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(54) **METHODS AND SYSTEMS FOR CLIENT SIDE SEARCH RANKING IMPROVEMENTS**

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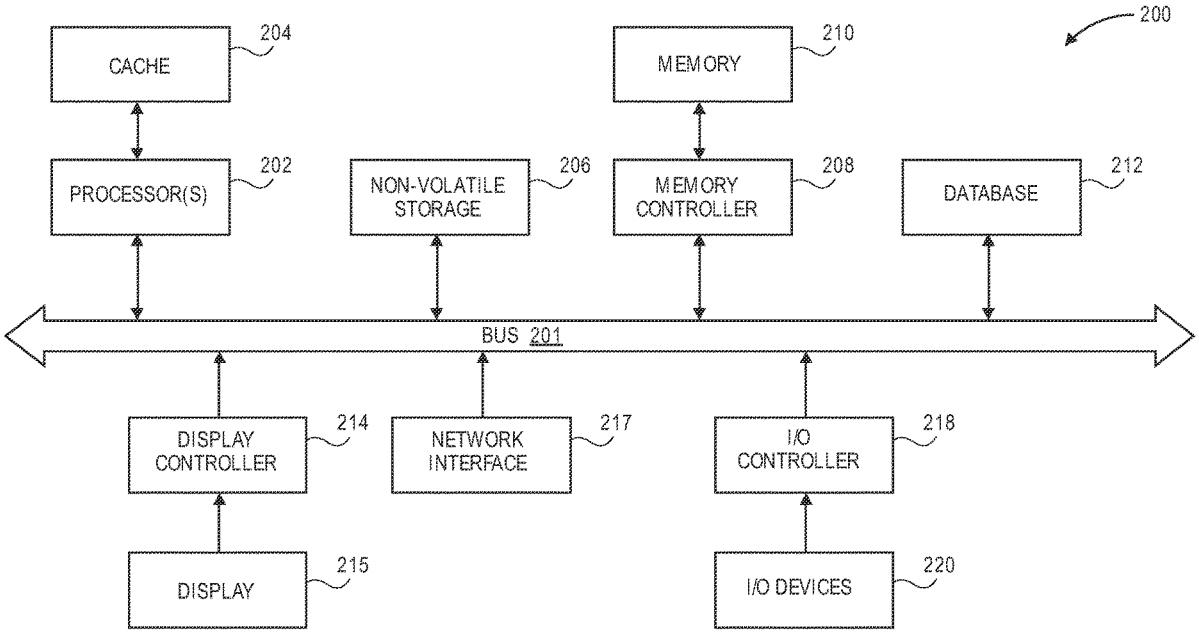
(57) **ABSTRACT**

Methods and systems for client side search ranking improvements are disclosed. In one example, a search query is received from a user on a client device. The local search results are filtered based on the received search query and one or more local ranking rules. Features for each filtered local search result are computed. The computed features of each filtered local search result are input to one or more machine learning (ML) models. Each ML model can generate a score for each filtered local search result. The filtered local search results are ranked based on the generated score within a category. In one example, local search results and remote server search results are obtained. The local search results and remote server search results are ranked using at least one machine learning (ML) ranking model. The ranked local search results and remote server search results are displayed on the client device by category.



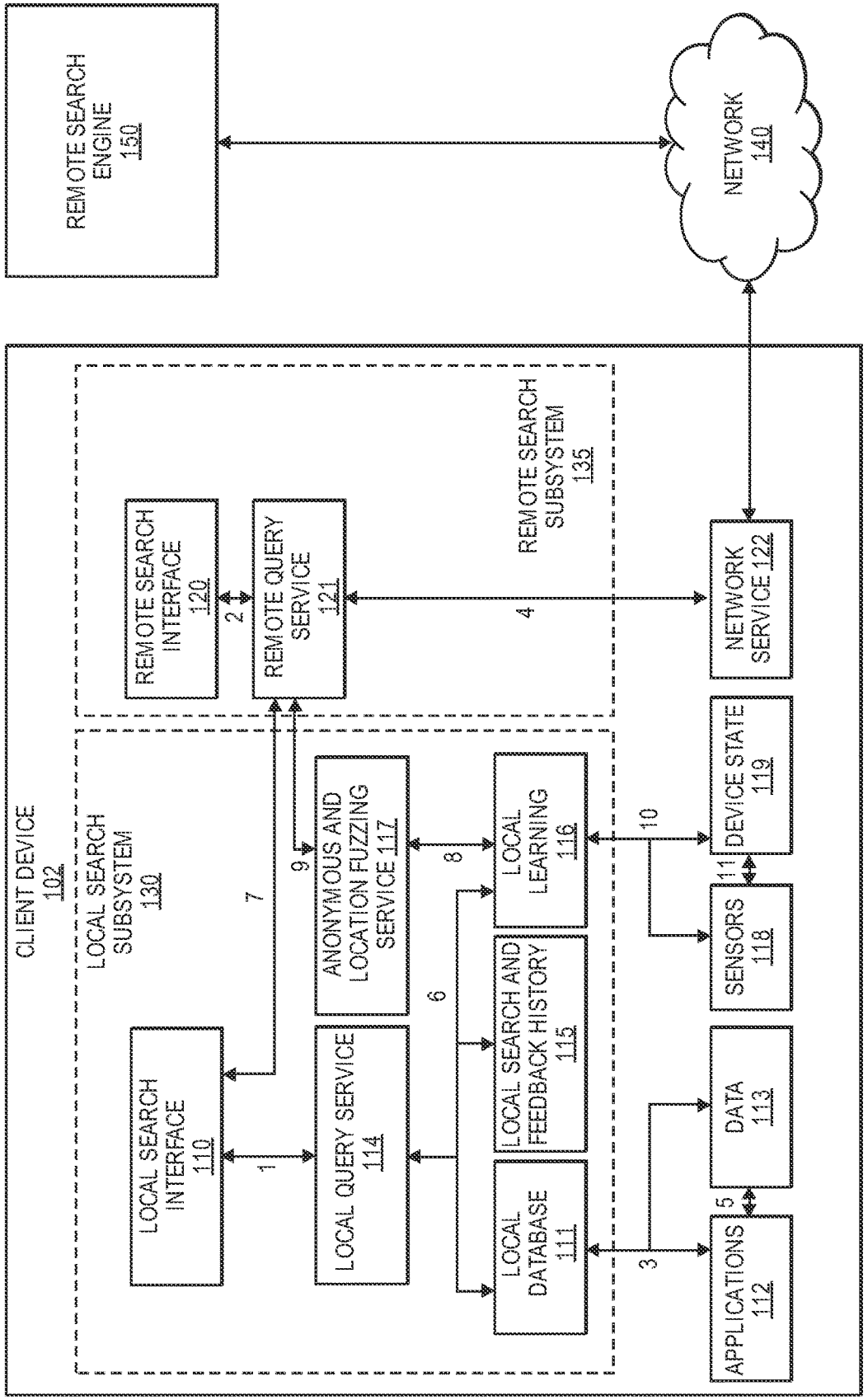

100
REMOTE SEARCH ENGINE 150
NETWORK 140
CLIENT DEVICE 102
LOCAL SEARCH SUBSYSTEM 130
REMOTE SEARCH SUBSYSTEM 135
LOCAL SEARCH INTERFACE 110
LOCAL QUERY SERVICE 114
LOCAL DATABASE 111
LOCAL SEARCH AND FEEDBACK HISTORY 115
ANONYMOUS AND LOCATION FUZZING SERVICE 117
LOCAL LEARNING 116
REMOTE SEARCH INTERFACE 120
REMOTE QUERY SERVICE 121
NETWORK SERVICE 122
APPLICATIONS 112
DATA 113
SENSORS 118
DEVICE STATE 119
1
2
3
4
5
6
7
8
9
10
11

FIG. 1A

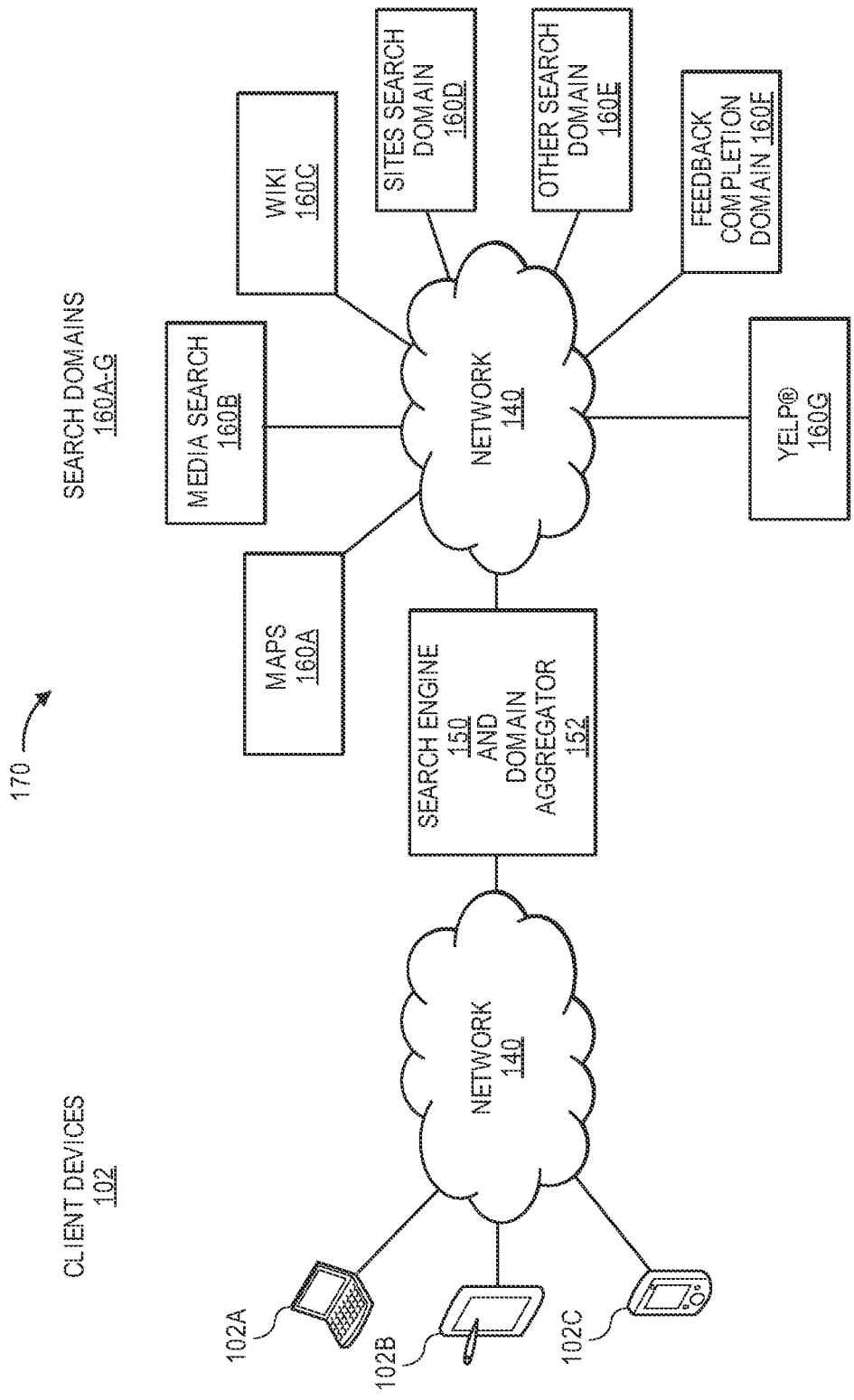

170
CLIENT DEVICES
102
102A
102B
102C
NETWORK
140
SEARCH ENGINE
150
AND
DOMAIN
AGGREGATOR
152
SEARCH DOMAINS
160A-G
MAPS
160A
MEDIA SEARCH
160B
WIKI
160C
SITES SEARCH
DOMAIN
160D
OTHER SEARCH
DOMAIN
160E
FEEDBACK
COMPLETION
DOMAIN 160F
YELP®
160G
NETWORK
140

FIG. 1B

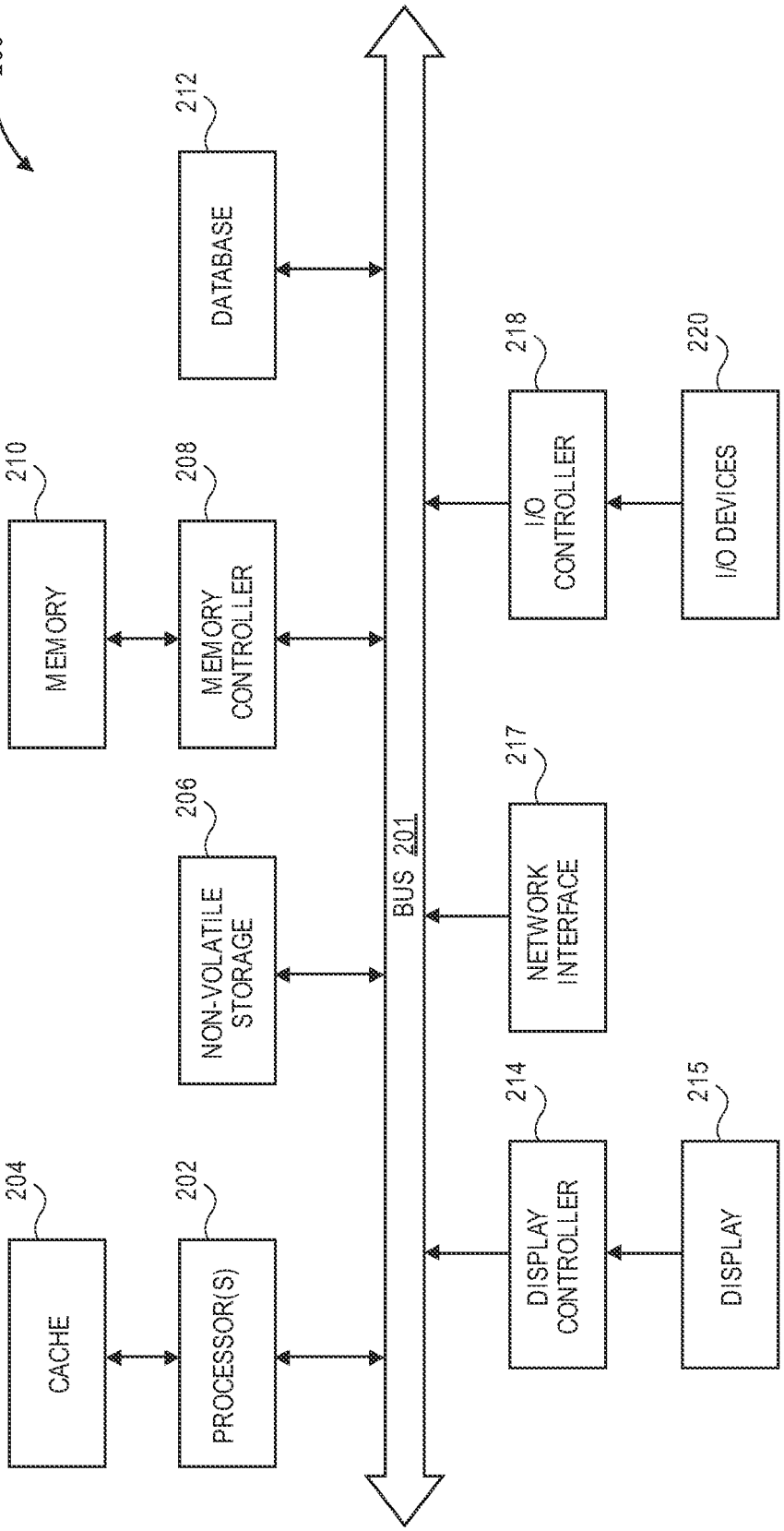

200
212
DATABASE
210
MEMORY
208
MEMORY CONTROLLER
218
I/O CONTROLLER
220
I/O DEVICES
206
NON-VOLATILE STORAGE
BUS 201
217
NETWORK INTERFACE
204
CACHE
202
PROCESSOR(S)
214
DISPLAY CONTROLLER
215
DISPLAY

