a supplier or customer may provide relevant context for effective adaptive e-commerce applications through self-profiling. For example, a potential supplier may include information on products or services offered in his or her profile. Self-profiling information may be used to infer preferences and/or intentions and interests with regard to system use and associated topical areas, and with regard to degree of affinity with other user community subsets. A user may identify preferred methods of information receipt or learning style, such as visual or audio, as well as relative interest levels in other communities.

A third category of usage behaviors **920** is known as collaborative behaviors. Collaborative behaviors are interactions among the one or more users. Collaborative behaviors may thus provide information on areas of interest and intensity of interest. Interactions including online referrals of elements or subsets of the one or more computer-based systems **925**, such as through email, whether to other users or to non-users, are types of collaborative behaviors obtained by the one or more computer-based systems **925**.

Other examples of collaborative behaviors include, but are not limited to, online discussion forum activity, contributions of content or other types of objects to the one or more computer-based systems **925**, or any other alterations of the elements, objects or relationships among the elements and objects of one or more computer-based systems **925**. Collaborative behaviors may also include general user-to-user communications, whether synchronous or asynchronous, such as email, instant messaging, interactive audio communications, and discussion forums, as well as other user-to-user communications that can be tracked by the one or more computer-based systems **925**.

A fourth category of process usage behaviors **920** is known as reference behaviors. Reference behaviors refer to the marking, designating, saving or tagging of specific elements or objects of the one or more computer-based systems **925** for reference, recollection or retrieval at a subsequent time. Tagging may include creating one or more symbolic expressions, such as a word or words, associated with the corresponding elements or objects of the one or more computer-based systems **925** for the purpose of classifying the elements or objects. The saved or tagged elements or objects may be organized in a manner customizable by users. The referenced elements or objects, as well as the manner in which they are organized by the one or more users, may provide information on inferred interests of the one or more users and the associated intensity of the interests.

A fifth category of process usage behaviors **920** is known as direct feedback behaviors. Direct feedback behaviors include ratings or other indications of perceived quality by individuals of specific elements or objects of the one or more computer-based systems **925**, or the attributes associated with the corresponding elements or objects. The direct feedback behaviors may therefore reveal the explicit preferences and/

or intentions of the user. In the one or more computer-based systems **925**, the advertisements **910** may be rated by users **200**. This enables a direct, adaptive feedback loop, based on explicit preferences and/or intentions specified by the user. Direct feedback also includes user-written comments and narratives associated with elements or objects of the computer-based system **925**.

A sixth category of process usage behaviors is known as physiological responses. These responses or behaviors are associated with the focus of attention of users and/or the intensity of the intention, or any other aspects of the physiological responses of one or more users **200**. For example, the direction of the visual gaze of one or more users may be determined. This behavior can inform inferences associated with preferences and/or intentions or interests even when no physical interaction with the one or more computer-based systems **925** is occurring. Even more direct assessment of the level of attention may be conducted through access to the brain patterns or signals associated with the one or more users. Such patterns of brain functions during participation in a process can inform inferences on the preferences and/or intentions or interests of users, and the intensity of the preferences and/or intentions or interests. The brain patterns assessed may include MRI images, brain wave patterns, relative oxygen use, or relative blood flow by one or more regions of the brain.

Physiological responses may include any other type of physiological response of a user **200** that may be relevant for making preference or interest inferences, independently, or collectively with the other usage behavior categories. Other physiological responses may include, but are not limited to, utterances, gestures, movements, or body position. Attention behaviors may also include other physiological responses such as breathing rate, heart rate, blood pressure, or galvanic response.

A seventh category of process usage behaviors is known as environmental conditions and physical location behaviors. Physical location behaviors identify physical location and mobility behaviors of users. The location of a user may be inferred from, for example, information associated with a Global Positioning System or any other positionally or locationally aware system or device, or may be inferred directly from location information input by a user (e.g., a zip code or street address), or otherwise acquired by the computer-based systems **925**. The physical location of physical objects referenced by elements or objects of one or more computer-based systems **925** may be stored for future reference. Proximity of a user to a second user, or to physical objects referenced by elements or objects of the computer-based application, may be inferred. The length of time, or duration, at which one or more users reside in a particular location may be used to infer intensity of interests associated with the particular location, or associated with objects that have a relationship to the physical location. Derivative mobility inferences may be made from location and time data, such as the direction of the user, the speed between locations or the current speed, the likely mode of transportation used, and the like. These derivative mobility inferences may be made in conjunction with geographic contextual information or systems, such as through interaction with digital maps or map-based computer systems. Environmental conditions may include the time of day, the weather, lighting levels, sound levels, and any other condition of the environment around the one or more users **200**.

In addition to the usage behavior categories depicted in Table 1, usage behaviors may be categorized over time and across user behavioral categories. Temporal patterns may be

associated with each of the usage behavioral categories. Temporal patterns associated with each of the categories may be tracked and stored by the one or more computer-based systems **925**. The temporal patterns may include historical patterns, including how recently an element, object or item of content associated with one or more computer-based systems **925**. For example, more recent behaviors may be inferred to indicate more intense current interest than less recent behaviors.

Another temporal pattern that may be tracked and contribute to preference inferences that are derived, is the duration associated with the access or interaction with the elements, objects or items of content of the one or more computer-based systems **925**, or the user's physical proximity to physical objects referenced by system objects of the one or more computer-based systems **925**, or the user's physical proximity to other users. For example, longer durations may generally be inferred to indicate greater interest than short durations. In addition, trends over time of the behavior patterns may be captured to enable more effective inference of interests and relevancy. Since delivered recommendations may include one or more elements, objects or items of content of the one or more computer-based systems **925**, the usage pattern types and preference inferencing may also apply to interactions of the one or more users with the delivered recommendations **250** themselves, including accesses of, or interactions with, explanatory information regarding the logic or rationale that the one more computer-based systems **925** used in deciding to deliver the recommendation to the user.

