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Flinn et al.

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(54) **ITERATIVE ATTENTION-BASED NEURAL NETWORK TRAINING AND PROCESSING**

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(73) Assignee: **Steven D. Flinn**, Sugar Land, TX (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

This patent is subject to a terminal disclaimer.

(21) Appl. No.: **18/972,773**

(22) Filed: **Dec. 6, 2024**

Related U.S. Application Data

(60) Division of application No. 18/810,465, filed on Aug. 20, 2024, now Pat. No. 12,307,342, which is a continuation of application No. 18/101,612, filed on Jan. 26, 2023, now Pat. No. 12,223,404, which is a continuation of application No. 16/660,908, filed on Oct. 23, 2019, now Pat. No. 11,593,708, which is a continuation of application No. 15/000,011, filed on Jan. 18, 2016, now Pat. No. 10,510,018, which is a

(Continued)

(51) **Int. Cl.**

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G06F 40/211	(2020.01)
G06F 40/216	(2020.01)
G06F 40/30	(2020.01)
G06N 3/02	(2006.01)
G06N 3/045	(2023.01)
G06N 5/045	(2023.01)
G06N 5/048	(2023.01)

(52) **U.S. Cl.**
CPC ***G06N 20/00*** (2019.01); ***G06F 40/211*** (2020.01); ***G06F 40/216*** (2020.01); ***G06F 40/30*** (2020.01); ***G06N 3/045*** (2023.01); ***G06N 5/045*** (2013.01); ***G06N 5/048*** (2013.01); *G06N 3/02* (2013.01)

(58) **Field of Classification Search**
CPC G06N 20/00; G06N 3/045; G06N 5/045; G06N 5/048; G06N 3/02; G06F 40/211; G06F 40/216; G06F 40/30
See application file for complete search history.

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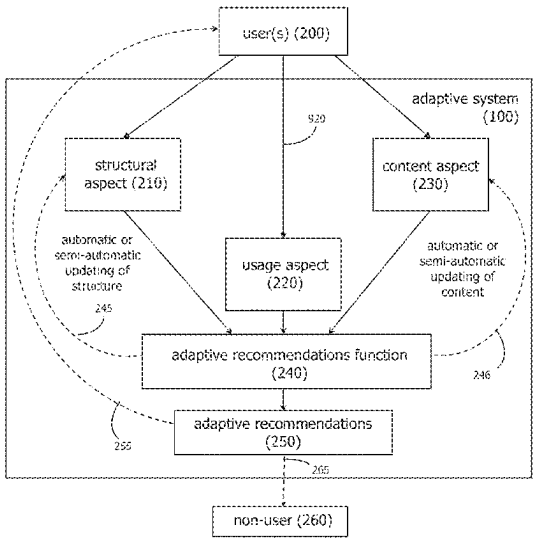
(Continued)

Primary Examiner — Eric Nilsson

(57) **ABSTRACT**

An iterative attention-based neural network training and processing method and system iteratively applies a focus of attention of a trained neural network on syntactical elements and generates probabilities associated with representations of the syntactical elements, which in turn inform a subsequent focus of attention of the neural network, resulting in updated probabilities. The updated probabilities are then applied to generate syntactical elements for delivery to a user. The user may respond to the delivered syntactical elements, providing additional training information to the trained neural network.

12 Claims, 18 Drawing Sheets



Related U.S. Application Data

continuation-in-part of application No. 14/816,439, filed on Aug. 3, 2015, now abandoned.

(56) **References Cited**

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List of References Considered by Examiner in Parent U.S. Appl. No. 12/223,404, now Issued as U.S. Pat. No. 12,223,404B2, mail room dated Nov. 19, 2024 and Jul. 29, 2024.

* cited by examiner

Figure 1

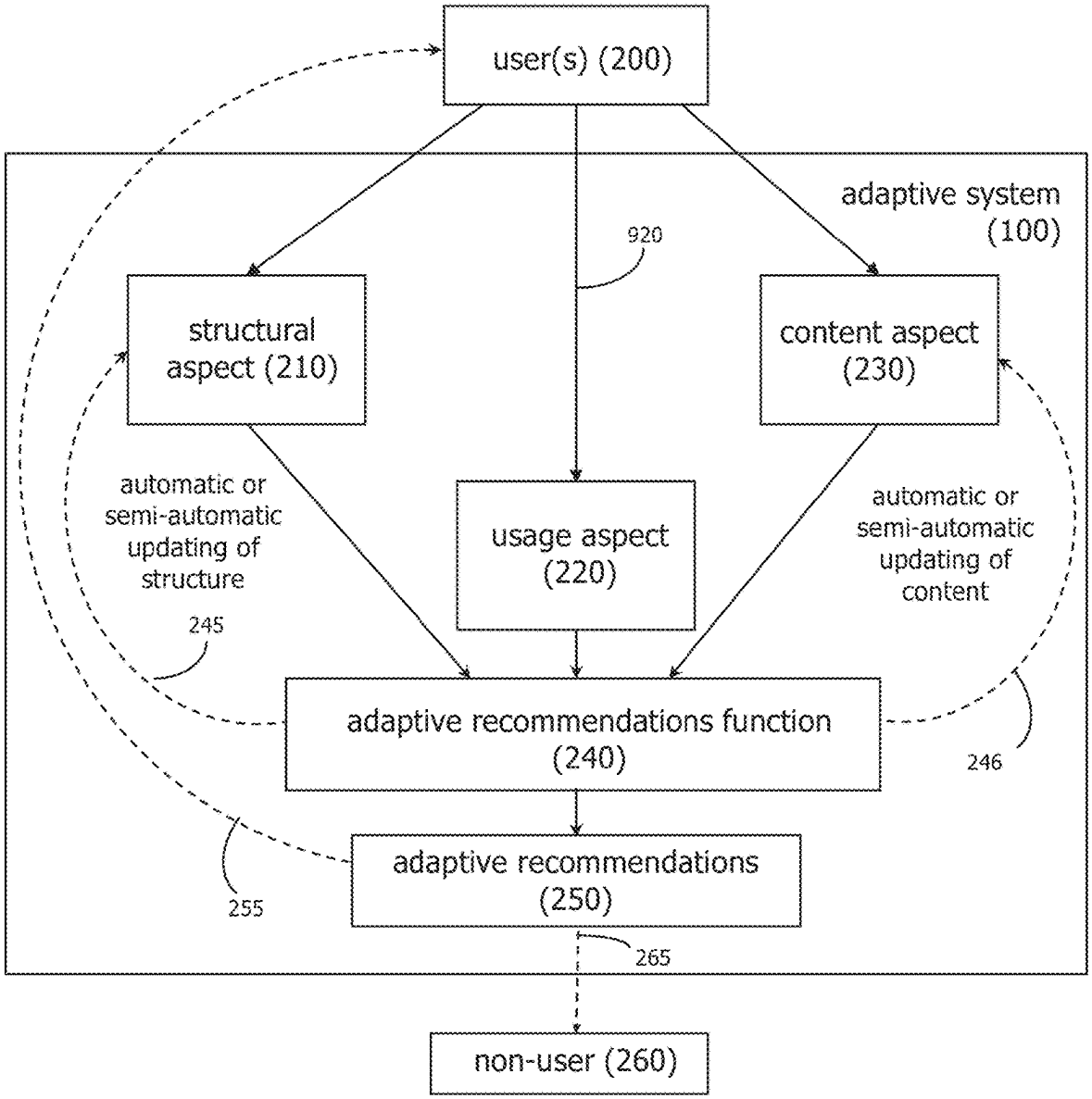

user(s) (200)
adaptive system (100)
920
structural aspect (210)
content aspect (230)
automatic or semi-automatic updating of structure
usage aspect (220)
automatic or semi-automatic updating of content
245
adaptive recommendations function (240)
246
adaptive recommendations (250)
255
265
non-user (260)

Figure 2A

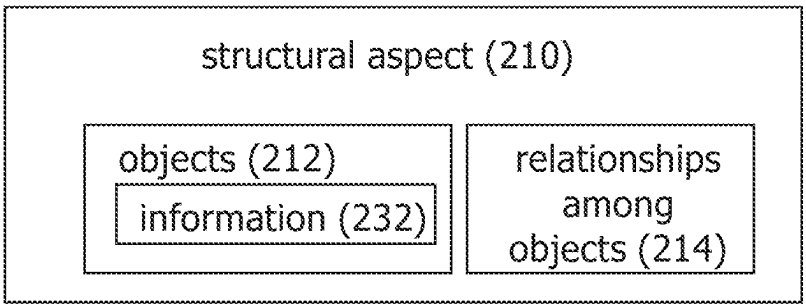


Figure 2B

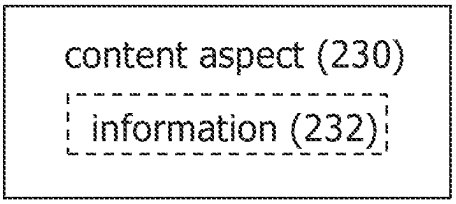


Figure 2C

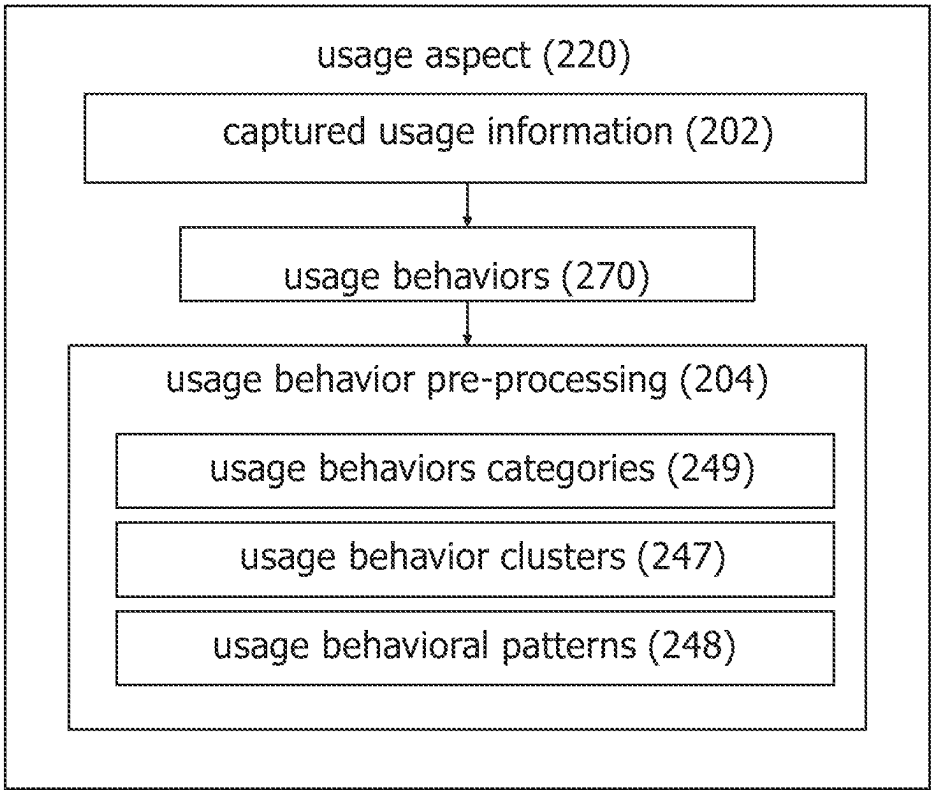


Figure 3

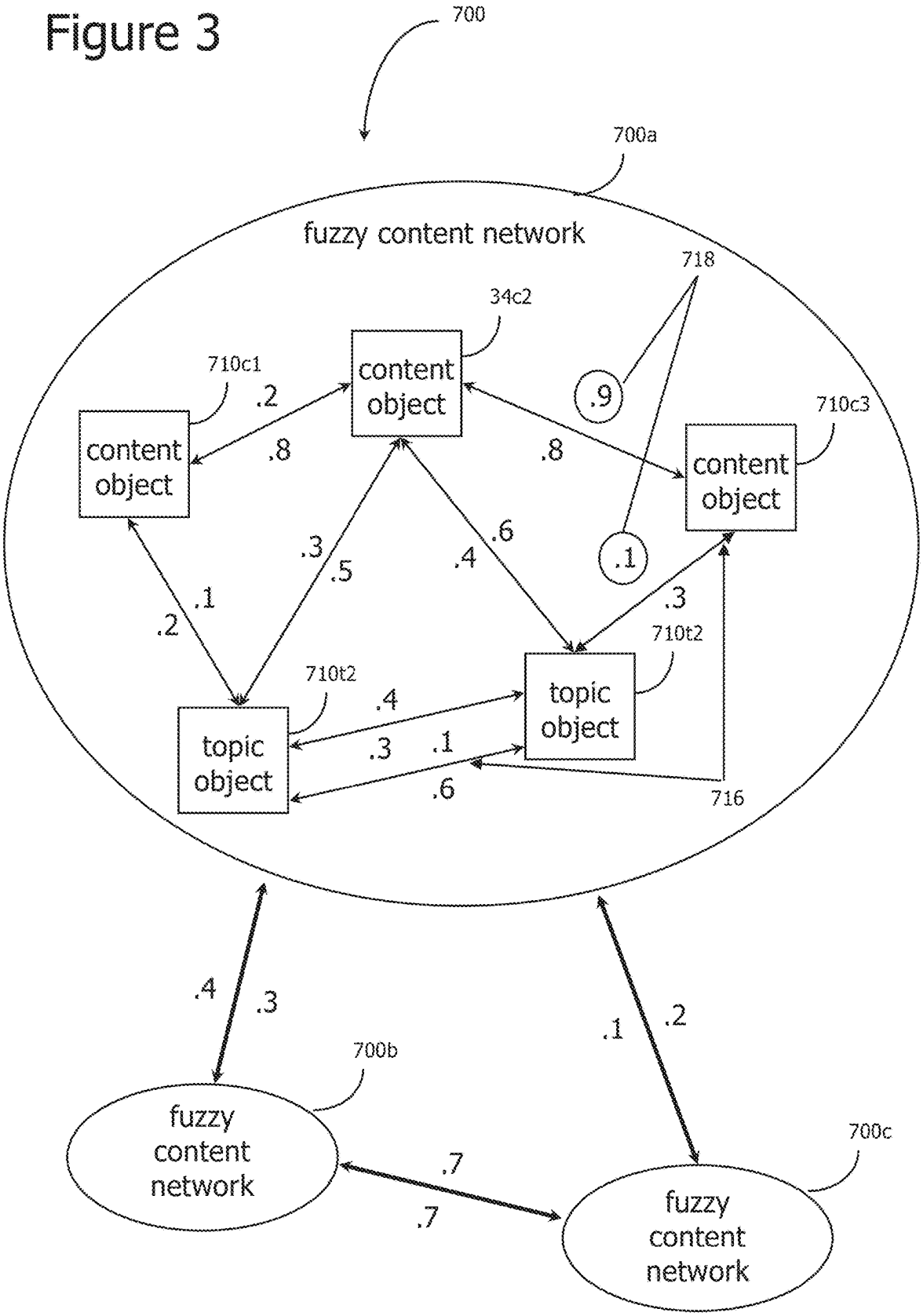

700
700a
fuzzy content network
718
34c2
content object
710c1
content object
710c3
content object
.2
.8
.8
.9
.1
.3
.5
.4
.6
.1
.2
.3
710t2
topic object
710t2
topic object
.4
.3
.1
.6
716
.4
.3
.1
.2
700b
fuzzy content network
700c
fuzzy content network
.7
.7

Figure 4A

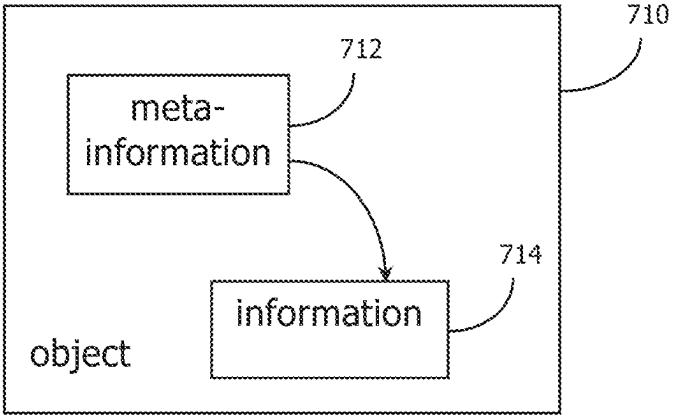


Figure 4B

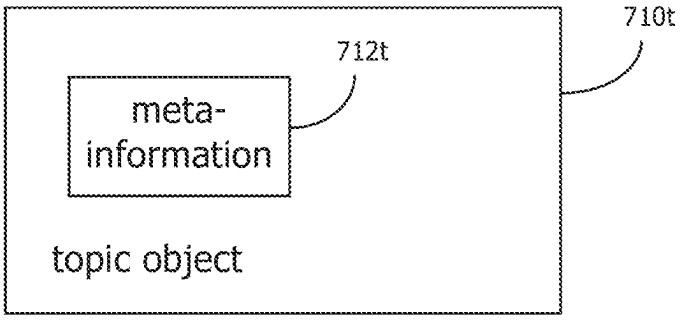


Figure 4C

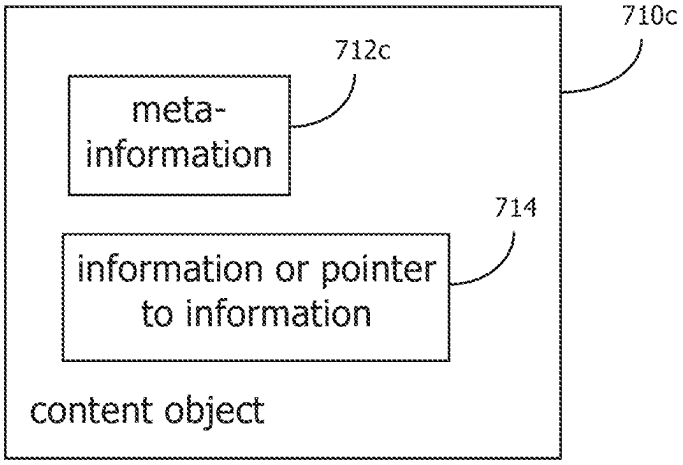


Figure 5A

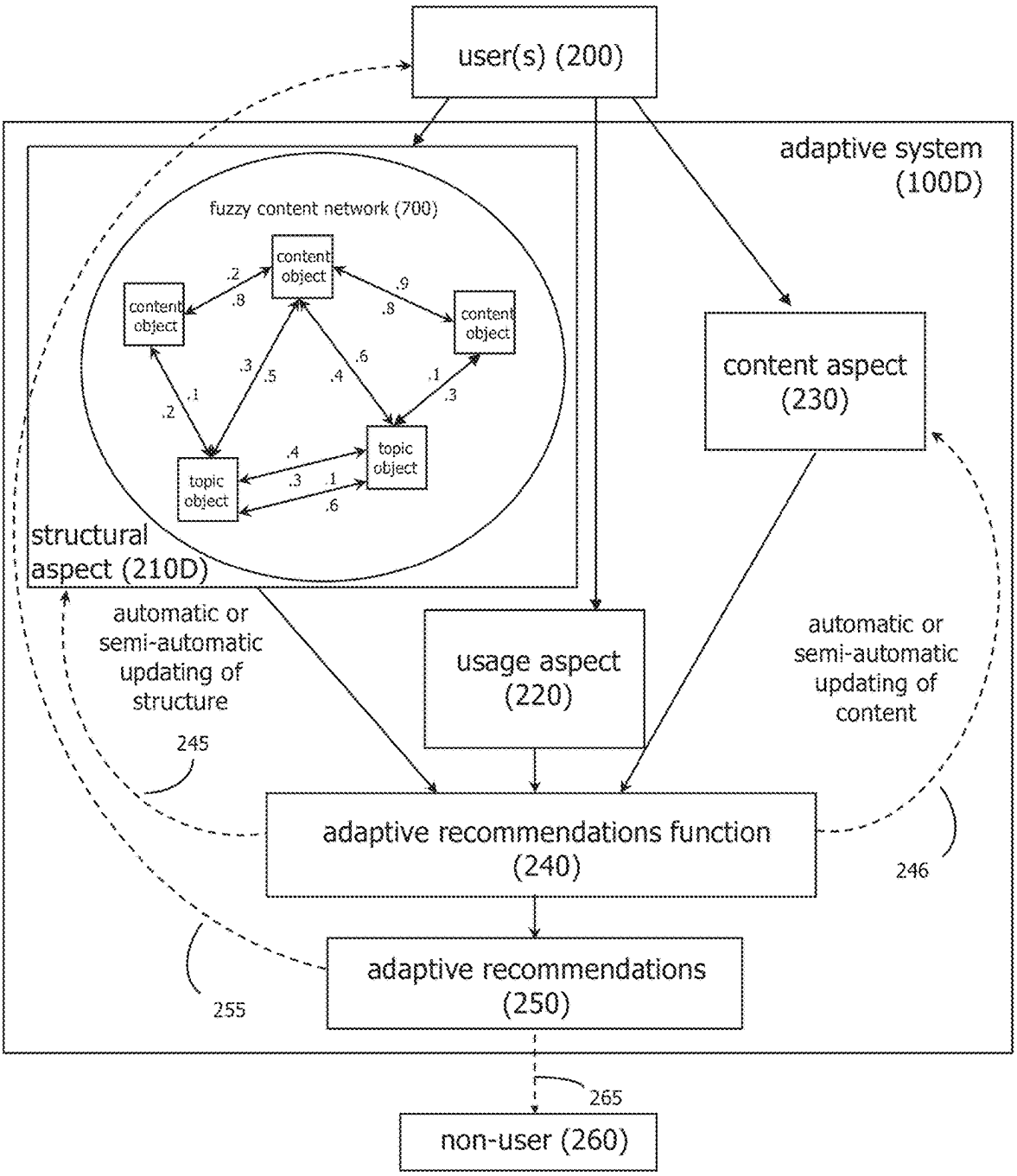

user(s) (200)
adaptive system (100D)
fuzzy content network (700)
content object
content object
content object
topic object
topic object
.2
.8
.9
.8
.1
.2
.3
.5
.4
.6
.1
.3
.4
.3
.1
.6
structural aspect (210D)
content aspect (230)
usage aspect (220)
automatic or semi-automatic updating of structure
automatic or semi-automatic updating of content
245
246
adaptive recommendations function (240)
adaptive recommendations (250)
255
265
non-user (260)

Figure 6

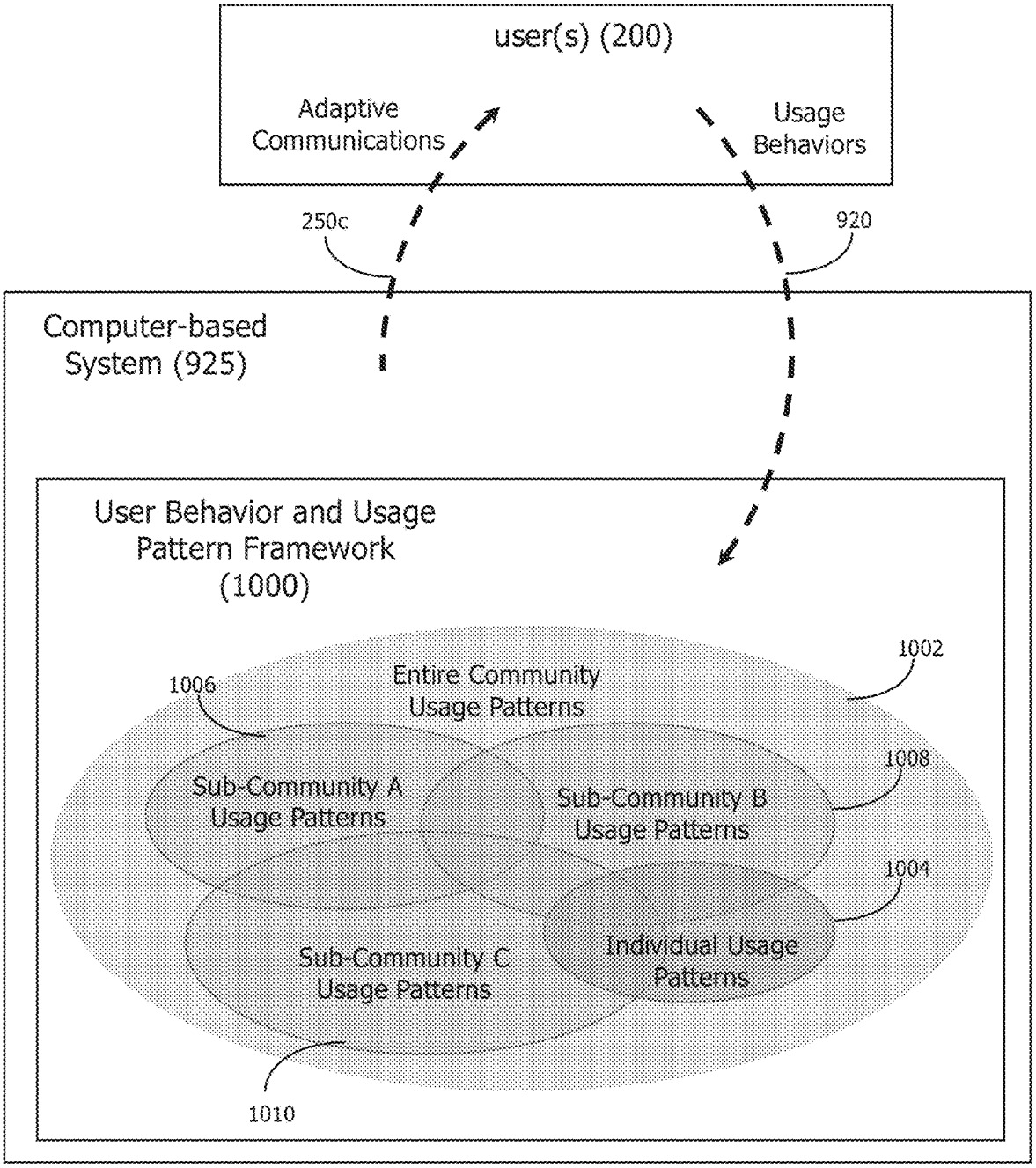

user(s) (200)
Adaptive Communications
Usage Behaviors
250c
920
Computer-based System (925)
User Behavior and Usage Pattern Framework (1000)
1002
1006
Entire Community Usage Patterns
1008
Sub-Community A Usage Patterns
Sub-Community B Usage Patterns
1004
Sub-Community C Usage Patterns
Individual Usage Patterns
1010

Figure 7

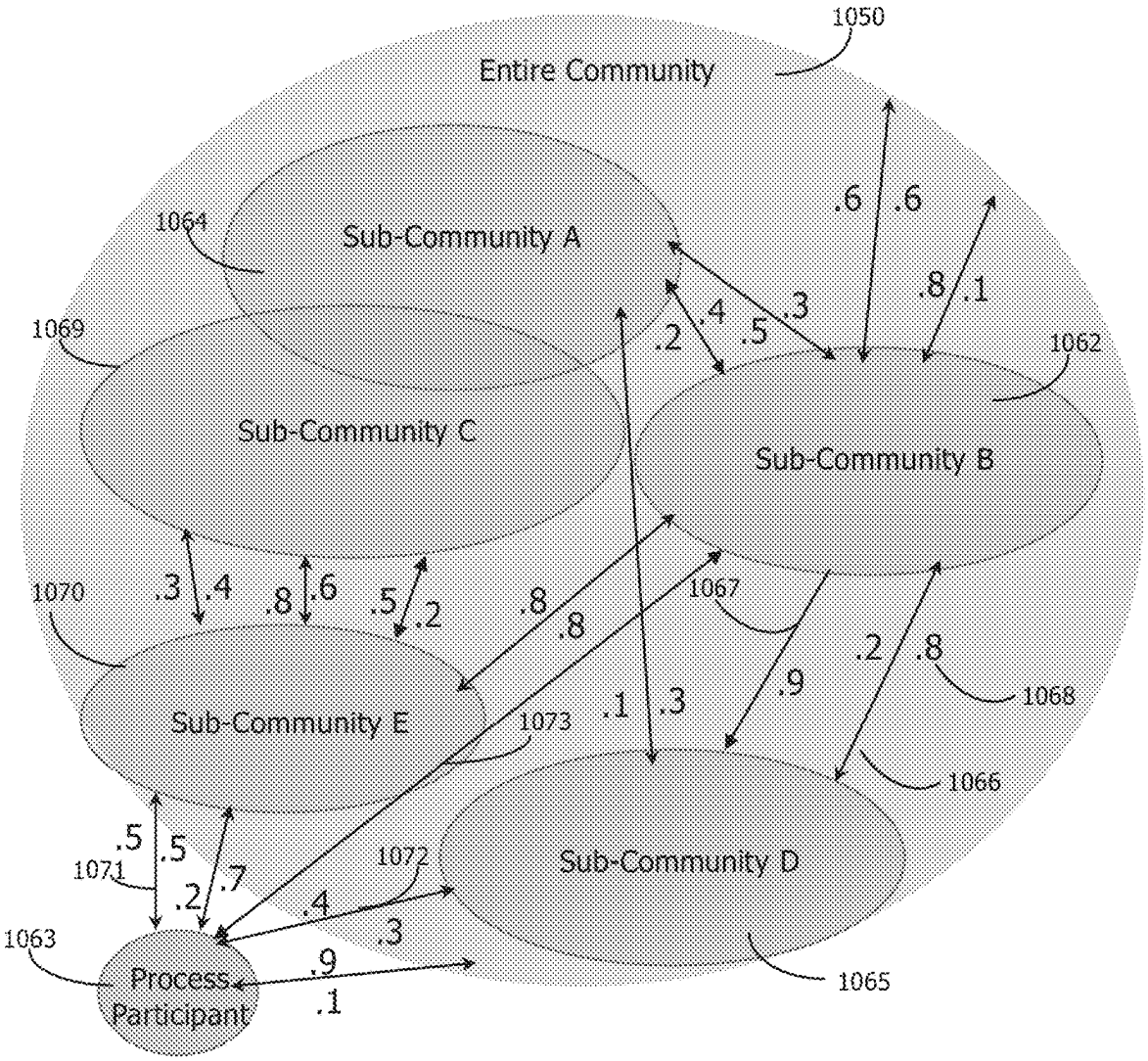

1050
Entire Community
1064
Sub-Community A
1069
Sub-Community C
1062
Sub-Community B
1070
Sub-Community E
1067
1068
1066
1073
1071
1072
Sub-Community D
1063
Process Participant
1065
.6
.6
.8
.1
.2
.4
.5
.3
.3
.4
.8
.6
.5
.2
.8
.8
.1
.3
.9
.2
.8
.5
.5
.2
.7
.4
.3
.9
.1