FIG. 2

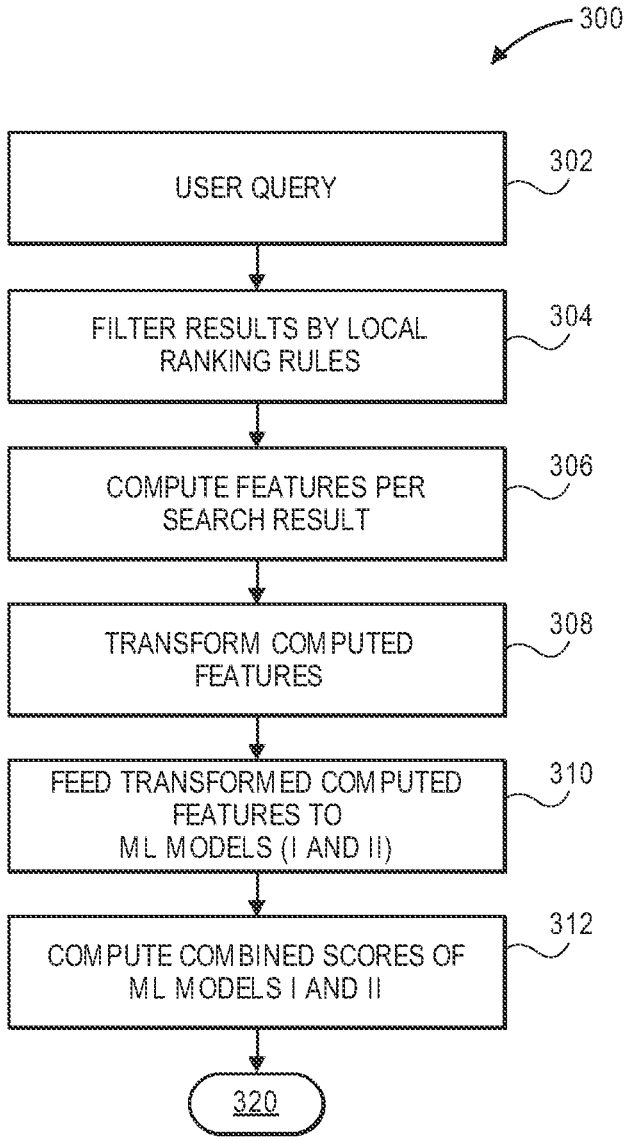

300
USER QUERY
302
FILTER RESULTS BY LOCAL RANKING RULES
304
COMPUTE FEATURES PER SEARCH RESULT
306
TRANSFORM COMPUTED FEATURES
308
FEED TRANSFORMED COMPUTED FEATURES TO ML MODELS (I AND II)
310
COMPUTE COMBINED SCORES OF ML MODELS I AND II
312
320

FIG. 3A

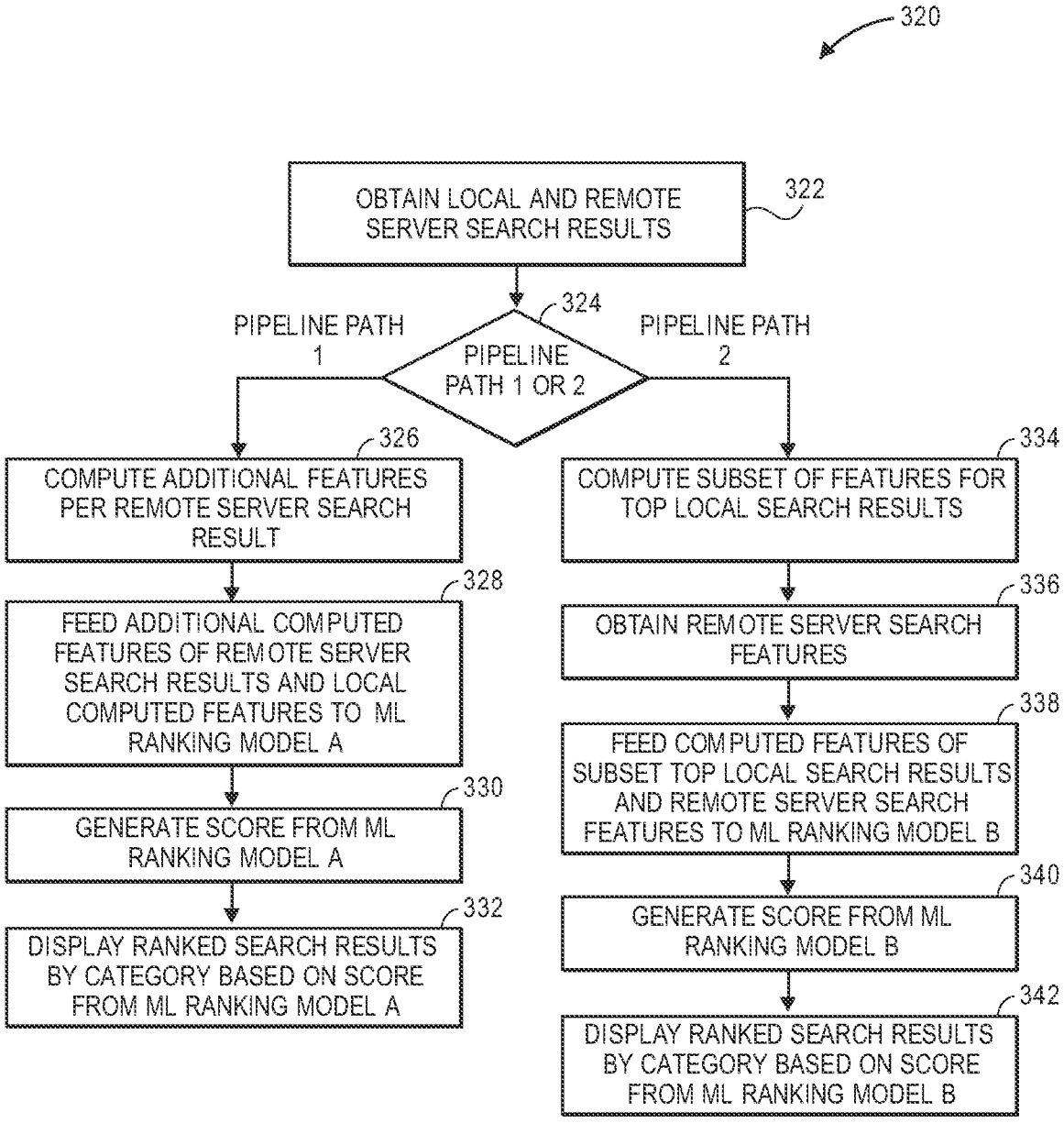

320
OBTAIN LOCAL AND REMOTE SERVER SEARCH RESULTS
322
324
PIPELINE PATH 1
PIPELINE PATH 2
PIPELINE PATH 1 OR 2
326
COMPUTE ADDITIONAL FEATURES PER REMOTE SERVER SEARCH RESULT
328
FEED ADDITIONAL COMPUTED FEATURES OF REMOTE SERVER SEARCH RESULTS AND LOCAL COMPUTED FEATURES TO ML RANKING MODEL A
330
GENERATE SCORE FROM ML RANKING MODEL A
332
DISPLAY RANKED SEARCH RESULTS BY CATEGORY BASED ON SCORE FROM ML RANKING MODEL A
334
COMPUTE SUBSET OF FEATURES FOR TOP LOCAL SEARCH RESULTS
336
OBTAIN REMOTE SERVER SEARCH FEATURES
338
FEED COMPUTED FEATURES OF SUBSET TOP LOCAL SEARCH RESULTS AND REMOTE SERVER SEARCH FEATURES TO ML RANKING MODEL B
340
GENERATE SCORE FROM ML RANKING MODEL B
342
DISPLAY RANKED SEARCH RESULTS BY CATEGORY BASED ON SCORE FROM ML RANKING MODEL B

FIG. 3B

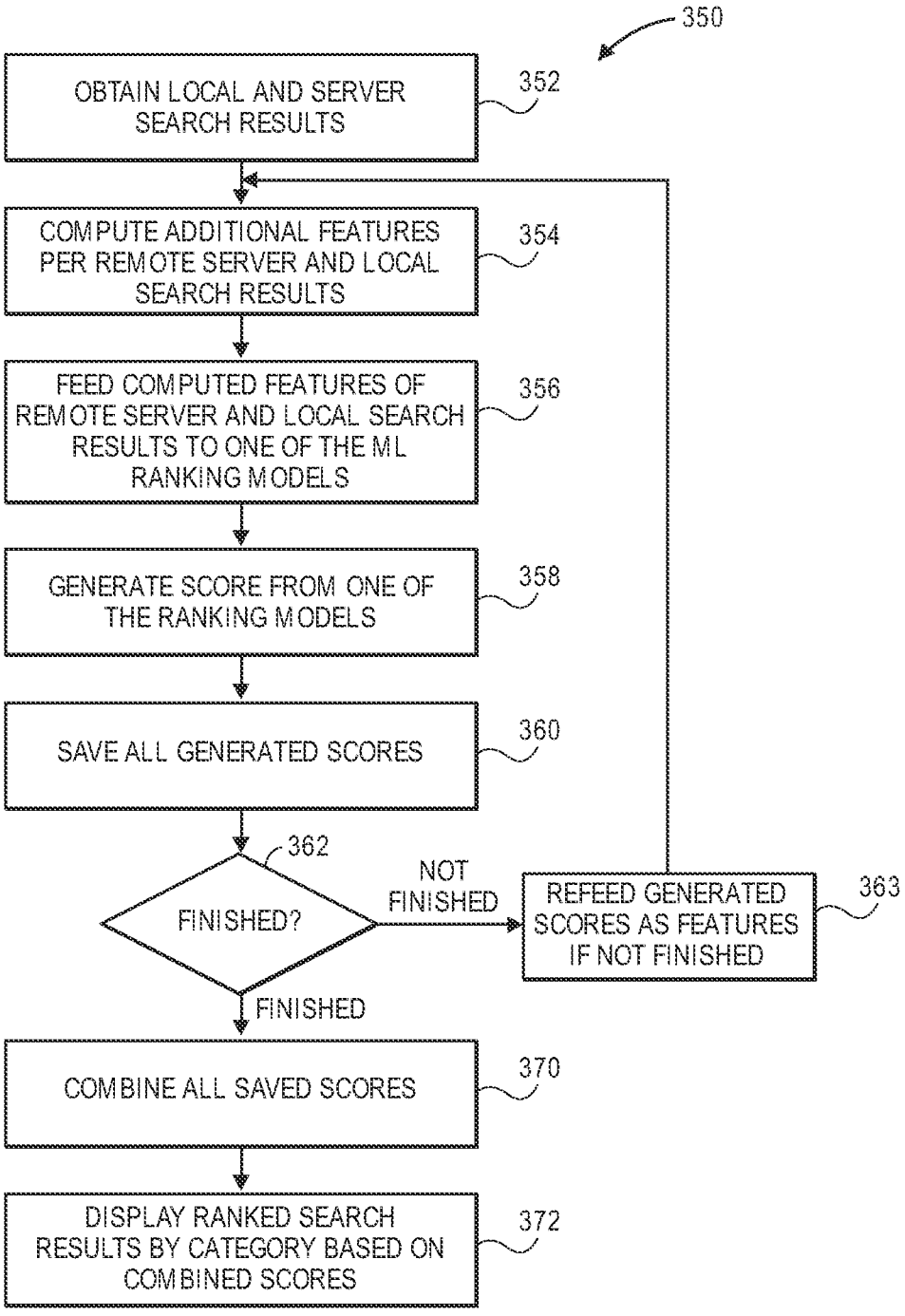

350
OBTAIN LOCAL AND SERVER SEARCH RESULTS
352
COMPUTE ADDITIONAL FEATURES PER REMOTE SERVER AND LOCAL SEARCH RESULTS
354
FEED COMPUTED FEATURES OF REMOTE SERVER AND LOCAL SEARCH RESULTS TO ONE OF THE ML RANKING MODELS
356
GENERATE SCORE FROM ONE OF THE RANKING MODELS
358
SAVE ALL GENERATED SCORES
360
362
FINISHED?
NOT FINISHED
REFEED GENERATED SCORES AS FEATURES IF NOT FINISHED
363
FINISHED
COMBINE ALL SAVED SCORES
370
DISPLAY RANKED SEARCH RESULTS BY CATEGORY BASED ON COMBINED SCORES
372