Adaptive Communications Generation

In some embodiments, adaptive communications **250c** or recommendations **250** may be generated for the one or more users **200** through the application of affinity vectors.

For example, in some embodiments, Member-Topic Affinity Vectors (MTAV) may be generated to support effective recommendations, wherein for a registered user or member **200** of the one or more computer-based systems **925** a vector is established that indicates the relative affinity (normalized to the [0,1] continuum) the member has for every object sub-network the member has access to. For computer-based systems **925** comprising a fuzzy content network-based structural aspect, the member affinity values of the MTAV may be in respect to topic networks.

So in general, for each registered member, e.g., member M, a hypothetical MTAV could be of a form as follows:

MTAV for Member M					
Topic 1	Topic 2	Topic 3	Topic 4	...	Topic N
0.35	0.89	0.23	0.08	...	0.14

The MTAV will therefore reflect the relative interests of a user with regard to all N of the accessible topics. This type of vector can be applied in two major ways:

- To serve as a basis for generating adaptive communications **250c** or recommendations **250** to the user **200**
- To serve as a basis for comparing the interests with one member **200** with another member **200**, and to therefore determine how similar the two members are

To generate the MTAV, any of the behaviors of Table 1 may be utilized. For example, in some embodiments the following example behavioral information may be used:

- The topics the member has subscribed to received updates

- The topics the member has accessed directly
- The accesses the member has made to objects that are related to each topic
- The saves the member has made of objects that are related to each topic

This behavioral information is listed above in a generally reverse order of importance from the standpoint of inferring member interests; that is, access information gathered over a significant number of accesses or over a significant period of time will generally provide better information than subscription information, and save information is typically more informative of interests than just accesses.

The following fuzzy network structural information may also be used to generate MTAV values:

- The relevancies of each content object to each topic
- The number of content objects related to each topic

Personal topics that are not shared with other users **200** may be included in MTAV calculations. Personal topics that have not been made publicly cannot be subscribed to by other members, and so could in this regard be unfairly penalized versus public topics. Therefore for the member who created the personal topic and co-owners of that personal topic, in some embodiments the subscription vector to may be set to "True," i.e. 1. There may exist personal topics that are created by a member **200** and that have never been seen or contributed to by any other member. This may not otherwise affect the recommendations **250** since the objects within that personal topic may be accessible by other members, and any other relationships these objects have to other topics will be counted toward accesses of these other topics.

In some embodiments the first step of the calculation is to use information 1-4 above to generate the following table or set of vectors for the member, as depicted in the following hypothetical example:

TABLE 2

Member 1 Behaviors	Topic 1	Topic 2	Topic 3	Topic 4	...	Topic N
Subscriptions	1	1	0	0		1
Topic Accesses	14	3	57	0		8
Weighted Accesses	112	55	23	6		43
Weighted Saves	6	8	4	0	...	2

The Subscriptions vector of Table 2 contains either a 1 if the member has subscribed to a topic or is the owner/co-owner of a personal topic or a 0 if the member has not subscribed to the topic. The Topic Accesses vector contains the number of accesses to that topic's explore page by the member to a topic over a period of time, for example, the preceding 12 months.

The Weighted Accesses vector of Table 1 contains the number of the member's (Member 1) accesses over the last 12 months of each object multiplied by the relevancies to each topic summed across all accessed objects. (So for example, if Object 1 has been accessed 10 times in the last 12 months by Member 1 and it is related to Topic 1 by 0.8, and Object 2 has been accessed 4 times in the last 12 months by Member 1 and is related to Topic 1 at relevancy level 0.3, and these are the only objects accessed by Member 1 that are related to Topic 1, then Topic 1 would contain the value $10*0.8+4*0.3=9.2$).

The Weighted Saves vector of Table 1 works the same way as the Weighted Accesses vector, except it is based on Member 1's object save data instead of access data.

In some embodiments, topic object saves are counted in addition to content object saves. Since a member saving a topic typically is a better indicator of the member's interest in

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the topic than just saving an object related to the said topic, it may be appropriate to give more “credit” for topic saves than just content object saves. For example, when a user saves a topic object, the following process may be applied:

If the Subscriptions vector indicator is not already set to “1” for this topic in Table 1, it is set to “1”. (The advantage of this is even if the topic has been saved before 12 months ago, the user will still at least get subscription “credit” for the topic save even if they don’t get credit for the next two calculations).

In exactly the same way as a saved content object, a credit is applied in the Weighted Accesses vector of Table 2 based on the relevancies of other topics to the saved topic.

A special “bonus” weighting in the Weighted Accesses vector of Table 2 for the topic itself using the weighting of “10”—which means a topic save is worth at least as much as 10 saves of content that are highly related to that topic.