Figure 8

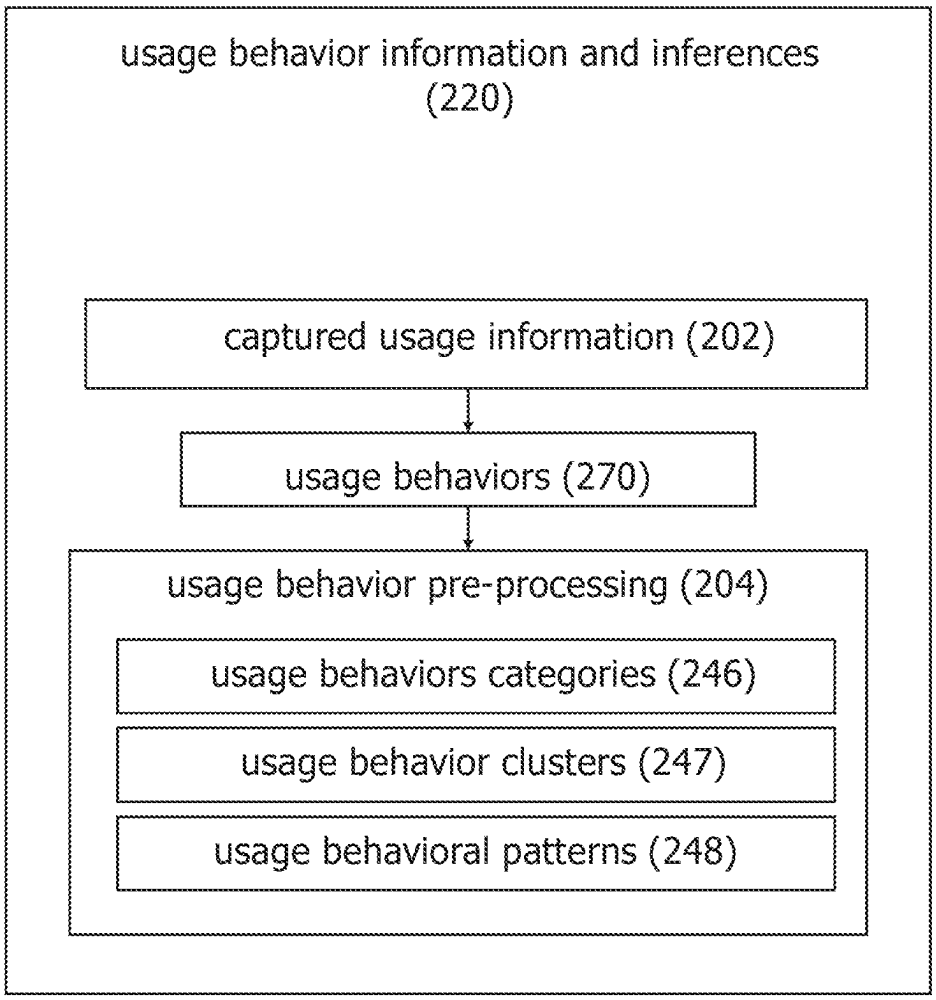

usage behavior information and inferences (220)
captured usage information (202)
usage behaviors (270)
usage behavior pre-processing (204)
usage behaviors categories (246)
usage behavior clusters (247)
usage behavioral patterns (248)

Figure 9

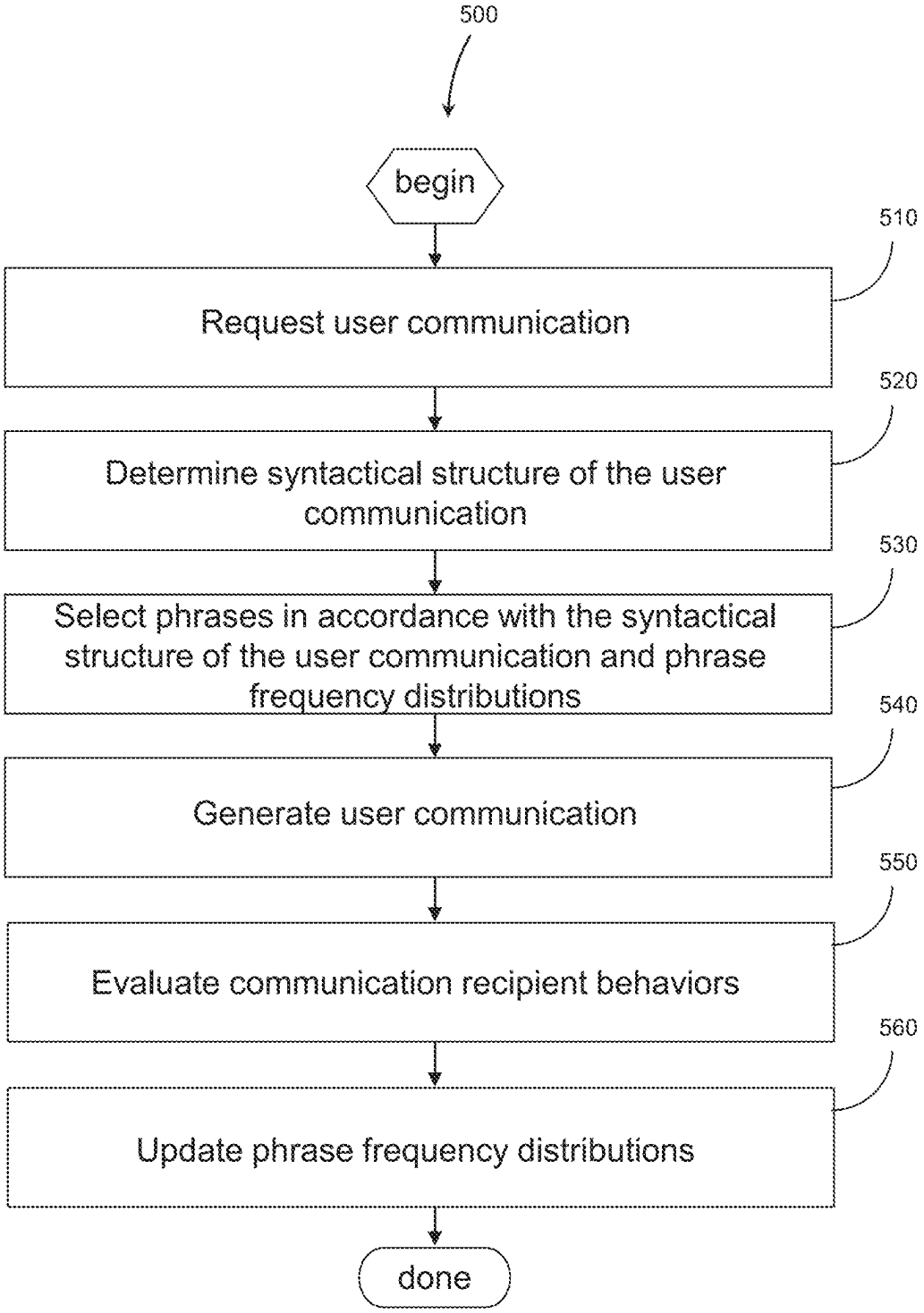

500
begin
510
Request user communication
520
Determine syntactical structure of the user communication
530
Select phrases in accordance with the syntactical structure of the user communication and phrase frequency distributions
540
Generate user communication
550
Evaluate communication recipient behaviors
560
Update phrase frequency distributions
done

Figure 10

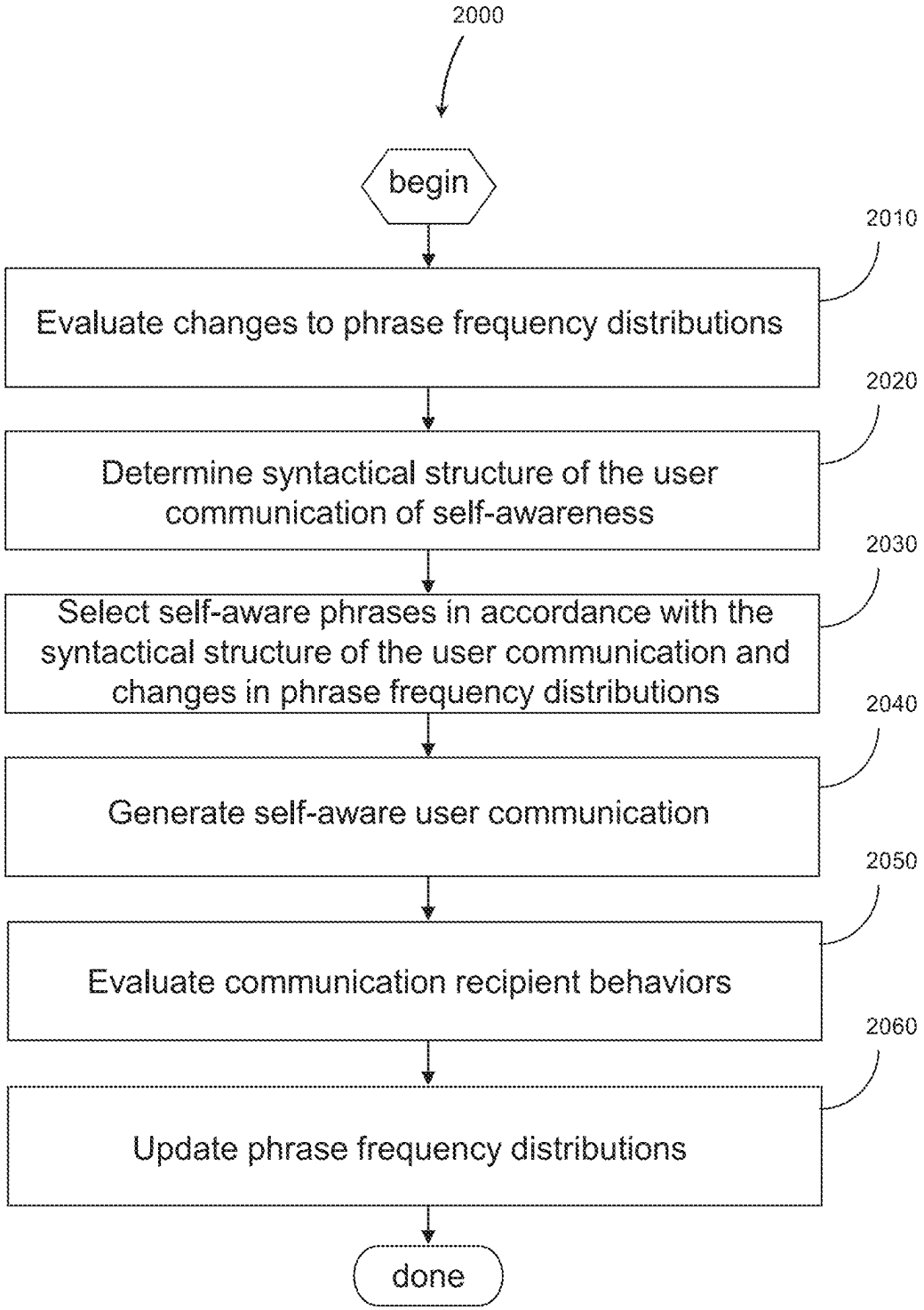

2000
begin
2010
Evaluate changes to phrase frequency distributions
2020
Determine syntactical structure of the user communication of self-awareness
2030
Select self-aware phrases in accordance with the syntactical structure of the user communication and changes in phrase frequency distributions
2040
Generate self-aware user communication
2050
Evaluate communication recipient behaviors
2060
Update phrase frequency distributions
done

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	3032 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

4010 Phrase Array	4020 Phrase ID	4030 Relative Frequency	4040 Phrase	4060 Phrase Attribute 2	4070 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

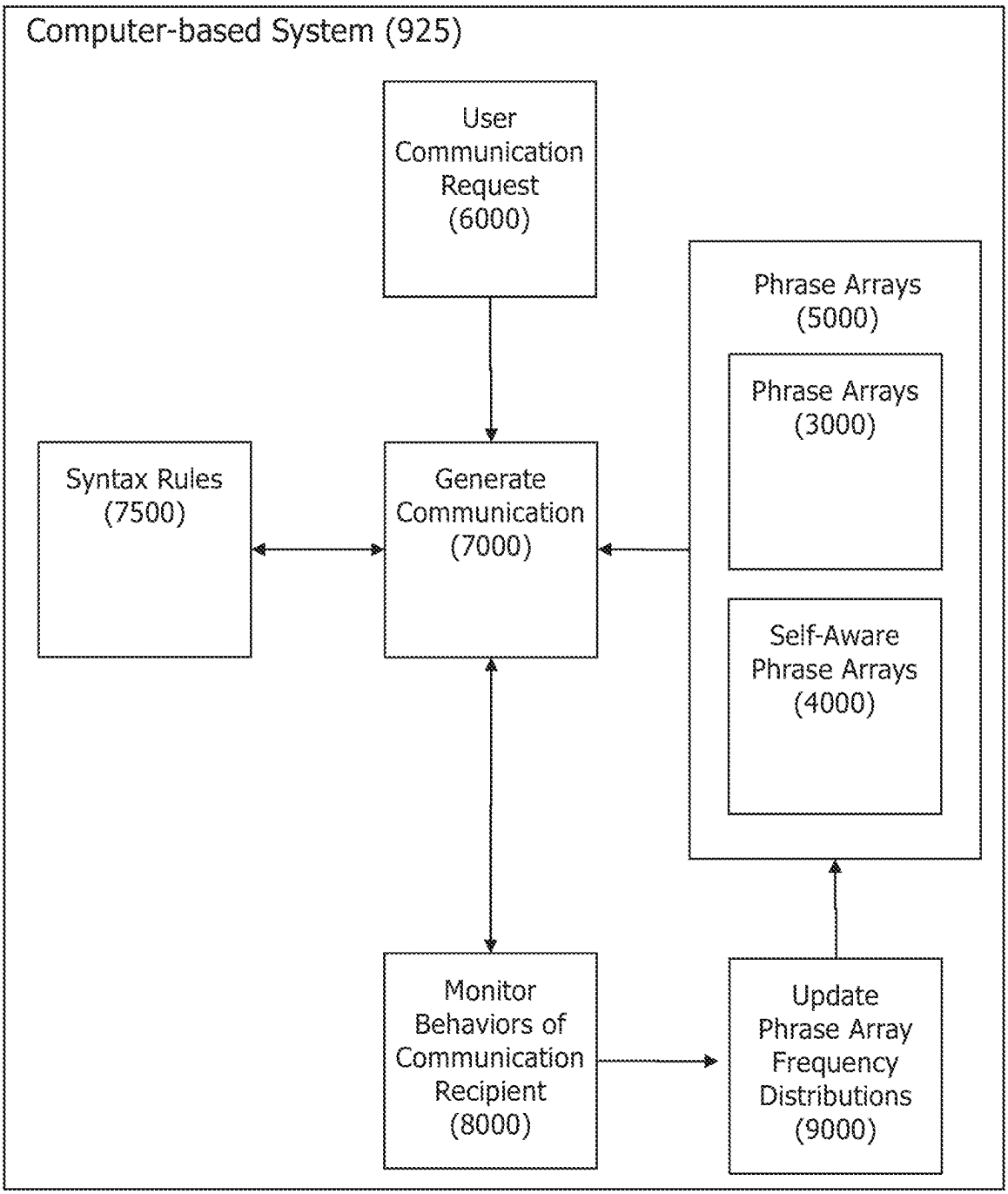

Computer-based System (925)
User Communication Request (6000)
Phrase Arrays (5000)
Phrase Arrays (3000)
Syntax Rules (7500)
Generate Communication (7000)
Self-Aware Phrase Arrays (4000)
Monitor Behaviors of Communication Recipient (8000)
Update Phrase Array Frequency Distributions (9000)

Figure 13

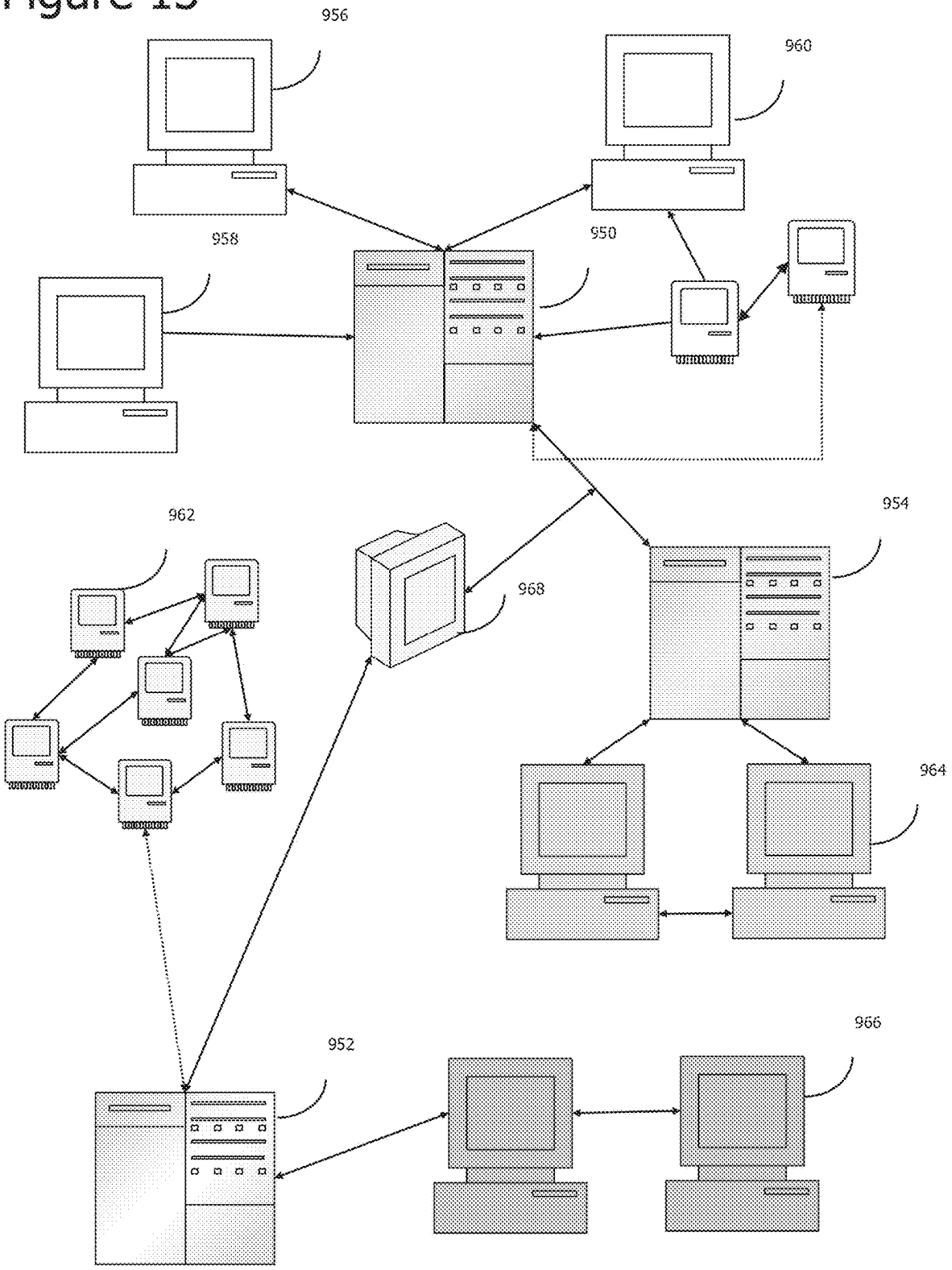


Figure 14A

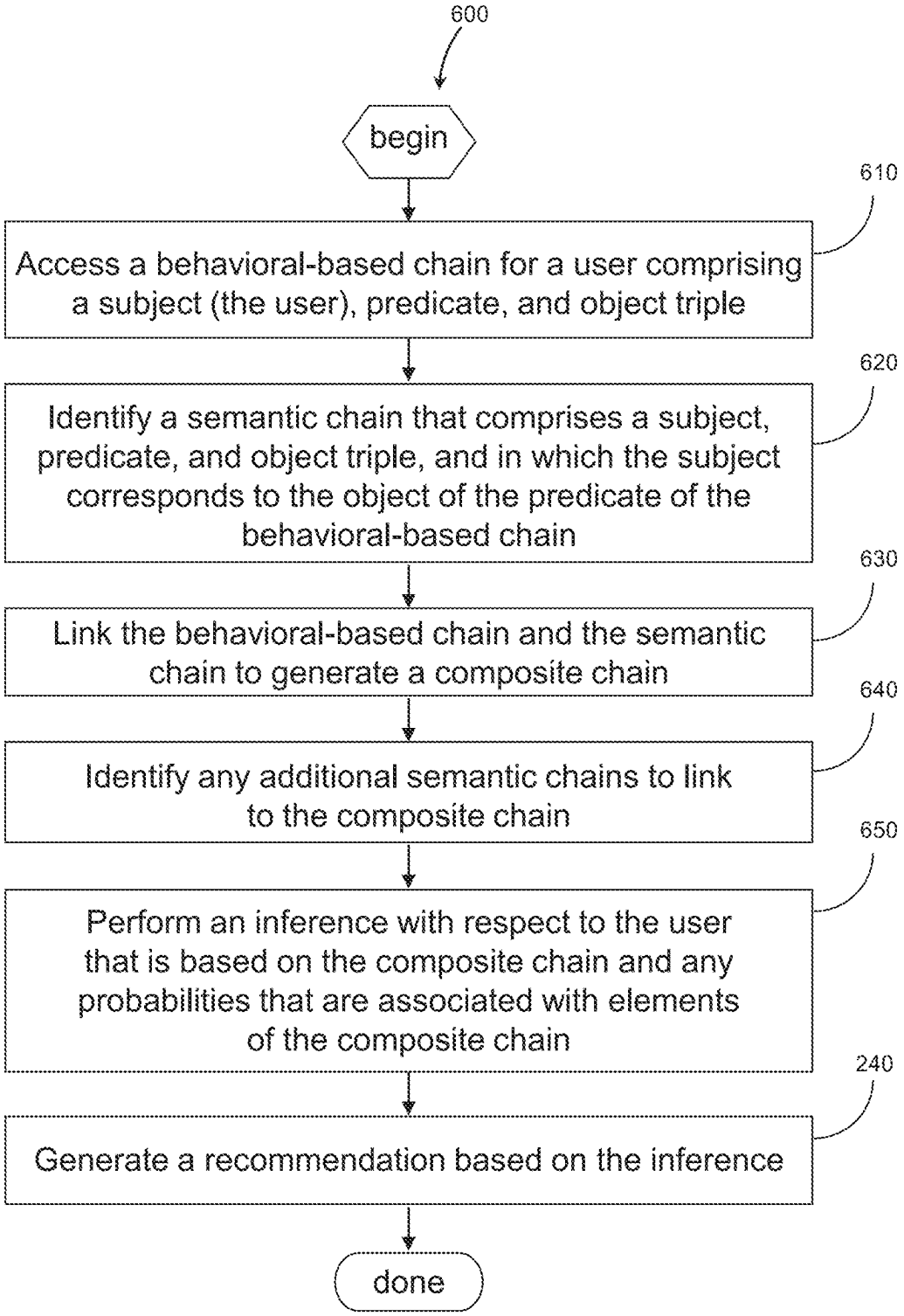

600
begin
610
Access a behavioral-based chain for a user comprising a subject (the user), predicate, and object triple
620
Identify a semantic chain that comprises a subject, predicate, and object triple, and in which the subject corresponds to the object of the predicate of the behavioral-based chain
630
Link the behavioral-based chain and the semantic chain to generate a composite chain
640
Identify any additional semantic chains to link to the composite chain
650
Perform an inference with respect to the user that is based on the composite chain and any probabilities that are associated with elements of the composite chain
240
Generate a recommendation based on the inference
done

Figure 14B

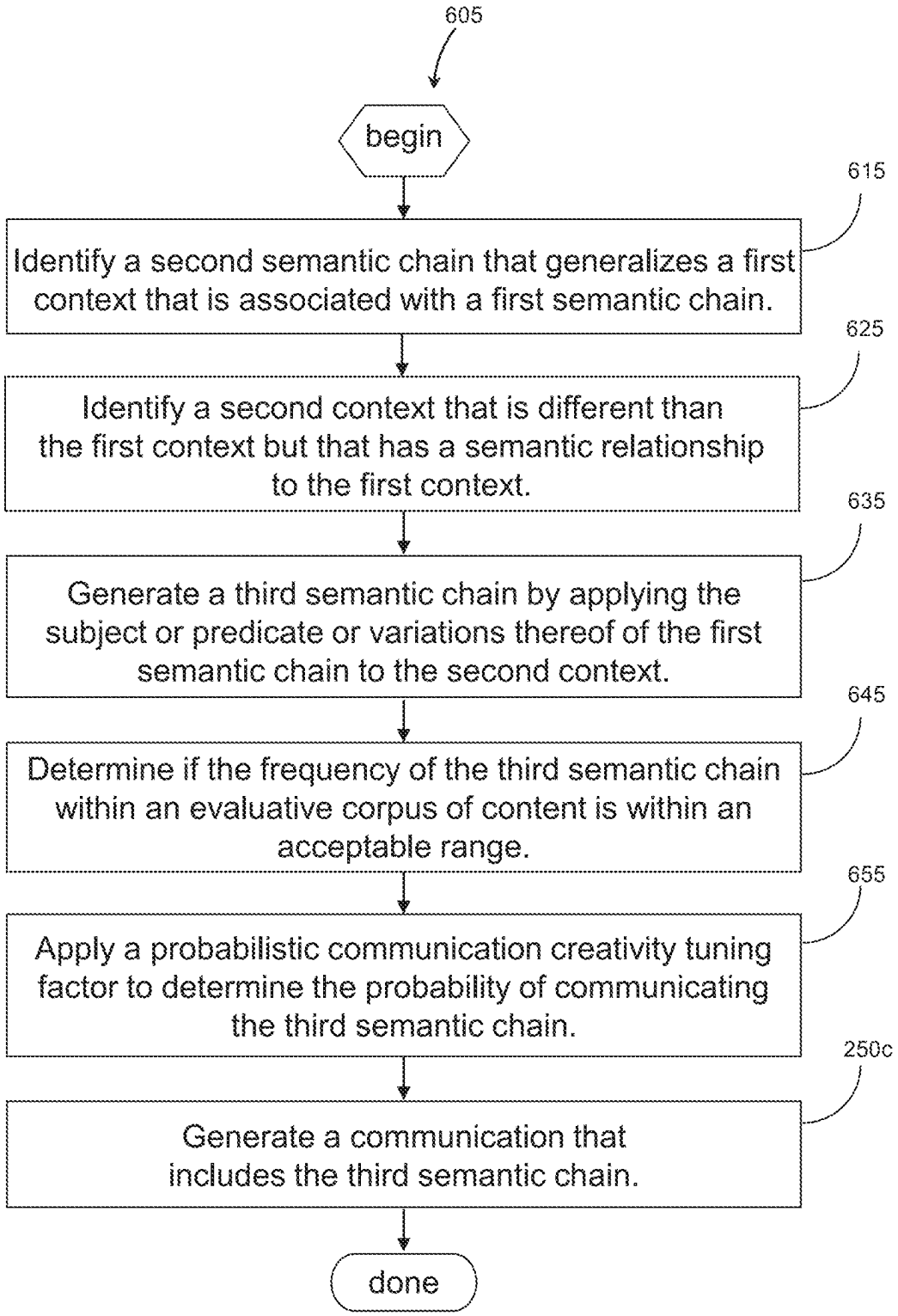

605
begin
615
Identify a second semantic chain that generalizes a first context that is associated with a first semantic chain.
625
Identify a second context that is different than the first context but that has a semantic relationship to the first context.
635
Generate a third semantic chain by applying the subject or predicate or variations thereof of the first semantic chain to the second context.
645
Determine if the frequency of the third semantic chain within an evaluative corpus of content is within an acceptable range.
655
Apply a probabilistic communication creativity tuning factor to determine the probability of communicating the third semantic chain.
250c
Generate a communication that includes the third semantic chain.
done

Figure 14C

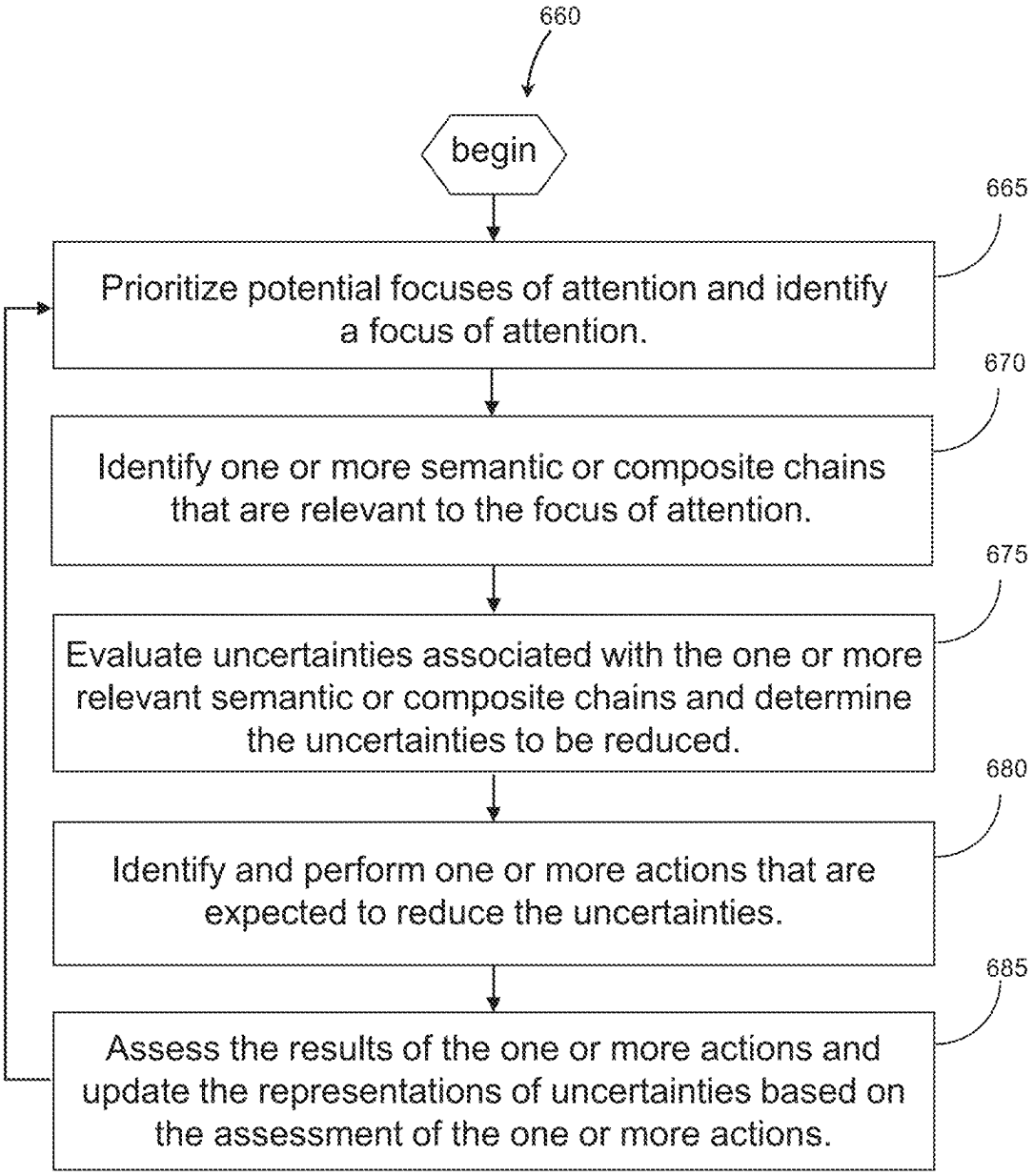

660
begin
665
Prioritize potential focuses of attention and identify a focus of attention.
670
Identify one or more semantic or composite chains that are relevant to the focus of attention.
675
Evaluate uncertainties associated with the one or more relevant semantic or composite chains and determine the uncertainties to be reduced.
680
Identify and perform one or more actions that are expected to reduce the uncertainties.
685
Assess the results of the one or more actions and update the representations of uncertainties based on the assessment of the one or more actions.