FIG. 3C

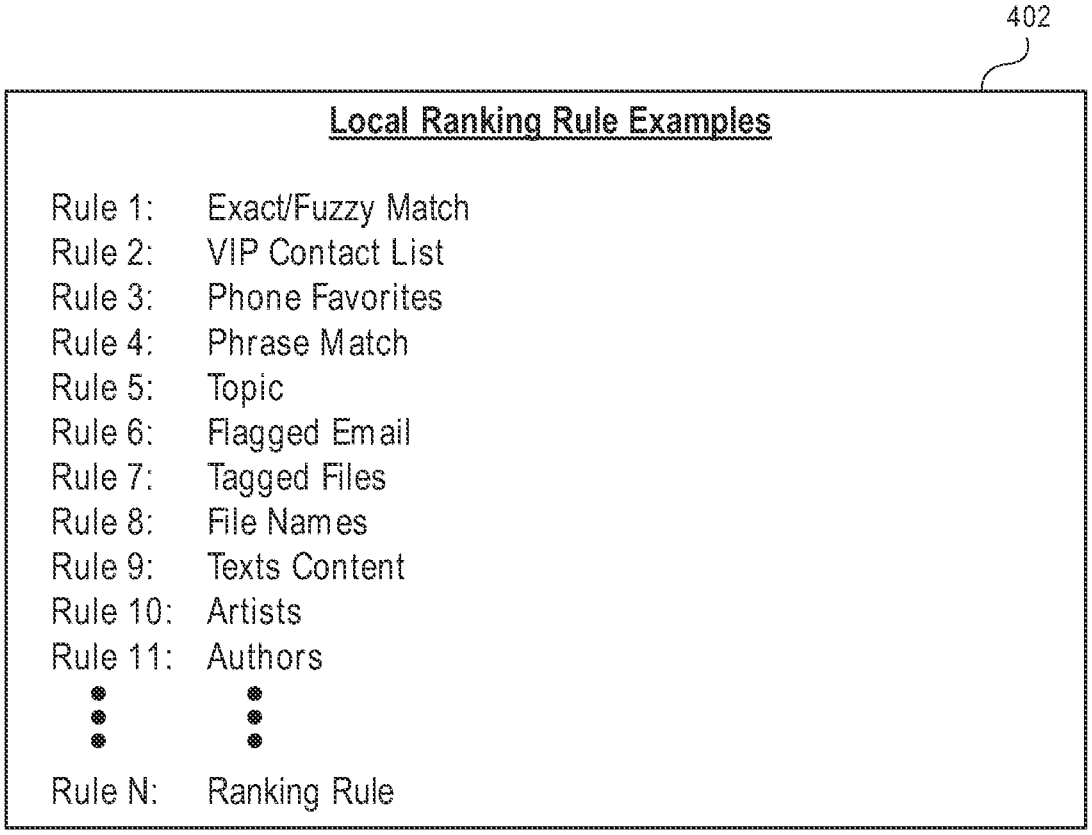

402
Local Ranking Rule Examples
Rule 1: Exact/Fuzzy Match
Rule 2: VIP Contact List
Rule 3: Phone Favorites
Rule 4: Phrase Match
Rule 5: Topic
Rule 6: Flagged Email
Rule 7: Tagged Files
Rule 8: File Names
Rule 9: Texts Content
Rule 10: Artists
Rule 11: Authors
Rule N: Ranking Rule

FIG. 4A

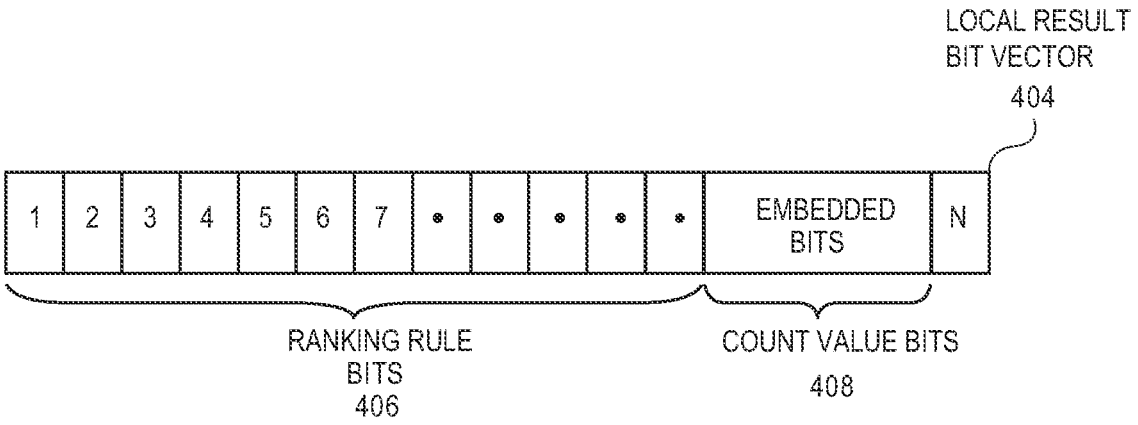

LOCAL RESULT BIT VECTOR
404
1
2
3
4
5
6
7
EMBEDDED BITS
N
RANKING RULE BITS
406
COUNT VALUE BITS
408

FIG. 4B

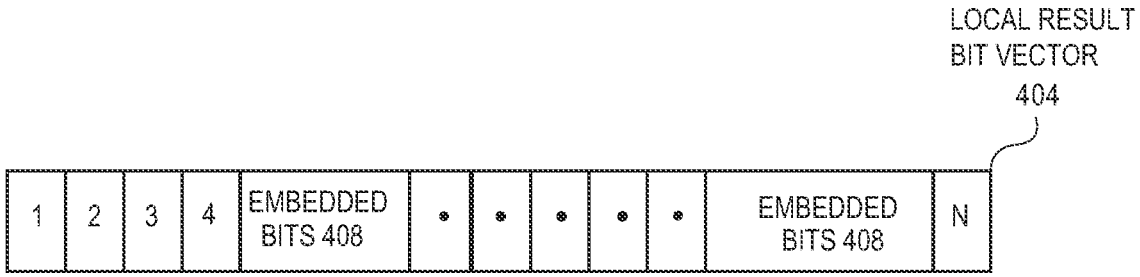

LOCAL RESULT BIT VECTOR
404
1
2
3
4
EMBEDDED BITS 408
EMBEDDED BITS 408
N

FIG. 4C

CONTACTS 502	FACETIME CALLS 504		MOST RECENT FACETIME CALL FEATURE 506	
CONTACT A	MAY 15, 2017	PRIVATE DATA 505	1	COMPUTED FEATURES 508
CONTACT B	MAY 12, 2017		2	
CONTACT C	JANUARY 5, 2016		3	

FIG. 5A

DOCUMENTS 512	LAST USED DATE 514	LAST USED TIMELINE 516			
		<24HRS	<1WK	<1MO	<1YR
DOC 1	MAY 16, 2017	0	0	0	1
DOC 2	MAY 8, 2017	0	0	0	1
DOC 3	JANUARY 1, 2016	0	0	0	0
	PRIVATE DATA 515	COMPUTED FEATURES 518			

FIG. 5B

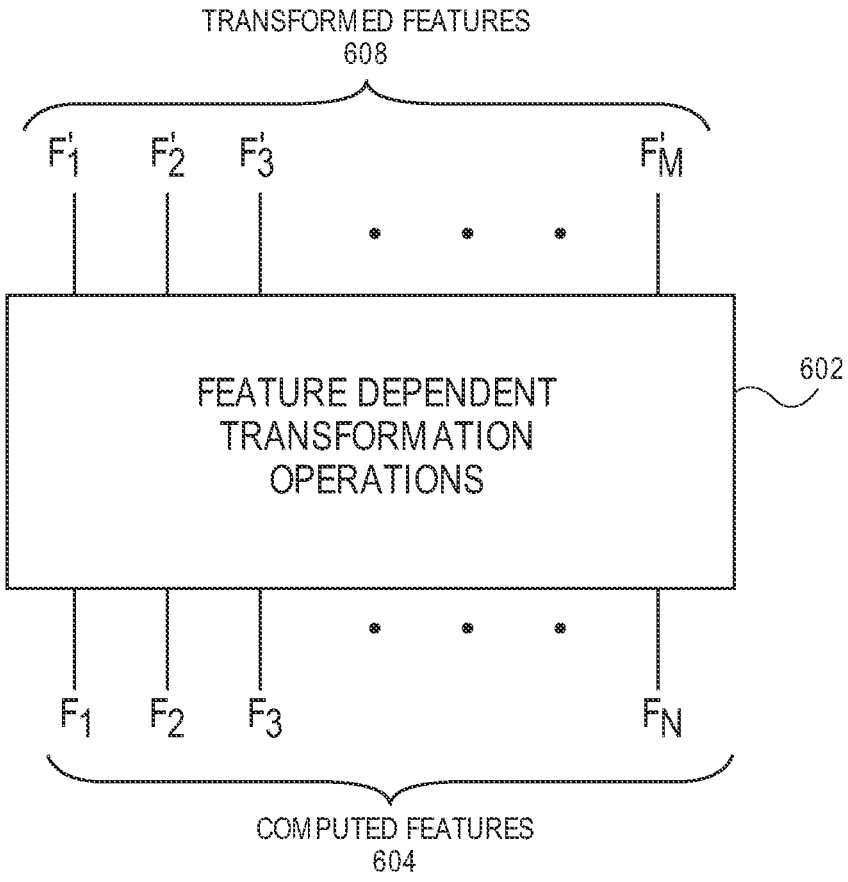

TRANSFORMED FEATURES
608
F'1
F'2
F'3
F'M
FEATURE DEPENDENT
TRANSFORMATION
OPERATIONS
602
F1
F2
F3
FN
COMPUTED FEATURES
604

FIG. 6

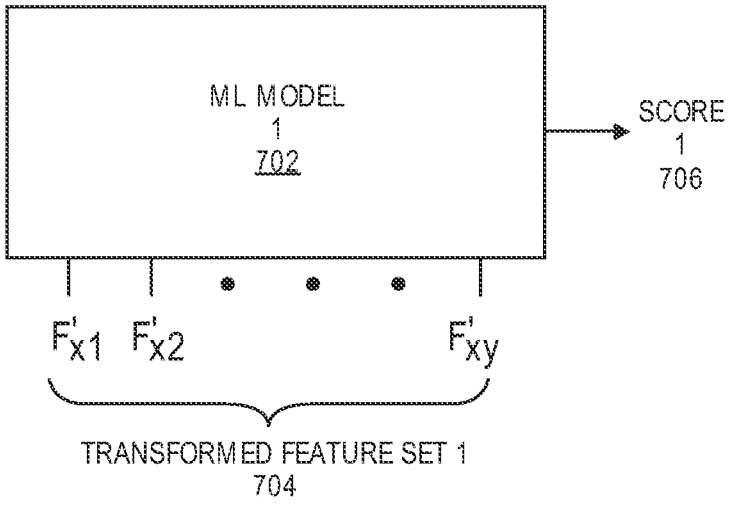

ML MODEL
1
702
SCORE
1
706
F'x1 F'x2 F'xy
TRANSFORMED FEATURE SET 1
704

FIG. 7A

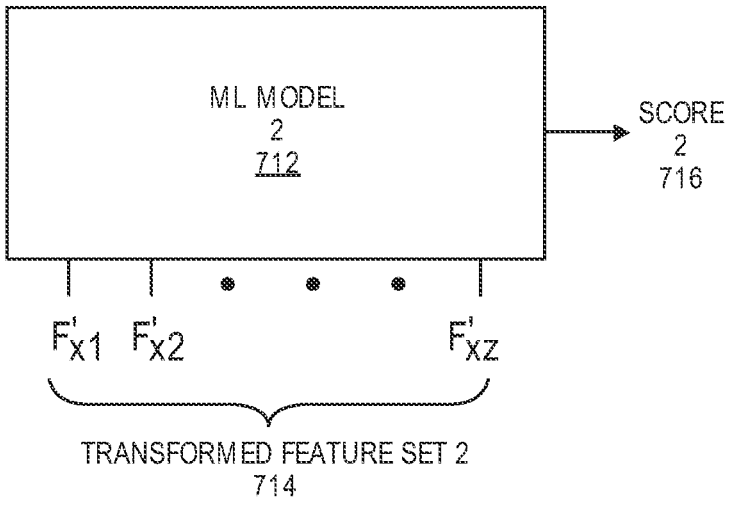

ML MODEL
2
712
SCORE
2
716
F'x1 F'x2 F'xz
TRANSFORMED FEATURE SET 2
714

FIG. 7B

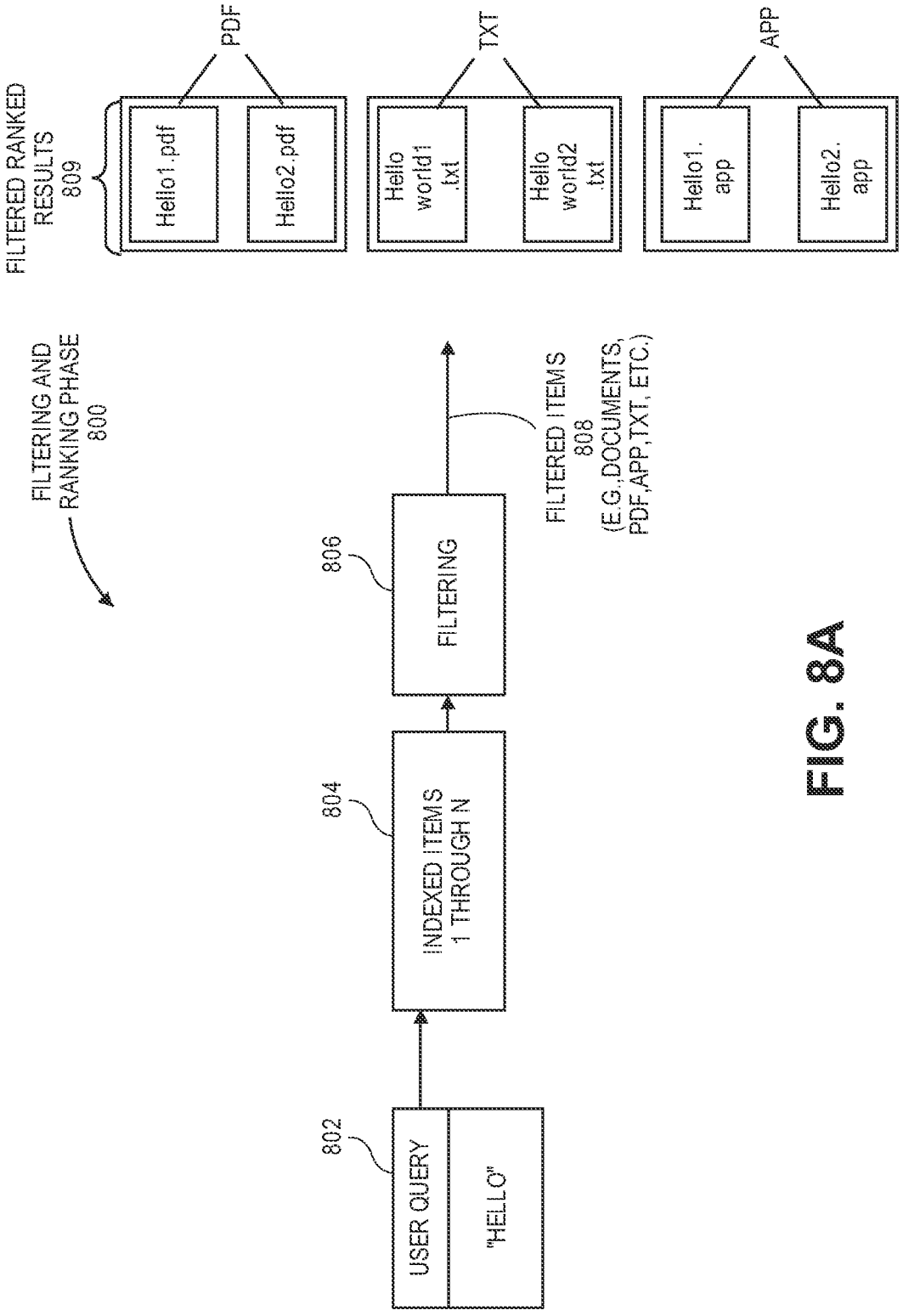

FILTERING AND RANKING PHASE 800
802
USER QUERY
"HELLO"
804
INDEXED ITEMS 1 THROUGH N
806
FILTERING
FILTERED ITEMS 808 (E.G., DOCUMENTS, PDF, APP, TXT, ETC.)
FILTERED RANKED RESULTS 809
PDF
Hello1.pdf
Hello2.pdf
TXT
Hello world1 .txt
Hello world2 .txt
APP
Hello1. app
Hello2. app