The next step is to make some adjustments to Table 1. For example, it may be desirable scale the Weighted Accesses and Weighted Saves vectors by the number of objects that is related to each topic. The result is the number of accesses or saves per object per topic. This may be a better indicator of intensity of interest because it is not biased against topics with few related objects. However, per object accesses/saves alone could give misleading results when there are very few accesses or saves. So as a compromise, the formula that is applied to each topic, e.g., Topic N, may be a variation of the following:

$$\frac{((\text{Weighted Accesses for Topic N})/(\text{Objects related to Topic N})) * \text{Square Root}(\text{Weighted Accesses for Topic N})}{\text{Topic N}}$$

This formula emphasizes per object accesses, but tempers this with a square root factor associated with the absolute level of accesses by the member. The result is a table, Table 2A, of the form:

TABLE 2A

Member 1 Behaviors	Topic 1	Topic 2	Topic 3	Topic 4	...	Topic N
Subscriptions	1	1	0	0		1
Topic Accesses	14	3	57	0		8
Weighted Accesses	9.1	12	3.2	0.6		2.3
Weighted Saves	0.9	1.3	1.1	0	...	0.03

The next step is to transform Table 2A into a MTAV. In some embodiments, indexing factors, such as the following may be applied:

Topic Affinity Indexing Factors	Weight
Subscribe Indexing Factor	10
Topic Indexing Factor	20
Accesses Indexing Factor	30
Save Indexing Factor	40

These factors have the effect of ensuring normalized MTAV values ranges (e.g. 0-1 or 0-100) and they enable more emphasis on behaviors that are likely to provide relatively better information on member interests. In some embodiments, the calculations for each vector of Table 1A are transformed into corresponding Table 2 vectors as follows:

1. Table 3 Indexed Subscriptions for a topic by Member 1=Table 2A Subscriptions for a topic * Subscribe Indexing Factor

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2. Table 3 Indexed Direct Topic Accesses by Member 1=Table 2A Topic Accesses* Topic Indexing Factor

3. Table 3 Indexed Accesses for a topic by Member 1=((Table 2A Weighted Accesses for a topic by Member 1)/(Max(Weighted Accesses of all Topics by Member 1)))*Accesses Indexing Factor

4. Table 3 Indexed Saves for a topic by Member 1=((Table 2A Weighted Saves for a topic by Member 1)/(Max(Weighted Saves of all Topics by Member 1)))*Saves Indexing Factor

The sum of these Table 3 vectors results in the MTAV for the associated member **200** as shown in the hypothetical example of Table 3 below:

TABLE 3

Member 1 Indexed Behaviors	Topic 1	Topic 2	Topic 3	Topic 4	...	Topic N
Subscriptions	0	10	10	10		10
Topic Accesses	5	1	20	0		8
Weighted Accesses	11	1	30	12		6
Weighted Saves	0	10	40	1		2
Member 1 MTAV	16	22	100	23	...	26

Member-to-member affinities can be derived by comparing the MTAV’s of a first member **200** and a second member **200**. Statistical operators such as correlation coefficients may be applied to derive a sense of the distance between members in n-dimensional topic affinity space, where there N topics. Since different users may have access to different topics, the statistical correlation for a pair of members must be applied against MTAV subsets that contain only the topics that both members have access to. In this way, a member-to-member affinity vector (MMAV) can be generated for each member or user **200**, and the most similar members, the least similar members, etc., can be identified for each member **200**.

With the MTAV’s and MMAV’s, and Most Similar Member information, a set of candidate objects to be recommended can be generated. These candidate recommendations will, in a later processing step, be ranked, and the highest ranked to candidate recommendations will be delivered to the recommendation recipient. Recall that recommendations **250** may be in-context of navigating the system **925** or out-of-context of navigating the system **925**. Following are more details on an exemplary set of steps related to generating out-of-context recommendations. At each of step the candidate objects may be assessed against rejection criteria (for example, the recommendation recipient has already recently received the candidate object may be a cause for immediate rejection) and against a maximum number of candidate objects to be considered.

1. Determine if there are objects that have been related to objects at a sufficient level of relatedness that have been “saved” by the recommendation recipient since the time the recommendation recipient saved the object. This may be a good choice for a first selection step because it would be expected that such objects would be highly relevant to the recommendation recipient.
2. Determine if the Most Similar Members to the recommendation recipient have “saved” (related) objects in the last 12 months to the recommendation recipient’s highest affinity topics.
3. Determine if the Most Similar Members to the recommendation recipient have rated objects at a level greater

than some threshold over some time period, that are related to the recommendation recipient's highest affinity topics.

4. Determine the most frequently accessed objects by the Most Similar Members over some period of time that are related to recommendation recipient's highest affinity topics.
5. Determine the highest influence objects that are related to recommendation recipient's highest affinity topics.

A variation of the out-of-context recommendation process may be applied for in-context recommendations, where the process places more emphasis of the closeness of the objects to the object being viewed in generating candidate recommendation objects.

For both out-of-context and in-context recommendations, a ranking process may be applied to the set of candidate objects, according to some embodiments. The following is an exemplary set of input information that may be used to calculate rankings.

1. Editor Rating: If there is no editor rating for the object, this value is set to a default
2. Community Rating (If there is no community rating for the object, this value can be set to a default)
3. Popularity: Indexed popularity (e.g., number of views) of the object.
4. Change in Popularity: Difference in indexed popularity between current popularity of the object and the object's popularity some time ago
5. Influence: Indexed influence of the object, where the influence of an object is calculated recursively based on the influence of other objects related to the said object, weighted by the degree of relationship to the said object, and where the initial setting of influence of an object is defined as its popularity.
6. Author's Influence: Indexed influence of the highest influence author (based on the sum of the influences of the author's content) of the content referenced by the object
7. Publish Date: Date of publication of the object
8. Selection Sequence Type: An indicator the sequence step in which the candidate object was selected
9. Object Affinity to MTAV: The indexed vector product of the Object-Topic Affinity Vector (OTAV) and the MTAV. The values of the OTAV are just the relevancies between the object and each topic. Here is an example of the OTAV-MTAV vector product.

A ranking is then developed based on applying a mathematical function to some or all or input items listed directly above, and/or other inputs not listed above. In some embodiments, user or administrator-adjustable weighting factors

may be applied to the raw input values to tune the object ranking appropriately. These recommendation preference settings may be established directly by the user, and remain persistent across sessions until updated by the user, in some embodiments.