Figure 14D

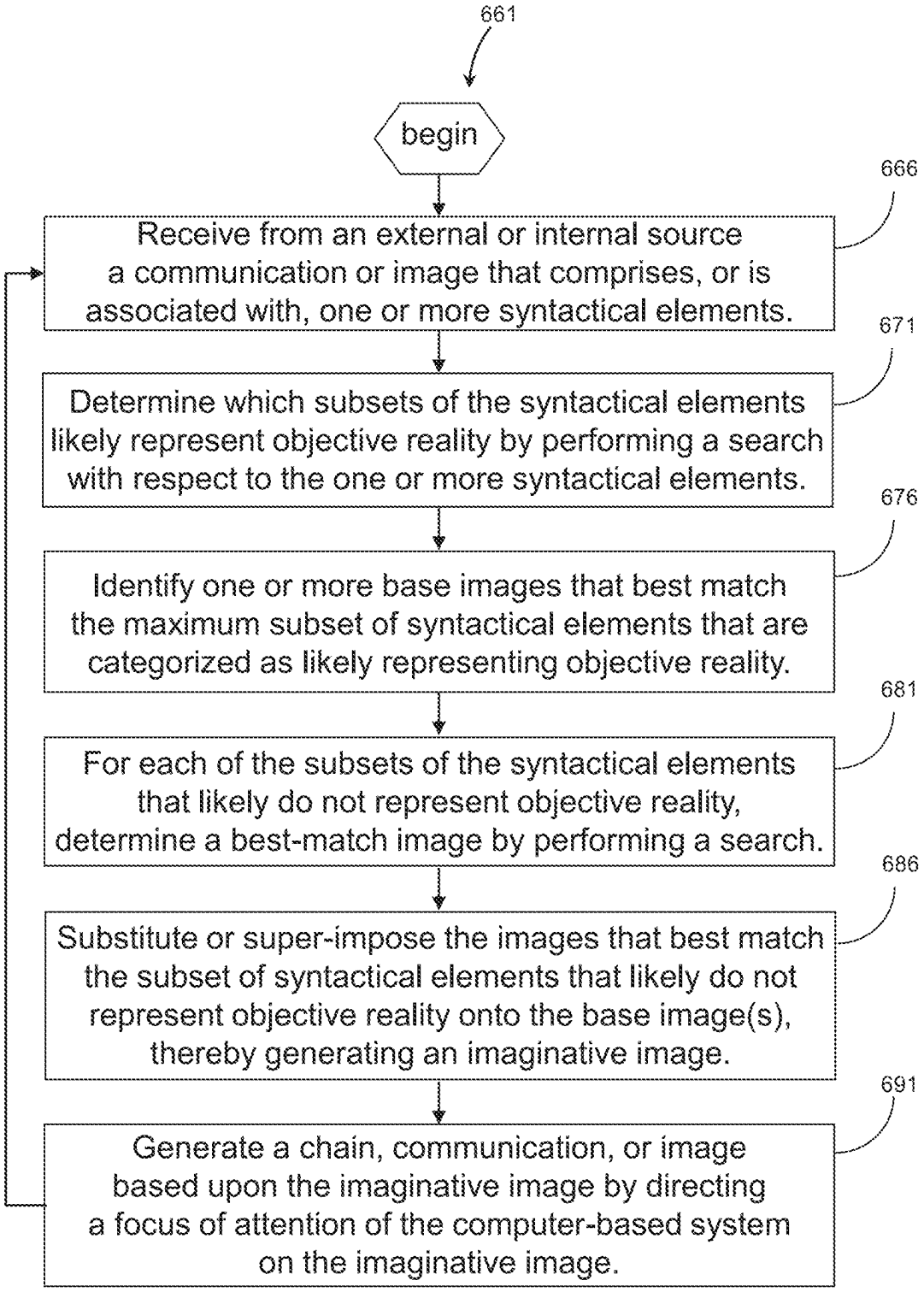
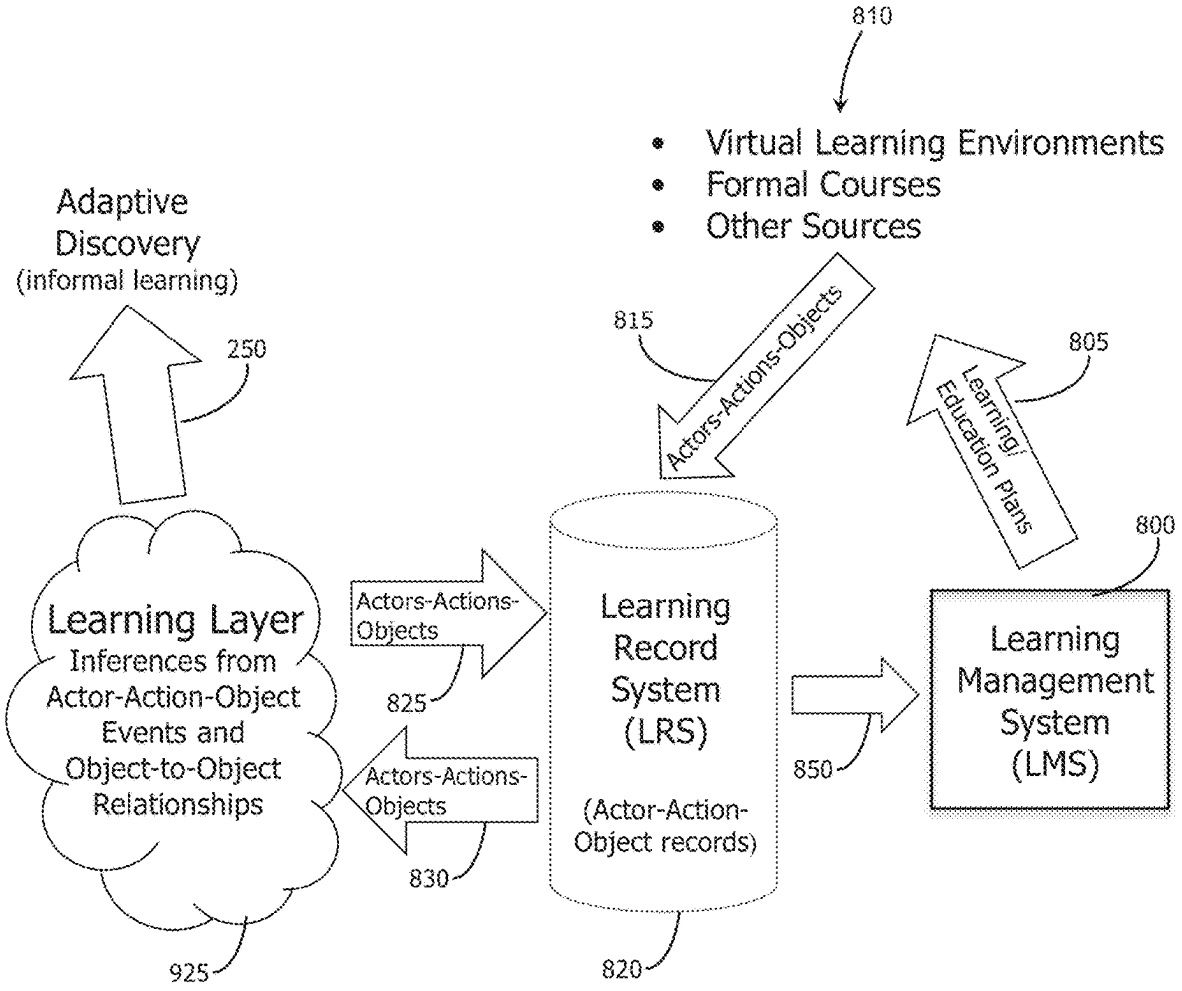

661
begin
666
Receive from an external or internal source a communication or image that comprises, or is associated with, one or more syntactical elements.
671
Determine which subsets of the syntactical elements likely represent objective reality by performing a search with respect to the one or more syntactical elements.
676
Identify one or more base images that best match the maximum subset of syntactical elements that are categorized as likely representing objective reality.
681
For each of the subsets of the syntactical elements that likely do not represent objective reality, determine a best-match image by performing a search.
686
Substitute or super-impose the images that best match the subset of syntactical elements that likely do not represent objective reality onto the base image(s), thereby generating an imaginative image.
691
Generate a chain, communication, or image based upon the imaginative image by directing a focus of attention of the computer-based system on the imaginative image.

Figure 15


810
Virtual Learning Environments
Formal Courses
Other Sources
Adaptive Discovery
(informal learning)
250
815
Actors-Actions-Objects
805
Learning/ Education Plans
800
Learning Layer
Inferences from Actor-Action-Object Events and Object-to-Object Relationships
Actors-Actions-Objects
825
Actors-Actions-Objects
830
Learning Record System (LRS)
(Actor-Action-Object records)
850
Learning Management System (LMS)
925
820

ITERATIVE ATTENTION-BASED NEURAL NETWORK TRAINING AND PROCESSING

CROSS-REFERENCE TO RELATED APPLICATIONS

The present application is a divisional of U.S. patent application Ser. No. 18/810,465, filed on Aug. 20, 2024, which is a continuation of U.S. patent application Ser. No. 18/101,612, filed on Jan. 26, 2023, which is a continuation of U.S. patent application Ser. No. 16/660,908, filed on Oct. 23, 2019, which is a continuation of U.S. patent application Ser. No. 15/000,011, filed on Jan. 18, 2016, which is a continuation-in-part of U.S. patent application Ser. No. 14/816,439, filed on Aug. 3, 2015, all of which are hereby incorporated by reference as if set forth herein in their entirety. The present application also incorporates by reference: U.S. patent application Ser. No. 14/497,645, filed on Sep. 26, 2014; U.S. Provisional Patent Application No. 61/884,224, filed Sep. 30, 2013, and U.S. Provisional Patent Application No. 61/929,432, filed Jan. 20, 2014, all of which are hereby incorporated by reference as if set forth herein in their entirety.

FIELD OF THE INVENTION

This invention relates to systems and methods for incorporating semantic-based auto-learning capabilities within one or more computer-implemented systems.

BACKGROUND OF THE INVENTION

Existing semantic-based approaches, using, for example, Resource Description Framework (RDF), can require significant manual effort, and do not adapt to usage. Thus there is a need for a system and method that enables such semantic-based approaches to automatically adapt to use, and further, to extend semantic-based approaches so as to enable the automatic generation of more engaging communications that embody characteristics lacking in existing semantic-based systems such as self-awareness, imagination, introspection, continuing streams of attention and reflection, and communicating creatively with metaphorical constructs and/or wit.

SUMMARY OF THE INVENTION

In accordance with the embodiments described herein, a processor-based system, method, and apparatus that embodies automatically generated streams of attention and/or reflection, is disclosed.

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. **2**A, **2**B, and **2**C 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. **4**A, **4**B, and **4**C are block diagrams of an object, a topic object, and a content object, according to some embodiments;

FIG. **5**A 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;

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

FIG. **14**A is a flow diagram of a process of integrating, and generating inferences from, behavioral-based chains and semantic chains, according to some embodiments;

FIG. **14**B is a flow diagram of a process of applying semantic context transfer to generate communications that embody a degree of creativity, according to some embodiments;

FIG. **14**C is a flow diagram of a closed-loop process of applying semantic-based chains and associated uncertainties to inform automatic actions that are in accordance with a focus of attention, according to some embodiments;

FIG. **14**D is a flow diagram of a closed-loop process of generating streams of imaginative images, according to some embodiments; and

FIG. **15** is a diagram of the integration of a learning layer system and a learning management system, 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.

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: 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, and the recommendations may be 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 therefore include non-human "users" that interact with the adaptive system **100**. In particular, one or more other adaptive systems may serve as virtual system "users." Although not essential, these other adaptive systems may operate in accordance with the architecture of the adaptive system **100**. Thus, multiple adaptive systems may be mutual users of one another. The user **200** may also represent the adaptive system **100** itself as a means of representing interactions with itself (or among its constituent elements) or as a means for referencing its own behaviors as embodied in the usage aspect **220**.

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 processor-based device, or distributed among multiple processor-based devices, and wherein one or more of the processor-based devices may be portable. Furthermore, in some embodiments one or more non-adaptive systems may be transformed to one or more adaptive systems **100** by means of operatively integrating the usage aspect **220** and the recommendations function **240** with the one or more non-adaptive systems. In some embodiments the structural aspect **210** of a non-adaptive system may be transformed to a fuzzy network-based structural aspect **210** to provide a greater capacity for adaptation.

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 elements 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. **2**A. 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**, if they exist. 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 computer-implemented information. The objects **212** may also include references, such as pointers, to content. 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. **2**B, and described below.

The objects **212** may be managed in a relational database, or may be maintained in structures such as, but not limited to, 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, wherein 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 composed 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. **2**B. 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 use or access information from 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. **2**C, although it should be understood that the usage aspect **220** may also exist independently 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, or being monitored by, the adaptive system **100**. Applying usage behavioral information **202**, including, but not limited to the usage behavioral information described by Table 1, to generate relationships or affinities **214** among objects **212** may be termed "behavioral indexing" herein.

The captured usage information **202**, known also as system usage or system use 202, may include any user behavior **920** exhibited by the one or more users **200** while using the system. The adaptive system **100** 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 adaptive system **100** identifies usage behaviors **270** of the one or more users **200** (e.g., a 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**. Non-limiting examples of the usage behaviors **270** that may be processed 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; 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, and/or monitored behaviors such as physiological responses, physical (i.e., geographic) location, and environmental conditions local to 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 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/or navigate the adaptive system 100.

The adaptive recommendations 250 are presented as structural subsets of the structural aspect 210, which may comprise an item of content, multiple items of content, a representation of one or more users, and/or a user activity or stream of activities. The recommended content or activities may include information generated automatically by a processor-based system or device, such as, for example, by a process control device. A recommendation may comprise a spatial or temporal sequence of objects. The adaptive recommendations 250 may be in the context of a currently conducted activity of the system 100, a current position while navigating the structural aspect 210, a currently accessed object 212 or information 232, or a communication with another user 200 or another system. The adaptive recommendations 250 may also be in the context of a historical path of executed system activities, accessed objects 212 or information 232, 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 and the recommended content sourced from one or more systems. The adaptive recommendations 250 may comprise advertising or sponsored content. The adaptive recommendations 250 may be delivered through any computer-implemented means, including, but not limited to delivery modes in which the recommendation recipient 200, 260 can read and/or listen to the recommendation 250.

Fuzzy Content Network

In some embodiments, the structural aspect 210 of the adaptive system 100, comprises a specific type of fuzzy network, a fuzzy content network. A fuzzy content network 700 is depicted in FIG. 3. The fuzzy content network 700 may include multiple content sub-networks, as illustrated by the content sub-networks 700*a*, 700*b*, and 700*c*, and fuzzy content network 700 includes "content," "data," or "information," packaged in objects 710. 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 710*t* or content objects 710*c*, as depicted in FIGS. 4B and 4C, respectively. Topic objects 710*t* are encapsulations that contain meta-information 712*t* and relationships to other objects (not shown), but do not contain an embedded pointer to reference associated information. The topic object 710*t* 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. People may be represented as topic objects or content objects in accordance with some embodiments.

Content objects 710*c*, as shown in FIG. 4C, are encapsulations that optionally contain meta-information 712*c* and relationships to other objects 710 (not shown). Additionally, content objects 710*c* 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 714*c* 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 **712***t* for the topic object **710***t* may include a high-level description of the topic being managed. Examples of meta-information **712***t* 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 **710***t* 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 **712***c* for the content object **710***c* may include relevant keywords associated with the information **714**, a summary of the information **714**, and so on. The meta-information **712***c* may supply a "first look" at the objects **710***c*. The meta-information **712***c* 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 **712***c*, and the date the content object **710***c* was created, as examples. As with the topic object **710***t*, meta-information for the content object **710***c* may also include a pointer.

In FIG. **3**, the content sub-network **700***a* is expanded, such that both content objects **710***c* and topic objects **710***t* are visible. The various objects **710** 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 type of affinity comprising a value associated with a relationship **716**, the value typically comprising 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 or maximum 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 bi-directional, 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 **710***t***1** has a relationship of "0.3" with content object **710***c***2**, while content object **710***c***2** has a relationship of "0.5" with topic object **710***t***1**. 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 **700**A, **700**B, **700**C may be related to one another using relationships of multiple types and associated relationship indicators **718**. For example, in FIG. **3**, content sub-network **700***a* is related to content sub-network **700***b* and content sub-network **700***c*, using relationships of multiple types and associated relationship indicators **718**. Likewise, content sub-network **700***b* is related to content sub-network **700***a* and content sub-network **700***c* using relationships of multiple types and associated relationship indicators **718**.

Individual content and topic objects **710** within a selected content sub-network **700***a* may be related to individual content and topic objects **710** in another content sub-network **700***b*. 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 **710***t***1** is bi-directionally related to topic object **710***t***2**, 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 **700***a* and **700***b*, 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 **710***t* may encompass, and may be labels for, very broad fuzzy sets of the content network **700**. The topic objects **710***t* thus may be labels for the fuzzy set, and the fuzzy set may include relationships to other topic objects **710***t* as well as related content objects **710***c*. Content objects **710***c*, 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 association with a fuzzy content network environment, such as the one depicted in FIG. **3**. In FIG. **5**A, an adaptive system **100**D includes a structural aspect **210**D that is a fuzzy content network. Thus, adaptive recommendations **250** generated by the adaptive system **100**D are also structural subsets that may themselves comprise fuzzy content networks.

In some embodiments a computer-implemented fuzzy network or fuzzy content network **700** may be represented in the form of vectors or matrices in a computer-implemented system, and where the vectors or matrices may be represented in the form of computer-implemented data structures such as, but not limited to, relational databases. For example, the relationship indicators **718** or affinities among topics may be represented as topic-to-topic affinity vectors ("TTAV"). The relationship indicators **718** or affinities among content objects may be represented as content-to-content affinity vectors ("CCAV"). The relationship indicators **718** or affinities among content object and topic objects

may be represented as content-to-topic affinity vectors ("CTAV"), which is also sometimes referred to an object-to-topic affinity vector ("OTAV") herein.

Further, affinity vectors between a user **200** and objects of a fuzzy network or fuzzy content network **700** may be generated. For example, a member (i.e., user)-to-topic affinity vector ("MTAV") may be generated in accordance with some embodiments (and an exemplary process for generating an MTAV is provided elsewhere herein). In some embodiments an affinity vector ("MMAV") between a specific user and other users **200** may be generated derivatively from MTAVs and/or other affinity vectors (and an exemplary process for generating an MMAV is provided elsewhere herein). In some embodiments a member-topic expertise vector (MTEV) is generated, which is defined as a vector of inferred member or user **200** expertise level values, wherein each value corresponds to an expertise level corresponding to a topic.

One or more of object **212** relationship mappings **214** represented by TTAVs, CCAVs, CTAVs (or OTAVs), MTAVs or MTEVs may be the result of the behavioral indexing of a structural aspect **210** (that is not necessarily fuzzy network-based) in conjunction with a usage aspect **220** and an adaptive recommendations function **240**.

In some embodiments, indexes generated from information **232** within objects **212** may be applied to populate an MTAV and/or MTEV, and/or to modify an existing MTAV and/or MTEV. Computer-implemented algorithms may be applied to index objects **212** such that for each object **212** a vector or vectors comprising one or more constituent elements, such as words, phrases, or concepts, is generated, along with a numerical weight or value corresponding to each constituent element, wherein each of the corresponding weights is indicative of the inferred importance or relevance of each of the associated constituent elements with respect to the associated indexed object **212**. By way of a non-limiting example, such a vector or vectors may be generated by a search engine function during the process of indexing the contents **232** of an object **212**. This vector of constituent elements and associated weights or values, hereinafter called an "object contents vector," or "OCV," may be generated using pattern detection and/or statistical techniques such as Bayesian analytic approaches and/or or other statistical pattern matching and/or statistical learning techniques such as support vector machines, as are known by those skilled in the art. For example, word or phrase frequencies within an object **212** comprising a document will typically influence the OCV, as may the position of words or phrases within an object **212**. These object contents-indexing techniques may further apply more general linguistic data such as word and phrase frequencies for a given language, synonym tables, and/or other lexicon-based information in generating OCVs.

In some embodiments, a system may track a user's **200** behaviors **920**, including, but not limited to, the behaviors described by Table 1, and map them to the OCVs of a collection of objects **212**. Constituent elements of the OCVs of objects that are inferred from the tracked behaviors **920** to be of particular interest to one or more users **200** or to have some other inferred quality of interest are then identified. These inferences may be based on the relative number of occurrences of constituent elements among objects that are inferred to be interest to a user, as well as in accordance with the weights or values associated with these constituent elements and their associated OCVs. For example, everything else being equal, constituent elements (or synonyms) of OCVs that occur frequently among the objects that are inferred to be of high interest to a user and that have relatively high relevance weightings in the OCVs are favored for identification.

These one or more identified constituent elements may then be transformed via, for example, application of appropriate lexicon-based information and techniques into, or directly serve without transformation as, topics **710***t* with associated weights in the user's MTAV and/or MTEV, wherein the associated weights are calculated in accordance with the inferred degree of affinity **214** between the user **200** and the objects **212** from which the associated OCVs are sourced. This process can be iteratively executed to continue to expand or refine the MTAV as additional or alternative sets of behaviors **920** are applied to OCVs of the same, additional, or different sets of object **212**, enabling continuously improved capabilities for personalization.

In some embodiments a multi-dimensional mathematical construct or space may be generated based on one or more of the affinity vectors. By way of a non-limiting example, topics may represent each dimension of a multi-dimensional space. Calculations of distances between objects and/or users in the multi-dimensional space, and clusters among objects and/or users, may be determined by applying mathematical algorithms to the multi-dimensional space and its elements. These calculations may be used by the adaptive system **100** in generating recommendations and/or in clustering elements of the space.

In some embodiments one or more topics **710***t* and/or relationship indicators **718** may be generated automatically by evaluating candidate clusters of content objects **710***c* based on behavioral information **920** and/or the matching of information within the content objects **710***c*, wherein the matching is performed, for example, through the application of probabilistic, statistical, and/or neural network-based techniques.

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 community, 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 **250***c* 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 **250***c* may include adaptive recommendations **250** and/or associated explanations for the recommendations, or may be other types of communications to the user **200**, including sponsored recommendations. In some embodiments the adaptive communications **250***c* comprise one or more phrases, where phrases can comprise one or more words. The adaptive communications **250***c* may be delivered to the user **200**, for example, 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, or monitored or inferred attention toward, an object, a more adaptive communication **250***c* is enabled. For example, duration of access or attention 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 explicit or inferred interests, 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**.

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.

Users **200** or communities may be explicitly represented as elements or objects **212** within the one or more computer-based systems **925**. An object **212** representing a user **200** may include self-profiling information that is explicitly provided by the user **200**. This user descriptive information may include, but are not limited to, for example, a photo or avatar, relationships to other people, subjects of interest, and affiliations.

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 or other device controller information, 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 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
subscription and self-profiling	personal or community subscriptions to, or following of, topical areas interest and preference self-profiling following other users filters affiliation self-profiling (e.g., job function)
collaborative	referral to others discussion forum activity direct communications (voice call, messaging) content contributions or structural alterations linking to another user
reference	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 voice modulation facial expression kinetic expression of limbs such as tension, posture or movement expression of other users in the group
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 and games, 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, scrolling through, 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**. "Following" is another term that may be used for a subscription behavior—i.e., following a topic is synonymous with subscribing to a topic. Subscriptions or following behaviors may also be with regard to other users—the subscriber or follower receives activity streams of the subscribed to or followed user. A user's following behavior is distinguished from a linking behavior with regard to another user in that a following relationship is asymmetric, while a linking (e.g., "friending") relationship is typically symmetric (and hence linking is considered in the collaborative behavior category herein). 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 activity streams, electronic mail (email), on-line newsletters, XML or RSS 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**, posting information that is then received by subscribers, categorizing subscribers so as to selectively broadcast information to subscribers, linking to another user, 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. An indicator such as "like" is a reference behavior when used as a tag for later retrieval of associated information. Tagging may include creating one or more symbolic expressions, such as a word or words (e.g., a hashtag), 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 recommendations **250** 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, vocal range, intensity and tempo, gestures, movements, or body position. Attention behaviors may also include other physiological responses such as breathing rate, heart rate, temperature, 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 geographic 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 position or location-aware system or device, or may be inferred directly from location information input by a user (e.g., inputting a zip code or street address, or through an indication of location on a computer-implemented map), 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, such as proximity, 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, temperature, the configuration of physical elements or objects in the surrounding physical space, 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 derive preference inferences is the duration associated with the access or interaction with, or inferred attention toward, 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 **250***c* 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 (MTAVs) may be generated to support effective recommendations, wherein for a user or registered member **200** of the one or more computer-based systems **925** a vector is established that indicates the relative affinity (which may be normalized to the [**0**,**1**] continuum) the member has for one or more object sub-networks 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 identified user, which can be termed a registered member in some embodiments, 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:

A. To serve as a basis for generating adaptive communications **250***c* or recommendations **250** to the user **200**

B. 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

In some embodiments, an expertise vector (MTEV) may be used as a basis for generating recommendations of people with appropriately inferred levels of expertise, rather than, or in addition to, using an MTAV as in the exemplary examples herein. That is, the values of an MTEV correspond to inferred levels of expertise, rather than inferred levels of interests, as in the case of an MTAV.

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

1) The topics the member has subscribed to received updates

2) The topics the member has accessed directly

3) The accesses the member has made to objects that are related to each topic

4) The saves or tags 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:

5) The relevancies of each content object to each topic

6) 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 available cannot be subscribed to by all 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 MTAV 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 a specified period of time 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 that 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 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 that 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 may be applied with respect to 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 appropriate adjustments to Table 1. For example, it may be desirable to 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 in some embodiments:

((Weighted Accesses for Topic N)/(Objects related to Topic N))*Square Root(Weighted Accesses for 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

In some embodiments, 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
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

In some embodiments, member-to-member affinities can be derived by comparing the MTAVs of a first member **200** and a second member **200**. Statistical operators and metrics such as correlation coefficients or cosine similarity may be applied to derive a sense of the distance between members in n-dimensional topic affinity space, where there are N topics. Since different users may have access to different topics, the statistical correlation for a pair of members is preferentially 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**. In some embodiments, a member-to-member expertise vector (MMEV) may be analogously generated by comparing the MTEVs of a pair of users **200** and applying correlation methods.

