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Blair-Goldensohn et al.

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(54) **SENTIMENT DETECTION AS A RANKING SIGNAL FOR REVIEWABLE ENTITIES**

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(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 619 days.

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(22) Filed: **Dec. 5, 2007**

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G06F 17/30 (2006.01)
G06F 7/00 (2006.01)
G06F 15/16 (2006.01)

(52) **U.S. Cl.**
USPC **707/751**; 707/748; 705/347; 706/45

(58) **Field of Classification Search** .... None
See application file for complete search history.

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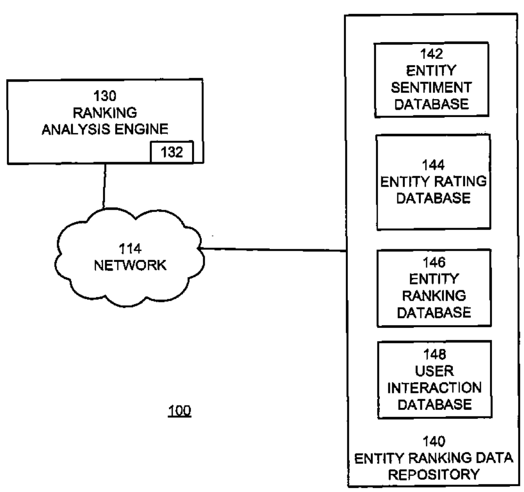
(57) **ABSTRACT**

A method, a system and a computer program product for ranking reviewable entities based on sentiment expressed about the entities. A plurality of review texts are identified wherein each review text references an entity. A plurality of sentiment scores associated with the plurality of review texts are generated, wherein each sentiment score for a review text indicates a sentiment directed to the entity referenced by the review text. A plurality of ranking scores for the plurality of entities are generated wherein each ranking score is based at least in part on one or more sentiment scores associated with one or more review texts referencing the entity. A plurality of search results associated with the plurality of entities are displayed based at least in part on the ranking scores.

18 Claims, 12 Drawing Sheets



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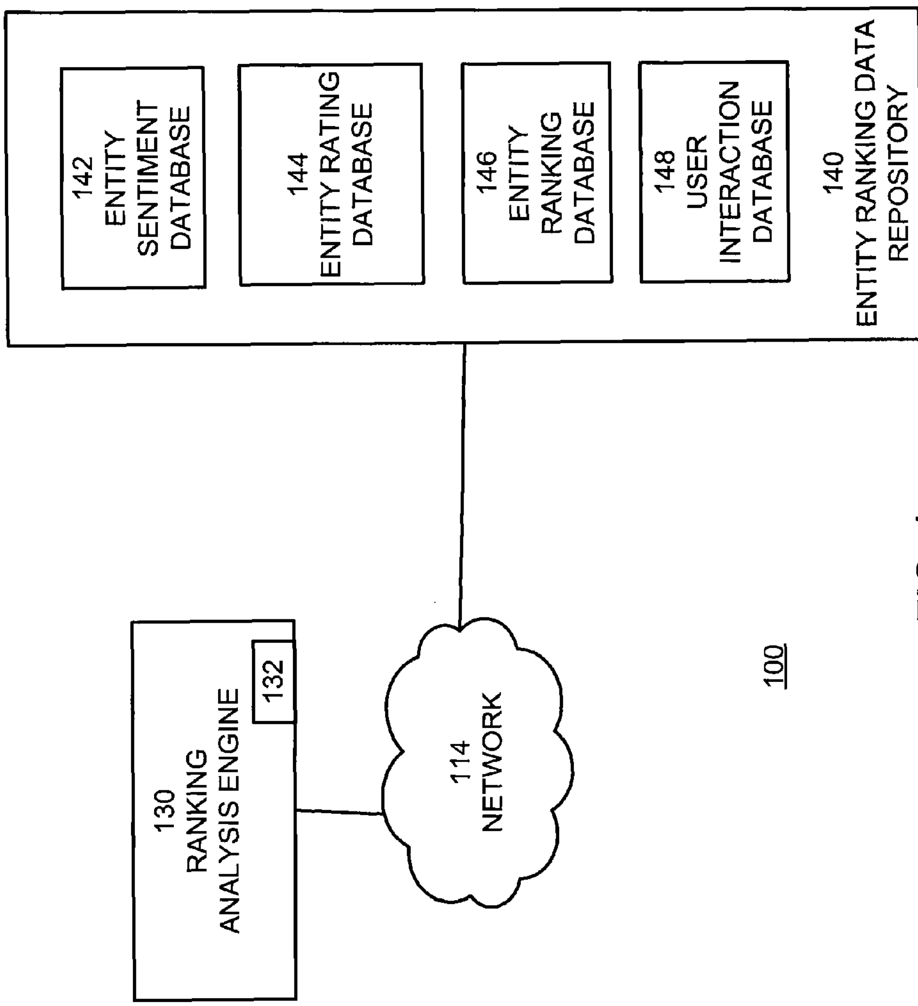
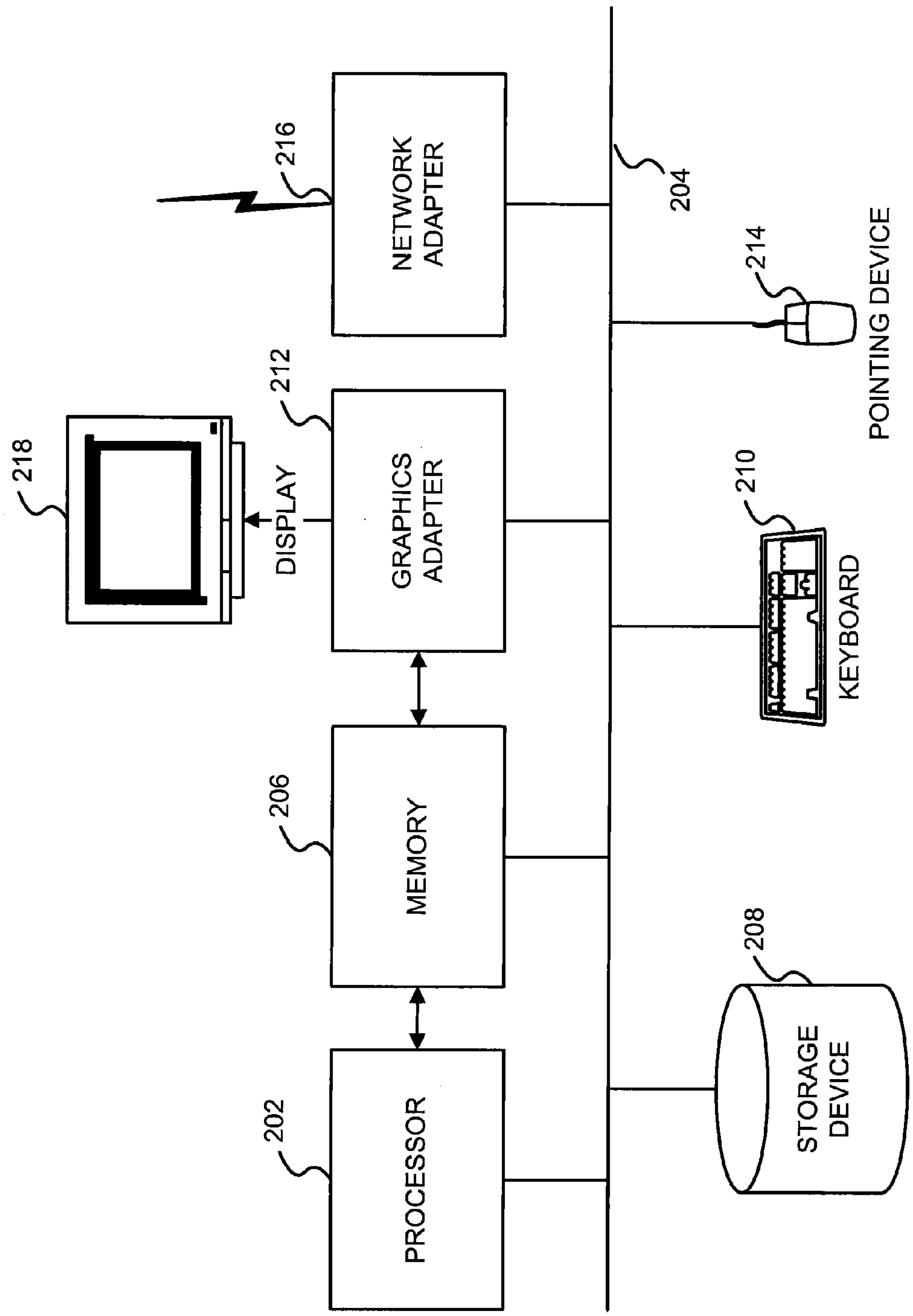

142
ENTITY
SENTIMENT
DATABASE
144
ENTITY RATING
DATABASE
146
ENTITY
RANKING
DATABASE
148
USER
INTERACTION
DATABASE
140
ENTITY RANKING DATA
REPOSITORY
130
RANKING
ANALYSIS ENGINE
132
114
NETWORK
100

FIG. 1


PROCESSOR
202
MEMORY
206
GRAPHICS ADAPTER
212
NETWORK ADAPTER
216
DISPLAY
218
204
STORAGE DEVICE
208
KEYBOARD
210
POINTING DEVICE
214

200

FIG. 2

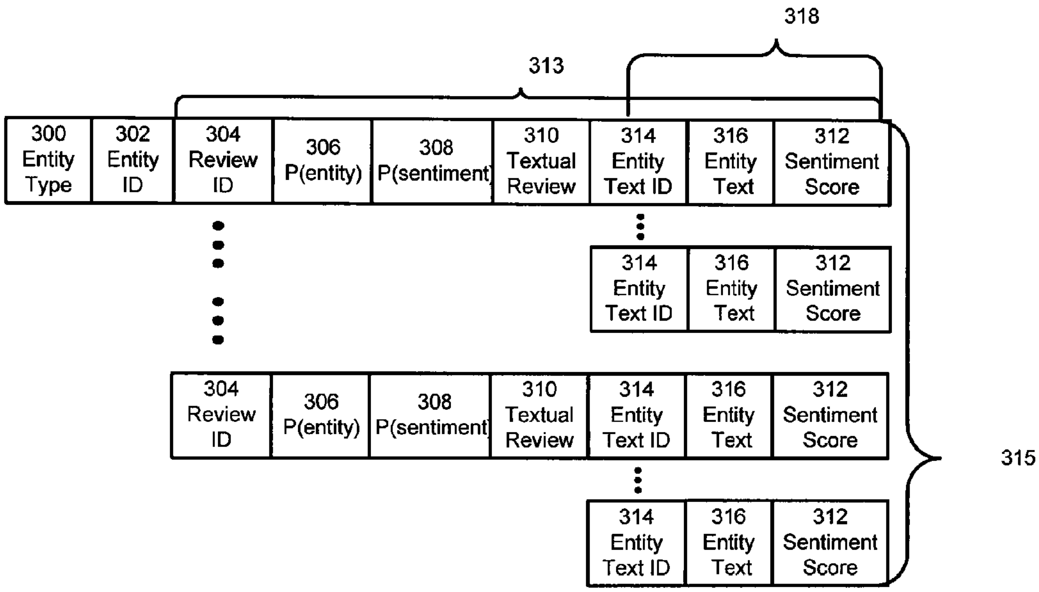

318
313
300 Entity Type
302 Entity ID
304 Review ID
306 P(entity)
308 P(sentiment)
310 Textual Review
314 Entity Text ID
316 Entity Text
312 Sentiment Score
315