Some example weighting factors that can be applied dynamically by a user or administrator are as follows:

1. Change in Popularity (What's Hot" factor)
2. Recency Factor
3. Object Affinity to MTAV

These weighting factors could take any value (but might be typically in the 0-5 range) and could be applied to associated ranking categories to give the category disproportionate weightings versus other categories. They can provide control over how important change in popularity, freshness of content, and an object's affinity with the member's MTAV are in ranking the candidate objects.

The values of the weighting factors are combined with the raw input information associated with an object to generate a rating score for each candidate object. The objects can then be ranked by their scores, and the highest scoring set of X objects, where X is a defined maximum number of recommended objects, can be selected for deliver to a recommendation recipient **200**. In some embodiments, scoring thresholds may be set and used in addition to just relative ranking of the candidate objects. The scores of the one or more recommended objects may also be used by the computer-based system **925** to provide to the recommendation recipient a sense of confidence in the recommendation. Higher scores would warrant more confidence in the recommendation of an object than would lower scores.

Recommendation Explanation Generation

In addition to delivering a recommendation **250** for an object, the computer-based application **925** may deliver a corresponding explanation **250c** of why the object was recommended. This can be very valuable to the recommendation recipient **200** because it may give the recipient a better sense of whether to bother to read or listen to the recommended content, without committing significant amount of time. For recommendations that comprise advertising content, the explanation may enhance the persuasiveness of the ad.

In some embodiments, variations of the ranking factors may be applied in triggering explanatory phrases. For example, the following table illustrates how the ranking information can be applied to determine both positive and negative factors that can be incorporated within the recommendation explanations. Note that the Ranking Value Range is the indexed attribute values before multiplying by special scaling factors Ranking Category Weighting Factors such as the "What's Hot" factor, etc.

TABLE 2E

1 Ranking Category	2 Ranking Value Range (RVR)	3 Transformed Range	4 1st Positive Threshold	5 2nd Positive Threshold	6 Negative Threshold
Editor Rating	0-100	RVR	60	80	20
Community Rating*	0-100	RVR	70	80	20
Popularity	0-100	RVR	70	80	10
Change in Popularity	-100-100	RVR	30	50	-30
Object Influence	0-100	RVR	50	70	5
Author's Influence	0-100	RVR	70	80	.01
Publish Date	-Infinity-0	100-RVR	80	90	35
Object Affinity to MTAV	0-100	RVR	50	70	20

An exemplary process that can be applied to generate explanations based on positive and negative thresholds listed in 2E is as follows:

Step 1: First Positive Ranking Category—subtract the 1st Positive Threshold column from the Transformed Range column and find the maximum number of the resulting vector (may be negative). The associated Ranking Category will be highlighted in the recommendation explanation.

Step 2: Second Positive Ranking Category—subtract the 2nd Positive Threshold column from the Transformed Range column and find the maximum number of the resulting vector. If the maximum number is non-negative, and it is not the ranking category we already selected, then include this second ranking category in the recommendation explanation.

Step 3: First Negative Ranking Category—subtract the Negative Threshold column from the Transformed Range column and find the minimum number of the resulting vector. If the minimum number is non-positive this ranking category will be included in the recommendation explanation as a caveat, otherwise there will be no caveats.

Although two positive and one negative thresholds are illustrated in this example, and unlimited number of positive and negative thresholds may be applied as required for best results.

In some embodiments explanations are assembled from component phrases and delivered based on a syntax template or function. Following is an example syntax that guides the assembly of an in-context recommendation explanation. In the syntactical structure below phrases within { } are optional depending on the associated logic and calculations, and “+” means concatenating the text strings. Other detailed syntactical logic such as handling capitalization is not shown in this simple illustrative example.

{[Awareness Phrase (if any)]}+{[Sequence Number Phrase (if any)]+[Positive Conjunction]}+[1st Positive Ranking Category Phrase]+{[Positive Conjunction]+[2nd Positive Ranking Category Phrase (if any)]}+{[Negative Conjunction]+[Negative Ranking Category Phrase (if any)]}+{[Suggestion Phrase (if any)]}

The following section provides some examples of phrase tables or arrays that may be used as a basis for selecting appropriate phrases for a recommendation explanation syntax. Note that in the following tables, when there are multiple phrase choices, they are selected probabilistically. “NULL” means that a blank phrase will be applied. [] indicates that this text string is a variable that can take different values.

System Awareness Phrases

Trigger Condition	Phrase
Apply these phrase alternatives if any of the 4 Sequence Numbers was triggered	1) I noticed that 2) I am aware that 3) I realized that 4) NULL

Out-of-Context Sequence Number Phrases

Trigger Condition	Phrase
Sequence 1	1) other members have related [this object] to [saved object name], which you have saved,
Sequence 2	1) members with similar interests to you have saved [this object]
Sequence 3	1) members with similar interests as you have rated [this object]highly 2) Members that have similarities with you have found [this object] very useful

-continued

Trigger Condition	Phrase
Sequence 4	1) [this object] is popular with members that have similar interests to yours 2) Members that are similar to you have often accessed [this object]

Positive Ranking Category Phrases

Trigger Category	Phrase
Editor Rating	1) [it] is rated highly by the editor
Community Rating*	1) [it] is rated highly by other members
Popularity**	1) [it] is very popular
Change in Popularity	1) [it] has been rapidly increasing in popularity
Object Influence	1) [it] is [quite] influential
Author's Influence	1) the author is [quite] influential 2) [author name] is a very influential author
Publish Date	1) it is recently published
Object Affinity to MTAV (1)	1) [it] is strongly aligned with your interests 2) [it] is related to topics such as [topic name] that you find interesting 3) [it] is related to topics in which you have an interest
Object Affinity to MTAV (2)	4) I know you have an interest in [topic name] 5) I am aware you have an interest in [topic name] 6) I have seen that you are interested in [topic name] 7) I have noticed that you have a good deal of interest in [topic name]