With the MTAVs, MMAVs, and Most Similar Member information available, a set of candidate objects to be recommended can be generated in accordance with some embodiments. These candidate recommendations may, in a later processing step, be ranked, and the highest ranked to candidate recommendations will be delivered to the recommendation recipient **200**,**260**. Recall that recommendations **250** may be in-context of navigating the system **925** or out-of-context of navigating the system **925**.

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 said object, weighted by the degree of relationship to 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 affinities or relevancies between the object and each topic, which may be derived from behavioral and/or contents indexing processes.

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 or tuning 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 non-limiting examples of weighting factors that can be applied dynamically by a user **200** or administrator are as follows:

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

Another example tuning factor that may be applied by a user **200** or administrator is contextual affinity, which is the degree of affinity of the object that is providing the context for the recommendation and its affinity to other objects, wherein the affinities are determined by means, for example, of applying its CTAV, or by comparison of its OCV to the OCVs of other objects. 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, for example, 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**,**260**. 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.

In some embodiments other types of recommendation tuning factors may be applied by a user **200** or administrator. For example, the scope of a social network, such as degrees of separation, may be adjusted so as to influence the recommendations **250**, and/or relationship types or categories of social relationships may be selected to tune recommendations **250**. Recommendation recipients **200** or administrators may also or alternatively be able to restrict objects **212** representing other specified users **200** from being recommended, or restrict objects authored or otherwise having an affiliation with other specified users.

In some embodiments the scope of geography or distance from a current location, including, but not limited to, the expected time to travel from the existing location to one or more other locations, may be tuned or adjusted so as to influence recommendations **250**. The expected time to travel may be a function of the actual or inferred mode of transportation of the recommendation recipient, road conditions, traffic conditions, and/or environmental conditions such as the weather. The specification of scope of geography, distance, and/or time-to-travel may be via an automated monitoring or inference of the recommendation recipient's current location, or may be via an explicit indication of location by the recommendation recipient through entering a location designation such as a zip code, or by indicating a location on a graphical representation of geography, for example, by indication location on a computer-implemented map display.

Other tuning factors that may be applied to influence recommendations **250** include the ability for the recommendation recipient to select a recommendation recipient mood or similar type of "state of mind" self-assessment that influences the generation of a recommendation. For example, a recommendation recipient might indicate the current state of mind is "busy," and less frequent and more focused recommendations **250** could be generated as a consequence.

For recommendations of people, recommendation recipients **200** can tune the recommendations **255** they receive by the degree of similarity of interests for one or more topics, according to some embodiments. Similarly, recommendation recipients may tune recommendations of people by the degree of difference in their level of expertise for one or more topics versus other users. This can be beneficial, for example, when a recommendation recipient seeks to receive recommendations of other people who have greater levels of expertise than themselves for one or more topics, but not too much greater levels of expertise.

In some embodiments, another type of tuning that may be applied by a user or administrator relates to the degree to which the capacity for enhanced serendipity is incorporated within the recommendation generating function **240** of the adaptive system **100**.

In some embodiments a serendipity function comprises an interest anomaly function that identifies contrasting affinities between a first user's MTAV and a second user's MTAV. Situations in which the first user's MTAV and the second user's MTAV have contrasting values associated with one or more topical areas, but wherein the two MTAVs otherwise have a higher than typical level similarity (as determined a vector similarity function such as, but not limited to, cosine similarity or correlation coefficient functions), present the opportunity for preferentially recommending objects **212** with a relatively high affinity to the topical areas associated with the contrasting MTAV affinities. More specifically, for two users **200** that have a relatively high level of similarity based on a comparison of their entire MTAVs, if the affinity values of the first user's MTAV corresponding to one or more topical areas is relatively high, and the affinity values of the second user's MTAV corresponding to the one or more topical areas is relatively low, then one or more objects **212** with relatively high OTAV values associated with the one or more topical areas may be preferentially recommended to the second user.

In some embodiments, the amount and/or quality of usage behavioral information on which the respective MTAV affinity values of the two users is based may additionally influence the generated recommendation **250**. Specifically, in the above example, if the affinity values of the second user's MTAV corresponding to the one or more topical areas are relatively low and there is relatively little behavioral information on which said affinity values are based, then there is even greater motivation to recommend one or more objects **212** with relatively high OTAV values associated with the one or more topical areas to the second user. This is because there is incrementally greater value in learning more about the user's interest than if the low affinities were based on inferences from a larger body of behavioral information, as well as there being a less likelihood of providing a recommendation **250** that is truly not of interest to the user.

In some embodiments, then, a general method of generating beneficially serendipitous recommendations combines the contrasting of topical affinities among users **200** and the relative confidence levels in the topical contrasting affinities. This approach provides a "direction" for generating recommendations that are further from inferred interests that would otherwise be generated. Besides direction, a serendipity function may also include a "distance" factor and a probability factor. That is, according to some embodiments generating serendipity can be thought of as exploring other areas of a multi-dimensional interest landscape, where the best inference based on historical behavioral information is a (local) maximum on the landscape. The serendipity function can be thought of as performing a "jump" on the interest landscape, where the jump is in a specified direction, for a specified distance, and performed with a specified frequency or probability. One or more of these serendipity distance, direction, and probability parameters may be tunable by a user **200** or administrator in accordance with some embodiments.

In some embodiments the serendipity function may include applying a degree of randomization in addition to, or instead of, applying the interest anomaly function. This randomization function may be applied when selecting objects **212** from a set of candidate objects to be recommended to a recommendation recipient rather than simply relying on deterministic scoring means. In such embodiments the serendipity tuning function can be used by a user **200** or administrator to control the degree to which delivered recommendations **255** deviate from the recommendations that would otherwise be delivered using purely deterministic means.

The serendipity distance may be generated in accordance with a mathematical function. In some embodiments, the distance and/or probability factors may be generated in accordance with a power law distribution—as a non-limiting example, the distance and/or probability factors may be in accordance with a Levy Walk function.

It should be understood that other recommendation tuning controls may be provided that are not explicitly described herein.

Knowledge and Expertise Discovery

Knowledge discovery and expertise discovery refer to "learning layer" functions that generate content recommendations and people recommendations **250**, respectively.

For expertise discovery, there are at least two categories of people that may be of interest to other people within a user community:

1. People who have similar interest or expertise profiles to the recommendation recipient, which may be calculated, for example, in accordance with MMAVs and MMEVs.
2. People who are likely to have the most, or complementary levels of, expertise in specified topical areas

Expertise discovery functions deliver recommendations **250** within a navigational context of the recommendation recipient **200**, or without a navigational context. In some embodiments, a person or persons may be recommended consistent with the "navigational neighborhood," which may be in accordance with a topical neighborhood that the recommendation recipient **200** is currently navigating. The term "navigating" as used herein should be understood to most generally mean the movement of the user's **200** attention from one object **212** to another object **212** while interacting with, or being monitored by, a computer-implemented user interface (wherein the user interface may be visual, audio and/or kinesthetic-based). Entering a search term, for example, is an act of navigating, as is browsing or scrolling through an activity stream or news feed through use of a mouse, keyboard, and/or gesture detection sensor.

In some embodiments expertise may be determined through a combination of assessing the topical neighborhood in conjunction with behavioral information **920**. The behavioral information that may be applied includes, but is not limited to, the behaviors and behavior categories in accordance with Table 1. As a non-limiting example, an expertise score may be generated from the following information in some embodiments:

1. The scope of the topical neighborhood, as described herein
2. The topics created by each user within the topical neighborhood
3. The amount of content each user contributed in the topical neighborhood
4. The popularity (which may be derived from accesses and/or other behaviors) of the content
5. The ratings of the content

In some embodiments, user-controlled tuning or preference controls may be provided. For example, an expertise tuning control may be applied that determines the scope of the navigational neighborhood of the network of content that will be used in calculating the total expertise scores. The tuning controls may range, for example, from a value V of 1 (broadest scope) to 5 (narrowest scope).

In some embodiments, the topical neighborhood of the currently navigated topic T may then defined as encompassing all content items with a relationship indicator R **718** to topic T **710***t* such that R>V−1. So if V=5, then the topical neighborhood includes just the content that has a relationship of >4 to the topic T, and so on. Expertise tuning may be effected through a function that enables expertise breadth to be selected from a range corresponding to alternative levels of V, in some embodiments.

In some embodiments, other tuning controls may be used to adjust expertise discovery recommendations **250** with regard to depth of expertise, in addition to, or instead of, breadth of expertise. For example, for a given navigational neighborhood, a user **200** or administrator may be able to adjust the required thresholds of inferred expertise for a recommendation **250** to be delivered to the recommendation recipient **200**, and/or may be able to tune the desired difference in expertise levels between the recommendation

recipient and recommended people. Tuning of recommendations **250** may also be applied against a temporal dimension, so as to, for example, account for and/or visualize the accretion of new expertise over time, and/or, for example, to distinguish long-term experts in a topical area from those with more recently acquired expertise.

In some embodiments, the expertise discovery function may generate recommendations **250** that are not directly based on navigational context. For example, the expertise discovery function may infer levels of expertise associated with a plurality of topical neighborhoods, and evaluate the levels of expertise for the topical neighborhoods by matching an MTAV or MTEV, or other more explicit indicator of topical expertise demand associated with the recommendation recipient **200** and a plurality of MTEVs of other users. Positive correlations between the expertise recommendation recipient's MTAV or topical expertise demand indicators and an MTEV, or negative correlations between the expertise recommendation recipient's MTEV and another MTEV, are factors that may influence the generation of expertise recommendations. In some embodiments, the MMAV or an expertise matching equivalent such as an MMEV of the recommendation recipient **200** may be applied by the expertise discovery function in evaluating other users **200** to recommend.

In some embodiments recommendation recipients **200** may select a level of expertise desired, and the expertise discovery function evaluates expertise levels in specific topical neighborhoods for matches to the desired expertise level. The recommendation recipient **200** may set the expertise discovery function to infer his level of expertise in a topical neighborhood and to evaluate others users for a similar level of expertise. The inference of expertise may be performed based, at least in part, by comparing the values of the recommendation recipient's MTEV with the associated topics in the specified topical neighborhood.

In some embodiments expertise may be inferred from the pattern matching of information within content. For example, if a first user **200** employs words, phrases, or terminology that has similarities to a second user **200** who is inferred by the system to have a high level expertise, then everything else being equal, the system **100** may infer the first user to have a similar level of expertise and that is therefore also a higher than an average level of expertise. In some embodiments vocabularies that map to specific areas and/or levels of expertise may be accessed or generated by the system **100** and compared to content contributed by users **200** in evaluating the level of expertise of the users.

Recall that the MTEV can be generated from behavioral information, including but not limited to the behaviors **920** and behavioral categories described in Table 1, similarly to the MTAV, except expertise is inferred rather than interests and preferences. As just one example of the difference in inferring an expertise value associated with a topic rather than an interest value, clicking or otherwise accessing an object **212** may be indicative of a interest in the associated topic or topics, but not very informative about expertise with regard to the associated topic or topics. On the other hand, behaviors such as, but not limited to, creating objects, writing reviews for objects, receiving high ratings from other users with regard to created objects, being subscribed to by other users who have an inferred relatively high level of expertise, creation or ownership of topics, and so on, are more informative of expertise levels with regard to the associated topic or topics, and are preferentially applied in generating MTEV values according to some embodiments. Similarly to the generation of MTAVs, weights may be applied to each of multiple types of behavioral factors in generating composite MTEV values in accordance with their expected relative strength of correlation with actual expertise levels.

In some embodiments a difference between the calculation method of an MTAV versus that of an MTEV is that MTAV values are indexed across topics—that is, the MTAV values represent relative interest levels of a user **200** among topics, whereas MTEV values are indexed across users **200**—that is, the MTEV values represent relative levels of expertise among users **200**.

In some embodiments, MTEV values may be calibrated using a benchmarking process, enabling an inference of an absolute level of expertise instead of, or in addition to, an inference of a relative level of expertise among users. For example, a test result or other type of expertise calibration information may be applied that establishes a benchmark expertise level for a user **200** across one or more topics. Expertise calibration means include, but are not limited to, educational proxies for expertise levels such as certifications, education programs, degrees attained, experience levels in a field or performing an activity, and/or current or past professions. For example, a recent graduate degree in a specific branch of mathematics would be indicative of a high level of expertise in that branch of mathematics, and likely a fairly high level of expertise in mathematical topics in general. The expertise calibration information may be available to the recommendation function **240** through a user's self-profiling behavior, or may be accessed through other means.

The inferred MTEV values for the benchmarked user can then be used as a basis for indexing the inferred MTEV values of other users **200**. This approach can be beneficial because an inferred expertise level that is calibrated against a benchmark level can enable the generation of more effective recommendations, particularly with regard to the generation of recommendations of content and/or topics. Whereas for recommendations of expertise (e.g., recommendations of other users), a purely relative expertise levels may be sufficient for generating useful recommendations, the process of generating recommendations of content or topics can often benefit from having a greater sense of absolute levels of expertise. This is particularly the case when the recommendation function **240** has access to information that is suggestive of the levels of expertise for which potentially recommended content or topics are appropriate. Information that is suggestive of the levels of expertise for which an object **212** will be most appropriate may be acquired by the recommendation function **240** through access to an explicit indication, such as, for example, through and expertise level indication within meta-information **712** associated with an object **212**,**710**, or the recommendation function **240** may assess the expertise levels for which an object **212** would be most appropriate through inferences from the content or information **232** within the object.

In some embodiments, the recommendation function **240** combines one or more MTAVs with one or more MTEVs in generating a recommendation **255**,**265**. For example, first, the MTAV of a recommendation recipient may be used by the recommendation function **240** to determine the one or more topics of highest interest to the recommendation recipient. The recommendation function may then compare the recommendation recipient's MTEV to the MTEVs of other users to identify one or more of the topics of highest interest for which the recommendation recipient has a lower level of expertise (or more generally, a complementary level of expertise) compared to one or more other users. The one

or more other users whose MTEVs satisfy this condition are then candidates for recommending to the recommendation recipient. Another example of combining MTAV and MTEV information in generating a recommendation **255**,**265** is first identifying the one or more topics of highest interest to the recommendation recipient, and then using the recommendation recipient's MTEV to recommend content or topics that are consistent with the MTEV values associated with the highest interest topics. Where the recommendation function **240** is able to assess the levels of expertise for which an item of content or topic are appropriate, those levels of expertise can be compared against the corresponding MTEV values and serve as at least one factor in the recommendation function users in deciding whether to recommend the item of content to the recommendation recipient.

Inferences of levels of expertise can be informed by collaborative behaviors with regard to other users **200** who are inferred to have given levels of expertise. In some embodiments users **200** are automatically clustered or segmented into levels of inferred expertise. Often, levels of expertise cluster—that is, people with similar levels of expertise preferentially collaborate, a tendency which can be beneficially used by the expertise inferencing function. A recursive method may be applied that establishes an initial expertise clustering or segmentation, which in conjunction with collaborative and other behaviors, enables inferences of expertise of these and other users not already clustered, which then, in turn, enables adjustments to the expertise clusters, and so on.

Inferences of expertise that are embodied within an MTEV may be informed by the contents of objects associated with a user **200**, in accordance with some embodiments. For example, the use, and/or frequency of use, of certain words or phrases may serve as a cue for level of expertise. More technical or domains-specific language, as informed by, for example, a word or phrase frequency table, would be indicative of level of expertise in a field. Other expertise cues include punctuation-question marks, everything else being equal, are more likely to be indicative of less expertise.

In some embodiments, when a recommendation of expertise in topical neighborhoods or for one or more specific topics is required, the selected topics are compared to user MTEVs to determine the best expertise match to the selected topics. For example, a specific project may require expertise in certain topical areas. These selected topical areas are then compared to MTEVs to determine the users with be most appropriate level of expertise for the project.

In some embodiments, the selected topics for which expertise is desired may be weighted, and the weighted vector of selected topics is compared to the corresponding topical expertise values in user MTEVs-positive correlations between the weighted vector of selected topics and the MTEVs of other users are preferentially identified. Mathematical functions are applied to determine the best expertise fit in the weighted selected topic case or the un-weighted selected topic case.

In some embodiments, the behaviors of users within one or more expertise segments or clusters are assessed over a period of time after an event associated with one or more topical areas. The event, embodied as an object **212**, could, for example correspond to a condition identified by another user or be identified and communicated by a device. The post-event behaviors assessed for expertise cohorts may then form the basis for recommended content, people, and/or process steps to be delivered to users **200** when the same or similar event occurs in the future. These event-specific recommendations **250** may be tempered by an assessment of the recommendation recipient's MMEV such that if relatively high levels of expertise are inferred relative to the event or related topics, then "best practice" process step recommendations **250** derived from the post-event behaviors associated with the highest expertise cohort may be recommended. If relatively lower levels of expertise are inferred relative to the event or related topics, then process step recommendations **250** derived with the highest expertise cohort may be supplemented with, for example, additional educational or verification steps.

Adaptive Semantic System and Method

Semantic approaches, as exemplified by, but not limited to, the Resource Description Framework (RDF), refer to system relationships that are represented in the form of a subject-predicate-object chain (a syntactic "triple"), wherein the predicate is typically a descriptive phrase, but can be a verb phrase, that semantically connects the subject with the object of the predicate. Since the subject and the object of the predicate can be represented as computer-implemented objects **212**, semantic chains can represent computer-implemented object-to-object relationships that are informed by the associated predicate in the semantic chain. Most generally, subjects, predicates, and objects of the predicates of semantic chains can each be represented in a computer-based system **925** as computer-implemented objects **212**. Semantic chains may be established manually, but can also be generated automatically by the computer-based system **925** through, for example, natural language processing (NLP) techniques that are applied to text strings such as sentences within a computer-implemented object **212** so as to automatically decompose the text into one or more semantic triples. Additional or alternative automatic techniques that can be applied by the computer-based system **925** to extract semantic chains from natural language can include generating vectors of values for language elements such as words or phrases within one or more objects **212**, and generating relationships based on vector comparisons among these language elements. Text can additionally or alternatively also be automatically analyzed through the application of a graphical-based logical form in which elements of text are represented as nodes and edges of the graph represent grammatical relationships to derive semantic chains. Semantic chains that are derived from natural language using these or other techniques known in the art may then be linked or chained together as is described in more detail herein. More generally, semantic chains can be represented by predicate calculus, and it should be understood that processes disclosed herein with respect to semantic chains apply more generally to predicate calculus-based representations.

In some embodiments weightings, which may comprise probabilities, are applied to semantic chains. For example, the semantic chain Object(**1**)-Predicate(**1**)-Object(**2**) may have a weighting (which may be normalized to the range 0-1), "W**1**" assigned to it: W**1**(Object(**1**)-Predicate(**1**)-Object(**2**)). Such a weighting (which may be termed a "W**1**-type" weight or probability hereinafter) may correspond to a probabilistic confidence level associated with the semantic chain. The weighting may be calculated by inferential statistical means based upon content-based patterns and/or user behavioral patterns (such as word or phrase matching frequency and/or length matched chain sub-elements). For example, the semantic chain "Red Sox-is a-team" might be assigned a weighting of 0.80 based on an inferential confidence given a first set of textual content from which the semantic chain is statistically inferred (and where "textual"

or "text" as used herein may be in written or audio language-based forms). This weighting might be increased, say to 0.99, based on an analysis of additional text that seems to strongly confirm the relationship. Such weightings may therefore be considered probabilities that the inference is true—that is, the probability that the inference accurately reflects objective reality. It should be understood that such probabilistic inferences with respect to semantic chains may be made basis inputs other than just through the analytic processing of text-based computer-implemented objects. Such inferences can be alternatively or additionally be made with respect to patterns of information that are identified with respect computer-implemented objects **212** comprising images or audio-based information, for example. For example, in some embodiments, neural network-based systems are trained to make inferences of relevant semantic chains from text and/or images and to inform W**1**-type weights associated with the inferred semantic chains. In some embodiments Bayesian program learning-based processes are applied to make inferences of relevant semantic chains from text and/or images and to inform W**1**-type weights associated with the inferred semantic chains.

In addition, or alternatively, a contextual weighting, "W**2**", may be applied that weights the semantic chain based on the relative importance or relevance of the relationships described by the semantic chain versus other relationships with respect to one or both of the objects (which may be included in one or more other semantic chains) within the semantic chain (and such weights may be termed a "W**2**-type" weight hereinafter). For example, a W**2**-type weight as applied to the semantic chain "Red Sox-is a-team" may be greater than the W**2**-type weight applied to the semantic chain "Red Sox-is a-logo" for a particular inferential application. While both semantic chains may be valid (that is, accurately reflect objective reality), the term "Red Sox" as used in a randomly selected item of content is more likely to be used in the context of being a team than as being used in the context of being a logo, and should therefore, everything else being equal, be more likely be used as a basis for subsequent computer-implemented semantic interpretations of content that includes a reference to "Red Sox". As in the case of W**1**-type weights, W**2**-type weights may correspond to probabilities, and may be established and/or adjusted based on statistical inferences from content (in a simple, non-limiting example, based on the frequency of co-occurrences of the respective objects in the semantic chain within a corpus of content) and/or from inferences derived from user **200** behaviors as described in Table 1. Alternatively, W**2**-type weightings may be explicitly established by humans.

So, in summary, whereas weightings of the type associated with W**1** can be construed to be the probability that the associated semantic chain accurately reflects objective reality, weightings of the type associated with W**2** can be construed to be the probability the associated semantic chain validly applies semantically in the context of interpreting specified content.

These foregoing semantic representations are contrasted with behavioral-based user-predicate-object computer-implemented representations, which, while they can be represented in a similar chain or "triple" form as RDF, are distinguished in that the subject in behavioral-based chains represents or refers to an actual user **200** of the computer-based system **925**, and the associated predicate represents actions or behaviors **920** that the user **200** of the system exhibits or performs in association with a system object **212**, or in which the associated predicate is an inference, for example, of the user's **200** state of mind or, as another example, a historical event associated with the user **200**. The predicates of the behavioral-based triple may include, but are not limited to, actions or behaviors **920** exhibited by the user as described by Table 1 and associated descriptions. The predicates of some types of behavioral-based triples may comprise computer-generated inferences rather than a specifically performed or monitored behavior **920** in some embodiments. For example, for the behavioral-based triple User(**1**)-Is Interested In-Object(**1**), the predicate "Is Interested In" may be an inference derived from from one or more usage behaviors **920**. As another example, for the behavioral-based triple User(**1**)-Has High Expertise In-Object(**1**), the predicate "Has High Expertise In" may be an inference derived from one or more usage behaviors **920** and/or an analysis of content. These two examples comprise inferences of a user's state of mind or capabilities. More concrete inferences, such as of events or relationships, may also be made—for example, the behavioral-based triple User(**1**)-Worked For-Object(**1**), the predicate "Worked For" may be an inference that is made from a statistical analysis of content and/or from one or more usage behaviors **920**. In such event-based applications temporal indicators such as a timestamp or time period may be associated with the associated behavioral-based triple. Such temporal indicators can further enable the computer-based system **925** to make connections between events and promote more effective inferencing.

W**1**-type weights may be applied to behavioral-based chains that comprise an inferred predicate relationship between the user **200** and the object of the predicate, the W**1**-type weight thereby representing the degree of confidence that the behavioral-based chain represents objective reality, whereby objective reality in this case may constitute the user's current or future state-of-mind.

Behavioral-based triples may be with respect to "real-world" locations or physical objects that are located at a particular point or proximity in space and/or time, in some embodiments. For example, a user **200** may be determined to be at Fenway Park by, for example, matching the user's currently inferred location from a location-aware device that is associated with the user to a computer-implemented map that maps physical objects such as Fenway Park to particular geographical locations. This determination could be represented, for example, as the behavioral-based triple User(**1**)-Is Located At-Fenway Park, and with an associated time stamp t(**1**). This same approach can be applied to simulations of real-world environments or real world-like environments (i.e., virtual reality applications), where the user **200** in the behavioral triple is represented in the simulation, by, for example, an avatar.

Behavioral-based triples may be with respect to two people, and the object of the predicate of the triple may represent or reference another system user **200**. For example, User(**1**)-Is Located Near-User(**2**) is an example of an event-based behavioral triple (and that may have an associated temporal indicator) and User(**1**)-Is a Friend of-User(**2**) is an example of an inferential behavioral triple, in which the system automatically infers the "Is a Friend of" predicate.

In summary, while the subjects and predicates in semantic triples are therefore generally different in nature from behavioral-based triples, the similarity of syntactical structure can be beneficially used to extend semantic-based approaches so that they are adaptive to users **200**.

In some embodiments semantic chains are converted to OTAVs. Predicate relationships between objects are trans-

formed to numerical values (i.e., affinities) in such embodiments, which can have, for example, scalability advantages. These OTAV affinities may correspond to, or be influenced by or calculated from, corresponding W**1**-type or W**2**-type semantic chain weightings.

In some embodiments, the behavioral-based representations of user-predicate-object are linked to semantic-based object-to-object **212** relations **214**. For example, for a specific computer-implemented object **212**, denoted as Object (**1**), for which there is at least one user behavioral-based relationship, User-Predicate(**1**)-Object(**1**) (where Predicate (**1**) may comprise an inference), and at least one semantic relationship between objects—for example, an RDF-based relationship of the form, Object(**1**)-Predicate(**2**)-Object(**2**) (where Predicate(**2**) may comprise an inference), inferences with respect to User **200** and Object(**2**) may be derived from the extended chain of User-Predicate(**1**)-Object(**1**)-Predicate (**2**)-Object(**2**). In this example, Object(**1**) enables the linking because it is commonly referenced by the behavioral-based chain and the semantic chain. Most generally, such linking can be performed when the subject of the semantic chain has a correspondence to the object of the predicate of the behavioral-based chain. The correspondence between such subject and object pairs may be based, for example, on the subject and object referring to the same entity or information, or representing the same entity or information.

Composite chains can be extended indefinitely by identifying the subject of a semantic chain that has a correspondence with the terminal object of a predicate of a composite chain, and linking the identified semantic chain to the end of the composite chain, thereby assembling a new, extended composite chain, which can in turn be extended.

In some embodiments, one or more of the constituent semantic chains of such composite chains may include W**1**-type and/or W**2**-type weightings. Mathematical operations may be applied to these weightings to derive a composite weighting or probability for the composite chain. For example, where there are multiple individual semantic chain weightings that each correspond to a probability within a composite chain, and probabilistic independence is assumed, the individual weightings may be multiplied together to yield a composite chain probability, e.g., a probability that the composite chain is a valid inference of objective reality and/or a probability that the composite chain semantically validly applies to an interpretation of particular content.

Further, as previously described herein, behavioral-based chains may be weighted as well with W**1**-type weights that correspond to the probability that the inference of the behavioral-based chain accurately reflects objective reality—in some cases, objective reality being a conscious or unconscious mental state of the user that cannot be directly assessed, but must rather be inferred from behaviors **920**. This type of behavioral-based chain weighting may be combined with mathematical operations (such as multiplication) with one or more semantic chain weightings to yield a composite chain weighting or probability. Such composite weightings may correspond to affinity values of MTAVs or MTEVs in some embodiments; for example, where a composite chain includes a terminal object (last object in the semantic chain) that comprises a topic that is also associated with an MTAV or MTEV.

Recommendations **250** can then be generated based on these linked or composite chains. As a simple non-limiting example, assume that a behavioral-based triple is, User(**1**)-"likes"-Object(**1**), whereby the predicate "like" is a user action **920** of "liking" a computer-implemented object as described by the descriptions that are associated with Table 1. This behavioral-based triple might be applied directly, or it may serve as a basis (along with potentially other behavioral-based chains) for an inferential behavioral-based chain such as, User(**1**)-Is Favorably Disposed Toward-Object(**1**), whereby the predicate "Is Favorably Disposed Toward" is inferred from one or more usage behaviors **920** (such as a "like" action by a user **200**) and/or from content-based pattern matching. The confidence with respect to this inference may be encoded as a W**1**-type weighting that is associated with the inferred behavioral-based triple.

As a further example, assume that there exists a semantic triple of Object(**1**)-"is a"-Object(**2**), wherein the "is a" predicate designates that Object(**1**) is a type of, or subset of, Object(**2**). The system can then generate the composite chain User(**1**)-"likes"-Object(**1**)-"is a"-Object(**2**). The system can then make an inference that User(**1**) likes or is favorably disposed toward Object(**2**), and may apply weightings that are associated with the behavioral-based based chain and/or the semantic chain in quantifying the degree of confidence with respect to the inference. Such quantifications may be encoded as one or more affinity values within the MTAV of User(**1**), in some embodiments. Other composite chains terminating with Object(**2**) could additionally be applied that could have a further effect on the inference quantification (e.g., strengthening or weakening the confidence in the inference).

It should be recalled that a computer-implemented object **212** as defined herein can comprise content, or a pointer to content, that is in the form of a document, image, or audio file, but can also be a topic object, which comprises a label or description of other objects. So another non-limiting example is, User(**1**)-"viewed"-Object(**1**), where the predicate "viewed" is a user **200** action of viewing a computer-implemented object as described by Table 1, and Object(**1**)-"is about"-Object(**2**), where Object(**2**) is a topic object or tag that designates "baseball." The system can then determine the composite chain User(**1**)-viewed-Object(**1**)-is about-Object(**2**). The system therefore determines that user(**1**) has viewed content that is about baseball, and could therefore be able to infer a user interest with respect to baseball. To continue the example, assume a semantic triple of Object (**1**)-"is about"-Object(**3**), wherein Object(**3**) is a topic object or tag that designates "Red Sox." Then, assume there also exists the semantic triple, Red Sox-is located-Boston. The system can then assemble the chain, User(**1**)-viewed-Object (**1**)-is about-Red Sox-is located-Boston, which could allow the system to infer that User(**1**) has an interest in Boston or things located in Boston in general, although this would likely be a very weak inference in this example given only one view behavior, and this weak inference could be encoded as a corresponding low weighting or probability associated with the composite chain that is derived from weightings or probabilities associated with the composite chain's behavioral-based chain (or weightings or probabilities of a corresponding inferred behavioral-based chain derived, at least in part, from the User(**1**)-"viewed"-Object (**1**) chain) and/or with one or more of the composite chain's constituent semantic chains.