FIG. 3A

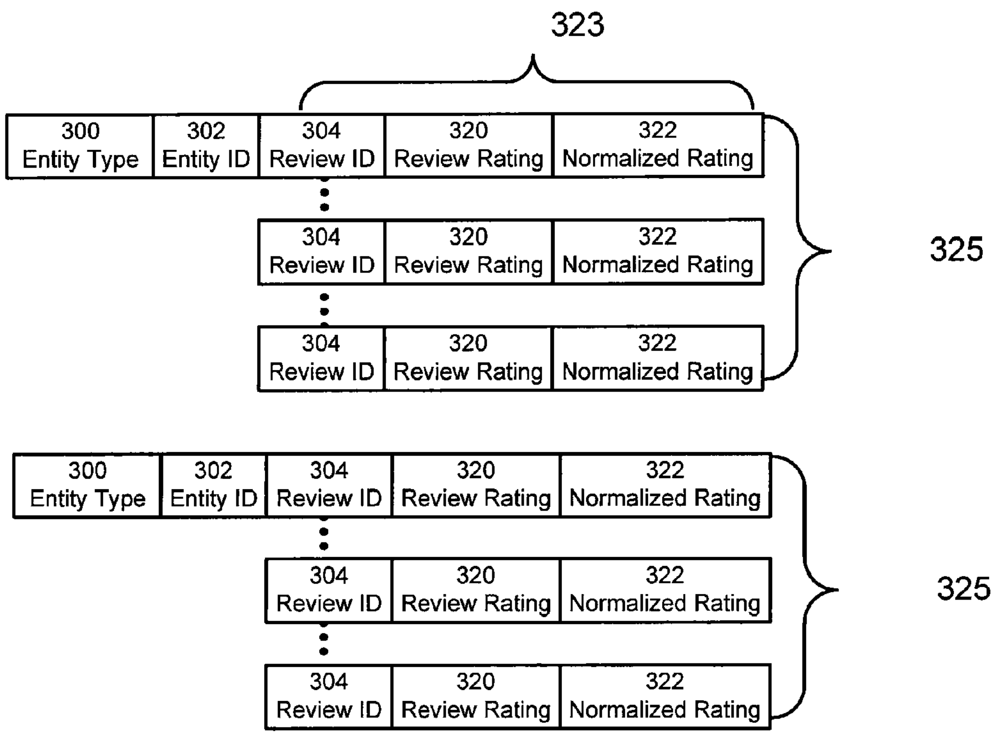
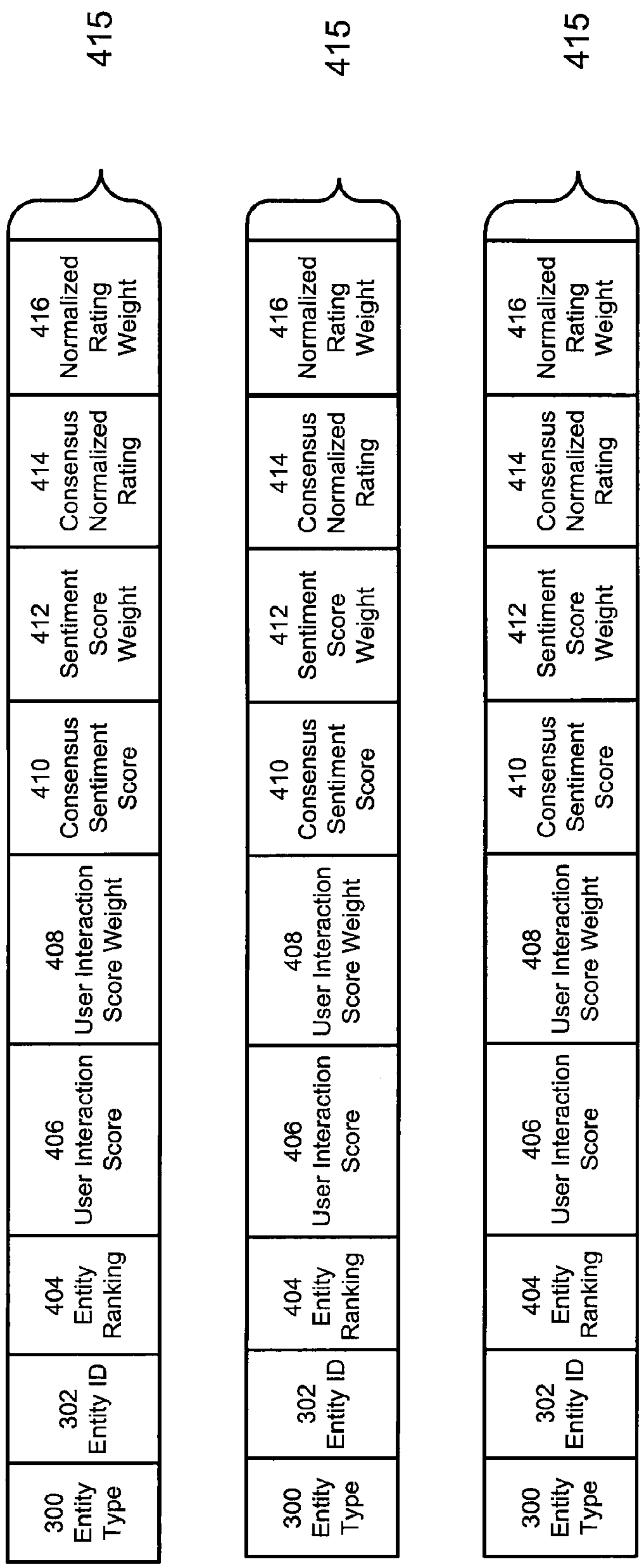

323
300 Entity Type
302 Entity ID
304 Review ID
320 Review Rating
322 Normalized Rating
325

FIG. 3B



415
300 Entity Type
302 Entity ID
404 Entity Ranking
406 User Interaction Score
408 User Interaction Score Weight
410 Consensus Sentiment Score
412 Sentiment Score Weight
414 Consensus Normalized Rating
416 Normalized Rating Weight
415
300 Entity Type
302 Entity ID
404 Entity Ranking
406 User Interaction Score
408 User Interaction Score Weight
410 Consensus Sentiment Score
412 Sentiment Score Weight
414 Consensus Normalized Rating
416 Normalized Rating Weight
415
300 Entity Type
302 Entity ID
404 Entity Ranking
406 User Interaction Score
408 User Interaction Score Weight
410 Consensus Sentiment Score
412 Sentiment Score Weight
414 Consensus Normalized Rating
416 Normalized Rating Weight

FIG. 4

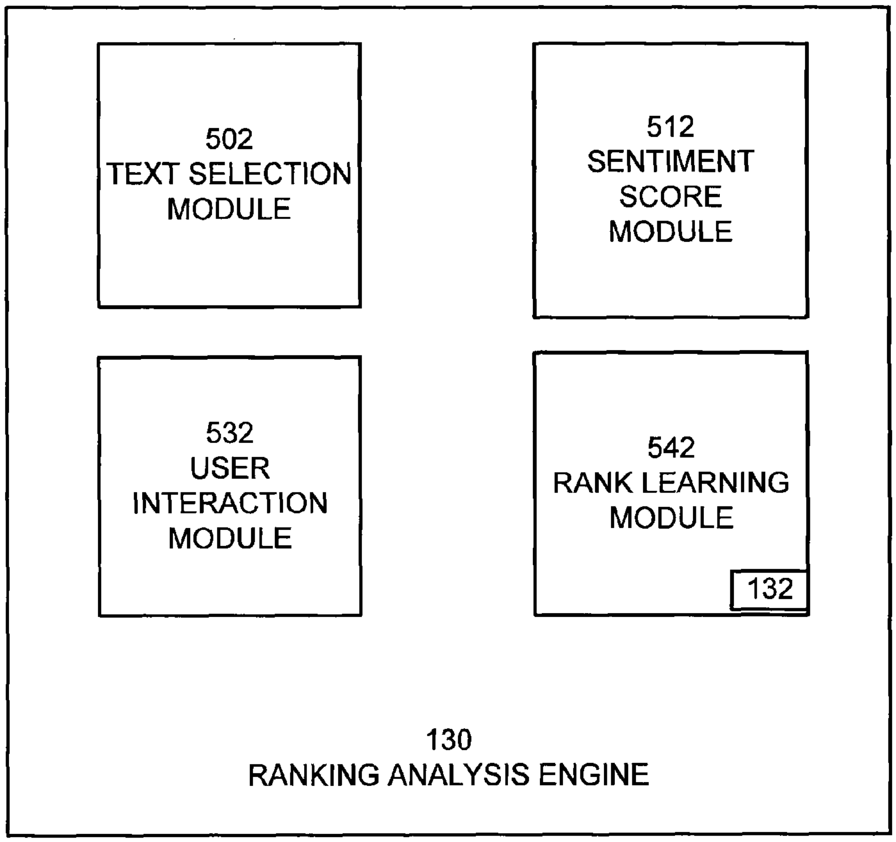

502
TEXT SELECTION
MODULE
512
SENTIMENT
SCORE
MODULE
532
USER
INTERACTION
MODULE
542
RANK LEARNING
MODULE
132
130
RANKING ANALYSIS ENGINE

FIG. 5

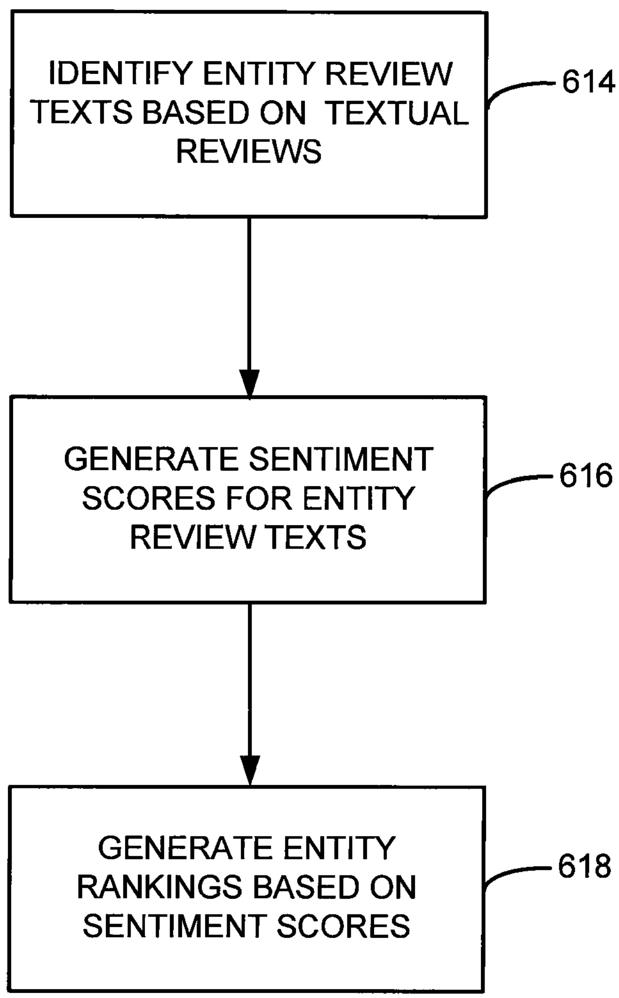

IDENTIFY ENTITY REVIEW TEXTS BASED ON TEXTUAL REVIEWS
614
GENERATE SENTIMENT SCORES FOR ENTITY REVIEW TEXTS
616
GENERATE ENTITY RANKINGS BASED ON SENTIMENT SCORES
618