Positive Conjunctions

Phrase
1) and

Negative Ranking Category Phrases

Trigger Category	Phrase
Editor Rating	1) it is not highly rated by the editor
Community Rating	1) it is not highly rated by other members
Popularity	1) it is not highly popular
Change in Popularity	1) it has been recently decreasing in popularity
Object Influence	1) it is not very influential
Author's Influence	1) the author is not very influential 2) [author name] is not a very influential author
Publish Date	1) it was published some time ago 2) it was published in [Publish Year]
Object Affinity to MTAV	1) it may be outside your normal area of interest 2) I'm not sure it is aligned with your usual interest areas

Negative Conjunctions

Phrase
1) , although 2) , however 3) , but

Suggestion Phrases (Use Only if No Caveats in Explanation)

Phrase
1) , so I think you will find it relevant
2) , so I think you might find it interesting
3) , so you might want to take a look at it
4) , so it will probably be of interest to you
5) , so it occurred to me that you would find it of interest
6) , so I expect that you will find it thought provoking
7) NULL

The above phrase array examples are simplified examples to illustrate the approach. In practice, multiple syntax templates, accessing different phrase arrays, with each phrase array many different phrases and phrase variations are required to give the feel of human-like explanations.

As mentioned above, a sense of confidence of the recommendation to the recommendation recipient can also be communicated within the recommendation explanation. The score level may contribute to the confidence level, but some other general factors may be applied, including the amount of usage history available for the recommendation recipient on which to base preference inferences and/or the inferred similarity of the user with one or more other users for which there is a basis for more confident inferences of interests or preferences.

Recommendation explanations are one type of behavioral-based communications **250c** that the one or more computer-based applications **925** may deliver to users **200**. Other types of adaptive communications **250c** may be delivered to a user **200** without necessarily being in conjunction with the recommendation of an object or item of content. For example, a general update of the activities of other users **200** and/or other trends or activities related to people or content may be communicated.

Adaptive communications **250c** may also comprise one or more phrases that communicate an awareness of behavioral changes in the user **200** over time, and inferences thereof. These behavioral changes may be derived, at least in part, from an evaluation of changes in the user's MTAV affinity values over time. In some cases, these behavioral patterns may be quite subtle and may otherwise go unnoticed by the user **200** if not pointed out by the computer-based system **925**. Furthermore, the one or more computer-based systems may infer changes in interests or preferences of the user **200** based on changes in the user's behaviors over time. The communications **250c** of these inferences may therefore provide the user **200** with useful insights into changes in his interest, preferences, and tastes over time. This same approach can also be applied by the one or more computer-based systems to deliver insights into the changes in interests, preferences and tastes associated with any user **200** to another user **200**. These insights, packaged in an engaging communications **250c**, can simulate what is sometimes referred to as "a theory of mind" in psychology.

The adaptive communications **250c** in general may apply a syntactical structure and associated probabilistic phrase arrays to generate the adaptive communications in a manner similar to the approach described above to generate explanations for recommendations. The phrase tendencies of the adaptive communications **250c** over a number of generated communications can be said to constitute a "personality" associated with the one or more computer-based applications **925**. The next section describes how in some embodiments of the present invention the personality can evolve and adapt

over time, based at least in part, on the behaviors of the communication recipients **200**.

Adaptive Personalities

FIG. **9** is a flow diagram of the computer-based adaptive personality process **1000** in accordance with some embodiments of the present invention. A user request for a communication **1010** initiates a function **1020** that determines the syntactical structure of the communication **250c** to the user **200**. The communication **250c** to user **200** may be an adaptive recommendation **250**, an explanation associated with a recommendation, or any other type of communication to the user. The communication **250c** may be in written format, or may be an audio-based format.

In accordance with the syntactical structure that is determined **1020** for the communication, one or more phrases are probabilistically selected **1030** based on frequency distributions **3030** associated with an ensemble of phrases to generate **1040** a communication **930** to the user.

User behaviors **920**, which may include those described by Table 1 herein, are then evaluated **1050** after receipt of the user communication. Based, at least in part, on these evaluations **1050**, the frequency distributions **3030** of one or more phrases that may be selected **1030** for future user communications are then updated **1060**. For example, if the user communication **250c** is an the explanation associated with an adaptive recommendation **250**, and it is determined that the recommendation recipient reads the corresponding recommended item of content, then the relative frequency of selection of the one or more phrases comprising the explanation of the adaptive recommendation **250** might be preferentially increased versus other phrases that we not included in the user communication. Alternatively, if the communication **250c** elicited one or more behaviors **920** from the communication recipient **200** that were indicative of indifference or a less than positive reaction, then the relative frequency of selection of the one or more phrases comprising the communication might be preferentially decreased versus other phrases that we not included in the user communication.

In FIG. **11**, an illustrative data structure **3000** supporting the adaptive personality process **1000** according to some embodiments is shown. The data structure may include a designator for a specific phrase array **3010**. A phrase array may correspond to a specific unit of the syntax of an overall user communication. Each phrase array may contain one or more phrases **3040**, indicated by a specific phrase ID **3020**. Associated with each phrase **3040** is a selection frequency distribution indicator **3030**. In the illustrative data structure **3000** this selection frequency distribution of phrases **3040** in a phrase array **3010** is based on the relative magnitude of the value of the frequency distribution indicator. In other embodiments, other ways to provide selection frequency distributions may be applied. For example, phrases **3040** may be selected per a uniform distribution across phrase instances in a phrase array **3010**, and duplication of phrase instances may be used to as a means to adjust selection frequencies.