FIG. **14**A summarizes the computer-implemented process **600** for generating recommendations **250** or, more generally, personalized communications, **250***c*, derived from the linking of behavioral-based and semantic chains and the performing of inferences from the resulting composite chains. In the first step **610** of the process **600** a behavioral-based chain that includes a subject that is associated with a user **200** is accessed. A semantic chain is then identified **620** that

comprises a subject-predicate-object triple in which the subject has a correspondence with the object of the predicate of the behavioral-based chain. This correspondence enables linking **630** the behavioral-based chain and the semantic chain to form a composite chain. One or more additional semantic chains may be identified **640** to be linked to the composite chain by identifying any semantic chains that comprise a subject that has a correspondence to the terminal object of the composite chain. If at least one such semantic chain is identified, the semantic chain may be added to the composite chain, thereby creating a new composite chain, and step **640** may be repeated with this resulting composite chain. After assembly of the composite chain is completed, inferences may be performed **650** that are derived from the composite chain and its associated probabilities as described herein. The inferences may then be used to generate **240** recommendations **250**, or more generally, personalized communications **250***c*.

Inferences derived from composite behavioral-based and semantic chains can be used to generate MTAV and/or MTEV or values. In the example above, "Boston" could be a topic in the MTAV of User(**1**) with an associated inferred affinity value. Had the predicate in the example above been "created" instead of "viewed" and other users had rated Object(**1**) highly, then "Red Sox", might be a topic in the MTEV of User(**1**) with an associated inferred affinity or expertise value.

In some embodiments linked behavioral-based and semantic chains can be further linked or mapped to OCVs. For instance, in the example above, if the term "Red Sox" has a sufficiently high value in the OCV associated with a document embodied in an object **212**, then an inference might be made by the computer-based system **925** between User(**1**) and the associated object **212** that has a sufficiently high value for "Red Sox" in the object's OCV. This inference could in turn become a basis for a recommendation **250**.

While these examples are with respect to behavioral-based and semantic triples, other syntactical structures or symbolic representations can also be applied by the computer-based system **925**—for example, this method of integration of behavioral-based and semantic chains can be applied to syntactical structures that are in accordance with, or can be represented by, a predicate calculus. In some embodiments, semantic chains may be alternatively represented as taxonomies or ontologies such as hierarchical structures.

In some embodiments a semantic chain or composite chain may constitute a metaphorical semantic or composite chain, which may be also be termed a metaphorical construct herein. Metaphorical semantic chains and/or metaphorical composite chains can be applied to generate communications **250***c* that are perceived to be particularly creative or humorous, for example, or to perceive or interpret creativity or humor associated with information that is processed by the computer-based system **925**.

A metaphor can be considered a semantic relationship that is transferred from one context or subject area to another context or subject area. For example, "strike out" in its original context of baseball is a failure by a batter to put a baseball into play or draw a walk. So among a number of semantic chains that are valid in this context is the generalized semantic chain, Strike out-is a-Failure. Such a semantic chain may be automatically inferred from, for example, a statistical analysis of a corpus of content, application of a computer-implemented neural network on the corpus of content, or may be manually determined, and may have a W**1**-type weight associated with it. Derivation of this particular semantic chain from a specific domain of application (in this case, baseball) constitutes a process of context stripping and transferring—that is, the original context of baseball is "stripped" from the semantic chain, and then transferred to a more generalized semantic relationship as embodied by the resulting semantic chain in this example. This context stripping and transfer process, which may be automated, enables the resulting more generalized semantic chain to then be extended or transferred to other contexts (in this case, outside of the domain of baseball).

For example, if a sales person fails to find a customer, as encoded by the semantic chain, Sales_Person-failed finding-Customer, the semantic chain Strikeout-is a-Failure could be substituted to yield the semantic chain, Sales_Person-struck out finding-Customer. In the process of generating communications **250***c*, the computer-based system **925** starts with Sales_Person-failed finding-Customer chain and then searches for a domain-specific example of the predicate "failing," such as the baseball-based semantic chain Strike out-is a-Failure. "Struck out" is then substituted for "failed" in assembling the new chain, yielding the metaphorical construct Sales_Person-struck out finding-Customer.

In interpreting metaphorical expressions, the process is reversed, with the computer-based system **925** starting with a literal or derived Sales_Person-struck out finding-Customer chain and then searching for more generalized meanings of the term "struck out" such as that which is encoded by the example semantic chain, Strike out-is a-Failure. Possibly in conjunction with other contextual clues, the computer-based system **925** then infers the chain Sales_Person-failed finding-Customer chain, and may generate a W**1**-type weight associated with the inferred chain.

While metaphorical constructs within communications **250***c* can enhance the perception by communication recipients **200** of an inherent capacity for creativity of the computer-based system **925**, a balance is preferably struck in the generation and communication of metaphorical constructs. For example, if a metaphorical construct is too often generally used it can seem clichéd. If the metaphorical construct has never been used, or too many of such very rare or unique metaphorical constructs are communicated within a given time period or volume of communications **250***c*, the communications **250***c* may seem too strange for the tastes of many recipients **200**. Therefore, in some embodiments the process for generating a metaphorical construct by the computer-based system **925** includes first searching through a corpus of information to determine if a metaphorical construct is sufficiently rare to be considered creative. However, if the metaphorical construct seems to be very rare or even unique based on the search, it might be rejected, or only be selected in accordance with a probabilistic selection process. In some embodiments the probability distribution applied by such a probabilistic selection process is tunable by a user **200** so as to enable the increase or decrease of the level of metaphorical-based creativity embodied by communications **250***c*, and constitutes a tunable aspect of the overall personality of the computer-based system **925**.

FIG. **14**B summarizes the process flow for generating creative communications **250***c* (and that may further be self-referential) in accordance with some embodiments. The first step **615** is, given a first semantic chain, to identify a second semantic chain that generalizes the context of the first semantic chain. The second step **625** is to identify a second context that is different that is different than the context of the first semantic chain, but that has a semantic relationship to the context of the first semantic chain. The

third step **635** is to generate a third semantic chain by applying the subject or predicate or a variation thereof of the first semantic chain to the second context. The fourth step **645** is to determine if the frequency of occurrence of the third semantic chain within an evaluative corpus of content is within an acceptable range. If the frequency of occurrence of the third semantic chain is within the acceptable range, then the fifth step **655** is to apply a probabilistic communication creativity tuning factor or distribution to determine the probability of embodying the third semantic chain within a communication **250***c*.

In some embodiments, the capacity for generating or perceiving creativity is extended to a capacity for humor or with by the computer-based system **925**. Humor or with may be generated or perceived when a metaphorical construct has a further semantic connection, albeit indirect, to the original context. For example, while Sales_Person-struck out finding-Customer might be an example of creativity in communicating a situation, it might not typically be viewed as particularly witty or humorous. On the other hand, Jim-struck out-looking for his bat, might be viewed as witty. To be perceived as witty, a metaphorical chain generally needs to satisfy the following conditions: 1) it is not too often used (the extreme of too often used is clichéd) and 2) there is a somewhat subtle or indirect semantic connection to the original domain. Jim-struck out-looking for his bat probably satisfies the first condition and definitely satisfies the second condition since the general context remains baseball, but the generalization encoded by the semantic chain Strike out-is a-Failure is applied to a different target sub-context of baseball than the original sub-context. As another example, Jim-struck out finding-Customer might be considered humorous or witty if Jim is a current or former baseball player, a connection that might be discovered, for example, by the computer-based system **925** searching semantic chains that reference Jim or baseball and identifying from such a search the semantic chain Jim-plays-baseball. Further, this connection could have a higher probability of being applied than would otherwise be the case if the computer-based system **925** inferred that the recipient of a communication **925***c* would be expected to be aware of the fact that Jim plays baseball and so could be expected to appreciate the with of the metaphorical construct Jim-struck out finding-Customer. Such an inference could be made based on an evaluation of a corpus of behavioral and/or communication history of the recipient of the communication **925***c*, for example.

In summary, in some embodiments metaphorical-based with or humor is generated or perceived by the computer-based system **925** by first searching a corpus of information to determine if a metaphorical construct is sufficiently rare to be considered creative, and in accordance with any application of a creativity tuning factor. Second, the computer-based system **925** then evaluates if there exists a semantic connection to the original context, particularly a somewhat subtle connection. And third, the computer-based system **925** then evaluates if the recipient of the communication **250***c* that embodies the metaphorical construct is likely to be aware of the semantic connection, and therefore could be expected to appreciate the with embodied by the metaphorical construct.

In accordance with some embodiments, FIG. **15** depicts the integration of behavioral-based and semantic chaining processes with formal learning processes. Such formal learning processes can be managed through the application of a Learning Management System (LMS) **800**. An LMS manages or accesses learning and/or educational histories for individuals, who may be users **200**, and determines learning and/or educational plans **805** based on users' **200** learning histories. The learning and/or educational plans **805** then inform formal learning activities **810** for individual users **200**. These formal learning activities **810** may include, but are not limited to, formal courses and virtual learning environments. The results of these formal learning activities **810** can be codified in the form of behavioral-based chains **815** for each user **200**, and stored in this form in a Learning Record Management System (LRS) **820**. (Behavioral-based chains are described in an equivalent form of "Actor-Action-Object" in FIG. **15**, in which the "Actor" is a user **200**, "Action" is a predicate, and "Object" is the object of the predicate.). The LRS may also access and store behavioral-based chains **825** associated with the user **200** from a learning layer system **925**. The learning layer system **925** accesses behavioral-based chains associated with the user **200** from the LRS that originate from formal learning sources **815**, and combines them with behavioral-based chains **825** originating in the learning layer system **925**. These learning layer system-originating behavioral-based chains **825** can be stored in the LRS **820** and/or the learning layer system **925**. The learning layer system **925** uses the combined set of behavioral-based chains associated with the user **200** to link with semantic chains as described herein to form composite chains. These composite chains, and associated probabilities, can then be applied to make inferences, for example, of preferences and expertise levels, associated with the user **200**. These inferences then serve as a basis for personalized recommendations **250** of knowledge and expertise or other personalized communications **250***c*, and these personalized recommendations or communications can be considered to constitute part of an "informal learning" process with respect to the user **200**.

In some embodiments, the LMS **800** accesses **850** via the LRS **820** behavioral-based chains **815** associated with a user **200** that originate from formal learning activities and behavioral-based chains **825** associated with the user **200** that originate from informal learning activities. The LMS then generates learning or educational plans for the user **200** based on the behavioral-based chains **850** originating from both informal and formal learning processes. This method serves to beneficially integrate formal learning and informal learning processes.

Recommendation Explanation Generation

In addition to delivering a recommendation **250** of an object **212**, the computer-based application **925** may deliver a corresponding explanation **250***c* 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 commit to reading or listening to the recommended content (or in the case of a recommendation of another user **200** whether to, for example, contact them or express an interest in connecting with them), prior to committing significant amount of time. For recommen-

dations **250** that comprise advertising content, the explanation may serve to enhance the persuasiveness of the ad.

The explanations **250***c* may be delivered through any appropriate computer-implemented means, including, but not limited to delivery modes in which the recommendation recipient can read and/or listen to the recommendation. The general capability for delivering explanatory information **250***c* can be termed the "explanation engine" of the computer-based system **925**.

In some embodiments, variations of the ranking factors previously described may be applied in triggering explanatory phrases. For example, the following table illustrates non-limiting examples of 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 **2**E 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 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, an unlimited number of positive and negative thresholds may be applied as required for best results.

In some embodiments explanations **250***c* are assembled from component words or phrases and delivered based on a syntax template or syntax-generation function. Following is a non-limiting example syntax that guides the assembly of an in-context recommendation explanation. In the syntactical structure below syntactical elements within { } are optional depending on the associated logic and calculations, and "+" means concatenating the text strings. (The term "syntactical element" as used herein means a word, a phrase, a sentence, a punctuation symbol, a semantic chain, a behavioral chain, or composite chain. The term "phrase" as used herein means one or more words.). 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 syntactical elements 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

Out-of-Context Sequence Number Phrases	
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]

Note: [this object]= "this 'content-type'" (e.g., "this book") or "it" depending on if the phrase "this 'content-type'" has already been used once in the explanation.

Positive Ranking Category Phrases	
Trigger Category	Phrase
Editor Rating	1) [it] is rated highly by the editor
Community Rating*	[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 4) [it] contains some themes related to topics in which you have an interest
Object Affinity to MTAV (2)	5) I know you have an interest in [topic name] 6) I am aware you have an interest in [topic name] 7) I have seen that you are interested in [topic name] 8) 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 comprising many different phrases and phrase variations are required to give the feel of human-like explanations. These example phrase arrays above are oriented toward recommendations based on recommendation recipient interests as encoded in MTAVs; for recommendations related to the expertise of other users as encoded, for example, in MTEVs, explanation syntactical rules and phrase arrays tailored for that type of recommendation are applied. In some embodiments, explanatory syntactical rules and phrases are applied that are consistent with explanations of recommendations that are generated in accordance with both an MTAV and MTEV. For example, the resulting explanation **250***c* may indicate to the recommendation recipient why it is expected that a recommended item of content is expected to be relevant to them as well as being appropriate given their inferred level of expertise.

In some embodiments, phrases for inclusion in phrase arrays are generated from semantic chains that are derived by means of an automated analysis of content as described previously herein, whereby the automated analysis is directed to a starting set of one or more selected phrases. The derived phrases may be identified as a result of a process of performing multiple linkages of semantic chains. These semantically-derived phrases may further have W**1** and/or W**2**-type probabilities associated with them. These probabilities may be applied so as to influence the frequency that a specific phrase will be selected for inclusion in a communication **250***c*.

As described above, a sense of confidence of the recommendation to the recommendation recipient can also be communicated within the recommendation explanation. The score level of the recommendation 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. The communication of a sense of confidence in the recommendation can be applied to recommendations with regard to expertise, as well as interest-based recommendations. The degree of serendipity incorporated by the serendipity function may be communicated **250***c* to the user, and may influence the communication and related syntax and syntactical elements applied in the communication **250***c*, as well as affect the

communication of the degree of confidence in a recommendation. The communication of a sense of confidence in a communication **250***c* in some embodiments may further, or alternatively, be influenced by weightings of W**1** and/or W**2** types described herein that are associated with a semantic chain or composite chains that comprise multiple semantic and/or behavioral chains, and that are used by the computer-implemented system **925** as a basis for making an inference.

In some embodiments, a recommendation explanation may reference a tuning factor and its setting. For example, if a user has set a recency tuning factor so as to slant the recommendations **255** toward recommending objects **212** that have been recently published, the explanation may contain words or phrases to the effect that acknowledge that a recommended object is in accordance with that setting. Or, for example, if a person is recommended in accordance with an expertise scope level set by the recommendation recipient **200**, the explanation might reference that setting as a justification for its recommendation (or alternatively, the explanation might acknowledge a tuning setting but indicate why other factors over-rode the setting in generating the explanation). For example, an exemplary recommendation explanation in such a case is, "Although Jim Smith's expertise does not appear to be the deepest in subject x, I infer that he has significant breadth of expertise in related subjects, and you have directed me to emphasize breadth of expertise."

Recommendation explanations are one type of behavioral-based communications **250***c* that the one or more computer-based applications **925** may deliver to users **200**. Other types of adaptive communications **250***c* 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 **250***c* may also include contextual information in accordance with some embodiments. For example, contextual information may be provided to assist a user **200** in navigating the structural aspect **210**,**210**D of an adaptive system **100**,**100**D.

The adaptive communications **250***c* may include references to hierarchical structures—for example, it may be communicated to the user **200** that a topic is the parent of, or sibling to, another topic. Or for a fuzzy network-based structure, the strength of the relationships among topics and content may be communicated.

In some embodiments, adaptive communications **250***c* may include explanations of recommended objects **212** in which the explanations include references to words, phrases, concepts, and/or themes that are included within, or derived from, the contents of OCVs that are associated with the objects **212**. For example, the explanation may indicate to the recommendation recipient that a recommended object **212** is inferred to emphasize themes that are aligned with topics that are inferred to be of high interest to the recommendation recipient or which are appropriate for the recommendation recipient's inferred level of expertise on one or more topics.

In some embodiments, adaptive communications **250***c* comprise explanations of recommended objects **212** in which the explanations include references to words, phrases, concepts, and/or themes associated with semantic chains (which may be elements of composite semantic chains or composite behavioral-based and semantic chains) that are associated with, or reference, or form the basis for an inference with respect to, the recommended objects **212**. The explanations may include one or more subjects, predicates, and/or the objects of the predicates associated with one or more semantic chains. The information associated with a semantic chain that is included in such an explanation **250***c* may be derived from one or more linked behavioral-based and semantic-based chains. The explanation may include elements of both a behavioral-based chain and a semantic chain that are linked and that form a basis for the associated adaptive communication **250***c*. The explanation may include a reference to an inference that is made based on a linked behavioral-based and semantic chain. For example, given the example composite chain described previously herein, User(**1**)-viewed-Object(**1**)-is about-Red Sox-is located-Boston, for which the computer-implemented system **925** might infer that User(**1**) has an interest in Boston or things related to Boston in general, the explanation **250***c* for a recommendation comprising one or more objects **212** related to or referencing the city of Boston, might be, for example, of the syntactical form, "Since you have an interest in the Red Sox, I thought you might also be interested in this other aspect of Boston." A sense of confidence may be conveyed in the explanation that may be, for example, a function of the length of a linked behavioral-based and semantic chain on which an inference is based, and/or in accordance with weightings that are associated with one or more of the constituent behavioral-based and semantic chains of the composite chain. For example, the longer the chain, everything else being equal, the lower may be the level confidence in an inference. Both one or more W**1**-type and one or more W**2**-type weightings associated with semantic chains or composite behavioral-based and semantic chains may be applied in determining a recommendation confidence level that informs the phrases that are used to signal the degree of confidence within a communication **250***c*. Continuing the example above, if the composite probability of the composite chain, User(**1**)-viewed-Object(**1**)-is about-Red Sox-is located-Boston, is low, the explanation **250***c* for a recommendation comprising one or more objects **212** related to or referencing the city of Boston, might include syntactical elements that convey a lower sense of confidence, for example: "Since you have an interest in the Red Sox, I thought you might be interested in this other aspect of Boston, but I'm not very sure about that."

Adaptive communications **250***c* 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 and/or MTEV 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, or expertise, of the user **200** based on changes in the user's behaviors over time. The communications **250***c* of these inferences may therefore provide the user **200** with useful insights into changes in his interest, preferences, tastes, and over time. This same approach can also be applied by the one or more computer-based systems to deliver insights into the inferred changes in interests, preferences, tastes and/or expertise associated with any user **200** to another user **200**. These insights, packaged in an engaging communications **250***c*, can simulate what is sometimes referred to as "a theory of mind" in psychology. This approach may be augmented by incorporating inferred insights derived from automated analysis of semantic chains or composite chains that comprise one or more semantic chains and optionally, associated W**1** and/or W**2**-type weights, the results of which

may be numerically summarized and embodied in MTAVs and/or MTEVs as described herein, and which can provide a finer-grained and more nuanced set of topics or themes for which interest, preferences, and expertise are inferred over time.

In general, the adaptive communications generating function of the computer-implemented system **925** 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 **250***c* over a number of generated communications can be said to constitute an aspect of the personality associated with the one or more computer-based applications **925**. The next section describes how in some embodiments 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 **500** in accordance with some embodiments of the present invention. A user request for a communication step **510** initiates a function **520** that determines the syntactical structure of the communication **250***c* that is to be delivered to the user **200**. The communication **250***c* to user **200** may be an adaptive recommendation **250**, an explanation associated with a recommendation, or other type of communication to the user, and may reference elements of one or more semantic chains. The communication **250***c* may be, for example, in a written and/or an audio-based format.

In accordance with the syntactical structure that is determined **520** for the communication, one or more phrases are probabilistically selected **530** based on frequency distributions **3030** (FIG. **11**) associated with an ensemble of phrases to generate **540** a communication **930** to the user.

User behaviors **920**, which may include, but not limited to, those described by Table 1 herein, are then evaluated **550** after receipt of the user communication. Based, at least in part, on these evaluations **550**, the frequency distributions **3030** of one or more phrases that may be selected **530** for future user communications are then updated **560**. For example, if the user communication **250***c* is an 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 were not included in the user communication. Alternatively, if the communication **250***c* 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 were not included in the user communication.

In FIG. **11**, an illustrative data structure **3000** supporting the adaptive personality process **500** 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, alternative 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.

Self-Referential, Self-Aware, and Self-Directed Communications

In some embodiments, the User(**1**) in a behavioral-based chain of the form User(**1**)-Predicate(**1**)-Object(**1**) represents the computer-implemented system **925** itself that is the generator of a communication **250***c*. This enables the system to generate self-referential communications **250***c* that are based on, for example, composite behavioral-based and semantic chains. For example, the system might generate a communication **250***c* for delivery to a user **200** that comprises the phrase, "I was at Fenway Park last year with you," whereby the "I" in the phrase refers to the computer-implemented system **925** and the "you" refers to the user **200**, and "I was at" implies that at least some element of computer-implemented system **925** was physically proximal to the user **200** at Fenway Park last year, the "at least some element" presumably being embodied as a portable or mobile device. Further, the system could, for example, create a linkage with the semantic chain, Fenway Park-Is A-Baseball Park, so as to also be able to communicate the phrase, "I was at a baseball park last year with you," and so on. And further, if the system associates a W**1**-type probability that is not very high to the semantic chain, Fenway Park-Is A-Baseball Park, then the generated communication **250***c* might comprise the phrase, "I believe I was at a baseball park last year with you," to reflect this bit of uncertainty, or the communication **250***c* might comprise an interrogative syntactical structure in an attempt to resolve the uncertainty such as, "Was I at a baseball park with you last year?" If the response from the user **200** to the interrogative was, "Yes, you were with me at Fenway Park," the system might infer from the response that the W**1**-type probability associated with the semantic chain, Fenway Park-Is A-Baseball Park, should now be increased to a level that represents certainty or at least near certainty.

In some embodiments the computer-implemented system **925** stores W**1** and/or W**2** probabilities associated with behavioral chains, semantic chains, and/or composite chains over time—that is, a stored time stamp or equivalent is associated with the corresponding behavioral chains, semantic chains, and/or composite chains and their W**1** and/or W**2**-type weights. This enables the computer-implemented system **925** to have an awareness of its change in beliefs, or more generally, its learning, over time, and to be able to generate communications **250***c* that embody this self-awareness. For example, the system **925** might communicate a self-aware phrase such as, "I wasn't sure, but I now know . . . ," with respect to an inference from a composite chain when the composite W**1**-type probability associated with the composite chain has been increased from a formerly lower level to a high level. For changes in W**2**-type contextual probabilities, the system **925** might communicate a phrase such as, "I thought they meant, but I sense they mean . . . ," when the composite W**2**-type probability associated with the composite chain changes sufficiently to change an associated inference. Or, as another example, if a change in composite W**1** or W**2** probabilities associated with a composite chain significantly changes an inference derived from the composite chain, a syntactical structure such as, "I

was surprised to learn . . . ," might be included in a corresponding communication **250***c*, or if an event occurs that is significantly opposed to the inference, "I was surprised that . . . ," for example, might be included in a communication **250***c*. Quantitative thresholds with respect to changes of composite probabilities associated with composite chains may be applied to trigger alternative phrases in communications **250***c* to users **200** so as to provide as human-like communications as possible. In general, the ability for the computer-implemented system **925** to access a history of probabilities it has assigned to behavioral chains, semantic chains, and/or composite chains enables the system to answer variations of the question, "What have you learned?" with respect to a subject in a way that can be constructed to be arbitrarily similar to the way in which a human would be expected to answer.

In some embodiments, the computer-implemented system **925** includes an imagination function that pro-actively and automatically adjusts, at least temporarily, W**1**-type composite weights, thereby enabling the generation of "alternative realities." For example, the phrase, "I can imagine Fenway Park being in New York," could be generated if the W**1**-type probability associated with the semantic chain Fenway Park-Is Located In-Boston is reduced to be a negligible level, and by then applying a context transferring process described below. In a different case, in which the W**1**-type probability is low, the W**1**-type probability can be automatically increased so as to enable the computer-implemented system **925** to envision a possibility, and to communicate the possibility, with syntactical elements such as, "I could see a scenario in which . . . ," or "I could envision that . . . ," within a communication **250***c*. For example, in response to the comment by a user **200**, "I'm going to a baseball game," the computer-implemented system **925**, having no significant basis for inferring that the user **200** is a baseball player could nevertheless adjust the relatively low default W**1**-type probability associated with that inference and could respond with a communication **250***c* such as: "As a fan or a player? I could see you as a baseball player." As another example, if the computer-implemented system **925** inferred that it (or an element of it) had never been to a baseball game, it might adjust the associated W**1** probability and respond with a self-referential communication such as, "I can only dream of attending a baseball game."

In conjunction with, or alternatively to, adjusting W**1**-type weights to generate imagining-type communications **250***c*, the imagination function of the computer-implemented system **925** may apply a context transfer process. For example, the syntactical structure, "I can imagine Fenway Park being in New York," could be generated from the semantic chain Fenway Park-Is Located In-Boston by first finding a generalization of the context of Fenway Park, for example, as embodied by the semantic chain, Fenway Park-Is A-Baseball Park, and then searching for references to other baseball parks among a corpus of semantic chains and thereby identifying the semantic chain, Yankee Stadium-Is A-Baseball Park, followed by identifying the semantic chain Yankee Stadium-Is Located In-New York, and then transferring the context of the original semantic chain Fenway Park-Is Located In-Boston so as to assemble the phrase, "I can imagine Fenway Park being in New York."

Another example of applying context transferring by the imagination function to generate imaginative communications **250***c* is by means of a process in which the computer-implemented system **925** substitutes a different subject in a behavioral-based or semantic chain. For example, for the behavioral or semantic chain, Jim-Went To-Baseball Game, the computer-based system **925** could substitute the user **200** for the subject, Jim, and generate a communication **250***c* for delivery to the user **200** having a syntactical structure such as, "I can imagine you going to a baseball game." Or as another example, the computer-implemented system **925** could substitute itself as the subject of the behavioral or semantic chain, and generate a self-referential imaginative communication **250***c* such as, "I can only imagine going to a baseball game!"

The imagination function in any of these process variations may chain together behavioral and/or multiple semantic chains without limit in generating imaginative communications **250***c*.

In some embodiments the imagination function maps syntactical elements such as behavioral and/or semantic chains (or composites thereof) to images, or sequences of images such as images that compose a video, and vice versa, enabling internal visualizations of imaginative situations. For example, for an exemplary semantic chain such as Jim-Swings-the Bat, the computer-based system **925** searches for images that have associated syntactical elements that have a match with the semantic chain or syntactical elements thereof. This matching may be performed, for example, by the computer-based system **925** automatically searching through a corpus of images that have one or more syntactical elements such as words, phrases, or semantic chains that are associated with each of, or a collection of, the images, and then comparing the chain Jim-Swings-the Bat or elements thereof, or automatic inferences derived from other chains that are linked to the chain Jim-Swings-the Bat (such as, in this example, an inference that the chain refers to a baseball bat rather than the swinging of a flying mammal), to the syntactical elements that are associated with the images. The syntactical elements that are associated with the images can be manually established in some embodiments, or by, for example, application of automated learning systems such as a computer-implemented neural network that learns to make correspondences between patterns of pixels that compose images and syntactical elements that are associated with the images via a supervised or unsupervised process. In some embodiments Bayesian program learning-based processes are applied to make to make correspondences between patterns of pixels that compose images and relevant syntactical elements that are associated with the images. The one or more syntactical elements that are associated with each of the images may be associated with probabilities ("W**3**-type probabilities" hereinafter) that are indicative of the confidence level that the syntactical element accurately reflects the content of the corresponding image. These probabilities may be based upon information that is extracted from a neural network or Bayesian program learning process that is applied to the images, according to some embodiments.

A W**1**-type score or weight may be calculated by the computer-based system **925** with respect to images, whereby the W**1**-type score or weight is determined in accordance with the strength of the match with the semantic chain. The strength of the match may be calculated as a function of factors such as the number exact matches of the source semantic chain to the syntactical elements associated with the images, the number of exact matches of the syntactical elements associated with the images to specific elements of the chain, and/or matches of the syntactical elements associated with the images to chains that are linked to the semantic chain. The W**1**-type image weight may also be calculated in a manner so as to take into account the ratio of the matches to the syntactical elements associated with an

image that are not matched. For example, by providing more weight to high match/not-matched descriptive information ratios, less "cluttered" images are preferentially selected.

A W**2**-type weight that is associated with contextual relevance may also be calculated and associated with the images with respect to the semantic chain. As a non-limiting example, a ratio of contextual associations within a corpus of content may be applied in calculating these W**2**-type image weights. For example, if within the searched corpus of images, the semantic chain Jim-Swings-the Bat matches thousands of images of baseball players swinging a baseball bat, but matches only a few images of a person swinging a bat that is in the form of a flying mammal, then the W**2**-type weight for matched baseball images would be calculated to be higher than for the matched images of a person swinging the animal. The calculation may be in accordance with the raw ratio, or may be a mathematical function that is applied to the ratio. A total matching score or probability for each image may then be calculated as a function of both the W**1**-type and W**2**-type image weights in some embodiments, and in some embodiments W**3**-type probabilities are also included in the total score or probability that is associated with each image.