FIG. 6

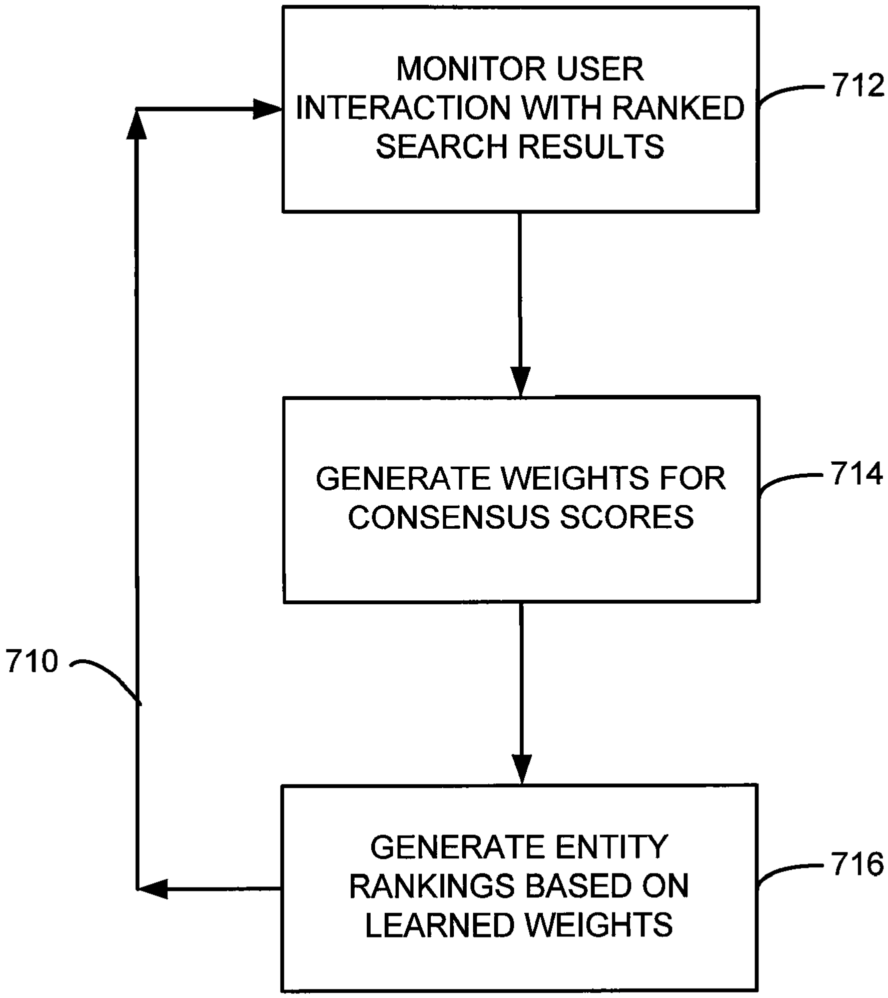
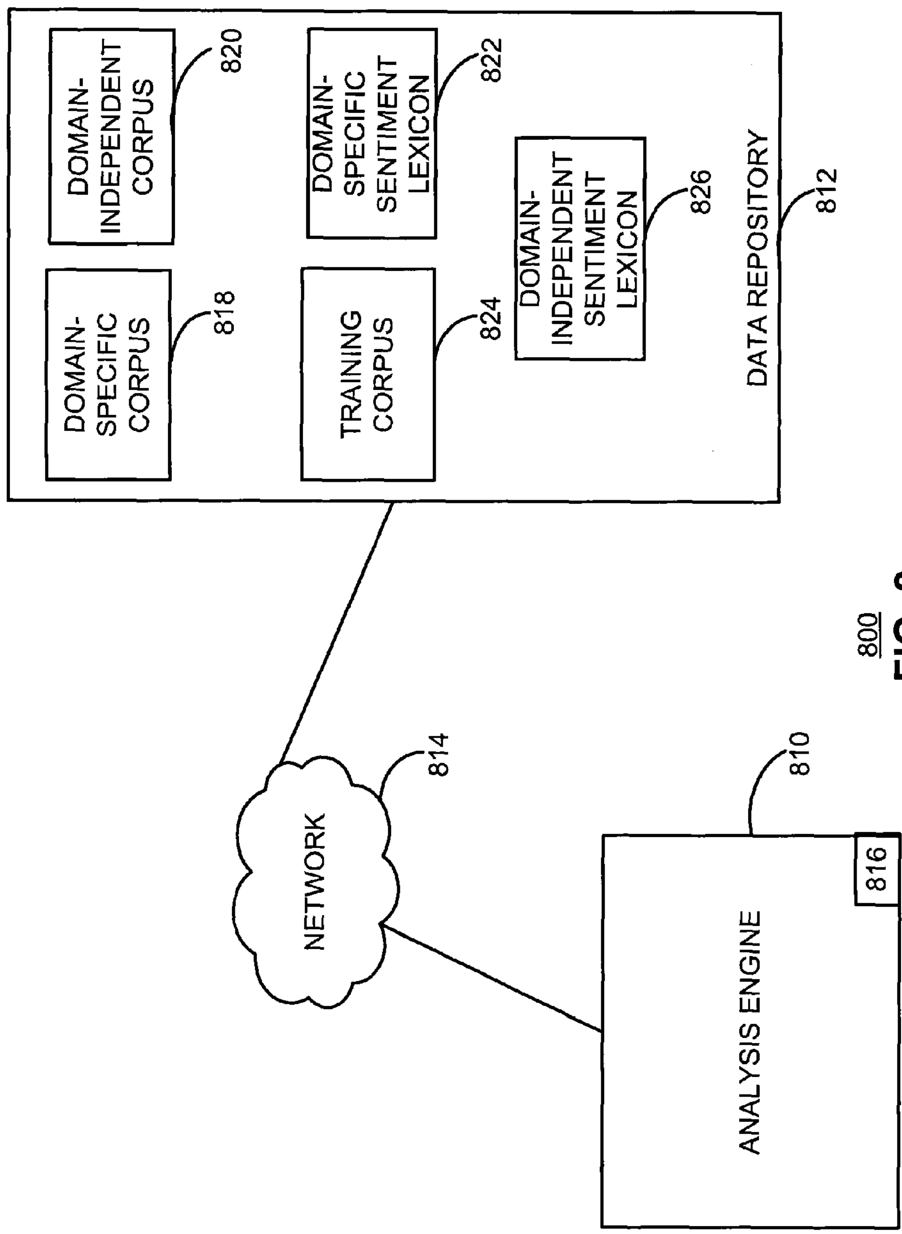

MONITOR USER INTERACTION WITH RANKED SEARCH RESULTS
712
GENERATE WEIGHTS FOR CONSENSUS SCORES
714
710
GENERATE ENTITY RANKINGS BASED ON LEARNED WEIGHTS
716

FIG. 7


DOMAIN-INDEPENDENT CORPUS
820
DOMAIN-SPECIFIC CORPUS
818
DOMAIN-SPECIFIC SENTIMENT LEXICON
822
TRAINING CORPUS
824
DOMAIN-INDEPENDENT SENTIMENT LEXICON
826
DATA REPOSITORY
812
NETWORK
814
ANALYSIS ENGINE
810
816

800
FIG. 8

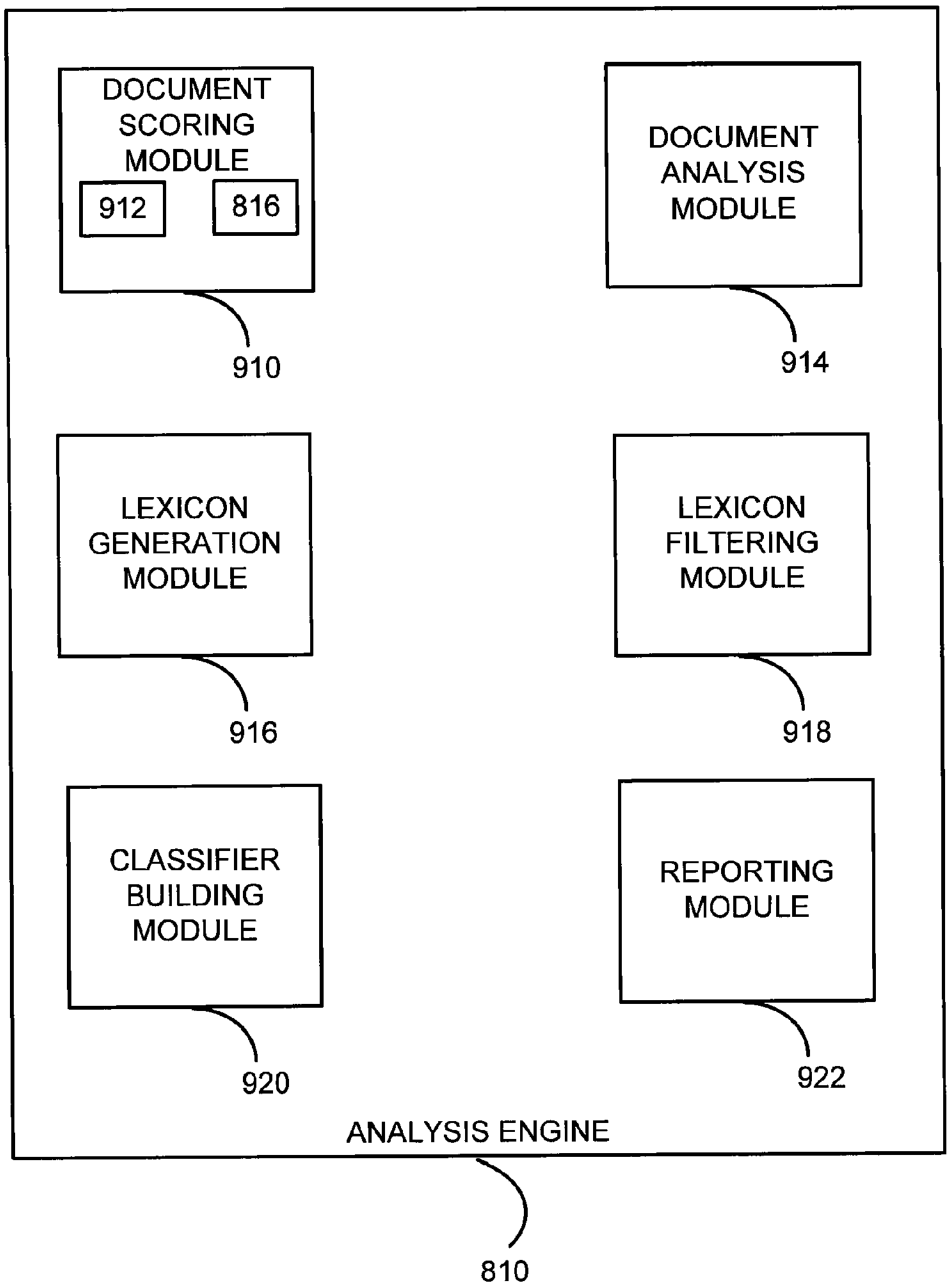

DOCUMENT SCORING MODULE
912
816
910
DOCUMENT ANALYSIS MODULE
914
LEXICON GENERATION MODULE
916
LEXICON FILTERING MODULE
918
CLASSIFIER BUILDING MODULE
920
REPORTING MODULE
922
ANALYSIS ENGINE
810

FIG. 9

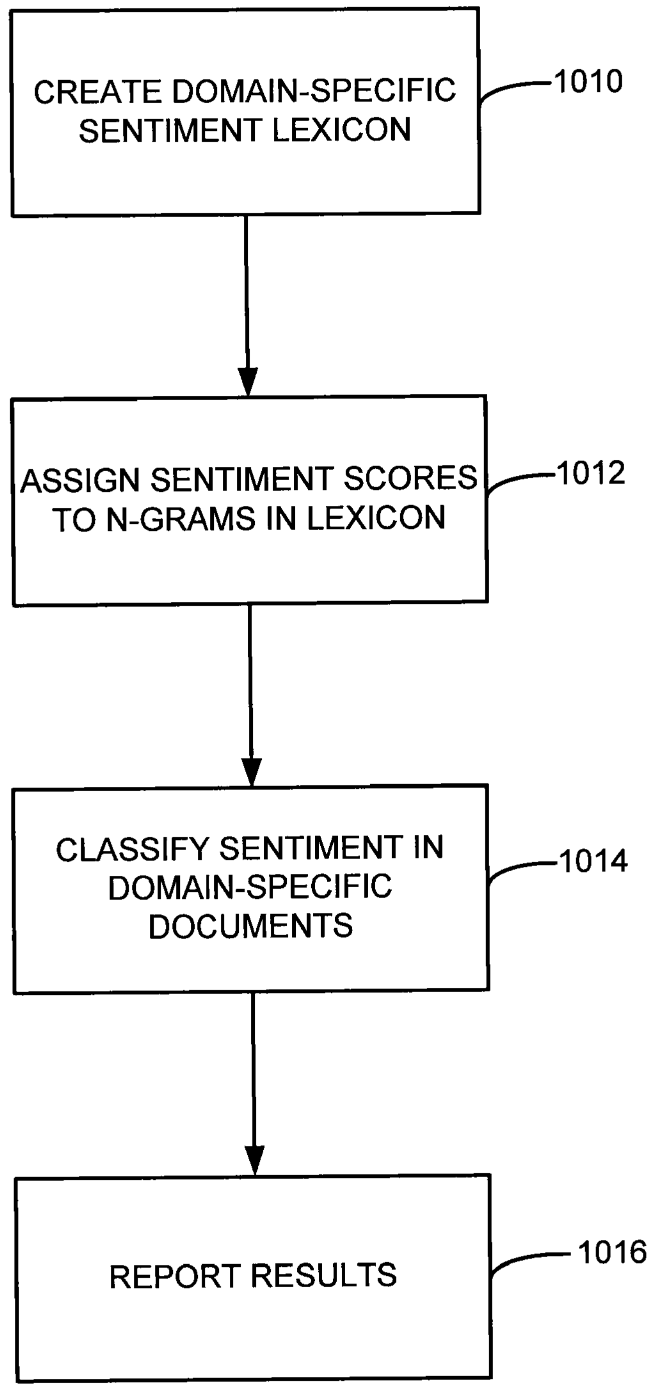

CREATE DOMAIN-SPECIFIC SENTIMENT LEXICON
1010
ASSIGN SENTIMENT SCORES TO N-GRAMS IN LEXICON
1012
CLASSIFY SENTIMENT IN DOMAIN-SPECIFIC DOCUMENTS
1014
REPORT RESULTS
1016