Communication of Self-Awareness

FIG. **10** is a flow diagram of the computer-based adaptive self-awareness communication process **2000** in accordance with some embodiments of the present invention. The process **2000** begins with an evaluation **2010** of phrase frequency distribution **3030** changes over time. Then the appropriate syntactical structure of the communication **250c** of self-awareness is determined **2020**. One or more phrases **3040** that embody a sense of self-awareness are then selected in accordance with the syntactical structure requirements and changes in phrase frequency distributions over time.

Returning to FIG. 11, in some embodiments, phrase attributes that are associated with specific phrases may be used as a basis for self-aware phrase selection. Two example phrase attributes **3050**, **3060** whose values are associated with specific phrases **3040** are shown. An unlimited number of attributes could be used as to provide as nuanced a level of self-awareness as desired.

When changes in phrase frequency distributions **3030** are evaluated **2010**, the corresponding attributes **3050**, **3060** are also evaluated. These attributes map to attributes **4050**, **4060** that are associated with self-aware phrases **4040** in self-aware phrase data structure **4000**. For example, if phrases **3040** that have the attribute value “humorous” have been increasing in frequency, then self-aware phrases that reference “humorous” may be appropriate to include in generating **2040** a communication of self-awareness **250c** to a user **200**. As is the case of any other communication **250c**, the behaviors **920** of the recipient **200** of the communication may be evaluated **2050**, and the self-aware phrase frequency distributions **4030** of the self-aware phrases **4040** may be updated **2060** accordingly. This recursive evaluation and updating of phrase frequency distributions can be applied without limit.

FIG. 12 depicts the major functions associated with a computer based system **925** that exhibits an adaptive personality, and optionally, a self-aware personality. Recall that in some embodiments, the computer-based system **925** comprises an adaptive system **100**.

A request **6000** for a communication to a user **200** is made. The request **6000** may be a direct request from a user **200**, or the request may be made by another function of the computer-based system **925**. In some embodiments the request **6000** for a communication to the user may be initiated by a function that generates **240** an adaptive recommendation. A communication to the user is then generated **7000**. This generation is done by first determining the appropriate syntactical rules or structure **7500** for the communication. In some embodiments, the syntax rules **7500** are of an “If some condition, Then apply a specific phrase array **3010**” structure. Once the appropriate syntax is established and associated phrase arrays **3010** are determined, specific phrases are probabilistically retrieved from the phrase array function **5000** based on selection frequency distributions associated with the corresponding phrase arrays. The communication **250c** is then assembled and delivered to a user **200**.

User behaviors **920** of the communication recipient **200** are then monitored **8000**. Based on inferences from these behaviors **920**, the phrase array frequency distributions of the phrase array function **5000** are updated **9000** appropriately. Computing Infrastructure

FIG. 13 depicts various computer hardware and network topologies on which the one or more computer-based applications **925** may operate.

Servers **950**, **952**, and **954** are shown, perhaps residing at different physical locations, and potentially belonging to different organizations or individuals. A standard PC workstation **956** is connected to the server in a contemporary fashion, potentially through the Internet. It should be understood that the workstation **956** can represent any computer-based device, mobile or fixed, including a set-top box. In this instance, the one or more computer-based applications **925**, in part or as a whole, may reside on the server **950**, but may be accessed by the workstation **956**. A terminal or display-only device **958** and a workstation setup **960** are also shown. The PC workstation **956** or servers **950** may be connected to a portable processing device (not shown), such as a mobile telephony device, which may be a mobile phone or a personal digital assistant (PDA). The mobile telephony device or PDA

may, in turn, be connected to another wireless device such as a telephone or a GPS receiver.

FIG. 13 also features a network of wireless or other portable devices **962**. The one or more computer-based applications **925** may reside, in part or as a whole, on all of the devices **962**, periodically or continuously communicating with the central server **952**, as required. A workstation **964** connected in a peer-to-peer fashion with a plurality of other computers is also shown. In this computing topology, the one or more computer-based applications **925**, as a whole or in part, may reside on each of the peer computers **964**.

Computing system **966** represents a PC or other computing system, which connects through a gateway or other host in order to access the server **952** on which the one or more computer-based applications **925**, in part or as a whole, reside. An appliance **968**, includes software “hardwired” into a physical device, or may utilize software running on another system that does not itself the one or more computer-based applications **925**. The appliance **968** is able to access a computing system that hosts an instance of one of the relevant systems, such as the server **952**, and is able to interact with the instance of the system.

While the present invention has been described with respect to a limited number of embodiments, those skilled in the art will appreciate numerous modifications and variations therefrom. It is intended that the appended claims cover all such modifications and variations as fall within the scope of this present invention.

What is claimed is:

1. A computer-based recommendation method comprising:

generating an affinity vector between a first user of a computer-based system and a plurality of computer-based objects based, at least in part, on the first user’s behaviors;

generating a similarity metric between the first user and a second user of the computer-based system based, at least in part, on the affinity vector of the first user and an affinity vector of the second user;

generating a recommendation for delivery to the first user based, at least in part, on the affinity vector of the first user and the similarity metric; and

generating an explanation for the recommendation comprising one or more phrases, wherein the selection of the one or more phrases is based, at least in part, on a plurality of user behaviors and in accordance with a computer-implemented syntactical structure.

2. The method of claim 1 wherein generating an affinity vector between a first user of a computer-based system and a plurality of computer-based objects based, at least in part, on the first user’s behaviors comprises:

generating affinities between the user and a plurality of topic objects.

3. The method of claim 1 wherein generating a recommendation for delivery to the first user based, at least in part, on the affinity vector of the first user and the similarity metric comprises:

recommending the second user to the first user.