FIG. 8A

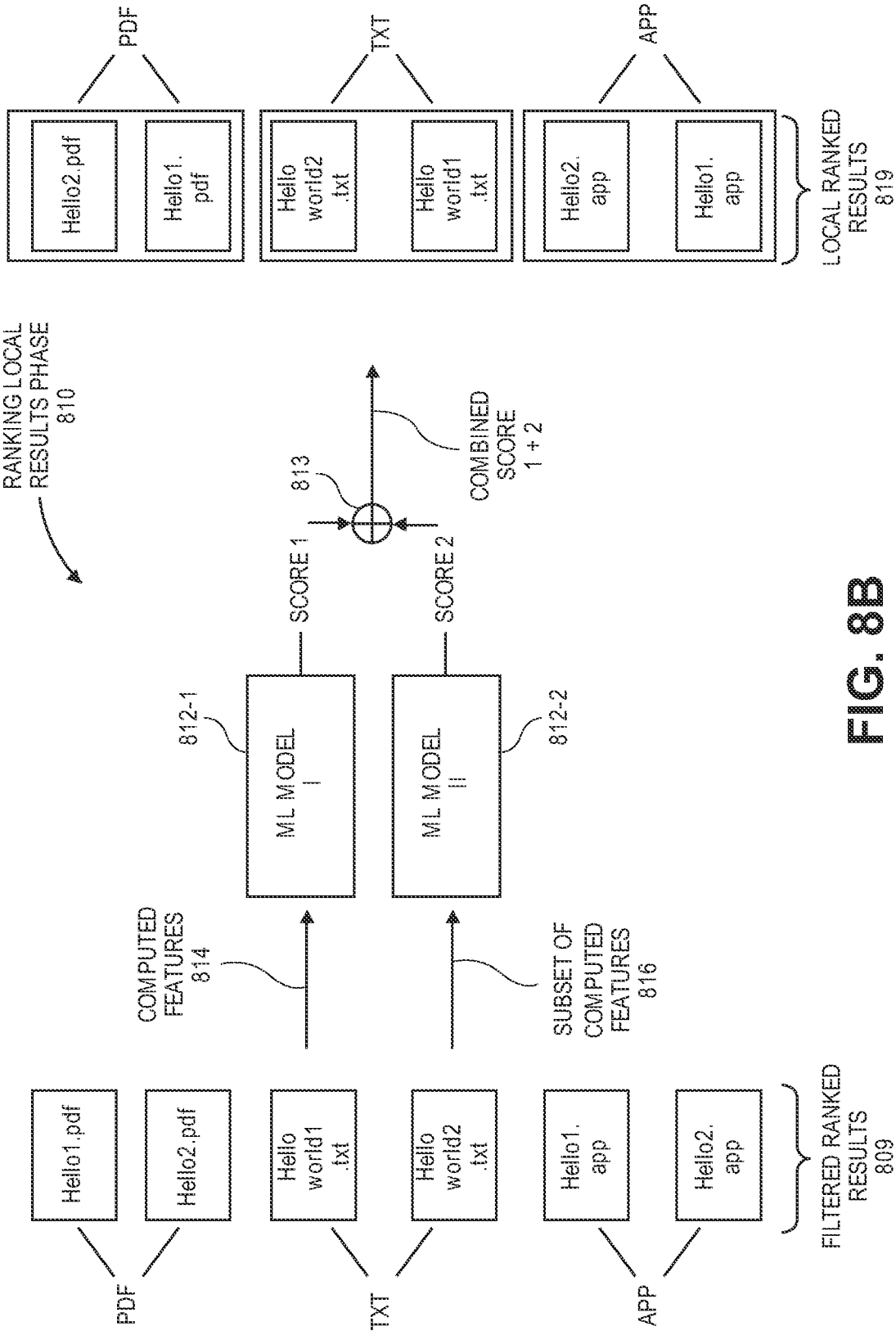

PDF
TXT
APP
Hello1.pdf
Hello2.pdf
Hello world1 .txt
Hello world2 .txt
Hello1. app
Hello2. app
FILTERED RANKED RESULTS 809
COMPUTED FEATURES 814
SUBSET OF COMPUTED FEATURES 816
812-1
812-2
ML MODEL I
ML MODEL II
SCORE 1
SCORE 2
813
COMBINED SCORE 1 + 2
RANKING LOCAL RESULTS PHASE 810
LOCAL RANKED RESULTS 819

FIG. 8B

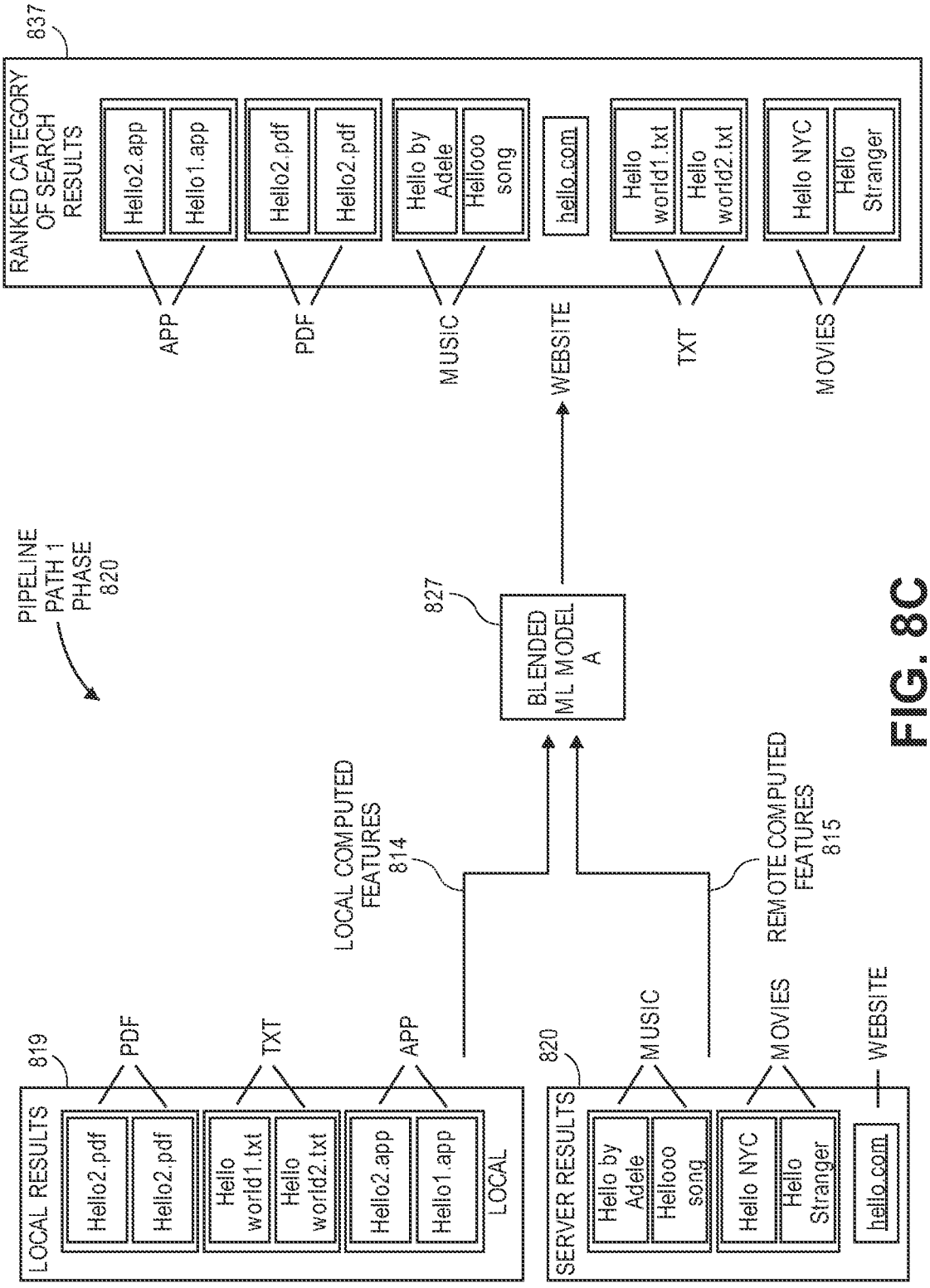

837
RANKED CATEGORY OF SEARCH RESULTS
Hello2.app
Hello1.app
Hello2.pdf
Hello2.pdf
Hello by Adele
Hellooo song
hello.com
Hello world1.txt
Hello world2.txt
Hello NYC
Hello Stranger
APP
PDF
MUSIC
WEBSITE
TXT
MOVIES
PIPELINE PATH 1 PHASE 820
827
BLENDED ML MODEL A
LOCAL COMPUTED FEATURES 814
REMOTE COMPUTED FEATURES 815
819
LOCAL RESULTS
PDF
TXT
APP
LOCAL
820
SERVER RESULTS
MUSIC
MOVIES
WEBSITE

FIG. 8C

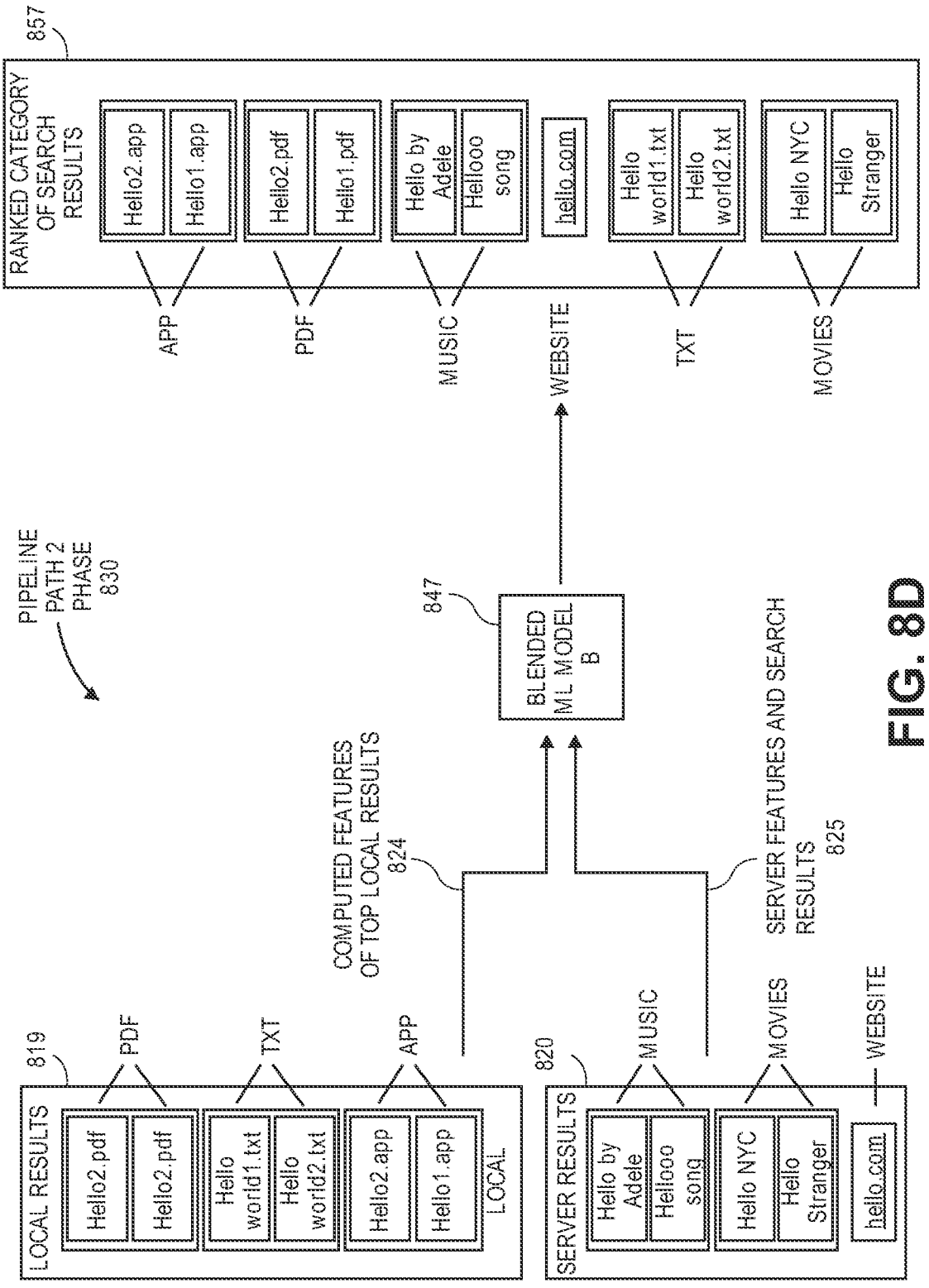

857
RANKED CATEGORY OF SEARCH RESULTS
Hello2.app
Hello1.app
Hello2.pdf
Hello1.pdf
Hello by Adele
Hellooo song
hello.com
Hello world1.txt
Hello world2.txt
Hello NYC
Hello Stranger
APP
PDF
MUSIC
WEBSITE
TXT
MOVIES
PIPELINE PATH 2 PHASE 830
847
BLENDED ML MODEL B
COMPUTED FEATURES OF TOP LOCAL RESULTS
824
SERVER FEATURES AND SEARCH RESULTS
825
819
LOCAL RESULTS
Hello2.pdf
Hello2.pdf
Hello world1.txt
Hello world2.txt
Hello2.app
Hello1.app
LOCAL
820
SERVER RESULTS
Hello by Adele
Hellooo song
Hello NYC
Hello Stranger
hello.com

FIG. 8D

METHODS AND SYSTEMS FOR CLIENT SIDE SEARCH RANKING IMPROVEMENTS

PRIORITY

[0001] This application is a continuation of U.S. patent application Ser. No. 15/860,597, filed Jan. 2, 2018, entitled "METHODS AND SYSTEMS FOR CLIENT SIDE SEARCH RANKING IMPROVEMENTS", which claims the benefit of priority of U.S. Provisional Patent Application No. 62/566,084, entitled "METHODS AND SYSTEMS FOR CLIENT SIDE SEARCH RANKING IMPROVEMENTS", filed on Sep. 29, 2017, each of which are hereby incorporated by reference and commonly assigned.