FIG. 10

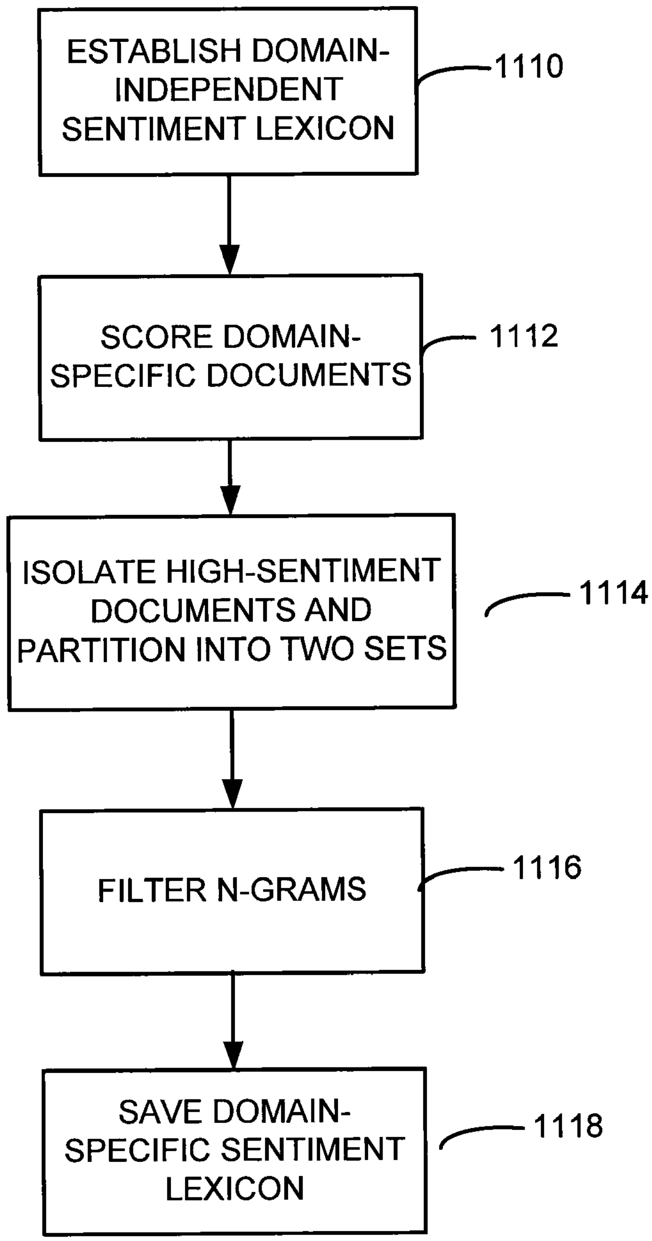

ESTABLISH DOMAIN-INDEPENDENT SENTIMENT LEXICON
1110
SCORE DOMAIN-SPECIFIC DOCUMENTS
1112
ISOLATE HIGH-SENTIMENT DOCUMENTS AND PARTITION INTO TWO SETS
1114
FILTER N-GRAMS
1116
SAVE DOMAIN-SPECIFIC SENTIMENT LEXICON
1118

FIG. 11

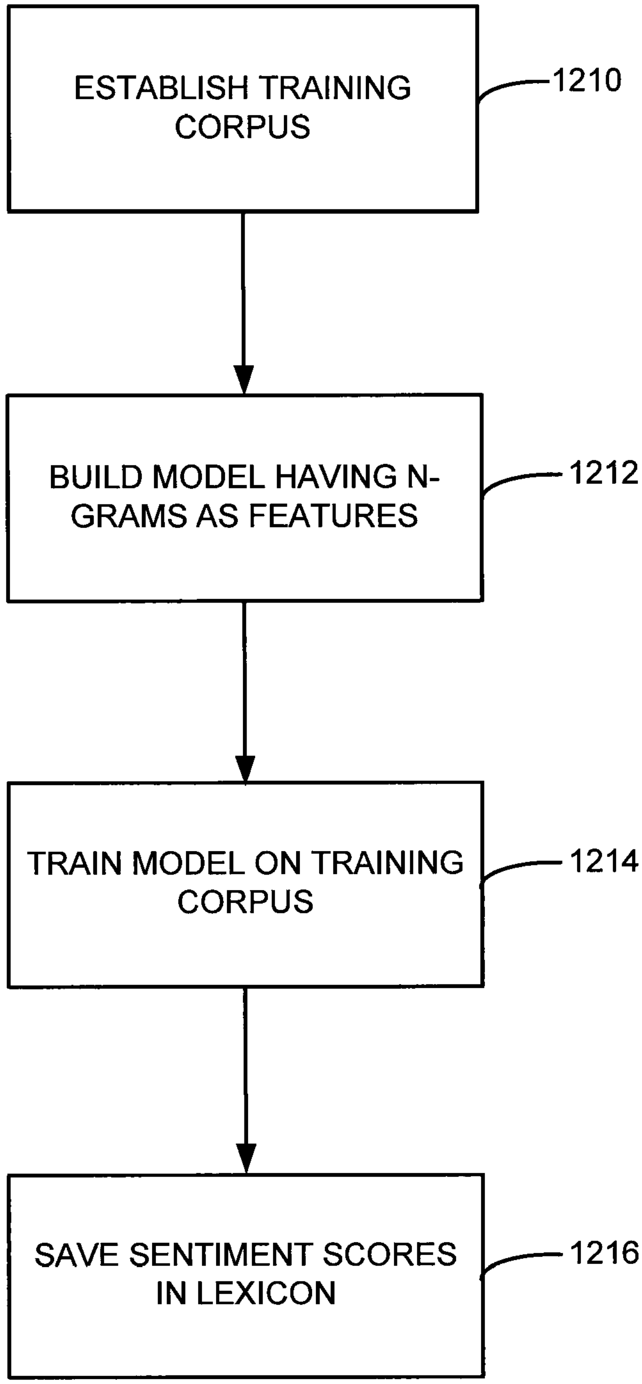

ESTABLISH TRAINING CORPUS
1210
BUILD MODEL HAVING N-GRAMS AS FEATURES
1212
TRAIN MODEL ON TRAINING CORPUS
1214
SAVE SENTIMENT SCORES IN LEXICON
1216

FIG. 12

SENTIMENT DETECTION AS A RANKING SIGNAL FOR REVIEWABLE ENTITIES

CROSS-REFERENCE TO RELATED APPLICATIONS

The present application is related to U.S. patent application Ser. No. 11/844,222 "Domain-Specific Sentiment Classification" filed Aug. 23, 2007, the disclosure of which is incorporated herein by reference.

BACKGROUND

1. Field

This invention pertains in general to natural language processing and in particular to automated sentiment classification to provide rankings of documents.

2. Description of the Related Art

Determining indicators of search result relevance and ranking the search results according to these indicators is an integral function of web search engines. Common indicators of search result relevance include indicators of popularity such as number of links to a web page or number of page hits a day. Other indicators of popularity may be collected through monitoring user-interaction with search results. Monitoring user-interaction with search results produces metrics which indicate search result relevance such as user click through rates or average time spent by the user at a web page associated with a search result.

Often searches are performed for entities about which public opinion is expressed such as movies, restaurants and hotels. This opinion or sentiment is also a valuable indicator of the relevance of search results. For instance, if a user searches for French restaurants, it is most likely that a user would like to know of the restaurants that are the most favorably reviewed. Similarly, most users who search for a listing of hotels in a geographic area wish to see results containing the hotels with the best reviews. Users may be interested in search results for reviewable entities such as books and films for which strong public opinion is expressed, whether or not the opinion is favorable or unfavorable.

Attempts to use sentiment as a ranking signal for search results have commonly used structured reviews. In structured reviews, the reviewer selects a rating in addition to providing a textual review of the entity. Structured reviews can be conveniently used in ranking systems as most structured reviews use a numeric rating (e.g. a 5 star system or a scale of 1 to 10) that can easily be used to rank results. Results are ranked by their average numeric rating from the structured review. However, in instances where an entity has mixed reviews valuable information may be lost due to the averaging.

Another limitation of solely using ratings from structured reviews as indicators of search result relevance is that valuable information in the textual review regarding the sentiment or public opinion about the reviewable entities is discarded. In textual reviews sentiment is expressed through statement, allowing a finer level of precision or "granularity" than rankings and the ability to express different types of sentiment within a review (e.g. "food great, service bad").

Textual reviews may also help correct for inconsistencies in ranking system normalization. For instance, a restaurant consistently rated at two stars by restaurant reviewers may be favorably reviewed by its patrons due to differences in ranking system scales. Incorporating the sentiment expressed within the textual reviews that accompany the ratings from both reviewers and patrons can help correct for these inconsistencies. Additionally, there are many other textual sources of sentiment outside of structured reviews such as blogs or personal web pages that may not be integrated into search result rankings based solely on structured ratings.

BRIEF SUMMARY OF THE INVENTION

The described embodiments provide a method, system and computer program product that generate ranking scores used to rank a plurality of reviewable entities.

One aspect provides a computer-implemented method of ranking reviewable entities. A plurality of review texts is identified, wherein each review text references an entity. A plurality of sentiment scores associated with the plurality of review texts are generated, wherein each sentiment score for a review text indicates a sentiment directed to the entity referenced by the review text. A plurality of ranking scores for the plurality of entities are generated wherein each ranking score is based at least in part on one or more sentiment scores associated with one or more review texts referencing the entity. The plurality of ranking scores are then stored.

In another aspect, the described embodiments provide a system for ranking reviewable entities. The system comprises a text selection module adapted to identify a plurality of review texts, wherein each review text references an entity. The system further comprises a sentiment score module adapted to generate a plurality of sentiment scores associated with the plurality of review texts, wherein each sentiment score for a review text indicates a sentiment directed to the entity referenced by the review text. The system further comprises a rank learning model adapted to generate a plurality of ranking scores for the plurality of entities wherein each ranking score is based at least in part on one or more sentiment scores associated with one or more review texts referencing the entity and store the plurality of ranking scores in a ranking database.

Another aspect is embodied as a computer-readable storage medium on which is encoded computer program code for ranking reviewable entities according to the above described method.

The features and advantages described in this summary and the following detailed description are not all-inclusive. Many additional features and advantages will be apparent to one of ordinary skill in the art in view of the drawings, specification, and claims hereof.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a high-level block diagram of a computing environment according to one embodiment of the present invention.

FIG. **2** is a high-level block diagram illustrating a functional view of a typical computer for use as the analysis engine and/or data repository illustrated in the environment of FIG. **1** according to one embodiment.

FIG. **3**A illustrates the storage of sentiment data associated with textual reviews of a reviewable entity in the Entity Sentiment Database **142** according to one embodiment.

FIG. **3**B illustrates the storage of rating data from structured reviews of an entity in the Entity Rating Database **144** according to one embodiment.

FIG. **4** illustrates the storage of the ranking data generated by the Ranking Analysis Engine **130**.

FIG. **5** is a high-level block diagram illustrating modules within the Ranking Analysis Engine **130** according to one embodiment.

FIG. **6** is a flowchart illustrating a more detailed view of steps performed by an embodiment of the Ranking Analysis

Engine **130** in generating Sentiment Scores **312** and initial Entity Rankings **404** based on the generated Sentiment Scores **312**.

FIG. **7** is a flowchart illustrating a more detailed view of steps performed by an embodiment of the Ranking Analysis Engine **130** in learning weights for generating Entity Rankings **404**.

FIG. **8** is a high level block diagram of a computing environment for generating sentiment scores according to one embodiment.

FIG. **9** is a high level block diagram illustrating modules within the analysis engine according to one embodiment.

FIG. **10** is a flow chart illustrating steps performed by the analysis engine to build the domain specific classifier and apply the classifier to a set of domain specific documents according to one embodiment.

FIG. **11** is a flow chart illustrating a more detailed view of steps performed by an embodiment of the analysis engine in creating the domain specific sentiment Lexicon as illustrated in FIG. **10**.

FIG. **12** is a flow chart illustrating a more detailed view of steps performed by an embodiment of the analysis engine as illustrated in FIG. **10**.

The figures depict an embodiment of the present invention for purposes of illustration only. One skilled in the art will readily recognize from the following description that alternative embodiments of the structures and methods illustrated herein may be employed without departing from the principles of the invention described herein.