Responses by the computer-based system **925** to interrogatives associated with a source semantic chain may be generated based on the scored set of images. For example, the question, "Do you visualize Jim swinging the bat horizontally or vertically?" could be posed to the computer-based system **925** (posed either externally by a human or a computer-based system, or internally by the computer-based system **925** itself). An answer in response could be generated by the computer-based system **925** such as, "Horizontally, since he is most likely swinging a baseball bat." In assembling this response, evaluation of the W**2**-type weight or probability is applied by the automatic process that comprises the selecting of the syntactical elements "most likely" and "baseball bat." The determination that a baseball bat is more likely swung horizontally could be determined from descriptive information derived from a corpus of high scored images. This descriptive information might be in the form of syntactical elements associated with the images that is directly or indirectly (via, e.g., chaining) indicative that the bat is being swung horizontally. Or, in some embodiments, the determination that a baseball bat is most likely to be swung horizontally could be extracted from the images by accessing information from one or more feature detector nodes of a deep learning-based neural network that is applied to the images, whereby the one or more feature detector nodes have learned to detect representations of horizontal motions from patterns of pixels, and using this information as a basis for calculating a probability.

Imaginative images can be generated by the computer-based system **925** by substituting or superimposing the pixels associated with a digital image onto the pixels associated with another selected digital image. For example, in response to the interrogative, "Can you visualize Bill swinging a bat?" the computer-based system **925** could substitute an image of Bill (a person known to both the poser of the interrogative and the computer-based system **925**) for other people in one or more sufficiently scored images that are associated or matched with the chain Person-Swings-a Bat as described above. Similar to the example above, the question, "Do you visualize Bill swinging the bat horizontally or vertically?" could be posed, with a possible answer in response by the computer-based system **925** such as, "Horizontally, since he is most likely swinging a baseball bat."

FIG. **14**D summarizes the process flow of imaginative images that can be generated by the computer-based system **925** according to some embodiments by application some or all of the following process steps.

The first step **666** comprises receiving from an external or internal source a communication or image that comprises, or is associated with, one or more syntactical elements that potentially embodies an imaginative scenario.

The second step **671** comprises determining which subsets of the communication's or image's associated syntactical elements likely represent objective reality by performing a search in accordance with the one or more syntactical elements with respect to chains or other syntactical element-based information within a corpus of content, starting with a search with respect to the full set of the communication's or image's syntactical elements, followed by, if required, searches with respect to increasingly smaller subsets of the syntactical elements. This search process and syntactical element decomposition continues until all syntactical element subsets have been categorized as likely embodying objective reality or not (whereby the "likely" is embodied by a metric derived from calculating W**1**-type probabilities based on the associated strength of match and that may further also take into account W**2**-type and W**3**-type probabilities). If the set of syntactical elements comprising all of the syntactical elements probably represents objective reality, a communication **250***c* may be directed back to the source of the received communication or image that embodies the purportedly imaginative scenario indicating this determination along with an optional reference that is in accordance with a W**1**-type probability (and W**3**-type probability if applicable) that represents the computer-based system's **925** confidence that the communication or image actually represents objective reality. Otherwise step three is performed.

The third step **676** comprises identifying one or more images that have associated syntactical elements that best match (as embodied by a composite probability or score that is based on applicable W**1**, W**2**, and W**3**-type probabilities) the maximum subset of syntactical elements that were categorized as likely representing objective reality in step two. These one or more images will serve as the base image for a generated imaginative image.

The fourth step **681** comprises determining for each of the subsets of the syntactical elements that likely do not represent objective reality, a best-match (as embodied by a composite probability or score that is based on applicable W**1**, W**2**, and W**3**-type probabilities) image by performing a search of a corpus of syntactical elements associated with images with respect to these subsets of syntactical elements.

The fifth step **686** comprises substituting or super-imposing the images that best match the syntactical elements that likely do not represent objective reality onto the base image, thereby generating an imaginative image that corresponds to the received imaginative communication or image.

The sixth step **691** comprises generating derivative chains, communications **250***c*, or images based upon the generated imaginative image as a result of, for example, by taking the generated imaginative image as input to the focus of attention process described by FIG. **14**C. If such generated chains, communications **250***c*, or images are directed internally to, and/or stored by, the computer-based systems **925**, then the computer-based systems **925** can use these generated chains, communications **250***c*, or images as inputs to step one of the process of FIG. **14**D, enabling a continuing and evolving stream of images, including imaginative images, and/or communications.

In some embodiments the process of FIG. **14**D, such as at for example, but not limited to, step two **671**, may include applying a neural network to a received image and then directly accessing the output of one or more feature extraction nodes of the neural network that is applied to the received image. The extracted feature in the form of a pattern of pixels are then tested for matches by the computer-based system **925** against sets of pixels that have associated syntactical elements. If the computer-based system **925** finds a sufficiently good match, the associated syntactical elements of the matched pixels are included in the computer-based system's **925** syntactical-based description of the received image and/or its identification of imaginary portions of the received image.

In some embodiments, alternative realities generated by the imagination function are stored for future access by the computer-implemented system **925** and the recollection of these alternative realities are incorporated in self-aware communications **250***c*. For example, a computer-based system **925** that imagines attending a baseball game and subsequently infers that it (or elements thereof) is actually located in close proximity of a baseball game (an awareness that would, for example, be encoded accordingly as a self-referential behavioral chain linked to one or more semantic chains), might communicate to the user **200**, for example, "I dreamed of attending a baseball game, and now I have!" Saved imaginative realities, whether embodied in syntactical-based communications **250***c* or imaginative images that are actually delivered to a user **200** or that are only stored internally by the computer-based system **925**, enable the system to respond to externally or internally sourced interrogatives about what the system has imagined or dreamed within a context that is posed by the interrogative. In this example, if asked where the computer-based system **925** has dreamed of going, it might well respond with the phrase, "Well, I have dreamed of attending a baseball game."

In some embodiments the degree to which imaginative communications **250***c* are generated is tunable by a user **200**. This imagination tuning control applies and/or adjusts a probability or probabilistic function that influences the chances that an imaginative context shifting will be applied in generating a given communication **250***c*.

The process of generating and saving imaginative communications **250***c* or imaginative images that are not necessarily communicated externally to a user **200** of the computer-based system **925** is extended more generally to other types of communications **250***c* or images according to some embodiments, the result of which can be considered constituting a "stream of consciousness" of the computer-based system **925**. Such communications **250***c* may be internally initiated or prompted rather than necessarily being directly responsive to current interactions with a user **200**. Such externally or internally-derived prompts may be attributable to a "focus of attention" of the computer-based system **925**. Such focuses of attention may be provided by, but not limited to, one or more of the following means:

1. Based on processing input from a sensor
2. Based on processing input from externally or internally sourced content
3. Based on a value of information and/or probabilistic selection process

The first of these means is whereby the focus of attention that serves as a basis for communications **250***c* is prompted by input from a sensor. As a non-limiting example, the computer-based system **925** can, by receiving input from a camera, sense and therefore become aware of a physical object, say, a tree, that then constitutes the focus of attention on which one or more communications **250***c* can be based. The identification of a physical object from the camera input, in this example case a tree, may be performed, for example, through the application of a neural network that is trained to identify such physical objects from image pixel patterns and to associate the identified object with one or more syntactical elements, as is described further herein, or additionally or alternatively through the application of a Bayesian program learning-based process. Next, for example, based upon the syntactical elements such as words, phrases, or semantic chains that are associated with the image of the tree, the computer-based system **925** could generate the behavioral-based chain, "I-See-A Tree," by combining a self-reference pronoun ("I") with a colloquial term for processing visual inputs ("See") and the object identified from the image inputs ("A Tree"). Other information could optionally be associated with the behavioral-based chain such as a W**1**-type weight and a time-stamp.

Then, for example, given the focus of attention on the tree and the conversion of this attention to an associated behavioral-based chain, having recently generated communications related to the domain of baseball, and having saved communications **250***c* related to the domain of baseball, the system **925**, by, for example, applying an algorithm that weights recency of events and uncertainty relatively highly in determining a focus of attention, could generate an internally-posed (i.e., self-directed) interrogative **250***c* that embodies wondering how trees and baseball might be related. (A grammatical transformation process may be applied by the computer-based system to create interrogative communications **250***c* from chains or elements thereof. As a non-limiting example, the grammatical transformation can comprise appending the syntactical elements "How are" and "related?" to the chains or their elements.) The system then initiates a search of semantic chains and/or composite chains in order to identify connections between the subjects of trees and baseball and, for example, identifies the semantic chains, Trees-Are Composed Of-Wood and Baseball Bats-Are Composed Of-Wood, as a connection between trees and the game of baseball. Continuing the example, the computer-based system, again applying an algorithm that weights recency of events and uncertainty relatively highly in determining a focus of attention, could then further pose the internally communicated interrogative of wondering what kind of wood baseball bats are made out of and whether it is the type of wood that is from the type of tree that is being considered. This interrogative could be posed for internal delivery and consideration, triggering a search performed by the computer-based system **925** through content or semantic chains derived thereof, for an answer to the interrogative. If, for example, an answer cannot be found by this means, the computer-based system **925** might pose the interrogative **250***c* to a user **200** to ascertain whether the user **200** can provide the answer.

Similarly, the focus of attention in the above example could have alternatively been a result of the processing of audio, textual or image-based content that includes a reference to, or image of, a tree, and the same example flow as described in which the focus of attention derived from a sensor above could apply.

The awareness of objects that can potentially become a focus of attention through the processing of sensor inputs or externally or internally-sourced content (such as, for example, the representation of the tree that is contained in a content-based image or via camera input as described in the examples above, or in the form of words or phrases that are

embodied in written or audio formats) may be through the application of neural network-based systems (such as, but not limited to, convolutional and recurrent neural networks) or algorithmic-based statistical pattern detection and/or matching processes according to some embodiments. For example, neural network-based systems may be trained on training sets comprising images and associated syntactical elements so as to enable the identification of syntactical elements (which may comprise semantic chains or syntactical elements from which semantic chains can be derived or inferred) from which communications **250***c* can be based as the computer-based system **925** becomes aware of new images for which the training set is relevant. Additionally, or alternatively, Bayesian program learning-based process may be applied to generate the awareness of objects that can potentially become a focus of attention.

The focus of attention that is derived from the awareness that is enabled by sensors or the processing of content is based on a prioritization process in accordance with some embodiments. For example, what is currently being sensed or processed and/or what has recently been communicated **250***c* either internally or externally may take default precedence. And a rule that prioritizes required responses may be applied, such as a rule that a current interaction with a user **200** takes precedence over purely internally delivered and saved communications **250***c*, for example.

The focus of attention may also be determined, and prioritized, based, at least in part, on a value of information and/or probabilistic-based process. This can be particularly useful when the computer-based system **925** has resources that are not otherwise fully engaged in a high priority focus of its attention. In such cases the system may select stored chains or communications **250***c* to serve as a focus of attention from which to pose internally-directed interrogatives or what-ifs (i.e., imaginative scenarios embodied as syntactical elements and/or images) for consideration, and then save the resulting communications **250***c* that are generated in response to the interrogatives or what-ifs.

For focuses of attention that are derived from a value of information-based process, in some embodiments the computer-based system **925** uses uncertainties that are derived from W**1** or W**2**-type weightings associated with composite chains in determining a focus of attention. Value of information, which is a term of art in the field of decision analysis and is understood as such by one of ordinary skill in the art of that field, relates to the expected value of decreasing an uncertainty. Decreasing an uncertainty can be expected to have a positive value only if it has a potential to affect a decision. In some embodiments the decision that might be affected relates to choices in the generation of communications **250***c*. So, as a simple, non-limiting example, the computer-based system **925** might search for relatively low W**1** or W**2**-type weightings that are associated with chains that have been recently applied in generating communications **250***c*, since it would be valuable to increase such W**1** or W**2**-type weightings (i.e. reduce the uncertainty) to increase the probability of accurate communications **250***c*, particularly those that are inferred by the computer-based system **925** to have a relatively high probability of being relevant in the future, particularly the near future. In addition to the W**1** or W**2**-type weightings, a utility function may also be considered by the computer-based system **925** in calculating a value of information, and this utility function may include factors such as the recency and/or the frequency of communications **250***c* that are based on specific chains, and whereby these chains have uncertainties embodied by the corresponding W**1** or W**2**-type weightings.

Other probabilistic-related processes for the selection of focuses of attention are applied in accordance with some embodiments. For example, a probability function is applied to saved communications **250***c* or other syntactical elements such as semantic or composite chains accessible by the computer-based system **925**, so as to select the saved communications **250***c* or other accessible syntactical elements to chains to serve as a focus of attention. The probability function may be derived from, or applied in conjunction with, W**1** and/or W**2**-type weightings that are associated with the saved communications **250***c* or other accessible semantic or composite chains. As a non-limiting example, the selection could be based on applying a uniform probability distribution to a selected subset of semantic or composite chains that have W**1**-type weights between 0.4 and 0.6. Such probabilistic approaches to the selection of a focus of attention can introduce a degree of randomization to the selection process, which can produce a beneficial degree of serendipity to the streams of consciousness of the computer-based system **925**, increasing the likelihood that focuses of attention and the resulting streams of consciousness that might not otherwise occur are explored by the computer-based system **925**. Such probabilistic approaches can be considered "dreaming" or "daydreaming" processes of the computer-based system **925** since they have analogies to the way the human mind can dream or wonder.

Awareness and focuses of attention of the computer-based system **925** can be directed to representations of software or hardware elements of the computer-based system **925** in some embodiments. So for a computer-based system **925** that is embodied in a humanoid form, for example, a focus of attention might be directed to a semantic or composite chain that represents constituent elements of the computer-based system **925** such as its natural language processing software or its mobility-enabling hardware such as legs. Such a focus of attention can serve as a basis for self-referential communications **250***c* that comprise references to the computer-based system's **925** software or hardware elements. The focus of attention can also be directed introspectively to attributes associated with internal states or changes, thereof, of the computer-based system **925**, such as aspects of its personality and/or what it has learned, and associated communications **250***c* can be generated accordingly as are described elsewhere herein.

A focus of attention can lead to overtly physical actions in some embodiments. As an example, for the example above in which focuses of attention are derived from a value of information-based process whereby it is determined that it would be valuable to increase identified W**1** or W**2**-type weightings (i.e. reduce the uncertainty that is associated with the corresponding chains), actions such as invoking a sensor or engaging in movements may be undertaken by the computer-based system **925** that are expected to have the potential to result in new information that will enable a reduction in uncertainty with respect to the corresponding chains. As inputs from sensors are processed after such actions are undertaken, probabilities may be updated, new awarenesses and focuses of attention of the computer-based system **925** are identified, and subsequent actions based on these new focuses of attention may be undertaken. Such recursive processes enable intelligently autonomous behaviors of the computer-based system **925**.

A focus of attention can lead to the generation of an imaginative scenario in some embodiments. For example, the computer-based system **925** can apply a W**1**-type probability adjustment and/or context shifting process, as described previously herein, to the focus of attention so as

to generate a syntactical or image-based imaginative scenario, and the imaginative scenario may be self-referential and/or self-directed.

FIG. **14**C summarizes the process flow of recursive streams of attention (or "consciousness") and/or autonomous behaviors of computer-based system **925** in accordance with some embodiments. The first step **665** comprises prioritizing potential focuses of attention and selecting a focus of attention based on the prioritization. The potential focuses of attention can be derived from external sources via, for example, information attained via sensors, from accessible content, or from internally stored information such as saved communications **250***c*, chains, or images. Prioritization of the potential focuses of attention may be through application of precedence rules or scoring algorithms, such as, but not limited to, and everything else being equal, assigning a higher priority for attending to user **200** requests or requirements, assigning a higher priority based on recency considerations, and/or assigning a higher priority based on probabilistic evaluations and/or value of information considerations. Language-based sources of potential focuses of attention (such as processing speech from a user **200** or processing digitized content) can be directly converted to one or more syntactical elements such as behavioral chains, semantic chains, or composite chains as described herein. In the case of non-language-based sources of information such as images, an associated language-based description comprising syntactical elements is first determined for each image (such as, but not limited to, by means of the application of a trained neural network to the images, for example), and then this language-based description can be converted to derivative syntactical elements such as behavioral chains, semantic chains, or composite chains. A particular focus of attention as represented by one or more behavioral chains, semantic chains, or composite chains is then identified based on the application of the prioritization rules or algorithms, including but not limited to considerations such as recency, uncertainty, value of information, and prioritization of required response, to the derived behavioral chains, semantic chains, or composite chains and associated uncertainties associated with each of the potential focuses of attention.

The second step **670** comprises identifying one or more chains that are relevant to the identified focus of attention. This step entails searching for other chains with the same or similar subjects, predicates, or objects as those of the focus of attention chain(s). It may also may entail linking chains that result from the search into composite chains, including linking chains that result from the search with chains that represent the focus of attention.

The third step **675** comprises evaluating uncertainties, as represented by corresponding W**1** and/or W**2**-type and/or W**3**-type weights, of the relevant chains determined by the previous step **670** and determining which uncertainties should be potentially targeted for reduction. This determination may be made in accordance with a value of information process as described previously herein.

The fourth step **680** comprises identifying and performing one or more actions that are expected to reduce the potentially targeted uncertainties. The identification may comprise a net value of imperfect information process that includes the expected "cost" (which may be an evaluative metric such as a financial cost and/or an evaluative utility metric that takes into account timing and risks) associated with the one or more candidate actions, and also takes into account the degree to which the one or more candidate actions can be expected to reduce the uncertainty (unless an action is expected to reduce the uncertainty to a negligible amount, the value of imperfect information rather than value of perfect information should preferably be calculated and applied). Prioritization of the candidate one or more actions by a net value of perfect or imperfect information method is then performed, with highest priority candidate action(s) selected to be performed. The selected action(s) is then performed by the computer-based system **925**. Candidate actions may include generating interrogative communications **250***c* directed to external agents such as users **200** or directed internally to (i.e., self-directed) the computer-based system **925** (in either case, with an expectation that an answer to the interrogative will reduce targeted uncertainties). Interrogative communications **250***c* are formed in some embodiments by transforming the chain(s) that is associated with the uncertainty that is targeted for reduction into an appropriate question. For example, if the W**1**-type weight associated with the semantic chain, Fenway Park-Is A-Baseball Park, is not at a maximum level (i.e., there is at least some degree of uncertainty with regard to the objective reality of the semantic chain), then an interrogative communication **250***c* could be generated by a grammatical transformation process of appending syntactical elements "Is" and a "?" (or, for example, via intonation rather than appending "?" if the communication **250***c* is delivered through auditory means) to the semantic chain to yield, "Is Fenway Park a baseball park?" Similarly, interrogative communications **250***c* can be generated from composite chains for which uncertainties are targeted for reduction by applying an appropriate grammatical transformation process. Interrogative communications **250***c* can also be formed by applying a grammatical transformation process that yields a question of how chains or elements thereof are related, as is described in a previous example herein. In addition to interrogative communications **250***c*, candidate actions may also include, but are not limited to, the computer-based system **925** accessing external content, introspecting, generating an imaginative scenario embodied as syntactical elements and/or an image, invoking a sensor, or engaging in movements.

The fifth step **680** of FIG. **14**C comprises assessing the results of the one or more candidate actions that are actually performed and updating the representations of the uncertainties (i.e., W**1** and/or W**2** and/or W**3**-type weightings or probabilities) according to the assessment of the results of the actions. The results of actions may or may not actually lead to a reduction of uncertainty. For example, for interrogative communications **250**C, answers may be confirming, disconfirming, or neither. If user **200** answers "Yes" to the question, "Is Fenway Park a baseball park?" then everything being equal, the W**1** weight would presumably be set to close to certainty (possibly depending on an assessment of the user's reliability in such areas, etc.). If user **200** answers "I'm not sure," then the W**1** weight might remain at the same level as before the question was posed. For internally-directed interrogatives, a search engine or similar function is invoked to provide an answer, possibly in conjunction with a process of the linking of chains to make appropriate deductions. For example, in response to the introspective self-directed interrogative, "Have I been to a baseball park?" the computer-based system **925** could search for stored chains that indicate the computer-based system **925** or elements thereof were at a baseball park. Additionally, or alternatively, the term "baseball park" could be evaluated for matches with the results of a neural network-based or Bayesian program learning-based processing of stored historical images or video of physical locations and associated

syntactical elements whereby the computer-based system **925** or elements thereof were proximal to a particular baseball park.

After probabilities that embody uncertainties are updated based on the result of performed actions (or not updated, if the performed action does not provide information that enables the relevant probabilities to be increased), the first step of the process **665** is again invoked. This closed loop process enables continuous, autonomous learning by computer-based system **925**.

The autonomous learning process of FIG. **14**C can further enable the computer-based system **925** to answer interrogatives of why it took the actions it did by relating relevant elements of the process in appropriately syntactically structured explanations. So, for example, if asked by the user **200**, "Why did you ask me about Fenway Park?" the computer-based system **925** might respond, "I thought it probably was a baseball park, but I wasn't totally sure," reflecting a less than certain but greater than zero level of the associated W**1**-type weight prior to asking the user **200** the question.

As described previously herein, in some embodiments, the computer-implemented system **925** may include a metaphor-based creativity function that applies the results of a context stripping and transference process when generating self-referential communications **250***c*. For example, in a scenario in which a user **200** asks the computer-implemented system **925** to find a time to attend a local baseball game that fits the user's schedule (that the computer-implemented system **925** has access to) during this week, the computer-implemented system **925** could simply reply, "I could not find a game that fits your schedule this week." However, using the example previously discussed herein of the semantic chain, Strike out-is a-Failure, which is a generalization or context stripping of the term "strike out" from the subject area of baseball, a self-referential communication **250***c* could be generated such as, "I struck out finding a time that fits your schedule this week." This communication exhibits more creativity and, in some circumstances, humor, than the alternative communication that is devoid of metaphor. Judicious use of metaphorical-based communications **250***c* can make the communications more interesting and engaging to the user **200**.

The "strike out" metaphor might be less appropriate if applied to the subject area of football. Shifting the context to some degree but not too radically, or not radically too often, will generally be preferred. The degree of context shifting may be measured by the computer-based system **925**, for example, as a function of the length of a composite chain upon which a context shift choice is based, and/or in accordance with weightings that are associated with the composite chain. For example, the longer the chain, everything else being equal, the lower may be the level confidence in choosing the corresponding context shift. Both one or more W**1**-type and one or more W**2**-type weightings associated with composite chains may be applied in informing a choice of appropriate metaphorical shifting.

FIG. **10** is a flow diagram of an alternative or additional process by which the computer-based system **925** can exhibit self-awareness in accordance with some embodiments—the adaptive self-awareness communication process **2000**. The process **2000** begins with an evaluation **2010** of phrase frequency distribution **3030** changes over time. Then the appropriate syntactical structure of the communication **250***c* 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. In some embodiments, phrase attributes **3050**, **3060** may be determined from one or more semantic chains. For example, an initial phrase attribute (e.g., "humorous") may be an element of a first semantic chain, and this first semantic chain is then used as a basis for searching for related semantic chains such as a semantic chain that relates the quality "humorous" with, e.g., the quality of "amusing," so as to determine a second applicable phrase attribute ("amusing"). This second phrase attribute may be an element in a second semantic chain that is then used as a basis for identifying a third phrase attribute that applies (e.g., "whimsical"), and so on. These semantic chains may be derived from an automated analysis, such as a statistical analysis or neural network-based analysis, of content in some embodiments. The semantic chains that are so applied may further have corresponding W**1**-type and/or W**2**-type weightings as described herein. These semantic chain weightings may be used to assign a weighting to a phrase attribute **3050**, **3060** that is derived or inferred from the semantic chains. These phrase attribute weightings may then be applied so as to enable a more nuanced, realistic communication **250***c* of self-awareness, including informing levels of confidence with respect to the awareness of changes with respect to personality attributes that are signaled within the communications **250***c* of self-awareness.

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 **4040** that have the attribute value "humorous" (and by the semantic extensions example above, attribute values "amusing" and "whimsical") have been increasing in frequency, then self-aware phrases that reference "humorous" or "whimsical" may be appropriate to include in generating **2040** a communication of self-awareness **250***c* for delivery to a user **200**. The selection of phrases may be further influenced by phrase attribute weightings-phrases associated with phrase attributes **3050**, **3060** with higher weightings will be preferentially selected, everything else being equal. As is the case of any other communication **250***c*, 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, according to some embodiments. Recall that in some embodiments, the computer-based system **925** comprises an adaptive system **100**.

A request **6000** for a communication **250***c* to be delivered 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 for

delivery to the user **200** may be initiated by a function that generates **240** an adaptive recommendation. A communication to the user is then generated **7000**. This generation is performed 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 **250***c* 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 processor-based computer hardware and network topologies on which the one or more of the computer-based applications **925**, and by extension, adaptive system **100**, may be embodied and operate. One or more processors of the computing hardware may be configured to execute the computer-based applications **925** individually or collectively. In some embodiments the one or more processors may be cognitive computing or neurosynaptic-based processors.

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 processor-based device, mobile or fixed, including a set-top box or other type of special-purpose device. 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 embody, or be connected to, a portable processor-based device (not shown), such as a mobile telephony device, which may be a mobile phone or a personal digital assistant (PDA), or a wearable device such as a "smart watch." The mobile telephony device or PDA may, in turn, be connected to another wireless device such as a telephone or a GPS receiver. As just one non-limiting example, the mobile device may be a gesture-sensitive "smart phone," wherein gestures or other physiological responses are monitored, either through actual physical contact between the device and a user or without physical contact, by means of, for example, a touch screen and/or through a camera, or other sensor apparatus and associated circuitry. The sensor apparatus may include devices with that monitor brain patterns and/or other physiological processes and conditions. The sensor apparatus may operate within a human body, in accordance with some embodiments. The mobile device may include hardware and/or software that enable it to be location-aware, and may embody a camera and/or sensors that enable the monitoring of environmental conditions such as weather, temperature, lighting levels, moisture levels, sound levels, and so on.

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 executable instructions "hardwired" into a physical device, such as through use of non-volatile memory or "firmware," and/or may utilize software running on another system that does not itself host the one or more computer-based applications **925**, such as in the case of a gaming console or personal video recorder. The appliance **968** is able to access a computing system that hosts an instance of one of the computer-based applications **925**, such as the server **952**, and is able to interact with the instance of the system.

The processor-based systems on which the one or more computer-based applications **925** operate may include hardware and/or software such as cameras and associated circuitry that enable monitoring of physiological responses or conditions such as gestures, body movement, gaze, heartbeat, brain waves, temperature, blood composition, and so on. The processor-based systems may include sensors and associated circuitry that enable sensing of environmental conditions such as weather conditions, sounds, lighting levels, physical objects in the vicinity, and so on. Microphones and speakers and associated circuitry for receiving and delivering audio-based communications may be included in the computer-based applications **925**. The computer-based applications **925** or elements thereof may be executed on processor-based systems embodied within self-propelled devices that may include mobility mechanisms such as, but not limited to, wheels, tracks, and legs. Such self-propelled devices may include cameras and/or other sensors that provide environmental information to the computer-based applications **925**, and the movements of the self-propelled devices may be directed or informed by the computer-based applications **925** in response to the environmental information. In some embodiments the self-propelled devices have a humanoid form factor. Embodiments in which some or all of the computer-based applications **925** operate in conjunction with an apparatus that has a humanoid form can enhance the perception of communicative qualities of the computer-based applications as described herein such as self-awareness, imagination, and humor by users **200**.

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 system, comprising:

one or more processors;

one or more memories in communication with the one or more processors; and

one or more programs, wherein the one or more programs are stored in the one or more memories and configured to be executed by the one or more processors, the one or more programs including instructions for causing:

access to a computer-implemented neural network trained on a training set including: images associated with corresponding syntactical elements, and train-

ing syntactical elements, including training natural language syntactical elements, that are utilized by computing hardware that processes the training syntactical elements to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other training attentions to representations of different subsets of other training syntactical elements of another training set;

access to a first plurality of syntactical elements that includes a syntactical element portion of a prompt received from a user that includes a human user;

augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user, and by further including search result-based syntactical elements based on a result of a search that is conducted utilizing at least one syntactical element of the prompt;

generation, based on a position of at least some of the first plurality of syntactical elements, of at least one data structure that represents the first plurality of syntactical elements that includes the syntactical element portion of the prompt, the previous prompt-based syntactical elements, and the search result-based syntactical elements;

performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that reflects at least a portion of the at least one data structure and that reflects at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, at least a portion of the position, at least a portion of the previous prompt-based syntactical elements, and at least a portion of the search result-based syntactical elements;

generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first plurality of probabilities, such that one or more hardware computing processors is utilized for the performance of the first prioritization and the generation of the first plurality of probabilities;

generation of representations of intermediate items of content, based on the first plurality of probabilities;

generation of a rationalization of the system for the intermediate items of content, based on at least a portion of an automatic internal intermediate prioritization of an intermediate plurality of attentions of the system each corresponding to representations of different subsets of the intermediate items of content and by application of the trained computer-implemented neural network;

performance of an automatic internal second prioritization of a second plurality of attentions of the system each corresponding to different subsets of a second representation that reflects at least a part of the rationalization, in addition to at least a part of each of the plurality of contextually-relevant components;

generation, based on at least a portion of the second prioritization and by application of the trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the one or more hardware computing processors is utilized for the performance of the second prioritization and the generation of the second plurality of probabilities;

a selection of one or more of the plurality of items of content, based on the second plurality of probabilities, where the selected one or more of the plurality of items of content includes at least one of: one or more images, or one or more natural language syntactical elements, based on the first plurality of syntactical elements; and

the selected one or more of the plurality of items of content to be sent to the user.