FIELD

[0002] The present invention relates generally to data processing and for improving relevance of search results and, more particularly, to methods and systems for client side search ranking improvements.

BACKGROUND

[0003] Computing devices, such as, e.g., mobile phones, laptops, accessories etc., can store and access vast amounts of data and content across numerous sources locally and remotely. Users can search for content and data on such computing devices by inputting a query into a search engine. The search engine can rank relevant search results for the query and provide the ranked search results to the user. Determining relevant search result and ranking them for the user can involve multiple fields, features and parameters, which can make the ranking process complex coupled with the need for a quick response time for the user. In addition, privacy issues regarding information about a user can also be a concern in determining relevant search results for the user.

SUMMARY

[0004] Methods and systems for client side search ranking improvements are disclosed. In the following examples and embodiments, improvements and refinements for client based predictive models in ranking search results are provided.

[0005] According to one example, a computer-implemented method is disclosed. A search query is received from a user on a client device. The local search results are filtered based on the received search query and one or more ranking rules. Features for each filtered local search result are computed. The computed features of each filtered local search result are input to one or more machine learning (ML) models. Each ML model can generate a score for each filtered local search result. The filtered local search results are ranked based on the generated score within a category. The categories of the filtered local search results can be ranked based on highest scored results in each category. In one example, some configurable decision rule based policies can override the order both within each and/or across categories.

[0006] In one example, filtering the local search results includes applying the one or more ranking rules to each local search result to generate a bit vector including one or more count values. The bit vector can include individual bits representing applicable ranking rules and a fixed combination of bits representing the one or more count values. In one example, the count value can be a number of ranking rules applicable to the local search result. The count values of each bit vector can be compared with each other to rank the local search results based on the comparison. For example, local search results with bit vectors having count values with higher numbers can be ranked higher than other local search results with bit vectors having count values with lower numbers. In one example, the filtered local search results include a set of top ranked local search results within a category. And, in one example, computing features for the filtered local search results includes computing ranking values or Boolean values for the computed features related to the filtered local search results.

[0007] In one example, the computed features of the filtered local search results are transformed for processing by the one or more ML models. The transformed computed features of the filtered local search results are input to the one or more machine learning (ML) models. Each ML model can generate a score for each filtered local search result. Transforming the computed features can use feature dependent transformation operations. In one example, a first set of transformed computed features are input to a first ML model and a second set of computed features are input to a second ML model. The first ML model generates a first score and the second ML model generates a second score. The first score and the second score can be combined to rank the filtered local search results. The first set and second set of computed features can include different computed features.

[0008] In one example, local search results and remote server search results are obtained. The local search results and remote server search results are ranked using at least one machine learning (ML) ranking model. The ranked local search results and remote server search results are displayed on the client device by category. In one example, a first processing path or a second processing path is selected to rank the obtained local search results and remote server search results.

[0009] In one example, if the first processing path is selected, additional features are computed for the remote server search results. The additional computed features for the remote server search results and computed features of top ranked local search results are input to a first machine learning (ML) ranking model. A score is generated for each of the local search results and remote server search results by the first ML ranking model. The local search results and remote server search results are ranked by category based on the generated score. The ranked local search results and remote server search results are displayed by category.

[0010] In one example, if the second processing path is selected, a subset of features is computed for top ranked local search results per local category. Features of remote server search results are obtained. The computed subset of features for top ranked local search results and features of remote server search results are input to a second machine learning (ML) ranking model. A score is generated for each of the local search results and remote server search results by the second ML ranking model. The local search results and remote server search results are ranked by category based on the generated score. The ranked local search results and remote server search results are displayed by category. Ranking of the local search results and remote server search results can include ranking the categories for the local search results and remote server search results. In other examples, processing can occur down both paths and a third and fourth

ML ranking models can generate scores which are combined to rank local search results and remote server search results and ranked results can be displayed by category.

[0011] Other methods and systems for client side search ranking improvements are described.

BRIEF DESCRIPTION OF THE DRAWINGS

[0012] The present invention is illustrated by way of example, and not limitation, in the figures of the accompanying drawings, in which like references indicate similar elements.

[0013] FIG. **1**A is a block diagram of an exemplary system having a client device with a local search subsystem and remote search subsystem for implementing improved client side search ranking techniques as disclosed herein.

[0014] FIG. **1**B is a block diagram of an exemplary system for a search engine and domain aggregator to aggregate search results returned from multiple domains in response to a query from client devices of FIG. **1**A.

[0015] FIG. **2** is one example of a block diagram of a data processing or computing system for a client device or a server for a search engine of FIGS. **1**A-**1**B.

[0016] FIGS. **3**A-**3**C are example flow diagrams of operations for improved client side search ranking of query results.

[0017] FIG. **4**A are local ranking rule examples.

[0018] FIGS. **4**B-**4**C are examples of local result bit vectors.

[0019] FIGS. **5**A-**5**B are examples of computing feature for local search results according to local feature categories.

[0020] FIG. **6** is one example block diagram of machine learning (ML) algorithms generating transformed features based on computed features.

[0021] FIGS. **7**A-**7**B are exemplary block diagrams of ML models generating scores for ranking local search results.

[0022] FIGS. **8**A-**8**D are example flow diagrams of processing a user query to provide improved search result ranking by categories.

DETAILED DESCRIPTION

[0023] Methods and systems for client side search ranking improvements are disclosed. In the following examples and embodiments, improvements and refinements for client based predictive models in ranking search results are provided.

[0024] For one example, a computer-implemented method is disclosed. A search query is received from a user on a client device. The local search results are filtered based on the received search query and one or more local ranking rules. Features for each filtered local search result are computed. The computed features of each filtered local search result are input to one or more machine learning (ML) models. Each ML model can generate a score for each filtered local search result of each category. The filtered local search results are ranked based on the generated score within a category. The categories of the filtered local search results can be ranked based on highest scored results in each category. In one example, some configurable decision rule based policies can override the order both within each and/or across categories.

[0025] The computed features of the filtered local search results can be transformed for processing by the one or more ML models. The transformed computed features of the filtered local search results are input to the one or more machine learning (ML) models. Each ML model can generate a score for each filtered local search result. Transforming the computed features can use feature dependent transformation operations. In one example, a first set of transformed computed features are input to a first ML model and a second set of computed features are input to a second ML model. The first ML model generates a first score and the second ML model generates a second score. The first score and the second score can be combined to rank the filtered local search results. The first set and second set of computed features can include different computed features.

[0026] In one example, local search results and remote server search results are obtained. The local search results and remote server search results are ranked using at least one machine learning (ML) ranking model. The ranked local search results and remote server search results are displayed on the client device by category.

[0027] Reference in the specification and detailed description to an "example" or "embodiment" indicates that a particular aspect, feature, structure, or characteristic described in conjunction with the example or embodiment can be included in at least one example and embodiment. The appearances of the phrase "in one example" or "in one embodiment" in various places in the specification do not necessarily all refer to the same embodiments. The processes depicted in the figures that follow can be performed by processing logic that comprises hardware (e.g. circuitry, dedicated logic, etc.), software, or a combination of both. Although the processes are described below in terms of some sequential operations, it should be appreciated that some of the operations described may be performed in a different order. Moreover, some operations may be performed in parallel rather than sequentially.

[0028] Processes and operations are depicted and disclosed in the Figures that follow and described in the Detailed Description. Such processes and operations can be performed by processing logic that comprises hardware (e.g., circuitry, dedicated logic, etc.), software (such as is run on a general-purpose computer system or a dedicated machine), or a combination of both. Although the processes and operations are described below in terms of some sequential operations, it should be appreciated that some of the operations described may be performed in different order. Moreover, some processes and operations may be performed in parallel rather than sequentially.

[0029] Various examples, embodiments and aspects will be described with reference to details discussed below, and the accompanying drawings will illustrate the various examples and embodiments. The following description and drawings are illustrative and are not to be construed as limiting. Numerous specific details are described to provide a thorough understanding of various embodiments. In certain instances, well-known or conventional details are not described in order to provide a concise discussion of the examples and embodiments.

Terminology

[0030] In the following detailed description, certain terms are used to describe the disclosed examples and embodiments. These terms, however, are not intended to limit the scope of the invention, but to aid in understanding the present invention.

[0031] "Server," "client," and "device" are intended to refer generally to data processing systems rather than specifically to a particular form factor for the server, client, and/or device.

[0032] "Local results" (or local query results) can refer to results returned from a local database on a client device in response to a query. "Local database" can refer to a database of information that is generally considered private to the user of a client device, which can store public information. A local database may reside physically on a client device or accessible remotely by the client device, which is used by, owned by, registered to, or authorized to use for a particular user. For example, the local database can also reside on a network or cloud storage that is accessible to the user of the client device via an account that is owned by, or registered to, a user of the client device.

[0033] "Private information" of a user is information that reasonable members of the public would deem personal and would not want to be shared with, for example, a remote search engine. "Anonymized version" of some private information may be shared with a remote search engine. For example, the exact address of the home of a user or a file name used by the user may be considered private and would not be sent to a remote search engine. Nevertheless, the fact that a user is not currently issuing a query from his home may be sufficiently anonymous to be sent to a search engine. In other words, anonymous information should not identify a particular user.

[0034] "Search engine results" can refer to results returned from a remote search engine that is generally accessible to the public, with or without a logon or other authentication to use the search engine, by way, e.g., the Internet. Examples of remote search engines include Ask®, Yahoo®, Google® Search, AolSearch®, Bing®, or a plurality of such search engines. Search engine results can include results returned to a search engine by search domains, such as Wikipedia, Yelp®, a maps domain, a media domain, Twitter®, etc. Search engine results can also refer to local search engines of a client device such as, for example, Spotlight® by Apple. Although a client device may send some information to a search engine, the information is typically sent in an anonymized form such that a particular person is not identified by information sent to the search engine. Further, private information is generally not sent to the search engine unless the information is sufficiently anonymized to preserve the privacy of the user of the client device.

[0035] "Results" (or search results) can refers to either local search results or remote search results, or both, and should be considered in the context in which it is used, and not in isolation.

[0036] "Crowd-source data" can refer to data generated as a consequence of a plurality of users issuing queries to a remote search engine and the feedback received from clients indicating a user's interaction with the search engine results to a user's query. Crowd source data includes queries issued to a remote search engine, and includes interaction data (feedback data) with search engine results, including engagement with a particular result, dwell time, click-through, rendering of the page, and abandonment of the result.

[0037] "Predictor" can refer to a machine learning (ML) model, which can use data mining and probability techniques to forecast (or predict) outcomes—i.e., relevant search results. In one example, a predictor can correlate a query and one or more features, with the user feedback regarding interaction, with results returned from the query. In one example, for local search results, there can be a feature for each ranking rule of local results such as shown in FIG. **4**A, e.g., local ranking rule examples such as VIP list, phone favorites, phrase match, etc. In other examples, that can be a predictor for categories such as local email results, local text results, local contact results, remote results from, e.g., Yelp® or Wikipedia®, remote results for media, remote results for maps, and etc.

[0038] "Machine learning" also referred to as "ML" can include supervised learning, unsupervised learning, and reinforcement learning. A predictor, or ML model, can be represented in a data structure having values. The data structure can be passed from a client device to a search engine, or received by a client device from a search engine. An example follows:

```
{
  "model_algorithm" : "naive_bayes",
  "model_type" : "main_tophit_model",
  "model_features" : [
  {
    "feature_name" : "query_most_recently_selected",
    "feature_type" : "boolean",
  },
  {
    "feature_name" : "query_previously_selected",
    "feature_type" : "boolean",
  },
  {
    "feature_name" : "previously_selected",
    "feature_type" : "boolean",
  },
  {
    "feature_name" : "name_matches",
    "feature_type" : "boolean"
  },
  {
    "feature_name" : "match_quality",
    "feature_type" : "real"
  },
  {
    "feature_name" : "domain",
    "feature_type" : "keypath"
  },
  {
    "feature_type" : "boolean",
    "feature_name" : "domain_tophit_candidate",
    "model_selector" : "domain"
    }
```

[0039] The above model algorithms, types, and features are exemplary any type of probabilistic or statistical analysis or ML algorithms can be used such as Bayes classification, Naïve Bayes classification, Gradient Boosting Decision Trees (GBDT) models, Deep Neural Networks (DNN), linear regression models or logistic regression models as examples of providing predictive ML algorithms for a predictor. For example, "feature-names" for above example data structure can refer to any of the features described in the following examples and embodiments.

[0040] "User feedback" can refer to how a user interacts with one or more results from query results. User feedback includes whether a result was rendered to a user, whether the user engaged with the result, such as by clicking on the result, whether the user "hovered" over the result (also referred to as "dwell time") such as by holding a mouse icon over a result, as if considering whether to engage with the

result, whether the user abandoned the result, or whether the user did not interact with the result. Each of these user feedback elements can be measured in time from a reference point, such as the time at which the query results were presented to the user. By measuring user feedback in time, it can further be determined the order in which each of the query results was interacted with, if at all. In a client device, user feedback will generally be a single user of the client device. On a search engine, user feedback will generally be crowd-source data.