DETAILED DESCRIPTION

I. Overview

FIG. **1** is a high-level block diagram of a computing environment **100** according to one embodiment. FIG. **1** illustrates an Entity Ranking Data Repository **140**, and a Ranking Analysis Engine **130** connected to a Network **114**. Although FIG. **1** illustrates the Ranking Analysis Engine **130** as a single engine, in some embodiments the Ranking Analysis Engine **130** can have multiple engines. Likewise, there can be multiple Entity Ranking Data Repositories **140** on the Network **114**. Only one of each entity is illustrated in order to simplify and clarify the present description. There can be other entities on the Network **114** as well. In some embodiments, the Ranking Analysis Engine **130** and Entity Ranking Data Repository **140** are combined into a single entity.

The Ranking Analysis Engine **130** supports ranking of documents associated with reviewable entities. The Ranking Analysis Engine **130** uses the reviews stored in the Entity Sentiment Database **142** to identify text regarding entities. The Ranking Analysis Engine **130** is adapted to generate sentiment scores based on sentiment in the text regarding the entities. The Ranking Analysis Engine stores entity rankings generated based on sentiment scores in the Entity Ranking Database **146**. The Ranking Analysis Engine **130** also functions to modify the rankings in the Entity Ranking Database **146** based on the Entity Rating Database **144**. The Ranking Analysis Engine **130** is further adapted to modify the rankings in the Entity Ranking Database **146** based on a User Interaction Database **148**. In one embodiment, the Ranking Analysis Engine **130** learns and stores weights used to modify the rankings as a mixture model **132**.

The Entity Ranking Data Repository **140** stores structured reviews, unstructured reviews and other data used to rank search results for Reviewable Entities **315**. Reviewable Entities **315** include any person, place or thing about which opinion is likely to be expressed such as restaurants, hotels, consumer products such as electronics, films, books and live performances.

Structured reviews are known reviews of the Reviewable Entity **315** which adhere to a specific format including a defined rating of the reviewable entity and/or a textual review of the Reviewable Entity **315**. A structured review will typically have the following format, "0 stars; The pizza was horrible. Never going there again.". In this instance, "0 stars" corresponds to the rating and "The pizza was horrible. Never going there again" corresponds to the Textual Review **310**. Structured reviews are collected through the Network **114** from known review web sites such as Google Maps, TripAdvisor, Citysearch or Yelp. Structured reviews can also be collected from other types of textual documents such as the text of books, newspapers and magazines.

Unstructured reviews are textual documents which reference the Reviewable Entity **315** that have a high likelihood of containing an opinion about the Reviewable Entity **315**. Unstructured reviews contain a Textual Review **310** but not a rating. Unstructured reviews usually contain sentiment expressed in documents with less structured formats than review websites such as newsgroups or blogs. Unstructured reviews are obtained through the Network **114** from sources of textual information which reference the entities including, but not limited to, web pages and/or portions of web pages, blogs, emails, newsgroup postings, and/or other electronic messages, etc. In some embodiments, unstructured reviews are analyzed to produce values which indicate the likelihood that the unstructured review pertains to the Reviewable Entity **315** and the unstructured review contains a sentiment or opinion about the Reviewable Entity **315**

In one embodiment, the Entity Ranking Data Repository **140** stores textual reviews from structured and unstructured reviews of the Reviewable Entity **315** in the Entity Sentiment Database **142** and ratings of the entity from structured reviews in the Entity Ratings Database **144**. In alternate embodiments, the textual reviews from structured and unstructured reviews of the reviewable entity and entity ratings may be stored in one corpus. According to the embodiment, the Entity Sentiment Database **142** may store a value which indicates the likelihood that an unstructured textual review contains an opinion or sentiment about the reviewable entity. In some embodiments, the Entity Sentiment Database **142** also contains a value which indicates the likelihood that the unstructured review pertains to the entity. In some embodiments, the ratings in the Entity Ratings Database **144** are normalized to a specified value.

The Entity Ranking Data Repository **140** further stores a User Interaction Database **148**. The User Interaction Database **148** stores user interaction metrics generated from monitoring user interactions with search results associated with entities.

The Entity Ranking Data Repository **140** further stores an Entity Ranking Database **146**. The Entity Ranking Database **146** combines and stores information from the Entity Sentiment Database **142**, the Entity Rating Database **144** and the User Interaction Database **148** used to rank the reviewable entities.

The Network **114** represents the communication pathways among the Ranking Analysis Engine **130**, the Entity Ranking Data Repository **140**, and any other entities connected to the Network **114**. In one embodiment, the Network **114** is the Internet. The Network **114** can also utilize dedicated or private communications links that are not necessarily part of the Internet. In one embodiment, the Network **114** uses standard communications technologies and/or protocols. Thus, the

Network **114** can include links using technologies such as Ethernet, 802.11, integrated services digital network (ISDN), digital subscriber line (DSL), asynchronous transfer mode (ATM), etc. Similarly, the networking protocols used on the Network **114** can include multiprotocol label switching (MPLS), the transmission control protocol/Internet protocol (TCP/IP), the hypertext transport protocol (HTTP), the simple mail transfer protocol (SMTP), the file transfer protocol (FTP), the short message service (SMS) protocol, etc. The data exchanged over the Network **114** can be represented using technologies and/or formats including the HTML, the extensible markup language (XML), the Extensible Hypertext markup Language (XHTML), the compact HTML (cHTML), etc. In addition, all or some of links can be encrypted using conventional encryption technologies such as the secure sockets layer (SSL), HTTP over SSL (HTTPS), and/or virtual private networks (VPNs). In other embodiments, the Sentiment Analysis Engine **110** and Sentiment Analysis Data Repository **112** use custom and/or dedicated data communications technologies instead of, or in addition to, the ones described above.

FIG. **2** is a high-level block diagram illustrating a functional view of a typical computer **200** for use as the Ranking Analysis Engine **130** and/or Entity Ranking Data Repository **140** illustrated in the environment **100** of FIG. **1** according to one embodiment. Illustrated are at least one processor **202** coupled to a bus **204**. Also coupled to the bus **204** are a memory **206**, a storage device **208**, a keyboard **210**, a graphics adapter **212**, a pointing device **214**, and a network adapter **216**. A display **218** is coupled to the graphics adapter **212**.

The processor **202** may be any general-purpose processor such as an INTEL x86 compatible-CPU. The storage device **208** is, in one embodiment, a hard disk drive but can also be any other device capable of storing data, such as a writeable compact disk (CD) or DVD, or a solid-state memory device. The memory **206** may be, for example, firmware, read-only memory (ROM), non-volatile random access memory (NVRAM), and/or RAM, and holds instructions and data used by the processor **202**. The pointing device **214** may be a mouse, track ball, or other type of pointing device, and is used in combination with the keyboard **210** to input data into the computer system **200**. The graphics adapter **212** displays images and other information on the display **218**. The network adapter **216** couples the computer **200** to the Network **114**.

As is known in the art, the computer **200** is adapted to execute computer program modules. As used herein, the term "module" refers to computer program logic and/or data for providing the specified functionality. A module can be implemented in hardware, firmware, and/or software. In one embodiment, the modules are stored on the storage device **208**, loaded into the memory **206**, and executed by the processor **202**.

The types of computers **200** used by the entities of FIG. **1** can vary depending upon the embodiment and the processing power required by the entity. The Ranking Analysis Engine **130** can include one or more distributed physical or logical computers operating together to provide the functionalities described herein. Likewise, the data repository can be provided by a storage area network (SAN), database management system (DBMS), or another storage system. The computers **200** can lack some of the components described above, such as keyboards **210**, graphics adapters **212**, and displays **218**.

FIG. **3**A illustrates the storage in memory of sentiment data associated with textual reviews of a Reviewable Entity **315** in the Entity Sentiment Database **142** according to one embodiment. Each Reviewable Entity **315** is represented by a tuple in the Entity Sentiment Database **142**. A tuple consists of an Entity ID **302**, an Entity Type **300** and one or more Reviews **313**. Each Review **313** consists of a Review ID **204**, a P(entity) value **306**, a P(sentiment) value **308**, and one or more Entity Review Texts **318**. Each Entity Review Text **318** contains an Entity Text ID **314**, Entity Text **316** and a Sentiment Score **312**. The Entity ID **302** be any kind of unique identifier that uniquely identifies (e.g., a primary key in the Entity Sentiment Database **142**) the Reviewable Entity **315**, such as an alphanumeric string, bit string, or a combination of data associated with the Reviewable Entity **315** such as name, location or owner of the Reviewable Entity **315**.

Entity Type **300** is a categorical variable used to define the type of the Reviewable Entity **315** in order to facilitate Entity Type **300** specific search and specify the domain to be used in Domain-Specific Sentiment Analysis. The Entity Type **300** can represent any type of Reviewable Entity **315** such as a place, service or consumer product. Example Entity Types **300** may include hotels, films, restaurants and cameras. In alternate embodiments, there may be more than one Event Type **300** associated with each Reviewable Entity **315**.

The Review ID **304** can be any unique identifier which uniquely identifies the Review **313** (e.g. a primary key in the Entity Sentiment Database **142**). The Review ID **304** may include any combination of information which uniquely identifies the Review **313** including the author of the Review **313**, the source from which the Review **313** was obtained and the date of the Review **313**.

The P(entity) value **306** represents the likelihood that the Review **313** is about the Entity **315**. For Reviews **313** including Textural Reviews **310** from unstructured reviews, the P(entity) value **306** can be a function of any information regarding the Review **313** such as the source of the Review **313** or the author of the Review **313**. The P(entity) value **306** can also be determined based on any metric generated from the analysis of the Textual Review **310**, such as the number of times the entity is mentioned in the Textual Review **310** or a title of the Textual Review **310**. According to the embodiment, the P(entity) value **306** may be a categorical (high, medium, low) or a numeric value. For Reviews **313** obtained from high quality or structured reviews, the P(entity) value **306** may be set to the corresponding numeric or categorical value which denotes the highest likelihood that the Review **313** pertains to the Entity **315**.

The P(sentiment) value **308** represents the likelihood that the Review **313** contains a sentiment about the Entity **315**. For Reviews **313** including Textual Reviews **310** from unstructured reviews, the P(sentiment) value **306** can be a function of any information regarding the entity such as the source of the Review **313** or the author of the Review **313**. The P(sentiment) value **308** can also be determined based on any metric generated from the analysis of the Textual Review **310**, such as the number of tokens representing adjectives in the Textual Review **310**. According to the embodiment, the P(sentiment) value **306** may be a categorical (e.g. high, medium, low) or a numeric value. For Reviews **313** including Textural Reviews **310** from high quality or structured reviews, the P(sentiment) value may be set to the corresponding numeric or categorical values which denotes the highest likelihood that the Review **313** pertains to the Reviewable Entity **315**. For example, a P(sentiment) value from an Review **313** obtained from a review website such as Yelp or TripAdvisor would be given a P(sentiment) value of 1 or 100%, indicating the highest likelihood that the Review **313** contained sentiment about the entity.

The Textual Review **310** includes the body of text that has been identified as a Review **313** of the Entity **315**. In one embodiment, the Textual Review **310** is tokenized to produce a set of tokens and each token is subject to part of speech (POS) tagging to associate parts of speech with the tokens. In some embodiments, the tokens comprising the Textural Review **310** are processed using a variety of natural language processing (NLP) techniques such as stemming, word sense disambiguation and compound recognition. Other applicable techniques will be apparent to those skilled in the art of natural language processing (NLP).

The Ranking Analysis Engine **130** processes each Textual Review **310** to create one or more Entity Review Texts **318**. Each Entity Review Text **318** comprises an Entity Text ID **314**, an Entity Text **316** and a Sentiment Score **312**. The Entity Text ID **314** is a unique identifier used to identify the Entity Review Text **318**. The Entity Text **316** is the portion of the Textual Review **310** which contains sentiment about the Reviewable Entity **315**. The Ranking Analysis Engine **130** identifies one or more Entity Texts **316** from the Textual Review **310**. The identification of Entity Review Texts **318** is discussed in detail below with respect to the Text Selection Module **502** in FIG. **5**.

The Ranking Analysis Engine **130** generates Sentiment Scores **312** for each Entity Text **316**. Sentiment Scores **312** are used to represent the type of sentiment contained in the Entity Texts **316** and the magnitude or strength of the type of sentiment in the Entity Texts **316**. The type of sentiment represents any kind of characterization of a sentiment that can associated with heuristics used to score the sentiment according to the characterization such as: polarity of the sentiment, the type of attitude expressed in the sentiment, confidence in the sentiment, identity of the source/author, overall amount of sentiment-laden text identified, and relative importance of features about which sentiment is expressed.