4. The method of claim 1 wherein generating a recommendation for delivery to the first user based, at least in part, on the affinity vector of the first user and the similarity metric comprises:

generating a recommendation responsive to [the] a user’s search request.

5. The method of claim 1 wherein generating a recommendation for delivery to the first user based, at least in part, on the affinity vector of the first user and the similarity metric comprises:

generating a recommendation based on a recommendation preference setting [established by] *associated with* the user.

6. The method of claim 1 wherein generating an explanation for the recommendation comprising one or more phrases, wherein the selection of the one or more phrases is based, at least in part, on a plurality of user behaviors and in accordance with a computer-implemented syntactical structure comprises:

selecting phrases for inclusion in the explanation based on a frequency distribution.

7. The method of claim 1 wherein generating an explanation for the recommendation comprising one or more phrases, wherein the selection of the one or more phrases is based, at least in part, on a plurality of user behaviors and in accordance with a computer-implemented syntactical structure comprises:

selecting phrases for inclusion in the explanation in accordance with the calculated confidence level of the recommendation.

8. A computer-based recommendation system comprising: means to generate an affinity vector between a first user of a computer-based system and a plurality of computer-based objects based, at least in part, on the first user's behaviors;

means to generate a similarity metric between the first user and a second user of the computer-based system based, at least in part, on the affinity vector of the first user and an affinity vector of the second user;

means to generate a recommendation for delivery to the first user based, at least in part, on the affinity vector of the first user and the similarity metric; and

means to generate an explanation for the recommendation comprising one or more phrases, wherein the selection of the one or more phrases is based, at least in part, on a plurality of user behaviors and in accordance with a computer-implemented syntactical structure.

9. The system of claim 8 wherein means to generate an affinity vector between a first user of a computer-based system and a plurality of computer-based objects based, at least in part, on the first user's behaviors comprises:

means to generate affinities between the user and a plurality of topic objects.

10. The system of claim 8 wherein means to generate a recommendation for delivery to the first user based, at least in part, on the affinity vector of the first user and the similarity metric comprises:

means to recommend the second user to the first user.

11. The system of claim 8 wherein means to generate a recommendation for delivery to the first user based, at least in part, on the affinity vector of the first user and the similarity metric comprises:

means to generate a recommendation responsive to [the] *a* user's search request.

12. The system of claim 8 wherein means to generate a recommendation for delivery to the first user based, at least in part, on the affinity vector of the first user and the similarity metric comprises:

means for generating a recommendation based on a recommendation preference setting [established by] *associated with* the user.

13. The system of claim 8 wherein means to generate an explanation for the recommendation comprising one or more

phrases, wherein the selection of the one or more phrases is based, at least in part, on a plurality of user behaviors and in accordance with a computer-implemented syntactical structure comprises:

means to select phrases for inclusion in the explanation based on a frequency distribution.

14. The system of claim 8 wherein means to generate an explanation for the recommendation comprising one or more phrases, wherein the selection of the one or more phrases is based, at least in part, on a plurality of user behaviors and in accordance with a computer-implemented syntactical structure comprises:

means to select phrases for inclusion in the explanation in accordance with the calculated confidence level of the recommendation.

15. A computer-based recommendation explanation system comprising:

means to generate a recommendation based, at least in part, on a plurality of usage behaviors;

a syntactical structure for an explanation [of an associated] *for the* recommendation;

a plurality of phrase arrays associated with the syntactical structure, wherein each phrase array comprises a plurality of phrases;

a mapping of usage behaviors and corresponding phrase arrays [appropriate to apply]; and

means to generate [an] *the* explanation for the recommendation, wherein the explanation is generated in accordance with the syntactical structure and associated phrase arrays, and the mapping of usage behaviors with the corresponding phrase arrays [appropriate to apply].

16. The system of claim 15 wherein *the* means to generate an explanation for the recommendation, wherein the explanation is generated in accordance with the syntactical structure and associated phrase arrays, and the mapping of usage behaviors with the corresponding phrase arrays [appropriate to apply] comprises:

means to probabilistically select from alternative syntactical structures.

17. The system of claim 15 wherein *the* means to generate an explanation for the recommendation, wherein the explanation is generated in accordance with the syntactical structure and associated phrase arrays, and the mapping of usage behaviors with the corresponding phrase arrays [appropriate to apply] comprises:

means to select phrases from a frequency distribution for inclusion in the explanation.

18. The system of claim 15 wherein *the* means to generate an explanation for the recommendation, wherein the explanation is generated in accordance with the syntactical structure and associated phrase arrays, and the mapping of usage behaviors with the corresponding phrase arrays [appropriate to apply] comprises:

means to apply behavioral thresholds to trigger [appropriate] phrase arrays.

19. The system of claim 15 wherein *the* means to generate an explanation for the recommendation, wherein the explanation is generated in accordance with the syntactical structure and associated phrase arrays, and the mapping of usage behaviors with the corresponding phrase arrays [appropriate to apply] comprises:

means to adjust the selection of phrases for inclusion in the explanation based on the phrase composition of previously generated explanations.

20. The system of claim 15 wherein *the* means to generate an explanation for the recommendation, wherein the explanation is generated in accordance with the syntactical struc-

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ture and associated phrase arrays, and the mapping of usage behaviors with the corresponding phrase arrays [appropriate to apply] comprises:

means to adjust the selection of phrases for inclusion in the explanation based on usage behaviors of recipients of previously generated explanations.

21. A method comprising:

generating, by a processing device, a recommendation of a computer-based object for delivery to a first user of a computer-based system based on first user behavior associated with a plurality of computer-based objects; and

generating, by the processing device, an explanation for the recommendation comprising one or more phrases based on a plurality of other user behaviors and in accordance with a computer-implemented syntactical structure.