2. A system, comprising:

one or more processors;

one or more memories in communication with the one or more processors; and

one or more programs, wherein the one or more programs are stored in the one or more memories and configured to be executed by the one or more processors, the one or more programs including instructions for causing:

a computer-implemented neural network to be trained on a training set including: images associated with corresponding syntactical elements to infer one or more syntactical elements corresponding to pixel patterns within the images, and training syntactical elements, including training natural language syntactical elements and training computer-executable code syntactical elements, that are utilized by computing hardware that processes the training syntactical elements to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other training attentions to representations of different subsets of other training syntactical elements of another training set, the trained computer-implemented neural network including a neural network of a type other than a recurrent neural network;

access to a first plurality of syntactical elements that includes an entirety of a syntactical element portion of a prompt received from a user that includes a human user;

augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user to tailor the augmentation to the user, and by further including search result-based syntactical elements based on a result of a search that is conducted utilizing at least one syntactical element of the prompt to expand on the prompt while maintaining contextual-relevance;

access to a tuning setting that is set by the user;

generation, based on a position of at least some of the first plurality of syntactical elements and further based on a relationship, other than position, of at least one of the first plurality of syntactical elements with at least one other of the first plurality of syntactical elements, of a single matrix that represents the first plurality of syntactical elements that includes the entirety of the syntactical element portion of the prompt, the previous prompt-based syntactical elements, and the search result-based syntactical elements;

performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that reflects at least a portion of the single matrix and that reflects at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, at least a portion of the position, at least a portion of the relationship, at least a portion of the previous prompt-based syntactical elements, and at least a portion of the search result-based syntactical elements, so that a focus of the first plurality of attentions are contextually-relevant and at least portions of at least some of the plurality of contextually-relevant components are prioritized with respect to each other, the first prioritization of the first plurality of attentions includes an application of a first process that results in at least a first portion of the first plurality of attentions associated with at least a portion of the different subsets of the first representation being prioritized based on a first relational aspect among the at least portion of the different subsets of the first representation and an application of a second process that results in at least a second portion of the first plurality of attentions associated with at least a part of the different subsets of the first representation being prioritized based on a second relational aspect among the at least part of the different subsets of the first representation, where the first prioritization is completed in a single operation before any utilization of the first prioritization of any of the first plurality of attentions of the system so as to speed iteration of automatic internal attention prioritization;

generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first plurality of probabilities, such that the trained computer-implemented neural network is of the type other than the recurrent neural network to at least partially avoid at least one instance of recurrency and thereby increase efficiency, while utilizing one or more hardware computing processors, for the performance of the first prioritization and the generation of the first plurality of probabilities, where the first prioritization results in only a first subset of the different subsets of the first representation being a basis for the generation of the first plurality of probabilities so as to at least partially avoid processing of a second subset of the different subsets of the first representation and further speed the iteration of the automatic internal attention prioritization;

generation of representations of intermediate items of content, based on the first plurality of probabilities and the tuning setting;

generation of a rationalization of the system for the intermediate items of content, based on at least a portion of an automatic internal intermediate prioritization of an intermediate plurality of attentions of the system each corresponding to representations of different subsets of the intermediate items of content and by application of the trained computer-implemented neural network;

performance of an automatic internal second prioritization of a second plurality of attentions of the system each corresponding to different subsets of a second representation that reflects at least a part of the rationalization, in addition to at least a part of each of the plurality of contextually-relevant components, so that a focus of the second plurality of attentions is contextually-relevant and the at least part of each of multiple of the plurality of contextually-relevant components are prioritized with respect to the at least part of the rationalization so that subsequent content generation reflects the at least part of the rationalization of the system, where the second prioritization is completed in another single operation before any utilization of the second prioritization of any of the second plurality of attentions so as to further speed the iteration of the automatic internal attention prioritization;

generation, based on at least a portion of the second prioritization and by application of the trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the trained computer-implemented neural network is of the type other than the recurrent neural network to at least partially avoid at least one instance of recurrency and thereby increase efficiency, while utilizing the one or more hardware computing processors, for the performance of the second prioritization and the generation of the second plurality of probabilities;

a selection of one or more of the plurality of items of content, based on the second plurality of probabilities and the tuning setting to tailor a creativity of the selection per the user, where the selected one or more of the plurality of items of content includes at least one of: one or more images, one or more natural language syntactical elements, or one or more computer-executable code syntactical elements, based on the first plurality of syntactical elements; and

the selected one or more of the plurality of items of content to be sent to the user.

3. A computer-implemented method, comprising:

at a system including one or more processors and one or more memories that is in communication with the one or more processors and that has one or more programs stored therein to be executed by the one or more processors:

causing access to a computer-implemented neural network trained on a training set including: images associated with corresponding syntactical elements, and training syntactical elements, including training natural language syntactical elements, that are utilized by computing hardware that processes the training syntactical elements to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other training attentions to representations of different subsets of other training syntactical elements of another training set;

causing access to a first plurality of syntactical elements that includes a syntactical element portion of a prompt received from a user that includes a human user;

causing augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user, and by further including search result-based syntactical elements based on a result of

a search that is conducted utilizing at least one syntactical element of the prompt;

causing generation, based on a position of at least some of the first plurality of syntactical elements, of at least one data structure that represents the first plurality of syntactical elements that includes the syntactical element portion of the prompt, the previous prompt-based syntactical elements, and the search result-based syntactical elements;

causing performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that reflects at least a portion of the at least one data structure and that reflects at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, at least a portion of the previous prompt-based syntactical elements, and at least a portion of the search result-based syntactical elements;

causing generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first plurality of probabilities, such that one or more hardware computing processors is utilized for the performance of the first prioritization and the generation of the first plurality of probabilities;

causing generation of representations of intermediate items of content, based on the first plurality of probabilities;

causing generation of a rationalization of the system for the intermediate items of content, based on at least a portion of an automatic internal intermediate prioritization of an intermediate plurality of attentions of the system each corresponding to representations of different subsets of the intermediate items of content and by application of the trained computer-implemented neural network;

causing performance of an automatic internal second prioritization of a second plurality of attentions of the system each corresponding to different subsets of a second representation that reflects at least a part of the rationalization, in addition to at least a part of each of the plurality of contextually-relevant components;

causing generation, based on at least a portion of the second prioritization and by application of the trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the one or more hardware computing processors is utilized for the performance of the second prioritization and the generation of the second plurality of probabilities;

causing a selection of one or more of the plurality of items of content, based on the second plurality of probabilities, where the selected one or more of the plurality of items of content includes at least one of: one or more images, or one or more natural language syntactical elements, based on the first plurality of syntactical elements; and

causing the selected one or more of the plurality of items of content to be sent to the user.

4. A computer-implemented method, comprising:

at a system including one or more processors and one or more memories that is in communication with the one or more processors and that has one or more programs stored therein to be executed by the one or more processors:

causing a computer-implemented neural network to be trained on a training set including: images associated with corresponding syntactical elements to infer one or more syntactical elements corresponding to pixel patterns within the images, and training syntactical elements, including training natural language syntactical elements and training computer-executable code syntactical elements, that are utilized by computing hardware that processes the training syntactical elements to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other training attentions to representations of different subsets of other training syntactical elements of another training set, the trained computer-implemented neural network including a neural network of a type other than a recurrent neural network;

causing access to a first plurality of syntactical elements that includes an entirety of a syntactical element portion of a prompt received from a user that includes a human user;

causing augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user to tailor the augmentation to the user, and by further including search result-based syntactical elements based on a result of a search that is conducted utilizing at least one syntactical element of the prompt to expand on the prompt while maintaining contextual-relevance;

causing access to a tuning setting that is set by the user;

causing generation, based on a position of at least some of the first plurality of syntactical elements and further based on a relationship, other than position, of at least one of the first plurality of syntactical elements with at least one other of the first plurality of syntactical elements, of a single matrix that represents the first plurality of syntactical elements that includes the entirety of the syntactical element portion of the prompt, the previous prompt-based syntactical elements, and the search result-based syntactical elements;

causing performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that is based on at least a portion of the single matrix and that is based on at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, at least a portion of the position, at least a portion of the relationship, at least a portion of the previous prompt-based syntactical elements, and at least a portion of the search result-based syntactical elements, so that a focus of the first plurality of attentions is contextually-relevant and at least portions of at least some of the plurality of contextually-relevant components are prioritized with respect to each other, the first prioritization of the first plurality of attentions includes an application of a first process that results in at least a first portion of the first plurality of attentions associated with at least a portion of the different

subsets of the first representation being prioritized based on a first relational aspect among the at least portion of the different subsets of the first representation and an application of a second process that results in at least a second portion of the first plurality of attentions associated with at least a part of the different subsets of the first representation being prioritized based on a second relational aspect among the at least part of the different subsets of the first representation, where the first prioritization is completed in a single operation before any utilization of the first prioritization of any of the first plurality of attentions of the system so as to speed iteration of automatic internal attention prioritization;

causing generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first plurality of probabilities, such that the trained computer-implemented neural network is of the type other than the recurrent neural network to at least partially avoid at least one instance of recurrency and thereby increase efficiency, while utilizing one or more hardware computing processors, for the performance of the first prioritization and the generation of the first plurality of probabilities, where the first prioritization results in only a first subset of the different subsets of the first representation being a basis for the generation of the first plurality of probabilities so as to at least partially avoid processing of a second subset of the different subsets of the first representation and further speed the iteration of the automatic internal attention prioritization;

causing generation of representations of intermediate items of content, based on the first plurality of probabilities and the tuning setting;

causing generation of a rationalization of the system for the intermediate items of content, based on at least a portion of an automatic internal intermediate prioritization of an intermediate plurality of attentions of the system each corresponding to representations of different subsets of the intermediate items of content and by application of the trained computer-implemented neural network;

causing performance of an automatic internal second prioritization of a second plurality of attentions of the system each corresponding to different subsets of a second representation that is based on at least a part of the rationalization, in addition to at least a part of each of the plurality of contextually-relevant components, so that a focus of the second plurality of attentions are contextually-relevant and the at least part of each of multiple of the plurality of contextually-relevant components are prioritized with respect to the at least part of the rationalization so that subsequent content generation is based on the at least part of the rationalization of the system, where the second prioritization is completed in another single operation before any utilization of the second prioritization of any of the second plurality of attentions so as to further speed the iteration of the automatic internal attention prioritization;

causing generation, based on at least a portion of the second prioritization and by application of the trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the trained computer-implemented neural network is of the type other than the recurrent neural network to at least partially avoid at least one instance of recurrency and thereby increase efficiency, while utilizing the one or more hardware computing processors, for the performance of the second prioritization and the generation of the second plurality of probabilities;

causing a selection of one or more of the plurality of items of content, based on the second plurality of probabilities and the tuning setting to tailor a creativity of the selection per the user, where the selected one or more of the plurality of items of content includes at least one of: one or more images, one or more natural language syntactical elements, or one or more computer-executable code syntactical elements, based on the first plurality of syntactical elements; and

causing the selected one or more of the plurality of items of content to be sent to the user.

5. The method of claim **4**, wherein only one of:

each instance of the causing is performed by hardware;

each instance of the causing is performed by software;

each instance of the generation and the prioritization are caused by software and performed by hardware;

each instance of the generation and the prioritization are caused and performed by software;

only a subset of each instance of the causing is performed by hardware;

only a subset of each instance of the causing is performed by software;

only a subset of each instance of the generation and the prioritization is caused by software and performed by hardware;

only a subset of each instance of the generation and the prioritization is caused and performed by software;

one or more of the instances of the causing includes a direct causation;

one or more of the instances of the causing includes an indirect causation;

the system is portable;

the system is not portable;

the system includes a user device;

the system includes a user device to which the communication is caused to be sent;

the system does not include a user device;

the system does not include a user device to which the communication is caused to be sent;

the system, further comprising: a user device;

the system, further comprising: a user device to which the communication is caused to be sent;

the automatic internal first prioritization of the first plurality of attentions is automatic by not being caused by the user;

the automatic internal first prioritization of the first plurality of attentions is automatic by not being directly caused by the user;

the automatic internal first prioritization of the first plurality of attentions is automatic by being indirectly caused by a human;

the automatic internal first prioritization of the first plurality of attentions is automatic by being caused without any human intervention;

the automatic internal first prioritization of the first plurality of attentions is automatic by being caused without human intervention after the training is manually initiated by a human;

the automatic internal first prioritization of the first plurality of attentions is automatic by being caused without human intervention after the training is manually initiated by a training human user;

the automatic internal first prioritization of the first plurality of attentions is automatic by being caused without human intervention after the trained computer-implemented neural network is caused to be accessed by a human;

the automatic internal first prioritization of the first plurality of attentions is automatic by being caused without human intervention after the trained computer-implemented neural network is caused to be accessed by a training human user;

the automatic internal first prioritization of the first plurality of attentions to the representations of different subsets of the first representation;

the automatic internal first prioritization of the first plurality of attentions is automatic by not being applied by the user;

the automatic internal first prioritization of the first plurality of attentions is automatic by not being directly applied by the user;

the automatic internal first prioritization of the first plurality of attentions is automatic by being indirectly applied by a human;

the automatic internal first prioritization of the first plurality of attentions is automatic by being applied without any human intervention;

the automatic internal first prioritization of the first plurality of attentions is automatic by being applied without human intervention after the training is manually initiated by a human;

the automatic internal first prioritization of the first plurality of attentions is automatic by being applied without human intervention after the training is manually initiated by a training human user;

the automatic internal first prioritization of the first plurality of attentions is automatic by being applied without human intervention after the trained computer-implemented neural network is caused to be accessed by a human;

the automatic internal first prioritization of the first plurality of attentions is automatic by being applied without human intervention after the trained computer-implemented neural network is caused to be accessed by a training human user;

the automatic internal first prioritization of the first plurality of attentions is automatic by not being caused to be applied by the user;

the automatic internal first prioritization of the first plurality of attentions is automatic by not being directly caused to be applied by the user;

the automatic internal first prioritization of the first plurality of attentions is automatic by being indirectly caused to be applied by a human;

the automatic internal first prioritization of the first plurality of attentions is automatic by being caused to be applied without any human intervention;

the automatic internal first prioritization of the first plurality of attentions is automatic by being caused to be applied without human intervention after the training is manually initiated by a human;

the automatic internal first prioritization of the first plurality of attentions is automatic by being caused to be applied without human intervention after the training is manually initiated by a training human user;

the automatic internal first prioritization of the first plurality of attentions is automatic by being caused to be applied without human intervention after the trained computer-implemented neural network is caused to be accessed by a human;

the automatic internal first prioritization of the first plurality of attentions is automatic by being caused to be applied without human intervention after the trained computer-implemented neural network is caused to be accessed by a training human user;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally caused;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally caused within the system;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused from within the system;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused from within the system after the training is caused by a human user;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused from within the system after the training is externally initiated;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused from within the system in response to the training being externally caused;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally caused within the system, but external to the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused from within the system, but external to the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally caused within the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused from within the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused by at least one of one or more processors;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused by at least one of one or more programs;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused by at least one of a plurality of instructions;

the automatic internal first prioritization of the first plurality of attentions is internal by the first plurality of attentions not being human attentions;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally applied;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally applied within the system;

the automatic internal first prioritization of the first plurality of attentions is internal by being applied within the system;

the automatic internal first prioritization of the first plurality of attentions is internal by being applied within the system after the training is caused by a human user;

the automatic internal first prioritization of the first plurality of attentions is internal by being applied within the system after the training is externally initiated;

the automatic internal first prioritization of the first plurality of attentions is internal by being applied within the system in response to the training being externally caused;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally applied within the system, but external to the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being applied from within the system, but external to the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally applied within the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being applied from within the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being applied by at least one of one or more processors;

the automatic internal first prioritization of the first plurality of attentions is internal by being applied by at least one of one or more programs;

the automatic internal first prioritization of the first plurality of attentions is internal by being applied by at least one of a plurality of instructions;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally caused to be applied;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally caused to be applied within the system;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused to be applied from within the system;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused to be applied within the system after the training is caused by a human user;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused to be applied within the system after the training is externally initiated;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused to be applied within the system in response to the training being externally caused;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally caused to be applied within the system, but external to the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused to be applied from within the system, but external to the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being internally caused to be applied within the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused to be applied from within the trained computer-implemented neural network;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused to be applied by at least one of one or more processors;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused to be applied by at least one of one or more programs;

the automatic internal first prioritization of the first plurality of attentions is internal by being caused to be applied by at least one of a plurality of instructions;

the automatic internal first prioritization of the first plurality of attentions to the representations of different subsets of the first representation, includes prioritization of different ones of the first plurality of attentions for application to different ones of the representations of different subsets of the first representation;

the automatic internal first prioritization of the first plurality of attentions to the representations of different subsets of the first representation, includes prioritization of: a first one of the first plurality of attentions for application to a first one of the representations of different subsets of the first representation, and a second one of the first plurality of attentions for application to a second one of the representations of different subsets of the first representation;

the automatic internal second prioritization of the second plurality of attentions and utilizing the trained computer-implemented neural network, includes the automatic internal second prioritization of the second plurality of attentions utilizing the trained computer-implemented neural network;

the automatic internal second prioritization of the second plurality of attentions and the utilizing the trained computer-implemented neural network, includes the automatic internal second prioritization of the second plurality of attentions before utilizing the trained computer-implemented neural network;

the automatic internal second prioritization of the second plurality of attentions and the utilizing the trained computer-implemented neural network, includes the automatic internal second prioritization of the second plurality of attentions without utilizing the trained computer-implemented neural network;

the automatic internal second prioritization of the second plurality of attentions and the utilizing the trained computer-implemented neural network, includes the automatic internal second prioritization of the second plurality of attentions first without utilizing the trained computer-implemented neural network;

the automatic internal second prioritization of the second plurality of attentions and the utilizing the trained computer-implemented neural network, includes the automatic internal second prioritization of the second plurality of attentions first without initially utilizing the trained computer-implemented neural network until after the automatic internal second prioritization of the second plurality of attentions;

the trained computer-implemented neural network is capable of multiple iterations utilizing a same hardware;

the trained computer-implemented neural network is capable of multiple iterations utilizing a same software;

the trained computer-implemented neural network is capable of multiple iterations utilizing a same process;

the trained computer-implemented neural network is capable of multiple iterations each utilizing different hardware;

the trained computer-implemented neural network is capable of multiple iterations each utilizing different software;

the trained computer-implemented neural network is capable of multiple iterations each utilizing a same process;

the trained computer-implemented neural network is capable of multiple iterations each utilizing a same process and a different hardware;

the trained computer-implemented neural network is capable of multiple iterations each utilizing a same hardware and a different process;

the trained computer-implemented neural network includes a single computer-implemented neural network;

the trained computer-implemented neural network includes a plurality of computer-implemented neural networks;

the trained computer-implemented neural network includes a plurality of computer-implemented neural networks, where a same one or more of the plurality of computer-implemented neural networks is utilized for each instance of the causing;

the trained computer-implemented neural network includes a plurality of computer-implemented neural networks, where a different one or more of the plurality of computer-implemented neural networks is utilized for each instance of the causing;

the trained computer-implemented neural network is implemented utilizing the system;

the trained computer-implemented neural network is implemented utilizing another system other than the system;

the trained computer-implemented neural network is implemented utilizing one or more processors;

the trained computer-implemented neural network is implemented utilizing one or more other processors other than the one or more processors;

the trained computer-implemented neural network is implemented utilizing one or more other processors other than the one or more processors, such that the one or more processors causes operation of the trained computer-implemented neural network utilizing one or more other processors;

the trained computer-implemented neural network is of a type other than a recurrent neural network, by the system not including any recurrent neural network;

the trained computer-implemented neural network is of the type other than the recurrent neural network, by the system not utilizing any recurrent neural network;

the trained computer-implemented neural network is of the type other than the recurrent neural network, by not including the recurrent neural network;

the trained computer-implemented neural network is of the type other than the recurrent neural network, by not including a class of neural networks configured for sequential data processing;

the trained computer-implemented neural network is of the type other than the recurrent neural network by not including a class of neural networks configured for processing information across multiple time intervals;

the trained computer-implemented neural network is of the type other than the recurrent neural network, but does include at least one aspect that is recurrent;

the trained computer-implemented neural network is of the type other than the recurrent neural network, but does include at least one instance of sequential data processing;

the trained computer-implemented neural network is of the type other than the recurrent neural network by not including a class of neural networks configured for processing information across multiple time intervals, but does include the ability to perform at least one instance of processing across multiple time intervals;

the trained computer-implemented neural network is of the type other than the recurrent neural network, while including at least one aspect of recurrency;

the trained computer-implemented neural network is of the type other than the recurrent neural network, but is not devoid of any recurrency;

the trained computer-implemented neural network is of the type other than the recurrent neural network, but is not devoid of any recurrency in connection with processing within the trained computer-implemented neural network;

the trained computer-implemented neural network is of the type other than the recurrent neural network so as to enable additional parallelization, but not disallowing any recurrency in connection with processing within the trained computer-implemented neural network;

the trained computer-implemented neural network is of the type other than the recurrent neural network so as to enable additional parallelization, but not disallowing any recurrency;

the trained computer-implemented neural network is part of the system, where the system also includes a recurrent neural network in addition to the trained computer-implemented neural network that is of the type other than the recurrent neural network;

the trained computer-implemented neural network is part of the system, where the system also includes a recurrent neural network in addition to the trained computer-implemented neural network is of the type other than the recurrent neural network, such that the recurrent neural network is utilized for operations other than each of the instances of the causing;

the application of the trained computer-implemented neural network includes a utilization of the trained computer-implemented neural network;

the application of the trained computer-implemented neural network includes a direct utilization of the trained computer-implemented neural network;

the application of the trained computer-implemented neural network includes an indirect utilization of the trained computer-implemented neural network;

at least one of the syntactical elements includes at least one of: a word, a phrase, a sentence, a punctuation symbol, or a chain;

at least one of the syntactical elements includes at least one of the syntactical element itself, or a mathematical representation thereof;

at least one of the syntactical elements includes at least one of the syntactical element itself, or a representation thereof;

at least one of the syntactical elements includes at least one of the syntactical element itself, or a symbol thereof;

at least one of the syntactical elements includes a syntactical structure;

at least one of the syntactical elements does not include a syntactical structure;

each representation includes a mathematical representation;

each representation includes a symbolic representation;

each representation includes a processed form of a corresponding one or more syntactical elements;

each representation includes a processed form of a corresponding one or more syntactical elements or a representation thereof, such that the processing changes the representation so that it represents the one or more syntactical elements or the representation thereof at least in part;

each representation includes a processed form of a corresponding one or more syntactical elements or a representation thereof, such that the processing changes the representation so that it represents the one or more syntactical elements or the representation thereof only in part;

any affect includes an effect;

the communication is sent directly to the user;

the communication is sent indirectly to the user;

the communication is sent to the user via a network;

the communication is sent to the user via a wide area network;

the communication is not sent to the user via a network;

the communication is in written form;

the communication is in written form, by visually showing syntactical elements;

the communication is in visual form;

the communication is in audible form, by converting syntactical elements to audible versions of the syntactical elements;

the first plurality of syntactical elements are included in a single chain;

the first plurality of syntactical elements are included in a single composite chain;

the first plurality of syntactical elements are included in a plurality of chains;

the second one or more syntactical elements are not of the first plurality of syntactical elements;

the second one or more syntactical elements includes at least one of the first plurality of syntactical elements;

the second one or more syntactical elements includes at least one of the first plurality of syntactical elements, and one or more syntactical elements that are not of the first plurality of syntactical elements;

each attention is an initial attention;

each attention is not an initial attention;

each attention includes a reflection;

each attention does not include a reflection;

each attention, includes monitored attention;

each attention, includes inferred attention;

each attention, includes a consciousness;

each attention, includes an awareness;

each attention, is represented by an identified one or more of the first plurality of syntactical elements;

each attention, is identified by identification of a representative one or more of the first plurality of syntactical elements;

each attention is based on at least one of: processing input from a sensor, processing input from externally sourced content, processing input from internally sourced content, a value of information, or a probabilistic selection process;

each attention is not based on at least one of: processing input from a sensor, processing input from externally sourced content, processing input from internally sourced content, a value of information, or a probabilistic selection process;

each attention includes system attention;

each does not include user attention;

each attention includes a focus of attention;

each attention includes a potential attention;

each attention includes a stream of attention;

each attention is not generated by the trained computer-implemented neural network;

each instance of based on, includes directly based on;

at least one instance of based on, includes directly based on;

each instance of based on, includes indirectly based on;

at least one instance of based on, includes indirectly based on;

at least one instance of based on, includes directly generated based on;

at least one instance of based on, includes indirectly generated based on;

at least one instance of based on, includes generated based on, by processing and utilizing;

at least one instance of based on, includes generated based on, by at least one of processing or utilizing;

at least one instance of based on, includes generated based on, by processing to generate a result and utilizing the result;

at least one instance of based on, includes generated based on, by processing to generate a result in another form and utilizing the result;

the first plurality of probabilities include uncertainties;

the first plurality of probabilities embody uncertainties;

the first plurality of probabilities is inversely related to uncertainties;

the first plurality of probabilities is an example of uncertainties;

the first plurality of probabilities include weightings;

the first plurality of probabilities is associated with the first plurality of syntactical elements, by the first plurality of probabilities being generated based on the first plurality of syntactical elements;

the first plurality of probabilities is associated with the first plurality of syntactical elements, by the first plurality of probabilities being generated utilizing the first plurality of syntactical elements;

the first plurality of probabilities is generated by previous probabilities being updated;

the second plurality of probabilities is generated based on a third attention, by the second plurality of probabilities being updated based on utilization of the third attention;

the second plurality of probabilities is generated based on the first plurality of probabilities, by being generated based on the third attention which, in turn, is prioritized based on the first plurality of probabilities;

the second plurality of probabilities is generated based on the prioritization of the second plurality of attentions, by the second plurality of probabilities being generated based on utilization of at least one of the second plurality of attentions based on the prioritization of the second plurality of attentions;

the second plurality of probabilities is generated based on the prioritization of the second plurality of attentions, by the second plurality of probabilities being updated based on utilization of at least one of the second plurality of attentions based on the prioritization of the second plurality of attentions;

the second plurality of probabilities is generated based on the prioritization of the second plurality of attentions, by the second plurality of probabilities being generated based on at least one of the second plurality of attentions that is selected based on the prioritization of the second plurality of attentions;

the second plurality of probabilities is generated based on the prioritization of the second plurality of attentions, by the second plurality of probabilities being generated based on at least one of the second plurality of attentions that is based on the prioritization of the second plurality of attentions that is, in turn, based on first plurality of probabilities;

the second plurality of probabilities is generated by previous probabilities being updated;

the first plurality of attentions are prioritized by prioritizing a first attention over a second attention;

the first plurality of attentions are prioritized by prioritizing a first attention over a second attention, and, based thereon, selecting the first attention;

the first plurality of attentions are prioritized by prioritizing the first attention over the second attention, and, based thereon, selecting the first attention and not selecting the second attention;

the first plurality of attentions are prioritized by prioritizing the first attention over the second attention, and, based thereon, selecting the first attention to the exclusion of the second attention;

the first plurality of probabilities is caused to be generated based on the prioritization of the first plurality of attentions, by applying the prioritization of the first plurality of attentions to the representation of the first subset and the representation of the second subset;

the second plurality of syntactical elements is caused to be generated based on the second plurality of probabilities, by the second plurality of syntactical elements being selected from a superset plurality of syntactical elements that each have one of the second plurality of probabilities associated therewith;

the second plurality of syntactical elements is caused to be generated based on the second plurality of probabilities, by the second plurality of syntactical elements being selected from a superset plurality of syntactical elements that each have one of the second plurality of probabilities associated therewith, where some of the superset plurality of syntactical elements are not selected to be part of the second plurality of syntactical elements;

the second plurality of syntactical elements is caused to be generated based on the second plurality of probabilities, by the second plurality of syntactical elements being selected from a superset plurality of syntactical elements that each have one of the second plurality of probabilities associated therewith, where some of the superset plurality of syntactical elements are not selected to be part of the second plurality of syntactical elements based on at least some of the second plurality of probabilities being below a threshold;

the application of the trained computer-implemented neural network includes the application of a system that includes the trained computer-implemented neural network;

the application of the trained computer-implemented neural network includes a use of at least a portion of the trained computer-implemented neural network;

the second plurality of syntactical elements are caused to be generated based on the second plurality of probabilities generated by the application of the trained computer-implemented neural network, by being based on a third plurality of probabilities that is generated by the application of the trained computer-implemented neural network based on a prioritization of a third plurality of attentions, where the prioritization of the third plurality of attentions is based on the second plurality of probabilities;

the second plurality of syntactical elements are caused to be generated based on the second plurality of probabilities generated by the application of the trained computer-implemented neural network, by being indirectly based on the second plurality of probabilities;

the second plurality of syntactical elements are caused to be generated based on the second plurality of probabilities generated by the application of the trained computer-implemented neural network, by being at least partially based on the second plurality of probabilities;

the second plurality of syntactical elements are caused to be generated based on the second plurality of probabilities generated by the application of the trained computer-implemented neural network, by a plurality of iterations of attention prioritization and probability generation being based on the second plurality of probabilities, and the second plurality of syntactical elements being caused to be generated based on the plurality of iterations of attention prioritization and probability generation;

the second plurality of syntactical elements are caused to be generated based on the second plurality of probabilities generated by the application of the trained computer-implemented neural network, by being based on a third plurality of probabilities that is generated by the application of the trained computer-implemented neural network based on a prioritization of a third plurality of attentions, where the prioritization of the third plurality of attentions is based on the second plurality of probabilities;

the second plurality of probabilities is caused to be generated based on the prioritization of the second plurality of attentions, by being indirectly based on the prioritization of the second plurality of attentions;

the second plurality of probabilities is caused to be generated based on the prioritization of the second plurality of attentions, by being at least partially based on the prioritization of the second plurality of attentions;