Polarity of a sentiment defines whether it is a positive or negative sentiment. Heuristics used to score sentiments based on polarity are based on the sentiment containing synonyms of words that indicate polarity such as "good" or "bad". In one embodiment, the generated Sentiment Scores **312** partition sentiments into two categories according to the polarity (i.e. positive or negative) of the sentiment.

Magnitude of sentiment is expressed as a value on a scale of 1 to 5 and represents the strength of the associated type of sentiment. In embodiments, where Sentiment Scores **312** are generated based on polarity, magnitude of sentiment and polarity of sentiment are combined to create a scale in which −5 represents the strongest negative sentiment; −1 represents the weakest negative sentiment; +1 represents the weakest positive sentiment and +5 represents the strongest positive sentiment.

In alternate embodiments, separate Sentiment Scores **312** are generated to represent type of sentiment and polarity of sentiment. Other representations of type of sentiment and magnitude of sentiment will be well known to those skilled in the art. For example, other representations may further partition sentiment into multiple types of sentiment or use different scales or categorical variables to represent magnitude.

FIG. **3**B illustrates the storage of rating data from structured reviews of an entity in the Entity Rating Database **144** according to one embodiment. Each Rated Entity **325** is represented by a tuple in the Entity Rating Database **144**. The Rated Entity **325** tuple consists of an Entity ID **302**, an Entity Type **300** and one or more Ratings **323**. Each Rating **232** consists of a Review ID **304**, a Review Rating **320** and a Normalized Rating **322**.

The Review Rating **320** is the rating assigned in a structured review. The Review Rating **320** includes both the rating scale and the numeric value of the rating. The rating scale can be a set of ordered categorical variables (e.g. A+ through F) or a numeric scale (5 start system, scale of 1-10). Some rating scales include negative values. Ratings **323** with multiple different rating scales are normalized to create Normalized Ratings **322** in which the Ratings **323** have the same numeric scale. In one embodiment, simple linear normalization is performed by representing all the ratings on a specified scale. Other methods of normalization will be apparent to those skilled in the art in light of this disclosure.

FIG. **4** illustrates the storage of the ranking data generated by the Ranking Analysis Engine **130**. Each Ranked Entity **415** is represented by a tuple in the Entity Ranking Database (X). Each tuple contains the Entity Type **300**, Entity ID **302**, Entity Ranking **404**, User Interaction Score **406**, User Interaction Score Weight **408**, Consensus Sentiment Score **410**, Sentiment Score Weight **412**, Consensus Normalized Rating **414** and Normalized Rating Weight **416**. In some embodiments, Ranked Entities **415** are organized by Entity Type **200** to facilitate search result retrieval for queries preformed for an Entity Type **200**.

The Ranked Entities **415** in the Entity Ranking Database **144** are displayed responsive to search queries which reference the Entity Type **302**. The Entity Rankings **404** are used as signals to rank the set of Ranked Entities **415** when displaying the Ranked Entities **415** as search results. For example, a user who enters "sushi" as a search query will receive an ordered list of Ranked Entities **415** of Entity Type **415** "sushi restaurant" ranked according to Entity Ranking **404**. According to the embodiment, the Entity Ranking **404** can be combined with other signals to rank the set of Ranked Entities **415** such as signals based on the number of times the Ranked Entity **415** is mentioned on an index of web pages or the geographic location of the Ranked Entities **415** relative to a geographic location of a user performing a search.

The User Interaction Score **406** is generated using user interaction metrics such as user click through and time spent at web pages associated with Ranked Entities **415** presented in search results. The Ranking Analysis Engine **130** monitors user interaction with results to generate user interaction metrics which are stored in the User Interaction Database **148**. This process is discussed in detail below with respect to step **712** in FIG. **7**. The User Interaction Score Weight **408** is the weight assigned to the User Interaction Score **406** in calculating the Entity Ranking **404**.

The Consensus Sentiment Score **410** of a Ranked Entity **415** is a representative sentiment score which combines the values of all calculated Sentiment Scores **312** associated with an Entity **315**. Sentiment Scores **312** associated with a Ranked Entity **315** may be combined in any way to generate a Consensus Sentiment Score **410**. Consensus Sentiment Scores **410** can be generated by averaging the Sentiment Scores **312** associated with a Reviewable Entity **315**, selecting the median Sentiment Score **312** of the Sentiment Scores **312** associated with a Reviewable Entity **315** or selecting the Sentiment Score **312** which is most frequently associated with a Reviewable Entity **315**. The Sentiment Scores **312** of Reviews **313** with Textual Reviews **310** from unstructured reviews may be weighted using the P(entity) value **306** and the P(sentiment) value **308**. Other methods of generating a Consensus Sentiment Score **410** from a plurality of Sentiment Scores **312** associated with a Reviewable Entity **315** will be apparent to those skilled in the art. The Sentiment Score Weight **412** is the weight assigned to the Consensus Sentiment Score **410** in calculating the Entity Ranking **404**.

The Consensus Normalized Rating **414** is a representative rating which combines the values of all calculated Normalized Ratings **322** associated with a Ranked Entity **325**. Normalized Ratings **322** associated with a Ranked Entity **325** may be combined in any way to generate a Consensus Normalized Rating **414**. Consensus Normalized Ratings **414** can be generated by averaging the Normalized Ratings **322** associated with a Ranked Entity **325**, selecting the median Normalized Rating **322** associated with a Ranked Entity **325** or selecting the Normalized Rating **322** which is most frequently associated with a Ranked Entity **325**. Other methods of generating a Consensus Normalized Rating **414** from a plurality of Normalized Ratings **322** associated with a Ranked Entity **325** will be apparent to those skilled in the art. The Normalized Rating Weight **416** is the weight assigned to the Consensus Normalized Rating **414** for generating the Entity Ranking **404**.

FIG. **5** is a high-level block diagram illustrating modules within the Ranking Analysis Engine **130** according to one embodiment.

A Text Selection Module **502** is used to identify one or more Reviewable Entity Texts **318** from the Textual Review **310** and store the Reviewable Entity Texts **318** in the Entity Sentiment Database **142**. In one embodiment, the Text Selection Module **502** runs as a batch program whenever new Reviews **313** are added to the Entity Sentiment Database **142**.

The Sentiment Score Module **512** generates Sentiment Scores **312** for each Entity Text **316**. In one embodiment, the Sentiment Score Module **512** is run as a batch program in association with the Text Selection Module **502** whenever new Reviews **313** are added to the Entity Sentiment Database **142**.

The User Interaction Module **532** functions to monitor user interactions with ranked search results for an Entity Type **300**. The User Interaction Module **532** further stores monitoring information in the User Interaction Database **148**. Monitoring user interaction with ranked search results is discussed in detail below with respect to step **712** in FIG. **7**.

The Rank Learning Module **542** functions to learn weights for generating Entity Rankings **404** based on user-interaction metrics stored in the User Interaction Database **148**. In one embodiment, the Rank Learning Module **542** iteratively learns and stores a mixture model **132** to generate weights for generating Entity Rankings **404**.

FIG. **6** is a flowchart illustrating a more detailed view of steps performed by an embodiment of the Ranking Analysis Engine **130** in generating Sentiment Scores **312** and initial Entity Rankings **404** based on the generated Sentiment Scores **312**. Other embodiments perform additional and/or different steps that the ones described in the figure. In addition, other embodiments perform the steps in different orders and/or perform multiple steps concurrently.

A Text Selection Module **502** identifies **614** one or more Entity Texts **316** from the Textual Review **310**. The Text Selection Module **502** first identifies **614** one or more tokens corresponding to the Reviewable Entity **315** in each Textual Review **310**. The Text Selection Module **502** then identifies **614** one or more Entity Texts **316** by identifying **614** a set of tokens proximate to the token corresponding to the Reviewable Entity **315**. In some embodiments, the set of tokens in each Entity Text **316** is of fixed size for all Textual Reviews **310**. In a specific embodiment, the set of tokens in each Entity Text **316** will correspond to 2 sentences adjacent to (i.e. before and after) the sentence containing the token corresponding to the Reviewable Entity **315**.

In an alternate embodiment, the set of tokens in each Entity Text **316** will be proportional to one or both of the P(entity) **306** value and the P(sentiment) **308** value. For instance, if the P(entity) value **306** or the P(sentiment) value **308** is low indicating a low likelihood that the Textual Review **310** is regarding the entity or contains sentiment about the entity, the set of tokens in the Entity Text **316** will be a smaller number of tokens than the set of tokens in the Entity Text **316** associated with a Textual Review **310** with a high P(entity) value **306** or P(sentiment) value **308**.

The Sentiment Score Module **512** generates **616** Sentiment Scores **312** representing the polarity and magnitude of sentiment in each of the Entity Review Texts **318**. The Sentiment Score Module **512** generates domain specific Sentiment Scores **312** based on the Entity Texts **316** and the Entity Types **300** which specify the domain of the entity. Suitable methods of generating domain-specific Sentiment Scores **312** are discussed below in reference to FIGS. **8-12**.

The Rank Learning Module **532** generates **618** Entity Rankings **404** based on the Sentiment Scores **312**. The Rank Learning Module **542** combines the Sentiment Scores **312** associated with each Reviewable Entity **315** to generate **618** the Consensus Sentiment Score **410** used to generate **618** the Entity Ranking **404**. Entity ID **302** is used to create a correspondence between the Ranked Entities **415**, the Rated Entities **425** and the Reviewable Entities **315**. In one embodiment, the User Interaction Score Weight **408** and the Normalized Rating Score Weight **416** are set to zero, meaning that the Entity Ranking **404** is generated **618** based solely on the Consensus Sentiment Score **410**. This weighting is also used to initialize the Entity Ranking Database **146** in embodiments which monitor user interactions to iteratively learn the User Interaction Score Weights **408**, Normalized Rating Score Weights **416** and the Sentiment Score Weights **412**.

In an alternate embodiment, the Entity Ranking **404** is generated **618** based on both the Consensus Sentiment Score **410** and the Consensus Normalized Rating **414** with the corresponding Sentiment Score Weight **412** and Normalized Rating Weight **416** both set to values greater than zero. The values of the Sentiment Score Weight **412** and the Normalized Rating Weight can be user-specified. Alternately, these values may be learned based on information in the User Interaction Database **148**.

According to the embodiment, the Entity Ranking **404** may be based on any combination of the polarity and magnitude of the Consensus Sentiment Scores **312** associated with the Ranked Entities **315**. In one embodiment, the Ranked Entities **315** with the strongest positive Consensus Sentiment Scores **410** will have the highest Entity Rankings **404** and the Ranked Entities **415** with the strongest negative Consensus Sentiment Scores **410** will have the lowest Entity Rankings **404**. In another embodiment, the Ranked Entities **315** with the strongest negative Consensus Sentiment Scores **410** will have the highest Entity Rankings **404** and the Ranked Entities **415** with the strongest positive Consensus Sentiment Scores **410** will have the lowest Entity Rankings **404**. In another embodiment, the Entity Rankings **404** may be based solely on the magnitude of the Sentiment Scores **312**, wherein Ranked Entities **415** with the strongest positive and negative Consensus Sentiment Scores **410** are assigned the highest Entity Rankings **404** and the Ranked Entities **415** with the weakest positive and negative Consensus Sentiment Scores **410** are assigned the lowest Entity Rankings **404**.

FIG. **7** is a flowchart illustrating a more detailed view of steps performed by an embodiment of the Ranking Analysis Engine **130** in learning weights for generating Entity Rankings **404**. Other embodiments perform additional and/or different steps that the ones described in the figure. In addition, other embodiments perform the steps in different orders and/

or perform multiple steps concurrently. In some embodiments, the steps described in the figure are iteratively repeated **710**.

The User Interaction Module **532** monitors **712** user interactions with search results associated with the Ranked Entities **415** to generate and store user interaction metrics in the User Interaction Database **148**. Search results associated with Ranked Entities **415** are typically presented as web pages for the Ranked Entities **415** but can also consist of directory listings for the Ranked Entity **415** or other documents which contain information about the Ranked Entity **415**. The User Interaction Module **532** is adapted to communicate with a search engine program on a server through the Network **114**. The User Interaction Module **532** monitors user interaction to generate user click through rates for each search result associated with a Ranked Entity **415**. The user click through rate represents the number of times a search result associated with a Ranked Entity **415** was clicked by a user, divided by the number of times that result was presented to a user.