22. The method of claim 21, further comprising,

generating, by the processing device, a first affinity vector associated with the first user based on the first user behavior associated with the plurality of computer-based objects;

generating, by the processing device, a similarity metric between the first user and a second user of the computer-based system based on the first affinity vector and a second affinity vector associated with the second user; wherein, the generating the recommendation is based on the first affinity vector and the similarity metric.

23. The method of claim 22 wherein the second affinity vector is based on the second user behavior associated with the plurality of computer-based objects.

24. The method of claim 22 wherein the second affinity vector is based on the second user behavior associated with a different plurality of computer-based objects.

25. The method of claim 22 wherein the generating the affinity vector further comprises generating, by the processing device, affinities between the user and a plurality of topic objects.

26. The method of claim 22 wherein the recommendation further comprises recommending the second user to the first user.

27. The method of claim 21 wherein the recommendation is responsive to a search request associated with the first user.

28. The method of claim 21 wherein the recommendation is based on a recommendation preference setting associated with the first user.

29. The method of claim 21 wherein the generating the explanation further comprises selecting, by the processing device, phrases for inclusion in the explanation based on a frequency distribution.

30. The method of claim 21 the generating the explanation further comprises selecting, by the processing device, phrases for inclusion in the explanation in accordance with the calculated confidence level of the recommendation.

31. An apparatus comprising:

means for generating a recommendation of a computer-based object for delivery to a first user of a computer-based system based on first user behavior associated with a plurality of computer-based objects; and

means for generating an explanation for the recommendation comprising one or more phrases based on a plurality of other user behaviors and in accordance with a computer-implemented syntactical structure.

32. The apparatus of claim 31, further comprising,

means for generating a first affinity vector associated with the first user based on the first user behavior associated with the plurality of computer-based objects;

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means for generating a similarity metric between the first user and a second user of the computer-based system based on the first affinity vector and a second affinity vector associated with the second user;

wherein, the generating the recommendation is based on the first affinity vector and the similarity metric.

33. The apparatus of claim 32 wherein the second affinity vector is based on the second user behavior associated with the plurality of computer-based objects.

34. The apparatus of claim 32 wherein the second affinity vector is based on the second user behavior associated with a different plurality of computer-based objects.

35. The apparatus of claim 32 wherein the means for generating the affinity vector further comprises means for generating affinities between the user and a plurality of topic objects.

36. The apparatus of claim 31 wherein the recommendation further comprises recommending the second user to the first user.

37. The apparatus of claim 31 wherein the recommendation is responsive to a search request associated with the first user.

38. The apparatus of claim 31 wherein the recommendation is based on a recommendation preference setting associated with the first user.

39. The apparatus of claim 31 wherein the means for generating the explanation further comprises means for selecting phrases for inclusion in the explanation based on a frequency distribution.

40. The apparatus of claim 31 wherein the means for generating the explanation further comprises means for selecting phrases for inclusion in the explanation in accordance with the calculated confidence level of the recommendation.

41. An apparatus, comprising:

computer hardware configured to:

store instructions associated with an application program; and

execute the stored instructions to:

generate a recommendation based, at least in part, on a plurality of usage behaviors;

associate a plurality of phrase arrays with a syntactical structure;

map the plurality of usage behaviors and corresponding phrase arrays selected from the plurality of phrase arrays; and

generate an explanation for the recommendation based on the map, the explanation comprising a phrase associated with one of the corresponding phrase arrays in accordance with the syntactical structure.

42. The apparatus of claim 41, wherein the corresponding phrase array comprises a plurality of phrases.

43. The apparatus of claim 41 wherein the computer hardware is further configured to select alternative syntactical structures based on probabilistic determination to generate the explanation.

44. The apparatus of claim 41 wherein the computer hardware is further configured to select the phrase from a frequency distribution for inclusion to generate the explanation.

45. The apparatus of claim 41 wherein the computer hardware is further configured to apply behavioral thresholds to map the plurality of usage behaviors and corresponding phrase arrays selected from the plurality of phrase arrays.

46. The apparatus of claim 41 wherein the computer hardware is further configured to adjust the selection of the phrase for inclusion in the explanation based on the phrase composition of previously generated explanations.

47. The apparatus of claim 41 wherein the computer hardware is further configured to adjust the selection of the phrase for inclusion in the explanation based on usage behaviors of recipients of previously generated explanations.

48. Computer hardware having instructions stored thereon 5
that, in response to execution by a processing device, cause the processing device to perform operations comprising:
generating a recommendation based, at least in part, on a plurality of usage behaviors;
associating a plurality of phrase arrays with a syntactical 10
structure;
mapping the plurality of usage behaviors and corresponding phrase arrays selected from the plurality of phrase arrays; and
generating an explanation for the recommendation based 15
on the map, the explanation comprising a phrase associated with one of the corresponding phrase arrays in accordance with the syntactical structure.

49. The computer-readable-memory device of claim 48, wherein the corresponding phrase array comprises a plurality of phrases.

50. The computer hardware of claim 48 wherein the operations further comprise selecting alternative syntactical structures based on probabilistic determination to generate the explanation.

51. The computer hardware of claim 48 wherein the operations further comprise selecting the phrase from a frequency distribution for inclusion to generate the explanation.

52. The computer hardware of claim 48 wherein the operations further comprise applying behavioral thresholds to map the plurality of usage behaviors and corresponding phrase arrays selected from the plurality of phrase arrays.

53. The computer hardware of claim 48 wherein the operations further comprise adjusting the selection of the phrase for inclusion in the explanation based on the phrase composition of previously generated explanations.

54. The computer hardware of claim 49 wherein the operations further comprise adjusting the selection of the phrase for inclusion in the explanation based on usage behaviors of recipients of previously generated explanations.

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