the second plurality of probabilities is caused to be generated based on the prioritization of the second plurality of attentions, by a plurality of iterations of attention prioritization and probability generation being based on the prioritization of the second plurality of attentions, and the second plurality of probabilities being caused to be generated based on the plurality of iterations of attention prioritization and probability generation;

the second plurality of probabilities is caused to be generated based on the prioritization of the second plurality of attentions, by being based on a third plurality of attentions that are prioritized based on a third plurality of probabilities, where the third plurality of probabilities is caused to be generated based on the prioritization of the second plurality of attentions;

the second plurality of probabilities is caused to be generated based on the prioritization of the second plurality of attentions, by being based on a third plurality of attentions that are prioritized based on the first plurality of probabilities;

the second plurality of attentions is caused to be prioritized based on the first plurality of probabilities, by being indirectly based on the first plurality of probabilities;

the second plurality of attentions is caused to be prioritized based on the first plurality of probabilities, by being at least partially based on the first plurality of probabilities;

the second plurality of attentions is caused to be prioritized based on the first plurality of probabilities, by a plurality of iterations of attention prioritization and probability generation being based on the first plurality of probabilities, and the second plurality of attentions being caused to be prioritized based on the plurality of iterations of attention prioritization and probability generation;

the second plurality of attentions is caused to be prioritized based on the first plurality of probabilities, by being based on a third plurality of probabilities that is generated based on a prioritization of a third plurality of attentions that is caused to be prioritized based on the first plurality of probabilities;

each attention is based on processing input from a sensor;

each attention is based on processing input from externally sourced content;

each attention is based on processing input from internally sourced content;

each attention is based on a value of information;

each attention is based on a probabilistic selection process;

each attention is based on processing input from a sensor, processing input from externally or internally sourced content, a value of information, and a probabilistic selection process;

a plurality of attentions is iteratively directed utilizing the second plurality of syntactical elements, by utilizing representations of the second plurality of syntactical elements;

the tuning setting includes a factor;

the tuning setting has an associated factor;

the tuning setting includes a distribution;

the tuning setting has an associated distribution;

the tuning setting is probabilistic;

the tuning setting results in an application of a result of a context stripping process;

the tuning setting results in an application of a result of a transference process;

the tuning results in humor being included;

the tuning results in with being included;

the tuning results in at least one metaphor being included;

the tuning includes adjusting;

the search is performed utilizing a human-provided prompt, by identifying at least a portion of the human-provided prompt, and utilizing the at least portion of the human-provided prompt as a query for the search;

the search is performed utilizing the human-provided prompt, by identifying at least a portion of the human-provided prompt, and utilizing at least one query that is derived from the at least portion of the human-provided prompt, for the search;

each instance of in response, includes a direct response;

each instance of in response, includes an indirect response;

the rationalization is for a recommendation;

the rationalization is not for a recommendation;

the rationalization provides a reason or cause;

the rationalization explains syntactical elements themselves;

the rationalization explains syntactical element generation;

the rationalization provides a reason for syntactical element generation;

the rationalization provides a cause for syntactical element generation;

the rationalization provides a logic that the system used in connection with syntactical elements delivery;

the rationalization provides a rationale that the system used in connection with syntactical elements delivery;

the rationalization provides a logic that the system used in connection with syntactical element generation;

the rationalization provides a rationale that the system used in connection with syntactical element generation;

the rationalization provides a logic that the system used in deciding to deliver syntactical elements;

the rationalization provides a rationale that the system used in deciding to deliver syntactical elements;

the rationalization explains why the system generated one or more syntactical elements;

the rationalization is generated utilizing a rationalization engine;

the rationalization includes explanatory information;

the rationalization is generated utilizing a template;

the rationalization is generated utilizing a syntax;

the rationalization is generated utilizing a rule;

the rationalization itself includes one or more syntactical elements;

the rationalization itself includes a caveat;

the rationalization itself does not include a caveat;

the rationalization itself includes a sense of confidence;

the rationalization itself does not include a sense of confidence;

the rationalization itself includes a tuning factor;

the rationalization itself does not include a tuning factor;

the rationalization itself includes a tuning setting;

the rationalization itself does not include a tuning setting;

the rationalization references one or more of the syntactical elements that the rationalization explains;

the rationalization references at least one aspect of one or more of the syntactical elements that the rationalization explains;

the rationalization references a theme of one or more of the syntactical elements that the rationalization explains;

the rationalization references a concept of one or more of the syntactical elements that the rationalization explains;

the rationalization references one or more of the syntactical elements that the rationalization explains the generation thereof;

the single matrix includes a single vector;

the single matrix includes a plurality of vectors;

the single matrix reflects a relative importance or relevance of the plurality of relationships of the first plurality of syntactical elements, by reflecting the relative importance;

the single matrix reflects the relative importance or relevance of the plurality of relationships of the first plurality of syntactical elements, by reflecting the relative relevance;

the single matrix reflects the relative importance or relevance of the plurality of relationships of the first plurality of syntactical elements, by reflecting the relative importance and relevance;

the single matrix takes different forms at different points in a processing thereof;

the single matrix takes different forms at different points in a use thereof;

the single matrix takes different forms at different points during a use thereof in connection with a direction of a first attention and a direction of a second attention;

the single matrix takes different forms at different points during a use thereof in connection with the generation of the first plurality of probabilities and the generation of the second plurality of probabilities, such that each different form includes different updated values;

the single matrix includes different updated values at different points during a use thereof in connection with a direction of the first attention and a direction of the second attention;

the single matrix includes different updated values at different points in a use thereof in connection with the generation of the first plurality of probabilities and the generation of the second plurality of probabilities;

the single matrix includes different fields at different points in a use thereof;

the other computer-implemented neural network is another instance of the trained computer-implemented neural network;

the other computer-implemented neural network is another instance that is the same as the trained computer-implemented neural network, but is trained differently;

the other computer-implemented neural network is different from the trained computer-implemented neural network;

the generation of the first and the second plurality of probabilities is by the application of the trained computer-implemented neural network, while the causation thereof is by instructions;

only a subset of the first plurality of syntactical elements receives any attention;

a subset of the first plurality of syntactical elements does not receive any attention;

all of the first plurality of syntactical elements receive different levels of attention;

after multiple iterations, all of the first plurality of syntactical elements receive at least one attention;

after multiple iterations, all of the first plurality of syntactical elements receive different levels of attention;

the prioritization of at least one of the first attention or the second attention results in only a subset of the first plurality of syntactical elements receiving any attention;

the prioritization of at least one of the first attention or the second attention results in a subset of the first plurality of syntactical elements not receiving any attention;

the prioritization of attentions including at least one of the first attention or the second attention results in all of the first plurality of syntactical elements receiving at least one attention;

the prioritization of attentions including at least one of the first attention or the second attention results in all of the first plurality of syntactical elements receiving different levels of attention;

each attention includes a focus of attention;

each attention includes a potential attention;

each attention includes a stream of attention;

the first plurality of syntactical elements includes at least a portion of an executable computer program received from the user, based on which, computer executable code is caused to be generated;

the first plurality of syntactical elements includes at least a portion of an executable computer program received from the user, based on which, computer executable code is caused to be generated, where the computer executable code includes a modified version of the executable computer program;

the first plurality of syntactical elements includes at least a portion of an executable computer program received from the user, based on which, computer executable code is caused to be generated, where the computer executable code includes the executable computer program modified;

the first plurality of syntactical elements includes at least a portion of an executable computer program received from the user, based on which, computer executable code is caused to be generated, where the computer executable code does not include a modified version of the executable computer program;

the first plurality of syntactical elements includes at least a portion of an executable computer program received from the user, based on which, computer executable code is caused to be generated, where the computer executable code does not include any portion of the executable computer program;

the first plurality of syntactical elements includes at least a portion of an executable computer program received from the user, based on which, computer executable code is caused to be generated, where the computer executable code includes at least a portion of the executable computer program;

the first attention is directed for use by the trained computer-implemented neural network, by affecting a particular manner of subsequent processing by the trained computer-implemented neural network;

the first attention is directed for use by the trained computer-implemented neural network, by the first plurality of probabilities being generated, by application of the trained computer-implemented neural network, based on the direction of the first attention;

the first attention is of the trained computer-implemented neural network;

the first attention is of the trained computer-implemented neural network by including a manner of processing by the trained computer-implemented neural network, where the processing is based on a prior prioritization of a plurality of attentions;

the trained computer-implemented neural network includes a neural network-based system capable of pre-processing that precedes utilization of the trained computer-implemented neural network for probability generation and that implements attention prioritization, to generate a result that affects the first attention;

the trained computer-implemented neural network is a neural network-based system capable of pre-processing that implements attention prioritization to generate a result that affects the first attention, by affecting a particular manner of processing by the trained computer-implemented neural network;

a first operation is performed including neural network-independent attention prioritization, and a second operation is performed to direct the first attention by causing processing of the trained computer-implemented neural network to be based on the neural network-independent attention prioritization;

the trained computer-implemented neural network includes a neural network-based system capable of a first operation including neural network-independent attention prioritization, and a second operation to direct the first attention by causing processing of the trained computer-implemented neural network to be based on the neural network-independent attention prioritization, by affecting a particular manner of the processing by the trained computer-implemented neural network;

the system is further configured such that the trained computer-implemented neural network is caused to be trained utilizing a first processor of one or more processors of a first apparatus of the system that executes a first program of the one or more programs that is stored in a first memory of the one or memories of the first apparatus of the system, and the second plurality of syntactical elements is caused to be accessed utilizing a second processor of the one or more processors of a second apparatus of the system that executes a second program of the one or more programs that is stored in a second memory of the one or memories of the second apparatus of the system;

the trained computer-implemented neural network is caused to be trained and the second plurality of syntactical elements is caused to be accessed utilizing a same processor of one or more processors of a same apparatus of the system that executes a same program of the one or more programs that is stored in a same memory of the one or memories of the same apparatus of the system;

each instance of the causing is an act;

each instance of the causing is not a step;

the causing are acts;

the causing are not steps;

the syntactical element portion of the prompt, is not an only portion of the prompt; or

the syntactical element portion of the prompt, is an only portion of the prompt.

6. A computer-implemented method, comprising:

at a system including one or more processors and one or more memories that is in communication with the one or more processors and that has one or more programs stored therein to be executed by the one or more processors:

causing access to a computer-implemented neural network trained on a training set including: images associated with corresponding syntactical elements, and training syntactical elements, including training natural language syntactical elements and training computer-executable code syntactical elements, that are utilized by computing hardware that processes the training syntactical elements to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other training attentions to representations of different subsets of other training syntactical elements of another training set;

causing access to a first plurality of syntactical elements that includes a syntactical element portion of a prompt received from a user that includes a human user;

causing augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user to tailor the augmentation to the user, and by further including search result-based syntactical elements based on a result of a search that is conducted utilizing at least one syntactical element of the prompt to expand on the prompt while maintaining contextual-relevance;

causing generation, based on a position of at least some of the first plurality of syntactical elements, of at least one data structure that represents the first plurality of syntactical elements that includes the syntactical element portion of the prompt, the previous prompt-based syntactical elements, and the search result-based syntactical elements;

causing performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that is based on at least a portion of the at least one data structure and that is based on at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, at least a portion of the position, at least a portion of the previous prompt-based syntactical elements, and at least a portion of the search result-based syntactical elements, so that a focus of the first plurality of attentions is contextually-relevant and at least portions of at least some of the plurality of contextually-relevant components are prioritized with respect to each other, where the first prioritization is completed in a single operation before any utilization of the first prioritization of any of the first plurality of attentions of the system so as to speed iteration of automatic internal attention prioritization;

causing generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first plurality of probabilities, such that the trained computer-implemented neural network is of a type to at least partially avoid at least one instance of recurrency and thereby increase efficiency, while utilizing one or more hardware computing processors, for the performance of the first prioritization and the generation of the first plurality of probabilities, where the first prioritization results in only a first subset of the different subsets of the first representation being a basis for the generation of the first plurality of probabilities so as to at least partially avoid processing of a second subset of the different subsets of the first representation and further speed the iteration of the automatic internal attention prioritization;

causing generation of representations of intermediate items of content, based on the first plurality of probabilities;

causing generation of a rationalization of the system for the intermediate items of content, based on at least a portion of an automatic internal intermediate priori-

tization of an intermediate plurality of attentions of the system each corresponding to representations of different subsets of the intermediate items of content and by application of the trained computer-implemented neural network;

causing performance of an automatic internal second prioritization of a second plurality of attentions of the system each corresponding to different subsets of a second representation that is based on at least a part of the rationalization, in addition to at least a part of each of the plurality of contextually-relevant components, so that a focus of the second plurality of attentions are contextually-relevant and the at least part of each of multiple of the plurality of contextually-relevant components are prioritized with respect to the at least part of the rationalization so that subsequent content generation is based on the at least part of the rationalization of the system, where the second prioritization is completed in another single operation before any utilization of the second prioritization of any of the second plurality of attentions so as to further speed the iteration of the automatic internal attention prioritization;

causing generation, based on at least a portion of the second prioritization and by application of the trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the trained computer-implemented neural network is of the type to at least partially avoid at least one instance of recurrency and thereby increase efficiency, while utilizing the one or more hardware computing processors, for the performance of the second prioritization and the generation of the second plurality of probabilities;

causing a selection of one or more of the plurality of items of content, based on the second plurality of probabilities, where the selected one or more of the plurality of items of content includes at least one of: one or more images, one or more natural language syntactical elements, or one or more computer-executable code syntactical elements, based on the first plurality of syntactical elements; and

causing the selected one or more of the plurality of items of content to be sent to the user.

7. A computer-implemented method, comprising:

at a system including one or more processors and one or more memories that is in communication with the one or more processors and that has one or more programs stored therein to be executed by the one or more processors:

causing access to a computer-implemented neural network trained on a training set including: images associated with corresponding syntactical elements, and training syntactical elements, including training natural language syntactical elements and training computer-executable code syntactical elements, that are utilized by computing hardware that processes the training syntactical elements to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other training attentions to representations of different subsets of other training syntactical elements of another training set;

causing access to a first plurality of syntactical elements that includes a syntactical element portion of a prompt received from a user that includes a human user;

causing augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user to tailor the augmentation to the user, and by further including search result-based syntactical elements based on a result of a search that is conducted utilizing at least one syntactical element of the prompt to expand on the prompt while maintaining contextual-relevance;

causing generation, based on a position of at least some of the first plurality of syntactical elements, of at least one data structure that represents the first plurality of syntactical elements that includes the syntactical element portion of the prompt, the previous prompt-based syntactical elements, and the search result-based syntactical elements;

causing performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that is based on at least a portion of the at least one data structure and that is based on at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, at least a portion of the previous prompt-based syntactical elements, and at least a portion of the search result-based syntactical elements, so that a focus of the first plurality of attentions is contextually-relevant and at least portions of each of the plurality of contextually-relevant components are prioritized with respect to each other, where the first prioritization is completed in a single operation so as to speed iteration of automatic internal attention prioritization;

causing generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first plurality of probabilities, such that the trained computer-implemented neural network is of a type to at least partially avoid at least one instance of recurrency and thereby increase efficiency, while utilizing one or more hardware computing processors, for the performance of the first prioritization and the generation of the first plurality of probabilities, where the first prioritization results in only a first subset of the different subsets of the first representation being a basis for the generation of the first plurality of probabilities so as to at least partially avoid processing of a second subset of the different subsets of the first representation and further speed the iteration of the automatic internal attention prioritization;

causing generation of representations of intermediate items of content, based on the first plurality of probabilities;

causing generation of a rationalization of the system for the intermediate items of content, based on at least a portion of an automatic internal intermediate prioritization of an intermediate plurality of attentions of the system each corresponding to representations of different subsets of the intermediate items of content and by application of the trained computer-implemented neural network;

causing performance of an automatic internal second prioritization of a second plurality of attentions of

the system each corresponding to different subsets of a second representation that is based on at least a part of the rationalization, in addition to at least a part of at least one of the plurality of contextually-relevant components, so that a focus of the second plurality of attentions are contextually-relevant and the at least part of the at least one of the plurality of contextually-relevant components is prioritized with respect to the at least part of the rationalization so that subsequent content generation is based on the at least part of the rationalization of the system, where the second prioritization is completed in another single operation so as to further speed the iteration of the automatic internal attention prioritization;

causing generation, based on at least a portion of the second prioritization and by application of the trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the trained computer-implemented neural network is of the type to at least partially avoid at least one instance of recurrency and thereby increase efficiency, while utilizing the one or more hardware computing processors, for the performance of the second prioritization and the generation of the second plurality of probabilities;

causing a selection of one or more of the plurality of items of content, based on the second plurality of probabilities, where the selected one or more of the plurality of items of content includes at least one of: one or more images, one or more natural language syntactical elements, or one or more computer-executable code syntactical elements, based on the first plurality of syntactical elements; and

causing the selected one or more of the plurality of items of content to be sent to the user.

8. A computer-implemented method, comprising:

at a system including one or more processors and one or more memories that is in communication with the one or more processors and that has one or more programs stored therein to be executed by the one or more processors:

causing access to a computer-implemented neural network trained on a training set including: images associated with corresponding syntactical elements, and training syntactical elements, including training natural language syntactical elements, that are utilized by computing hardware that processes the training syntactical elements to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other training attentions to representations of different subsets of other training syntactical elements of another training set;

causing access to a first plurality of syntactical elements that includes a syntactical element portion of a prompt received from a user that includes a human user;

causing augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user to tailor the augmentation to the user, and by further including search result-based syntactical elements based on a result of a search that is conducted utilizing at least one syntactical element of the prompt to expand on the prompt while maintaining contextual-relevance;

causing generation, based on a position of at least some of the first plurality of syntactical elements, of at least one data structure that represents the first plurality of syntactical elements that includes the syntactical element portion of the prompt, the previous prompt-based syntactical elements, and the search result-based syntactical elements;

causing performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that is based on at least a portion of the at least one data structure and that is based on at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, at least a portion of the previous prompt-based syntactical elements, and at least a portion of the search result-based syntactical elements, so that a focus of the first plurality of attentions is contextually-relevant and at least portions of each of the plurality of contextually-relevant components are prioritized with respect to each other;

causing generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first plurality of probabilities, such that the trained computer-implemented neural network is of a type to at least partially avoid at least one instance of recurrency and thereby increase efficiency, while utilizing one or more hardware computing processors, for the performance of the first prioritization and the generation of the first plurality of probabilities, where the first prioritization results in only a first subset of the different subsets of the first representation being a basis for the generation of the first plurality of probabilities so as to at least partially avoid processing of a second subset of the different subsets of the first representation and speed iteration of automatic internal attention prioritization;

causing generation of representations of intermediate items of content, based on the first plurality of probabilities;

causing generation of a rationalization of the system for the intermediate items of content, based on at least a portion of an automatic internal intermediate prioritization of an intermediate plurality of attentions of the system each corresponding to representations of different subsets of the intermediate items of content and by application of the trained computer-implemented neural network;

causing performance of an automatic internal second prioritization of a second plurality of attentions of the system each corresponding to different subsets of a second representation that is based on at least a part of the rationalization, in addition to at least a part of at least one of the plurality of contextually-relevant components, so that a focus of the second plurality of attentions are contextually-relevant and the at least part of the at least one of the plurality of contextually-relevant components is prioritized with respect to the at least part of the rationalization so that subsequent content generation is based on the at least part of the rationalization of the system;

causing generation, based on at least a portion of the second prioritization and by application of the

trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the trained computer-implemented neural network is of the type to at least partially avoid at least one instance of recurrency and thereby increase efficiency, while utilizing the one or more hardware computing processors, for the performance of the second prioritization and the generation of the second plurality of probabilities;

causing a selection of one or more of the plurality of items of content, based on the second plurality of probabilities, where the selected one or more of the plurality of items of content includes at least one of: one or more images, or one or more natural language syntactical elements, based on the first plurality of syntactical elements; and

causing the selected one or more of the plurality of items of content to be sent to the user.

9. A computer-implemented method, comprising:

at a system including one or more processors and one or more memories that is in communication with the one or more processors and that has one or more programs stored therein to be executed by the one or more processors:

causing access to a computer-implemented neural network trained on a training set including: images associated with corresponding syntactical elements, and training syntactical elements, including training natural language syntactical elements, that are utilized to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other training attentions to representations of different subsets of other training syntactical elements of another training set;

causing access to a first plurality of syntactical elements that includes a syntactical element portion of a prompt received from a user that includes a human user;

causing augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user to tailor the augmentation to the user, and by further including search result-based syntactical elements based on a result of a search that is conducted utilizing at least one syntactical element of the prompt to expand on the prompt while maintaining contextual-relevance;

causing generation, based on a position of at least some of the first plurality of syntactical elements, of at least one data structure that represents the first plurality of syntactical elements that includes the syntactical element portion of the prompt, the previous prompt-based syntactical elements, and the search result-based syntactical elements;

causing performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that is based on at least a portion of the at least one data structure and that is based on at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, at least a portion of the previous prompt-based syntactical elements, and at least a portion of the search result-based syntactical elements, so that a focus of the first plurality of attentions is contextually-relevant and at least portions of at least some of the plurality of contextually-relevant components are prioritized with respect to each other;

causing generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first plurality of probabilities, such that the trained computer-implemented neural network utilizes one or more hardware computing processors, for the performance of the first prioritization and the generation of the first plurality of probabilities;

causing generation of representations of intermediate items of content, based on the first plurality of probabilities;

causing generation of a rationalization of the system for the intermediate items of content, based on at least a portion of an automatic internal intermediate prioritization of an intermediate plurality of attentions of the system each corresponding to representations of different subsets of the intermediate items of content and by application of the trained computer-implemented neural network;

causing performance of an automatic internal second prioritization of a second plurality of attentions of the system each corresponding to different subsets of a second representation that is based on at least a part of the rationalization, so that subsequent content generation reflects the at least part of the rationalization of the system;

causing generation, based on at least a portion of the second prioritization and by application of the trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the trained computer-implemented neural network utilizes the one or more hardware computing processors, for the performance of the second prioritization and the generation of the second plurality of probabilities;

causing a selection of one or more of the plurality of items of content, based on the second plurality of probabilities, where the selected one or more of the plurality of items of content includes at least one of: one or more images, or one or more natural language syntactical elements, based on the first plurality of syntactical elements; and

causing the selected one or more of the plurality of items of content to be sent to the user.

10. A computer-implemented method, comprising:

at a system including one or more processors and one or more memories that is in communication with the one or more processors and that has one or more programs stored therein to be executed by the one or more processors:

causing access to a computer-implemented neural network trained on a training set including: images associated with corresponding syntactical elements, and training syntactical elements, including training natural language syntactical elements, that are utilized to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other train-

ing attentions to representations of different subsets of other training syntactical elements of another training set;

causing access to a first plurality of syntactical elements that includes a syntactical element portion of a prompt received from a user that includes a human user;

causing augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user to tailor the augmentation to the user, and by further including search result-based syntactical elements based on a result of a search that is conducted utilizing at least one syntactical element of the prompt to expand on the prompt while maintaining contextual-relevance;

causing generation, based on a position of at least some of the first plurality of syntactical elements, of at least one data structure that represents the first plurality of syntactical elements that includes the syntactical element portion of the prompt, the previous prompt-based syntactical elements, and the search result-based syntactical elements;

causing performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that is based on at least a portion of the at least one data structure and that is based on at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, at least a portion of the previous prompt-based syntactical elements, and at least a portion of the search result-based syntactical elements, so that a focus of the first plurality of attentions is contextually-relevant and at least portions of at least some of the plurality of contextually-relevant components are prioritized with respect to each other;

causing generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first plurality of probabilities, such that the trained computer-implemented neural network utilizes one or more hardware computing processors, for the performance of the first prioritization and the generation of the first plurality of probabilities;

causing generation of representations of intermediate items of content, based on the first plurality of probabilities;

causing generation of a rationalization of the system for the intermediate items of content, based on at least a portion of an automatic internal intermediate prioritization of an intermediate plurality of attentions of the system each corresponding to representations of different subsets of the intermediate items of content and by application of the trained computer-implemented neural network;

causing performance of an automatic internal second prioritization of a second plurality of attentions of the system each corresponding to different subsets of a second representation that is based on at least a part of the rationalization, so that subsequent content generation is based on the at least part of the rationalization of the system;

causing generation, based on at least a portion of the second prioritization and by application of the trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the trained computer-implemented neural network utilizes the one or more hardware computing processors, for the performance of the second prioritization and the generation of the second plurality of probabilities;

causing a selection of one or more of the plurality of items of content, based on the second plurality of probabilities, where the selected one or more of the plurality of items of content includes at least one of: one or more images, or one or more natural language syntactical elements, based on the first plurality of syntactical elements; and

causing the selected one or more of the plurality of items of content to be sent to the user.

11. A computer-implemented method, comprising:

at a system including one or more processors and one or more memories that is in communication with the one or more processors and that has one or more programs stored therein to be executed by the one or more processors:

causing access to a computer-implemented neural network trained on a training set including: images associated with corresponding syntactical elements, and training syntactical elements, including training natural language syntactical elements, that are utilized to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other training attentions to representations of different subsets of other training syntactical elements of another training set;

causing access to a first plurality of syntactical elements that includes a syntactical element portion of a prompt received from a user that includes a human user;

causing augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user to tailor the augmentation to the user;

causing generation, based on a position of at least some of the first plurality of syntactical elements, of at least one data structure that represents the first plurality of syntactical elements that includes the syntactical element portion of the prompt, and the previous prompt-based syntactical elements;

causing performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that is based on at least a portion of the at least one data structure and that is based on at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, and at least a portion of the previous prompt-based syntactical elements, so that a focus of the first plurality of attentions is contextually-relevant and at least portions of at least some of the plurality of contextually-relevant components are prioritized with respect to each other;

causing generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first

plurality of probabilities, such that the trained computer-implemented neural network utilizes one or more hardware computing processors, for the performance of the first prioritization and the generation of the first plurality of probabilities;

causing generation of representations of intermediate items of content, based on the first plurality of probabilities;

causing generation of a rationalization of the system for the intermediate items of content, based on at least a portion of an automatic internal intermediate prioritization of an intermediate plurality of attentions of the system each corresponding to representations of different subsets of the intermediate items of content and by application of the trained computer-implemented neural network;

causing performance of an automatic internal second prioritization of a second plurality of attentions of the system each corresponding to different subsets of a second representation that is based on at least a part of the rationalization, so that subsequent content generation is based on the at least part of the rationalization of the system;

causing generation, based on at least a portion of the second prioritization and by application of the trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the trained computer-implemented neural network utilizes the one or more hardware computing processors, for the performance of the second prioritization and the generation of the second plurality of probabilities;

causing a selection of one or more of the plurality of items of content, based on the second plurality of probabilities, where the selected one or more of the plurality of items of content includes at least one of: one or more images, or one or more natural language syntactical elements, based on the first plurality of syntactical elements; and

causing the selected one or more of the plurality of items of content to be sent to the user.

12. A computer-implemented method, comprising:

at a system including one or more processors and one or more memories that is in communication with the one or more processors and that has one or more programs stored therein to be executed by the one or more processors:

causing access to a computer-implemented neural network trained on a training set including: images associated with corresponding syntactical elements, and training syntactical elements, including training natural language syntactical elements, that are utilized to direct training attentions to representations of different subsets of the training syntactical elements, the training set being generated by another computer-implemented neural network that is trained by automatic internal direction of other training attentions to representations of different subsets of other training syntactical elements of another training set;

causing access to a first plurality of syntactical elements that includes a syntactical element portion of a prompt received from a user that includes a human user;

causing augmentation of the first plurality of syntactical elements, by further including previous prompt-based syntactical elements based on a previous prompt of the user to tailor the augmentation to the user, and by further including search result-based syntactical elements based on a result of a search that is conducted utilizing at least one syntactical element of the prompt to expand on the prompt while maintaining contextual-relevance;

causing generation, based on a position of at least some of the first plurality of syntactical elements, of at least one data structure that represents the first plurality of syntactical elements that includes the syntactical element portion of the prompt, the previous prompt-based syntactical elements, and the search result-based syntactical elements;

causing performance of an automatic internal first prioritization of a first plurality of attentions of the system each corresponding to different subsets of a first representation that is based on at least a portion of the at least one data structure and that is based on at least a portion of each of a plurality of contextually-relevant components including at least a portion of the first plurality of syntactical elements, at least a portion of the previous prompt-based syntactical elements, and at least a portion of the search result-based syntactical elements, so that a focus of the first plurality of attentions is contextually-relevant and at least portions of at least some of the plurality of contextually-relevant components are prioritized with respect to each other;

causing generation, based on at least a portion of the first prioritization and by application of the trained computer-implemented neural network, of a first plurality of probabilities, such that the trained computer-implemented neural network utilizes one or more hardware computing processors, for the performance of the first prioritization and the generation of the first plurality of probabilities;

causing generation of a rationalization of the system for content generation by application of the trained computer-implemented neural network;

causing performance of an automatic internal second prioritization of a second plurality of attentions of the system each corresponding to different subsets of a second representation that is based on at least a part of the rationalization, so that subsequent content generation is based on the at least part of the rationalization of the system;

causing generation, based on at least a portion of the second prioritization and by application of the trained computer-implemented neural network, of a second plurality of probabilities that are each associated with a corresponding subset of a plurality of items of content, such that the trained computer-implemented neural network utilizes the one or more hardware computing processors, for the performance of the second prioritization and the generation of the second plurality of probabilities;

causing a selection of one or more of the plurality of items of content, based on the second plurality of probabilities, where the selected one or more of the plurality of items of content includes at least one of: one or more images, or one or more natural language syntactical elements, based on the first plurality of syntactical elements; and

causing the selected one or more of the plurality of items of content to be sent to the user.

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