The User Interaction Module **532** also monitors **712** user interactions to generate metrics representing the time spent at search result associated with a Ranked Entity **415**. The User Interaction Module **532** monitors **712** and records the amount of time the user spends at a search result associated with a Ranked Entity **415** before returning to the web page displaying the ranked search results associated with the Ranked Entities **415**. In some embodiments, the User Interaction Module **532** monitors **712** other metrics of user interaction. Other suitable user-interaction metrics will be apparent to those skilled in the art of web search engines. The user interaction metrics are stored in the User Interaction Database **148** and may be combined in any way to generate the User Interaction Score **408** stored in the Entity Ranking Database **146**.

The Rank Learning Module **542** generates **716** the values of the Sentiment Score Weight **412** and Normalized Rating Weight **416** based on the User Interaction Score **148**. In one embodiment, the Sentiment Score Weight **412** and Normalized Rating Weight **416** are determined based on generating a correlation coefficient between both the Consensus Sentiment Score **410** and the Consensus Normalized Rating **414** and the User Interaction Score **406**. Each of the generated correlation coefficients is then divided by the sum of the two correlation coefficients to generate the Sentiment Score Weight **412** and the Normalized Rating Weight.

In other embodiments, the Sentiment Score Weight **412** and Normalized Rating Weight **416** are determined by generating a mixture model **132** to approximate the weight of influence of the Consensus Sentiment Score **410** and the Consensus Normalized Rating **414** on the User Interaction Score **406**. Suitable mixture models **132** to determine the weight of the Consensus Sentiment Score **410** and the Consensus Normalized Rating **414** on the User Interaction Score **406** include expectation maximization (EM) models, Markov Chain Monte Carlo models and Spectral models. In an alternate embodiment, the mixture model **132** may also incorporate the User Interaction Score **406** to determine an optimal User Interaction Score Weight **408**. Alternate embodiments may use predictive models such as classifiers to determine the values of the Sentiment Score Weight **412** and Normalized Rating Weight. Other methods of determining the Sentiment Score Weight **412** and Normalized Rating Weight **416** will be readily apparent to those skilled in the art.

The Rank Learning Module **542** generates **716** the Entity Rankings **404** based on the learned Sentiment Score Weights **412** and Normalized Rating Weights **416**. In one embodiment, the Rank Learning Module **542** generates the Entity Ranking **404** based on a linear combination of each score and its corresponding weight. That is, the Entity Ranking **404** is the sum of the Consensus Sentiment Score **410** multiplied by the Sentiment Score Weight **412**, the Consensus Normalized Rating **414** multiplied by the Normalized Rating Weight **416**, and the User Interaction Score **406** multiplied by the User Interaction Score Weight **408**. Alternate methods of combining the weights and scores to produce a single Entity Ranking **404** will be apparent to those skilled in the art.

FIG. **8** is a high-level block diagram of a computing environment **800** for generating Sentiment Scores **312** according to one embodiment. FIG. **8** illustrates an analysis engine **810** and a data repository **812** connected to a network **814**. Although FIG. **8** illustrates only a single analysis engine **810**, embodiments can have multiple engines. Likewise, there can be multiple data repositories on the network **814**. Only one of each entity is illustrated in order to simplify and clarify the present description. There can be other entities on the network **814** as well. In some embodiments, the analysis engine **810** and data repository **812** are combined into a single entity.

The analysis engine **810** supports domain-specific sentiment classification for documents stored in the repository **812** and/or other locations. In one embodiment, the analysis engine **810** uses the documents in the repository **812** to identify a domain-specific sentiment lexicon **822** of n-grams. In addition, the analysis engine **810** uses the n-grams in the domain-specific sentiment lexicon **822** as features in a model in order to build a highly-accurate domain-specific sentiment classifier **816**. The analysis engine **810** uses the classifier **816** to classify the sentiment of documents stored in the repository **812** and/or on the network **814**. In one embodiment, the analysis engine **810** is controlled by an administrator or other user who uses it to build the classifier and/or perform automated sentiment classification of documents.

The data repository **812** stores documents and other data utilized by the analysis engine **810** to build a domain-specific sentiment classifier **816**. In one embodiment, the data repository stores sets of documents organized into various corpora. The corpora include a domain-specific corpus **818** holding domain-specific documents and a domain-independent corpus **820** holding domain-independent (i.e., non-specific) documents. In one embodiment, the domain-specific corpus **818** contains enough documents to constitute a representative sample of how sentiment is expressed in the domain. Likewise, the domain-independent corpus **820** contains enough documents to constitute a representative sample of how sentiment is expressed generally, exclusive of any specific domain.

As used herein, the term "domain" refers to a particular sphere of activity, concern or function, such as restaurants, electronic devices, international business, and movies. The term "domain" does not necessarily refer to Internet domain names, although certain web sites at certain Internet domains might include documents related to a particular sphere of activity, concern or function.

In one embodiment, both corpora hold documents obtained via the network **814**. The documents include web pages and/or portions of web pages, the text of books, newspapers, and magazines, emails, newsgroup postings, and/or other electronic messages, etc. For example, the documents in the domain-specific corpus **818** can include documents related to restaurants, such as portions of web pages retrieved from web sites specializing in discussions about restaurants. Likewise, the domain-specific documents in the corpus **818** can include web pages retrieved from web sites that include reviews and/or discussion related to portable electronic devices, such as mobile telephones and music players. In contrast, the documents in the domain-independent corpus **820** can include documents associated with a variety of different domains, so that no single domain predominates. In addition, the documents in the domain-independent corpus **820** can be drawn from sources unrelated to any particular source, such as general interest magazines or other periodicals.

In some embodiments, the corpora hold documents obtained from sources other than the network. Moreover, in some embodiments the corpora are virtual in the sense that they are not stored at a single location. For example, the domain-specific corpus can be defined as the contents of one or more web sites devoted to restaurant reviews or other topics.

In one embodiment, the data repository **812** also includes the domain-specific sentiment lexicon **822** and a domain-independent sentiment lexicon **826**. The domain-specific sentiment lexicon **822** contains a set of n-grams (i.e., words and/or phrases) that express sentiment in a particular domain. The domain-independent sentiment lexicon **826**, in contrast, contains a set of n-grams that express sentiment in a general or non-specific domain. In one embodiment, each n-gram in the lexicons **822**, **826** has an associated score indicating the polarity (i.e., positive or negative) and magnitude of the sentiment it expresses.

In one embodiment, the domain-independent sentiment lexicon **826** is based on a lexical database, such as the WordNet electronic lexical database available from Princeton University of Princeton, N.J. The lexical database describes mappings between related words. That is, the database describes synonym, antonym, and other types of relationships among the words. In one embodiment, the administrator selects initial terms for the domain-independent sentiment lexicon **826** by reviewing the lexical database and manually selecting and scoring words expressing high sentiment. The administrator initially selects about 360 such words in one embodiment although the number of words can vary in other embodiments. This initial set of words is expanded through an automated process to include synonyms and antonyms referenced in the lexical database. The expanded set of words constitutes the domain-independent sentiment lexicon **826**.

An embodiment of the data repository **812** also includes a training corpus **824**. In one embodiment, the training corpus **824** includes domain-specific documents labeled with corresponding sentiment scores. In some embodiments the domain-specific documents are manually labeled with sentiment scores. For example, in one embodiment the documents in the training corpus **824** are drawn from popular product review web sites such as Amazon, CitySearch, and Cnet. These sites include textual product reviews that are manually labeled by the review submitters with corresponding numeric or alphabetic scores (e.g., 4 out of 5 stars or a grade of "B−"). Further, in some embodiments the domain-specific documents are automatically labeled with sentiment scores. For example, in one embodiment the documents in the training corpus **824** include high-sentiment documents from the domain specific corpus **818** that are labeled with sentiment scores through an automated process as described below.

The network **814** represents the communication pathways among the analysis engine **810**, the data repository **812**, and any other entities connected to the network. In one embodiment, the network **814** is the Internet. The network **814** can also utilize dedicated or private communications links that are not necessarily part of the Internet. In one embodiment, the network **814** uses standard communications technologies and/or protocols. Thus, the network **814** can include links using technologies such as Ethernet, 802.11, integrated services digital network (ISDN), digital subscriber line (DSL), asynchronous transfer mode (ATM), etc. Similarly, the networking protocols used on the network **814** can include multiprotocol label switching (MPLS), the transmission control protocol/Internet protocol (TCP/IP), the hypertext transport protocol (HTTP), the simple mail transfer protocol (SMTP), the file transfer protocol (FTP), the short message service (SMS) protocol, etc. The data exchanged over the network **814** can be represented using technologies and/or formats including the HTML, the extensible markup language (XML), the Extensible Hypertext markup Language (XHTML), the compact HTML (cHTML), etc. In addition, all or some of links can be encrypted using conventional encryption technologies such as the secure sockets layer (SSL), HTTP over SSL (HTTPS), and/or virtual private networks (VPNs). In other embodiments, the analysis engine **810** and data repository **812** use custom and/or dedicated data communications technologies instead of, or in addition to, the ones described above.

FIG. **9** is a high-level block diagram illustrating modules within the analysis engine **810** according to one embodiment. Other embodiments have different and/or additional modules than the ones shown in FIG. **9**. Moreover, other embodiments distribute the functionalities among the modules in a different manner.

A document scoring module **910** scores documents to determine the magnitude and polarity of the sentiment they express. In one embodiment, the document scoring module **910** includes one or more classifiers. These classifiers include a lexicon-based classifier **912** and the domain-specific classifier **816** created by the analysis engine **810**.

An embodiment of the lexicon-based classifier **912** uses the domain-independent sentiment lexicon **826** to calculate sentiment scores for documents in the domain-specific corpus **818**. The scoring performed by the lexicon-based classifier **912** essentially looks for n-grams from the domain-independent lexicon **826** that occur in the documents of the corpus **818**. For each n-gram that is found, the classifier **912** determines a score for that n-gram based on the techniques/factors described below. The sentiment score for the document is the sum of the scores of the n-grams occurring within it.

Embodiments of the lexicon-based classifier **912** use one or more of the following techniques/factors to determine the score for an n-gram found in a document:

- the n-gram score in the lexicon: An n-gram in the lexicon **826** has an associated score representing the polarity and magnitude of the sentiment it expresses. For example, "hate" and "dislike" both have negative polarities, and "hate" has a greater magnitude than "dislike;"
- part-of-speech tagging: The part of speech that an n-gram represents is classified and a score is assigned based on the classification. For example, the word "model" can be an adjective, noun or verb. When used as an adjective, "model" has a positive polarity (e.g., "he was a model student"). In contrast, when "model" is used as a noun or verb, the word is neutral with respect to sentiment.
- negation detection: An n-gram that normally connotes one type of sentiment can be used in a negative manner. For example, the phrase "This meal was not good" inverts the normally-positive sentiment connoted by "good."
- location in document: A score is influenced by where the n-gram occurs in the document. In one embodiment, n-grams are scored higher if they occur near the beginning or end of a document because these portions are more likely to contain summaries that concisely describe the sentiment described by the remainder of the document.

stemming: Reverse conjugation of a word in an n-gram is performed in order to identify its root word. A score is assigned to the word based on its root.

A document analysis module **914** analyzes documents scored by the document scoring module **910**. In one embodiment, the document analysis module **914** analyzes the documents scored by the lexicon-based classifier **912** and isolates the highest-scoring documents. An embodiment of the module **914** uses two scoring thresholds to partition the documents into a set of documents that express very negative sentiment and a set of documents that express very positive sentiment. Thus, documents that have a sentiment score lower than the negative sentiment threshold are placed in the "very negative sentiment" set while documents that have a sentiment score higher than the positive sentiment threshold are placed in the "very positive sentiment" set. Documents falling in the middle range are ignored for purposes of this analysis.

A lexicon generation module **916** creates the domain-specific lexicon **822** based on the sets of high-sentiment documents isolated by the document analysis module **914**. The lexicon generation module **916** identifies all n-grams up to a predetermined value of 'n' that occur in the documents in each set. "N" is five in one embodiment. Further, the lexicon generation module **916** identifies the most frequently occurring n-grams in each of the high-sentiment document sets (i.e., the most frequently occurring n-grams from the very negative sentiment document set and the most frequently occurring n-grams from the very positive sentiment document set).

A lexicon filtering module **918** filters the n-grams produced by the lexicon generation module **916** to produce a set of domain-specific sentiment-expressing n-grams. In one embodiment, the filtering module **918** removes extremely common n-grams (i.e., stop words) from the very negative and very positive sets. This filtering removes words and phrases like "the," "or," "he," and "she" that are unlikely to express sentiment. The n-grams that remain after filtering constitute the domain-specific sentiment lexicon **822**.