[0041] "Feature" (also known as a sensor, in machine learning ML) of a predictor can refer to an input to the predictor that will be used to train the predictor to predict the results that a user will likely interact with. In one example, features can be a physical sensor, such as a light sensor, motion detector, vibration detector, horizontal/vertical switch or orientation sensor, sound detector (e.g. microphone), signal strength of network connection, such as WiFi or cellular network, or a location sensor, such as an RF receiver for triangulation of cell towers or GPS receiver that provides GPS coordinates. A feature can be obtained from a combination of physical sensors, such as a GPS receiver and an accelerometer and an orientation sensor can in combination detect whether the user is walking, running, driving, or stationary. In other examples, features can be obtained from information sources available to a client device, such as the current date, time, time zone, weather, or temperature.

[0042] Features can also be a state, or combination of states of a client device, such as which applications are open, how long the applications have been open, whether a user has issued a query that relates to an application that is open, such as a user query regarding music when iTunes® is open, calendar events in the user's calendar, or whether a user is on a call, writing a text, or answering an email. Features can also be obtained from tags in results. For example, Yelp® may tag restaurant results with a price rating with a certain number of "$" signs or tag results with a service quality rating measured in a certain number of stars. The "$" tag may be in the form of an integer value, rather than a text tag. For example, Yelp® may return results tagged with a field: integer: yelp_dollars=3. Netflix® may tag results with an MPAA® rating, such as G, PG-13 or R, a price, a duration of a movie, or a genre of a movie. These tags can be used as features for a predictor. For example, Bob frequently selects PG-13 action movies priced under $9.99 that are less than two hours long, on weekend evenings. A feature may also be in the form of a key path. For example, a Netflix® result may have a tag: key path: genre="movie.horror. japanese," wherein each field of the key path can be a sub-genre of the result. A feature can further be identified in a boolean field, such as "boolean: Top-Hit=TRUE." A feature can alternatively be expressed as a real value, e.g. "real: Average_Stars=3.5". Features can also be computed to indicate how a search result matched with a user query, e.g., which facetime call was the most recent by giving values "1", "2" and "3" where 1 indicates the most recent facetime call and 3 the least recent facetime call.

[0043] In some examples, a predictor can treat each of these possible features as an individual feature (input) to the predictor. In some examples, a client device may maintain an aggregate, current state of a combination of features that a plurality of predictors can use as a single feature. For example, a user's location, the current day of the week, the current time of day, and a list of applications open on a device are features that may frequently appear together in predictors. A client device can maintain these features in a current state, as an aggregate feature (input) to any predictor that uses these features. A feature can additionally be a distinction learned from analyzing results data. For example, whether "football" refers to American football or soccer is a feature than a predictor can train upon to determine whether this particular user interacts with soccer results of American football results. A remote search engine can request that one or more features be calculated by the client device at the beginning of a search session.

[0044] Features can also be learned either on local results or on remote search results. When a predictor is generated to learn on a new feature, the feature can be tagged with "local" or "remote" based upon whether the feature was learned on local results or remote search results. "Learning a new feature" refers to generating a new predictor, or extending or modifying an existing predictor, to train on that new feature. For example, an existing predictor may have trained on restaurant selections at lunch time during week days near the current location of a client device. A new feature may be that results returned from Yelp® now include a tag indicating a price range for menu items in restaurant results. The existing predictor can be extended to train on the price range tag as a new feature in the predictor having the features lunch time, week day, and near the user of the client device.

[0045] "Feature metadata" can refer to data structures passed from a search engine to client device, or from a client device a search engine. Features can utilize this format with values in the fields. Exemplary features set be represented as follows where any feature name and fields can be used:

```
feature_metadata : [
  {
    "feature_name" : "popularity",
    "feature_type" : "real",
    "normalized" : 1,
    "feature_value" : 0.9
  },
  {
    "feature_name" : "high_traffic",
    "feature_type" : "boolean",
    "feature_value" : 1
  },
  {
    "feature_name" : "site_domain",
    "feature_type" : "string",
    "feature_value" : "apple.com"
  },
  {
    "feature_name" : "site_type",
    "feature_type" : "keypath",
    "feature_value" :"company.consumer_electronics.frontpage"
  },
{
    "feature_name" : "site_language",
    "feature_type" : "keypath",
    "feature_value" : "en.us"
  },
]
```

[0046] "Computed Features" in the following examples and embodiments can be grouped into "feature groups." Examples of feature groups can include any number of groups in which Groups 1 through 7 are detailed below as exemplary.

[0047] Group 1 can include result only features. These features can be computed a single result at a time without

using a query or any other results in the result set. For example, such features can be computed using only certain pre-existing attributes (or some statistical measure derived from those attributes) of the result at the time right before a user enters a query. Examples can include: (a) for application results: computing number of times an application has been launched by the user (could be launched with and/or without, e.g., a search application such as Spotlight) in the last week; (b) for music results, computing number of times the user has played a certain song.

[0048] Group 2 can include result query features. These features can be computed a single result at a time using the query. In one example, these features can be computed without using any other results in the result set. For example, these features can be computed using certain pre-existing attributes (or some statistical measure derived from those attributes) of the result, and the user query itself. Examples can include: (a) for an application result: determining the first matching position (in terms of character position, and the first character position starts at 0 within the display name of the app ("Facebook", for example) that matches the full word of any query terms ("any" because the user could have entered more than 1 query terms); (b) for mail results: computing the minimum matching span within the mail snippet that contains all the query terms in the order entered by the user; (c) for contact results: computing the number of times any query terms prefix matches ("prefix match" means a query terms matches portion of the display name, starting from the beginning. For example, the query term "ja" prefix matches the display name "jack") the display name of a contact.

[0049] Group 3 can include result-set features. These features can be computed a single result at a time using all other results in the result set. For example, these features can be using certain pre-existing attributes (or some statistical measure derived from those attributes) of the result including a whole result set. An example can be computing the number of application results in the result set that have been launched more than once in the past week, and this can be a feature computed for all the results, including non-application results.

[0050] Group 4 can include result query result-set features. These features can be computed a single result at a time using the query and all other results in the result set. For example, these features can be computed using certain pre-existing attributes (or some statistical measure derived from those attributes) of the result including the user query itself and the whole result set. An example can be computing the minimum value of all the mail results (those in the result set) minimum match span (of snippet that contains all the query terms in order).

[0051] Group 5 can include result user features. These features can be computed a single result at a time using an identity or attribute (or some statistical measure derived from those attributes) of the user and the result. An example can be for a mail result determining whether the mail is sent by the user.

[0052] Group 6 can include result user query result set features. These features can be computed a single result at a time using the query and whole result set. For example, these features can be computed using attribute (or some statistical measure derived from those attributes) of the result, identify or attribute (or some statistical measure derived from those attributes) of the user, and attribute (or some statistical measure derived from those attributes) of the result set. An example can be for any result computing the number of mail results sent by the user in the result set.

[0053] Group 7 can include query only features. These features can be computed a single result at a time using some attributes (or some statistical measure derived from those attributes) of the query. An example can be after the local search engine returns the result set computing what percentage of responses is user continue to search in an app store instead of engaging with any of the results returned.

[0054] "Search session" can refer to a time-limited session of interaction between a client device and a search engine. For example, a search engine can collect significant amounts of information about a user of a client device through the queries and selections (user interaction data) that a user makes during a search session. Even though the search engine should not know, with any specificity, the exact identity of a particular user, an unlimited accumulation of user interaction data may identify a user with a high degree of specificity. To preserve privacy when interacting with a search engine, a search engine can limit collection of data to a time-limed session. The session has a unique session identifier (session ID). The timer may be set for, e.g., 15 minutes. At expiration of the session timer, the user is issued a new session ID. Although the search engine may retain and analyze the 15-minute block of information, the search engine should not associate the new session ID with the old session ID, else there would still be an accumulation of user interaction data and the session limits would have no privacy protecting effect.

[0055] "Application programming interfaces (APIs)" can refer to an environment with calling program code interacting with other program code being called through the one or more interfaces. Various function calls, messages or other types of invocations, which further may include various kinds of parameters, can be transferred via the APIs between the calling program and the code being called. In addition, an API may provide the calling program code the ability to use data types or classes defined in the API and implemented in the called program code. Examples disclosed herein can include an environment with a calling software component interacting with a called software component through an API. A method for operating through an API in this environment includes transferring one or more function calls, messages, other types of invocations or parameters via the API.

Exemplary Systems for Improved Client Side Search Ranking

[0056] FIG. **1**A is a block diagram of exemplary system **100** having a client device **102** with a local search subsystem **130** and remote search subsystem **135** for implementing improved client side search ranking techniques in the disclosed examples and embodiments. Local search subsystem **130** includes local search interface **110**, local query service **114**, local search and feedback history **115**, and local learning system **116**, which can be used to improve ranking of local search results for a user inputting a search query via local search interface **110** of client device **102**. In one example, local search interface can be a graphical interface provided to a user of client device **102** such as Apple Spotlight® or any type of navigational browser or interface for client device **102**.

[0057] In one example, a user of client device **102** can use a remote search interface **120** and remote query service **121** of remote search subsystem **135** to obtain remote search results, e.g., by remote search engine **150** via network **140**. In one example, client device **102** can return search results for queries entered via local search interface **110** and remote search interface **120** without exposing private information of a user. In one example, private information is anonymized by anonymization and location fuzzing service **117** before sending information to remote search engine **150** via remote query service **121**. In one example, local learning system **116** can be pre-set with machine learning (ML) models including ML ranking models (which can be used to rank search results of different types) or reset so that ML models are flushed and relearning can be implemented by local learning system **116**. In other examples, local learning system **116** can modify existing ML models.

[0058] Local search subsystem **130** for client device **102** also includes local database **111**, which can store and access data **113** including data and metadata for applications **112** for computing device **102**. In one example, local database **111** stores and can access local information about data sources by category or ranking rule examples as shown in FIG. **4**A. In other examples, local database **111** stores and can access data sources such as a contacts database, titles of documents or words in documents, titles of applications and data and metadata associated with applications, such as emails, instant messages, spreadsheets, presentations, databases, music files, pictures, movies, and other data that can be stored locally on client device **102**.

[0059] In other examples, local database **111** can store and access information about data sources stored in a user's Cloud storage. Applications **112** can include a calculator program, a dictionary, a messaging program, an email application, a calendar, a phone, a camera, a word processor, a spreadsheet application, a presentation application, a contacts management application, a map application, a music, video, or media player, local and remote search applications, and other software applications other types of applications for computing device **102**. In one example, a user can generate a query using local search interface **110** and query results returned from local database **111**, via communication interface path **1**, and displayed in local search interface **110**. In one example, the results are ranked and displayed to a user of computing device **102** using techniques in the disclosed examples and embodiments.

[0060] In one example, local search interface **110** can also pass queries to remote query service **121**, via communication interface path **7**, so that local search interface **110** receives search results from both local database **111** and from remote search engine **150**, which can also be ranked according to techniques in the disclosed examples and embodiments. Local query service **114** can remove redundant white space, remove high frequency-low relevance query terms, such as "the" and "a", and package the query into a form that is usable by the local database **111**. Remote query service **121** can perform analogous functionality for the remote search engine **150**. In an embodiment, local search interface **110** can pass the query to the remote query service **121**, via communication interface path **7**, to obtain query results from remote search engine **150**. In one example, remote query service **121** can receive a query feature learned by local learning system **116** via communication interface path **8**. Such a query feature can be used to extend the query and/or bias a query feature to the remote search engine **150**. In one example, remote query service **121** can pass a query feature, returned from the remote search engine **150**, to local learning system **116** for training on that feature via communication interface path **8**.

[0061] Local search and feedback history **115** can store the history of all search queries issued using the local query interface **110**, including queries that are sent to the remote query service **121** via communication interface path **7**. Local search and feedback history **115** can also store user feedback associated with both local and remote results returned from a query. Feedback can include an indication of whether a user engaged with a result, e.g. by clicking-through on the result, how much time the user spent viewing the result, whether the result was the first result that the user interacted with, or other ordinal value, whether result was the only result that a user interacted with, and whether the user did not interact with a result, i.e. abandoned the result. User feedback can be encoded and stored in association with the query that generated the results for which the feedback was obtained. In one example, local search and feedback history **115** can store a reference to one or more of the results returned by the query. Information stored in local search and feedback history **115** can be deemed private user information and would not be available to, or accessible by, the remote search subsystem **135**. In one example, local search and feedback history **115** can be flushed. In another example, local search and feedback history **115** can be aged-out after a certain time period. In one example, age-out timing can be analyzed so that stable long-term trends are kept longer than search and feedback history showing no stable trend.

[0062] Local learning system **116** can analyze local search and feedback history **115** to identify features upon which the local learning system **116** can train. Once a feature is identified, local learning system **116** can generate a local predictor to train upon the feature. In one example, computing device **102** may be have an initial set of one or more local predictors installed on computing device **102** before a user begins using the device for the first time. In another example, local learning system **116** can modify a predictor by adding a feature to the predictor, deleting a feature from the predictor using feature reduction, or replace a predictor with a predictor received from remote search engine **150**.

[0063] In one example, a predictor is an instance of a software component that operates on one or more pieces of data. In one embodiment, local predictors can train using statistical or probabilistic classification methods and models such as Bayes classification, Naïve Bayes classification, Gradient Boosting Decision Trees (GBDT) models, Deep Neural Networks (DNN), linear regression models or logistic regression models as examples. In one example, a predictor can be specific to a category such as, e.g., contacts, emails, calculator results, media results, maps results, Yelp® results, Wiki results, site search results, etc.

[0064] Anonymization and location fuzzing service **117** ("anonymization service") can ensure that private information of the user that is stored in local database **111**, local search and feedback history **115** and local learning **116** is kept private and is not sent to a remote search engine **150** without first anonymizing the data to be sent to the remote search engine **150**. For example, anonymization and location fuzzing service **117** may substitute "at home" as a status of the user, instead of sending the user's home address, nearby

cell tower identifiers, cell network IP address, WiFi IP address, or other information that could identify the user's location with a high degree of specificity. Similarly, anonymization service **117** may substitute "romantic comedy" as a genre that the user prefers in place of exact information identifies a particular movie that the user has previously selected for viewing, such as "Something About Mary."