A classifier building module **920** builds the domain-specific classifier **816** used by the document scoring module **910**. In one embodiment, the classifier building module **920** assigns a score to each n-gram in the domain-specific sentiment lexicon **822** that represents the polarity and magnitude of the sentiment it expresses. The domain-specific classifier **816** uses the n-gram scores in the domain-specific sentiment lexicon **822**, along with the techniques and factors described above with respect to the lexicon-based classifier **912**, to classify the sentiment expressed by domain-specific documents.

To assign the scores to the n-grams in the domain-specific sentiment lexicon **822**, the classifier building module **920** uses the n-grams as feature in a model, such as a maximum entropy model, and trains the model on documents. Other models used in some embodiments to assign sentiment scores to the n-grams are based on support vector machines, Naïve Bayes, perceptron, Winnow, and LASSO (Least Absolute Shrinkage and Selection Operator) instead of, or in addition to, maximum entropy.

In one embodiment, the classifier building module **920** trains the model on the labeled documents in the training corpus **824**. Recall that in one embodiment the documents in the training corpus **824** include documents with manually-labeled sentiment scores. In other embodiments, the documents in the training corpus **824** include the set of high-sentiment documents having the scores assigned by the document scoring module **910** and isolated by the document analysis module **914** via the automated process described above. The set of high-sentiment documents can be used, for example, if obtaining the manually-labeled documents is too expensive or difficult, or if there are not enough manually-labeled documents available. Some embodiments train on both manually- and automatically-labeled documents. The training assigns accurate sentiment scores to the n-grams in the domain-specific lexicon **822**.

A reporting module **922** reports results of operations performed by the analysis engine **810**. The reports can include generating a presentation on the display of a computer, storing data in a log file describing the operations performed, storing data resulting from the operations performed by the analysis engine in the repository **812** or elsewhere, and the like. For example, the reporting module **922** can save the output of the lexicon filtering module **918** in the repository **812** as the domain-specific sentiment lexicon **822**. Likewise, the reporting module **922** can store the sentiment scores for the n-grams in the filtered high-sentiment n-gram set generated by the classifier building module **920**, and sentiment scores for documents generated by the domain-specific classifier **816**, in the data repository **812** or elsewhere.

FIG. **10** is a flowchart illustrating steps performed by the analysis engine **810** to build the domain-specific classifier **816** and apply the classifier to a set of domain-specific documents according to one embodiment. Other embodiments perform additional and/or different steps that the ones described in the figure. In addition, other embodiments perform the steps in different orders and/or perform multiple steps concurrently. Certain embodiments perform only some of the steps, such as only the steps directed to building the classifier **816**.

The analysis engine **810** creates **1010** a domain-specific lexicon **822** and saves it in the data repository **812**. The analysis engine **810** uses the training corpus **824** to associate **1012** sentiment scores with the n-grams in the lexicon **822**. The n-grams and associated scores are used by the domain-specific classifier **816**. In one embodiment, the analysis engine **810** uses the domain-specific classifier **816** to classify **1014** sentiment in domain-specific documents. The analysis engine **810** reports **1016** the results of the classifications. The report can be used to track the sentiment of an entity within the specific domain, to influence rankings of search results, and/or for other purposes.

FIG. **11** is a flowchart illustrating a more detailed view of steps performed by an embodiment of the analysis engine **810** in creating the domain-specific sentiment lexicon as illustrated in step **1010** of FIG. **10**. Other embodiments perform additional and/or different steps that the ones described in the figure. In addition, other embodiments perform the steps in different orders and/or perform multiple steps concurrently.

The analysis engine **810** establishes **1110** a domain-independent sentiment lexicon **826**. As described above, in one embodiment this lexicon **826** is created by manually selecting words having high sentiment from a lexical database and identifying antonyms and synonyms of the selected words. The selected words, antonyms, and synonyms are included in the domain-independent sentiment lexicon **826**. Other embodiments use a pre-defined domain-independent sentiment lexicon or use other techniques to create the lexicon.

The analysis engine **810** uses the domain-independent sentiment lexicon **826** to score **1112** sentiment of documents in a domain-specific corpus **818**. Then, the analysis engine **810** isolates the high-sentiment documents and partitions **1114** those documents into a set of very negative sentiment documents and a set of very positive sentiment documents. The analysis engine **810** extracts n-grams from the negative- and positive-sentiment documents. These n-grams are filtered

1116 to remove extremely common words and phrases. The remaining n-grams are saved 1118 as a domain-specific sentiment lexicon 822.

FIG. 12 is a flowchart illustrating a more detailed view of steps performed by an embodiment of the analysis engine 810 in assigning sentiment scores to n-grams in the domain-specific sentiment lexicon 822 as illustrated in step 1012 of FIG. 10. Other embodiments perform additional and/or different steps that the ones described in the figure. In addition, other embodiments perform the steps in different orders and/or perform multiple steps concurrently.

The analysis engine 810 establishes 1210 a training corpus 824 of labeled documents. As described above, in some embodiments the training corpus 824 is established by collecting domain-specific documents that are manually labeled with sentiment scores while in other embodiments the training corpus 824 is established using the automatically-labeled set of high-sentiment documents isolated by the document analysis module 914. The analysis engine 810 builds 1212 a model, such as a maximum entropy model, having the n-grams of the domain-specific sentiment lexicon 822 as features. The model is trained 1214 on the labeled documents in the training corpus 824 to determine sentiment scores for the n-grams. These scores are saved 1216 in the domain-specific sentiment lexicon 822.

Those of skill in the art will recognize that the techniques described herein can be used to build multiple sentiment classifiers for documents in different domains. To this end, some embodiments have multiple domain-specific lexicons, domain-specific corpora, and training corpora. This description refers to a single domain-specific classifier 816 and domain for purposes of clarity.

The above description is included to illustrate the operation of certain embodiments and is not meant to limit the scope of the invention. The scope of the invention is to be limited only by the following claims. From the above discussion, many variations will be apparent to one skilled in the relevant art that would yet be encompassed by the spirit and scope of the invention.

What is claimed is:

1. A computer-implemented method for ranking reviewable entities comprising:
   using at least one processor and memory to perform steps comprising:
      identifying a plurality of review texts, wherein each review text references at least one entity from a plurality of entities;
      generating a plurality of sentiment scores based on the plurality of review texts, wherein each sentiment score for a review text indicates a sentiment directed to an entity referenced by the review text;
      identifying a plurality of reviews, the reviews comprising ratings of the plurality of entities, the ratings separate from the review texts;
      determining, from the plurality of reviews, ratings associated with the plurality of entities;
      determining values indicating likelihoods that the review texts reference a particular one of the plurality of entities;
      generating ranking scores for corresponding ones of the entities, wherein the ranking score of an entity is based upon the sentiment scores associated with review texts referencing the entity, the values indicating likelihoods that the review texts reference the entity, and the ratings associated with the entity in the plurality of reviews;
      ranking the entities according to their associated ranking scores; and
      storing the plurality of ranking scores.

2. The method of claim 1, further comprising displaying a plurality of search results associated with the plurality of entities based at least in part on the ranking scores.

3. The method of claim 2, further comprising monitoring a plurality of user interactions with the search results and generating ranking scores for the plurality of entities based at least in part on the plurality of user interactions with the search results.

4. The method of claim 3, wherein the generating ranking scores for corresponding ones of the entities comprises generating the ranking scores based at least in part on the plurality of user interactions with the search results comprises generating a mixture model based on the plurality of sentiment scores, a plurality of ratings from a plurality of structured reviews referencing the plurality of entities and the plurality of user interactions.

5. The method of claim 1, wherein the generating the ranking scores for corresponding ones of the entities comprises generating the ranking scores based on a first weight associated with at least a first sentiment score associated with a review text referencing the entity and a second weight associated with at least a first rating from a review referencing the entity.

6. The method of claim 1, further comprising:
   determining a value that indicates a likelihood that a review text includes a sentiment directed to one of the plurality of entities; and wherein
   the ranking score for the one of the plurality of entities is further based on the value that indicates the likelihood that the review text includes the sentiment directed to one of the plurality of entities.

7. A non-transitory computer-readable storage medium encoded with computer program code for ranking reviewable entities, the computer program code comprising:
   computer program code for identifying a plurality of review texts, wherein each review text references at least one entity from a plurality of entities;
   computer program code for generating a plurality of sentiment scores based on the plurality of review texts, wherein each sentiment score for a review text indicates a sentiment directed to an entity referenced by the review text;
   computer program code for identifying a plurality of reviews, the reviews comprising ratings of the plurality of entities, the ratings separate from the review texts;
   computer program code for determining, from the plurality of reviews, ratings associated with the plurality of entities;
   computer program code for determining values indicating likelihoods that the review texts reference a particular one of the plurality of entities;
   computer program code for generating ranking scores for corresponding ones of the entities, wherein the ranking score of an entity is based upon the sentiment scores associated with review texts referencing the entity, the values indicating likelihoods that the review texts reference the entity, and the ratings associated with the entity in the plurality of reviews;
   computer program code for ranking the entities according to their associated ranking scores; and
   computer program code for storing the plurality of ranking scores.

8. The storage medium of claim **7**, further comprising computer program code for displaying a plurality of search results associated with the plurality of entities based at least in part on the ranking scores.

9. The storage medium of claim **8**, further comprising computer program code for monitoring a plurality of user interactions with the search results and computer program code for generating ranking scores for the plurality of entities based at least in part on the plurality of user interactions with the search results.

10. The storage medium of claim **9**, wherein the computer program code for generating ranking scores for corresponding ones of the entities comprises computer program code for generating the ranking scores based at least in part on the plurality of user interactions with the search results comprises computer program code for generating a mixture model based on the plurality of sentiment scores, a plurality of ratings from a plurality of structured reviews referencing the plurality of entities and the plurality of user interactions.

11. The storage medium of claim **7**, wherein the computer program code for generating the ranking scores for corresponding ones of the entities comprises computer program code for generating the ranking scores based on a first weight associated with at least a first sentiment score associated with a review text referencing the entity and a second weight associated with at least a first rating from a structured review referencing the entity.

12. The storage medium of claim **7**, further comprising computer program code for:

determining a value that indicates a likelihood that a review text includes a sentiment directed to one of the plurality of entities; and wherein

the ranking score for the one of the plurality of entities is further based on the value that indicates the likelihood that the review text includes the sentiment directed to one of the plurality of entities.

13. A system for ranking reviewable entities, the system comprising:

at least one processor for executing instructions in program modules, the program modules including:

a text selection module to identify a plurality of review texts, wherein each review text references at least one entity from a plurality of entities;

a sentiment score module to generate a plurality of sentiment scores based on the plurality of review texts, wherein each sentiment score for a review text indicates a sentiment directed to an entity referenced by the review text;

a rating module to identify a plurality of reviews, the reviews comprising ratings of the plurality of entities, the ratings separate from the review texts, and to determine, from the plurality of reviews, ratings associated with the plurality of entities; and

a rank learning module to determine values indicating likelihoods that the review texts reference a particular one of the plurality of entities, and to generate ranking scores for corresponding ones of the entities, wherein the ranking score of an entity is based upon the sentiment scores associated with review texts referencing the entity, the values indicating likelihoods that the review texts reference the entity, and the ratings associated with the entity in the plurality of reviews, further to rank the entities according to their associated ranking scores, and to store the plurality of ranking scores in a ranking database.

14. The system of claim **13**, further comprising a user interaction module to display a plurality of search results associated with the plurality of entities based at least in part on the ranking scores.

15. The system of claim **14**, wherein the rank learning module generates the ranking scores for corresponding ones of the entities based on a first weight associated with at least a first sentiment score associated with a review text referencing the entity and a second weight associated with at least a first rating from a review referencing the entity.

16. The system of claim **14**, wherein the user interaction module monitors a plurality of user interactions with the search results and the rank learning module generates ranking scores for the plurality of entities based at least in part on the plurality of user interactions with the search results.

17. The system of claim **16**, wherein the rank learning module generates a mixture model based on the plurality of sentiment scores, a plurality of ratings from a plurality of structured reviews referencing the plurality of entities and the plurality of user interactions.

18. The system of claim **13**, wherein the rank learning module

determines a value that indicates a likelihood that a review text includes a sentiment directed to one of the plurality of entities; and wherein

the ranking score for the one of the plurality of entities is further based on the value that indicates the likelihood that the review text includes the sentiment directed to one of the plurality of entities.

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