[0065] Anonymization service **117** can further include a location "fuzzing" service. The location fuzzing service ensures that the exact location of a user is kept private. The location fuzzing service can take into account the population density of the current location of the user and obfuscate (or "fuzz") the user's location sufficiently to ensure privacy. For example, a user may currently be located in a highly dense city, looking for Italian restaurants having a price rating on Yelp® of "$$$$" and a dinner service rating of 4.5 stars on Columbus Ave. in San Francisco Calif. Since the current location of the user is fairly dense, the anonymizer service **117** may substitute a "fuzzed" location of the user, accurate within few blocks, in place of the user's exact GPS coordinates (accurate within a few feet) to remote search engine **150** to obtain search results that are within walking distance of the user. In contrast, if the user is currently located on a remote farm in Ireland, and may be the only user within the area, anonymizer service **117** may substitute a "fuzzed" location for the exact location of the user that is accurate within a few square miles.

[0066] Computing device **102** can also include remote search subsystem **135** having remote search interface **120** and remote query service **121**. Remote search interface **120** can include a web browser such as Apple® Safari®, Mozilla®, or Firefox®. Query service **121** can perform intermediary processing on a query prior to passing the query to network service **122** and on to remote search engine **150** via network **140**. Network service **122** can receive results back from remote search engine **150** for display on remote query interface **120** or on local search interface **110**. Remote query service **121** can be communicatively coupled to network service **122** via communication interface path **4**. Network **140** can include the Internet, an 802.11 wired or wireless network, a cellular network, a local area network, or any combination of these. Communication paths **1-8** can be implemented using inter-process communication, shared memory, sockets, or an Application Programming Interface (API).

[0067] FIG. **1**B is a block diagram of an exemplary system **170** for search engine **150** and domain aggregator **152** to aggregate search results returned from multiple domains **160**A-G in response to a query from client devices **102**A-C for client device **102** of FIG. **1**A. Referring to FIG. **1**B, client device **102** can be represented by different types of devices such as client devices **102**A-C in which client device **102**A can be a laptop computer, client device **102**B can be a tablet, and client device **102**C can be a portable hand-held device such as a cell phone or smart phone, fitness tracker, or gaming device as examples. Client devices **102**A-C are coupled to search engine **150** and aggregator **152** via network **140**.

[0068] In one example, when a user of client devices **102**A-C initiates a query session with search engine **150**, search engine **150** can generate a unique session identifier (session ID) for client devices **102**A-C and can also start a session timer for the session. During the session, search engine **150** can store a history of the queries issued by the user, and can store an indication of which query results the user interacted with, and other user feedback data. The query results and feedback data can be stored by search engine **150** in association with the session ID. The stored queries and user interaction data represent a "user intent" or "query context" indicating what the user of the client devices **102**A-C has been querying about during the session. Since the stored queries and interaction data are private to the user of client device **100**, the information can be retained on client devices **102**A-C even after the session timer has expired, thereby ending the session. When a session ends, and the user of the client device continues to interact with search engine **150** or query results returned during the session, search engine **150** can generate a new session ID and can transmit the new session ID to the user.

[0069] In one example, to preserve privacy of the user, the new session ID and the expired session ID are not associated with one another within search engine **150**. In response to receiving the new session ID, client devices **102**A-C can transmit "user intent" or "query context" information to search engine **150** so that search engine **150** has a context for the user's continued interaction with the search engine **150**. For example, a user may be searching for flights from the San Francisco Bay Area to Portland International Airport on a specific date. When the session expires, and a new session ID is generated and transmitted to client devices **102**A-C, the user intent data can be transmitted to search engine **150** in conjunction with the new session ID so that search engine **150** can continue returning query results related to flights from the San Francisco Bay Area to Portland Oreg. on a specific date. In one example, the user intent data can be anonymized before transmission to the search engine **150** by anonymization and location fuzzing service **117**.

[0070] Search engine **150** can be coupled to a plurality of search domains **160**A-G (collectively, search domains **160**) via network **140**. Search domains can be, for example, a maps domain **160**A, a media search domain **160**B, a Wiki domain **160**C, a site's search domain **160**D, and "other" search domain **160**E, a feedback completion domain **160**F, or a Yelp® domain **160**G. Other domains can include a Twitter® domain, an iTunes® domain, a Netflix®, a LinkedIn® domain, or other search domain. Search engine **150** can receive a query from client devices **102**A-C. Search engine **150** can pass the search query across network **140** to search domains **160**. Search domains **160** can return query results that match the query received by search engine **150**. Search engine **150** can include an aggregator **152** that aggregates query results for transmission to the querying client device **100**. Aggregating query results can include grouping query results by the search domain **160** that provided a subset of the query results. Aggregating query results can alternatively, or in addition, including filtering results based upon a predetermined threshold relevance value. A relevance value from a particular query result can be determined by the search domain **160** that provided the query result. In an embodiment, a relevance value can be determined by search engine **150** or aggregator **152**.

[0071] In one example, search engine **150** can determine that a particular query is a frequent, or common, query issued by users. In such a case, search engine **150** can store the query and at least some of the search results in a cache on search engine **150**. In an embodiment, search engine **150** can analyze the queries received from client devices **100**, the query results returned to a user, and the user feedback

collected. Search engine **150** can further determine a new feature from such analysis and can further generate a predictor for search engine **150** that trains on the query and the feature over the user feedback received from one or more client devices **102**A-C. In one example, search engine **150** can instruct one or more client devices **100** to train upon a predictor. Search engine **150** can further instruct one or more client devices **100** to report their respective training progress on the predictor to search engine **150**.

[0072] In one example, search engine **150** can include aggregator **152** and multiple search domains **160**A-G. In one example, aggregator **152** receives requests for query completions based on at least a partial input query ("input query prefix"). In response to receiving the input query prefix, aggregator **152** sends the input query prefix to each of the search domains **160**A-G. Each of the search domains **160**A-G uses the input query prefix to determine possible query completions in that domain. For example, map search domain **160**A can receive an input query prefix and searches this domain for possible query completions. In one example, aggregator **152** receives the query completions from each of the search domains **160**A-G, and ranks the received query completions based on the relevance scores for each of the completions determined by the corresponding search domain and weights based on the query prefix context.

[0073] In one example, maps search domain **160**A is a search domain that includes information related to a geographical map. In this embodiment, the maps information can include information about places, addresses, places, businesses, places of interest, or other type of information relating to maps. In one example, the maps information can also include information related to places of interest, such as opening hours, reviews and ratings, contact information, directions, and/or photographs related to the place. In one example, media search domain **160**B is a search domain related to media. In one example, media search domain **160**B includes information related to music, books, video, classes, spoken word, podcasts, radio, and/or other types of media. In another example, media search domain **160**B can include information related to applications that can run on the device, such as computing devices **102**A-C.

[0074] In one example, media search domain **160**B is a media store that includes different types of media available for purchase (e.g., music, books, video, classes, spoken word, podcasts, radio, applications, and/or other types of media). In one embodiment, the wiki search domain **160**C is an online encyclopedia search domain. For example, wiki search domain **106**C can be WIKIPEDIA. In one example, sites search domain **160**D is a search domain of websites. For example, sites search domain **160**D can include business, governmental, public, and/or private websites such as "apple.com," "whitehouse.gov," "yahoo.com," etc. In one embodiment, the other search domain **160**E is a set of other search domains that can be accessed by the aggregator **152** (e.g., a news search domain). In one example, feedback completion domain **160**F is a search index that is based on query feedback collected by browsers running on various devices. In one example, feedback completion domain **160**F includes a feedback index that maps queries to results based on the collected query feedback. In one embodiment, Yelp® search domain **160**G returns query results from Yelp® reviews generated by individual people commenting upon businesses which they have patronized. Yelp® query results can include tags for a price rating, e.g. "$$," and a service quality rating measured in stars, e.g. 1 to 5 stars indicating poor to excellent service.

[0075] As described above, each search domain **160**A-G includes information that allows each of the search domains **160** to give a set of query completions based on an input query prefix. In one embodiment, each of the search domains includes a query completion tree that is used to determine the query completion as well as determine scores for each of those query completions. Based upon the query completions of each domain **160**A-G, query results are returned to search engine **150** and domain aggregator **152** by each of the search domains **160**A-G. In one example, a particular search domain in **160**A-G may not return any results for a particular query. In another example, a search domain may not return any results if the particular search domain does not have any results matching the query, or if the relevance score of the results the particular search domain has are below a threshold value. The threshold value for returning results can be a part of a query received from client devices **102**A-C, or set by search engine **150**, domain aggregator **152**, or by the particular search domain **160**.

[0076] FIG. **2** is one example of a block diagram of a data processing or computing system **200** for a client device **102** or a server for a search engine **150** of FIGS. **1**A-**1**B. Computing system **200** can represent desktop computer systems, laptop computer systems, cellular telephones, personal digital assistants (PDAs) including cellular-enabled PDAs, fitness trackers, set-top boxes, entertainment systems or other consumer electronic devices. Alternative computing systems may include more, fewer and/or different components. Computing system **200** can represent a server providing a remote search engine for computing device **102**.

[0077] Referring to FIG. **2**, in one example, computing system **200** includes a bus **203**, which is coupled to processor(s) **202** coupled to cache **204**, display controller **214** coupled to a display **215**, network interface **217**, non-volatile storage **206**, memory controller coupled to memory **210**, I/O controller **218** coupled to I/O devices **220**, and database **212**. Processor(s) **202** can include one or more central processing units (CPUs), graphical processing units (GPUs), a specialized processor or any combination thereof. Processor(s) **202** can retrieve instructions from any of the memories including non-volatile storage **206**, memory **210**, or database **212**, and execute the instructions to perform operations described in the disclosed examples and embodiments.

[0078] Examples of I/O devices **220** include mice, keyboards, printers and other like devices controlled by I/O controller **218**. Network interface **217** can include modems, wired and wireless transceivers and communicate using any type of networking protocol including wired or wireless WAN and LAN protocols. Memory **210** can be any type of memory including random access memory (RAM), dynamic random-access memory (DRAM), which requires power continually in order to refresh or maintain the data in the memory. Non-volatile storage **206** can be a mass storage device including a magnetic hard drive or a magnetic optical drive or an optical drive or a digital video disc (DVD) RAM or a flash memory or other types of memory systems, which maintain data (e.g. large amounts of data) even after power is removed from the system.

[0079] In one example, network interface **217** provides access to network **104** of FIGS. **1**A-**1**B, which can be a wide area network (WAN) or a local area network (LAN). Net-

work interface **217** may include, for example, a wireless network interface having antenna **1385**, which may represent one or more antenna(e). In one example, computing system **200** can include multiple wireless network interfaces such as a combination of Wi-Fi, Bluetooth® and cellular telephony interfaces. Network interface **217** may also include, for example, a wired network interface to communicate with a remote server providing remote search engine **150** via network **140**. In one example, network interface **217** may provide access to a local area network, for example, by conforming to IEEE 802.11 b and/or IEEE 802.11 g standards, and/or the wireless network interface may provide access to a personal area network, for example, by conforming to Bluetooth standards. Other wireless network interfaces and/or protocols can also be supported. In addition to, or instead of, communication via wireless LAN standards, network interface **217** may provide wireless communications using, for example, Time Division, Multiple Access (TDMA) protocols, Global System for Mobile Communications (GSM) protocols, Code Division, Multiple Access (CDMA) protocols, and/or any other type of wireless communications protocol.

[0080] Database **212** is used by computing system **200** and can store massive amounts of data including indexing data used by search engine **150** or local query service **114** and remote query service **121** of FIG. **1**A. And, in one example, database **212** can store or be the same as local database of FIG. **1**A. Database **212** can also store ML models or other statistical or probabilistic models to implement the techniques in the disclosed examples and embodiments. Although database **212** is shown coupled to system bus **201**, computing system **200** can be coupled to any number of external databases locally or remotely connected to computing system **200** via network interface **217**. In one example, computing system **200** can be a server having search engine **150** using database **212**.

Improved Client Side Search Ranking Techniques

[0081] FIGS. **3**A-**3**B illustrate one example of operations **300** and **350** for improved client side search ranking of query results which can be implemented by a client device (e.g., client device **102** of FIGS. **1**A-**1**B). Operation **300** of FIG. **3**A includes operations **302** through **312**. Operation **320** of FIG. **3**B includes operations **322** through **342**.

[0082] Referring to FIG. **3**A, at operation **302**, a user query is issued using, e.g., local search interface **110** of FIG. **1**A. As described above, local search interface **110** can pass the query to one, or both, of local database **111** and remote search engine **150** via local query service **114** or remote query service **121**, respectively. Search results can be provided from both the local query service **114** and remote query service **121** from local or remote search domains. A user query can be a single term, e.g., "pizza", "bars", "john" etc. A user query can also be a phrase, e.g., "baseball games", "rock concerts", etc. or groups of phrases, sentences, or questions. A user query can also be prefix of a query that the user is intending to type out, e.g., a user my type "yel" for the application "Yelp." Each word, term, or phrase in the user query can have an index in a database corresponding to content such as, e.g., files, documents, messages, emails, etc. In one example, search results can include indexed content related to the user query locally found on client device **102** (e.g., from a local search domain) as local search results.

[0083] At operation **304**, in one example, local search results from a local search domain are filtered using local ranking rules. Initial search results can identify a large number of documents, files, or content indexed to the user query found locally or in a local domain on client device **102**, e.g., in local database **111**, which can be filtered and reduced in size using ranking rules. In one example, in order to identify relevant search results for a user, the local search results can be filtered and ranked using ranking rules, e.g., local ranking rule examples **402** of FIG. **4**A. Referring to FIG. **4**A, ranking rules can include any number of ranking rules such as Rule **1** through Rule N. Each ranking rule relates to an attribute and is applied to each local search result to determine a score for ranking the local search results within a category. For example, Rule **1** can determine if local search results have attributes such as exact/fuzzy match with the user query. Rules **2**-**11** can determine if local search results have attributes related to or found in, e.g., a VIP contact list, phone favorites, phrase match, topic, flagged email, tagged files, file names, texts content, artists, and authors up to Rule N for any type of ranking rule.

[0084] In one example, each local search result can be given a score using a local result bit vector **404** described in FIGS. **4**B-**4**C. The local result bit vector **404** can include bits **1** through N including ranking rule bits **406** and count value bits **408** which can be embedded bits in bit vector **404**. Ranking rule bits **406** can be individual bits where each bit represents a ranking rule, e.g., local ranking rule examples **402** in FIG. **4**A. If the local search result has an attribute related to a ranking rule, its corresponding bit can be set to "1" and if not its corresponding bit is set to "0." For example, bit **2** can represent the VIP Contact List, and if its search result has an attribute related to the VIP Contact List, bit **2** would be set to "1." That is, the search result could be an email from a person in the VIP Contact List and its bit **2** would then be set to "1." In one example, count value bits **408** can provide a count value corresponding to the number of matches for one of the ranking rules for the local search result. This number can be used to rank the local search results within a category. In one example, count value bits **408** can be a fixed combination of embedded bits **408** in any location within bit vector **404**, which is shown at the end of the bit vector **404** in FIG. **4**B, and can be embedded in bits **1** through N of local result bit vector **404** as shown in FIG. **4**C. Any number of count values or embedded bits **408** can be used in bit vector **404** to provide other count values such as, e.g., the number of exact or fuzzy matches with a search query. In one example, relevance of information related to ranking rule bits **406** and count value bits **408** can be determined based on location within bit vector **404**, e.g., more relevant information can be located at the left of bit vector **404** and least relevant information at the right of bit vector **404**.

[0085] Referring to FIGS. **4**B-**4**C, in one example, each local search result can have a respective local result bit vector **404** including ranking rule bits **406** and a number of sets of count value **408**, where each set of count value bits comprise a number of embedded bits. For example, count value bits set A can have a different number of embedded bits from count value set B which can represent a number of ranking rules related to attributes of the local search result. This number, in one example, can represent a score for the local search result. In one example, the number represented by corresponding sets of count value bits **408** of each bit

vector **404** for a local search result can be compared to rank the local search results based on the compared numbers. For example, local search results with bit vectors **404** having count values with higher numbers can be ranked higher than other local search results with bit vectors having count values with lower numbers. In one example, the top number of local search results, e.g., top 20, per ranking rule within a category based on the score or count value from the local result bit vector **404** are selected as filtered local search results for further processing in order to display the most relevant local search results to a user.

[0086] In one example, local result bit vector **404** can be stored in local search and feedback history **115** or in local database **111** or data **1113** for later use. Bit vector **404** can also provide information for machine learning (ML) models or algorithms in ranking local search results to be displayed to a user via local search interface **110**. In other examples, bit vector **404** can provide metadata information used by search engines.

[0087] At operation **306**, features are computed per filtered local search result. For example, features for the top number of local search results by ranking rules can be computed for further processing in determining which local search results are relevant for display to the user. In one example, any number of features can be computed for the filtered local search results in operation **304**. Computed features can include ranking values or Boolean values, e.g., as illustrated in computed feature examples of FIGS. **5**A-**5**B. In some examples, thousands of features can be computed for filtered search results in each category. Referring to FIG. **5**A, an example of computing ranking values is shown as computed features **508**. For example, a user query can pull search results from a local domain to client device **102** from contacts and filtered to a "phone favorites" category in which search results are indexed to contacts **502** and facetime calls **504**. Most recent call feature **506** can be computed that provides ranking values as computed features **508** indicating which facetime calls were most recent in connection with a particular contact such as Contacts A-C and ranked as 1, 2 and 3. In this example, "1" refers to the most recent facetime call with Contact A and "3" refers to the latest facetime call with Contact C. Ranking can be based on any number of criteria, e.g., document last used etc.

[0088] In one example, search results can be indexed for contacts **502** listing Contacts A-C tied to specific dates in which facetime calls **504** were made. Computed features **508** can provide useful information without divulging private data **505** such as the exact dates facetime calls **504** were made. In this example, Contact A made a facetime call on May 15, 2017, Contact B made a facetime call on May 12, 2017, and Contact C made a facetime call on Jan. 5, 2016. The exact dates for these facetime calls can be considered private data **505** and would not be designated for distribution or use. To anonymized private data **505**, most recent call feature **506** can be computed by giving ranking values "1", "2" and "3" to identify the most recent facetime call to Contact A without identifying exact dates of the facetime calls, which may expose or identify the user or contact and private data **505**. Thus, private data **505** can be anonymized or masked while providing useful feature information giving indications on how a user interacts with client device **102**.

[0089] Referring to FIG. **5**B, an example of computing Boolean values is shown as computed features **518**. For example, a user query can pull search results from documents in the "phrase match" category in which search results are indexed to documents **512** and last used date **514**. Last used timeline feature **516** can be computed that provides computed values **518** providing timeline information on when documents **512** were last used. In one example, documents **512** includes three documents (DOC **1**, DOC **2**, and DOC **3**) matching a user query. Last used date **512** can indicate that DOC **1** was last used, e.g., on May 16, 2017, and DOC **2** was last used on May 8, 2017, and DOC **3** was last used on Jan. 1, 2016. Last used data **514** can be considered private data **515**, which should not be distributed or shared. In masking private data **515**, last used timeline features **516** can be computed providing computed features **518** such as:

<24 hours	<1 week	<1 month	<1 year
0	0	0	1
0	0	0	1
0	0	0	0

[0090] In the above timeline for computed feature **518**, e.g., the "1" under <1 year indicates a Boolean value that a document, e.g., DOCS **1** and **2** was last used less than a year ago, and a "0" indicates a Boolean value that a document was not last used, e.g., <24 hours ago etc. Any type of Boolean expression can be used to determine Boolean values, e.g., are text messages from Contact A, was music file played last, etc. These Boolean values can also mask exact dates of the last time the document was used in hiding private data **505**. Computed features can be provided for search results according to local ranking rule examples **402** or any other additional categories which can be used by local query service **114** and remote query service **121** in ranking search results for a user.

[0091] At operation **308**, computed features can be transformed based on feature dependent transformation operations in a format for a ML model to process and understand. For example, referring to FIG. **6**, computed features **604** can have ranking or Boolean values, e.g., as shown in FIGS. **5**A-**5**B. In one example, feature dependent transformation operations **602** can implement one hot encoding on computed features **604** which can transform categorical features to a format that works better with ML algorithms. For example, referring to FIG. **5**A, computed features **508** of 1 2 3 can be for Contacts A-C can be transformed by one hot encoding such that only Boolean values are provided for each Contact A-C in categories, e.g., was face time call most recent, second most recent, and third most recent and either a "1" or "0" is used for that category expression for Contacts A-C. In other examples, feature dependent transformation operations **602** can apply mathematical operations (or weights) such as multiplying or adding numbers to generate different values, e.g., floating point numbers, for use by the ML models depending on computing architecture used. In some examples, computed features **604** can pass directly on a one-to-one basis to ML models without transformation. In one example, computed features **604** can include computed features F_1 through F_N. Operations **602** can transform one or more of the computed features F_1 through F_N to generate and output transformed features F'_1 through F'_M. In one example, M and N can be the same integer or, in another example, M<N or M>N in which the number of transformed features **608** is reduced or increased in size compared to computed

features **604**. For example, outputs for transformed features F'_1 through F'_M can have integers added to ranking values such as 1, 2, or 3 so ML models can understand and process them or divided by an integer. In other examples, a computed feature for a result in a category can be a Boolean value and transformed into multiple features with the same Boolean value across multiple categories for use by a ML model.

[0092] At operation **310**, the transformed computed features (e.g., transformed computed features **608**) for each search result in a category are fed into ML models to obtain a score for the search results in the category. Any number of ML models can be used to generate scores for further ranking the search results within a category. In one example, each ML model can be trained on different data and focus on different features of the search results to improve ranking of search results. Referring to FIGS. **7**A-**7**B, in one example, two ML models I and II (**702**, **712**) are implemented receiving as inputs transformed feature set **1** (**704**) and transformed feature set **2** (**714**) based on transformed features **608** in FIG. **6**, respectively. For example, ML models I and II can process different transformed features and apply boosting if necessary to improve ranking of search results per category. In one example, transformed feature set **1** (**704**) can include features F'_{X1} through F'_{XY} and fed into ML model I (**702**), which can a subset of transformed features **608**. In one example, transformed feature set **2** (**714**) can include features F'_{Y1} through F'_{YZ} and fed into ML model II (**712**), which can be a different subset of transformed features **608**. In one example, ML models I and II (**702**, **712**) can include ML models disclosed in U.S. patent application Ser. No. 14/721,945, entitled "MACHINE LEARNING BASED SEARCH IMPROVEMENT," filed on May 26, 2015, which is commonly assigned and incorporated herein by reference.

[0093] At operation **312**, transformed feature sets **1** and **2** (**704**, **714**) can be input into ML models I and II (**702**, **712**) that generate scores **1** and **2** (**706**, **716**), which can be combined for each search result in a category. In one example, scores **1** and **2** are combined to generate a combined score used for ranking search results per category related to transformed features **608**. For example, a combined score can be calculated as: W**1**×Score **1**+W**2**×Score **2**—where W**1** and W**2** and weights which can be tuned according changing search habits of a user or a system. For example, depending on features processed by Score **2**, that score can be given a higher weighting using W**2** for a particular user and Score **1** can be given a lower weighting using W**1**. In one example, the search results in each category can be ranked using the combined scores. In some examples, a single ML can be used and a single score is generated, which can be weighted and user for ranking results per category. Operation **300** can continue to operation **320** in FIG. **3**B.

[0094] In one example, ML models I and II (**702**, **7212**) can include neural networks having any number of layers and nodes as known in ML modeling. Computed features **608** or transformed features sets **1** and **2** (**704**, **714**) can feed into nodes of the lower layer of the neural network, where there is a set of intermediate layers with receiving nodes and a final layer of nodes. The output of the final layer of nodes can provide predictive information on whether a search result is likely to be engaged or unlikely to be engaged, e.g., score **1** (**706**) or score **2** (**716**) which can be used to rank search results. Each node can apply weighted values for each input and the ML model can be trained such that the final nodes output predictive information with known outcomes. In other examples, decision trees can be sued for the ML model, and any type of ML model can be used to generate outputs for transformed features **604**.

[0095] For example, referring to FIGS. **5**A-**5**B, most recent facetime call feature **506** can represent F'_1 and last used timeline feature **516** can represent F'_2 as part of transformed features **608** input to ML models I or II (**702**, **712**). In one example, Boolean terms using transformed features **506** and **516** can be used by ML models I or II, e.g., "is most recent facetime call from Contact A and was DOC **1** used more than a year ago," which can be fed into a decision tree providing provide predictive values as score **1** and **2** (**706**, **716**) for a search result. For example, score **1** (**706**) can be given a value 0.75 by ML model I (**702**) indicating that 75% of the time if most recent facetime call is from Contact A it is relevant. Such predictive values for transformed features **608** can be given for each search result in operation **304**. Any type of predictive ML modeling can be used including linear equations such as F=a*x+b for ML models I and II (**702**, **712**) where "a" is weighted value, "x" is computed feature, and "b" a constant value.

[0096] Referring to FIG. **3**B, at operation **322**, local and remote server search results can be obtained. For example, referring to FIG. **1**A, local search interface **110** can pass a search query to local query service **114** and remote query service **121** in the remote search subsystem **135** of client device **102**, via communication interface paths **1** and **7**, so that local search interface **110** receives search results from both the local database **111** and from remote search engine **150**. In one example, local search results are initially ranked using scores from ML models in operation **312** of FIG. **3**A, and remote search results can be initially ranked. In one example, local and remote search results can be result specific or result set specific for processing down pipeline path **1** or pipeline path **2**.

[0097] At operation **324**, obtained local and remote search results are processed down pipeline path **1** or pipeline path **2** using one or more ML ranking models (e.g., ML ranking models can rank search results of different types) to display ranked search results within a category to a user. In one example, pipeline path **1** can feed or be input to a ML ranking model (e.g., ML ranking model A referring to a ML model for pipeline path **1**) the computed features from operation **306** for local search results and additional computed features for each remote server search results. In another example, pipeline path **2** can feed a different ML ranking model (e.g., ML ranking model B for a ML model for pipeline path **2**) a subset of computed features for the top ranked search results from each category in operation **306** and remote server search features along with results. ML ranking models A and B can be machine learning models trained to rank search results of different types. In one example, ML ranking models disclosed in U.S. patent application Ser. No. 15/648,364, entitled "RE-RANKING SEARCH RESULTS USING BLENDED LEARNING MODELS," filed on Jul. 12, 2017, which is commonly assigned and incorporated herein by reference, can be used. In other examples, for pipeline path **1** or **2**, any number of ML ranking models can be used to further improve ranking of local and remote server search results. In one example, based on user feedback or performance of the different ML models, pipeline path **1** or pipeline path **2** can be selected for

processing the local and remote server search results. In one example, a remote server can send instructions to client device **102** to select pipeline path **1** or pipeline path **2** for processing the local and remote search results.

[0098] For pipeline path **1**, at operation **326**, additional features from remote server search results are computed per result providing ranking values or Boolean values. In one example, remote server search results can have results displayed within different categories than local search results. In one example, categories for the search results can be ranked. Examples of remote server search result categories can include music, movies, website categories, etc. In one example, a set number of features are computed for each remote server search results, which can be fed to ML ranking model A for pipeline path **1** to rank the categories of search results. Features for server search results can be computed to provide ranking values or Boolean values and transformed prior to processing by ML ranking model A.

[0099] At operations **328** and **330**, the additional computed features from operation **326** and local computed features are fed or input to blended ML model A for pipeline path **1**. In one example, local computed features can include filtered results by local ranking rules in operation **304** of FIG. **3**A. In other examples, local computed features can include computed features **604** or transformed features **608** of FIG. **6**. ML ranking model A can then be used to generate a score used to and rank categories of search results from the local and remote server search results. At operation **332**, the local and remote server search results are ranked within a category and displayed based on the score from the ML ranking model A as illustrated in FIGS. **8**A-**8**D using an example user query. In one example, a category for remote search results can have a higher score than a category for local search results and displayed to the user at the top of a list and vice versa a category for local search results can have higher score than a category for remote search results and displayed at the top as shown in FIGS. **8**A-**8**D.

[0100] For pipeline path **2**, at operation **334**, a subset of features of the top local search results per category are computed. In one example, the top local computed features can include a set of number of the top ranked filtered results by local ranking rules in operation **304** of FIG. **3**A. In other examples, the top local computed features can include a set of number of the top computed features **604** or transformed features **608** of FIG. **6**.

[0101] At operation **336**, remote server search features and results are obtained. For example, referring to FIG. **1**A, remote search engine **150** can provide client device **102** by way remote search interface remote search results in different categories and features which can also be initially ranked. At operation **338**, the computed features of the subset of top local search results and remote server search results and features are fed or input to ML ranking model B for pipeline path **2** to generate and score and rank the categories for the local and remote server search results based on the generated score. At operations **340** and **342**, a score is generated from the ML ranking model B the local and remote search results are ranked and displayed within a category based on the generated score from the ML ranking model B as illustrated in the examples of FIGS. **8**A-**8**D.

[0102] Referring to FIG. **3**C, in another example, operation **350** includes operations **352**-**372**. At operation **352**, local and remote server search results are obtained. At operation **354**, additional features are computed per remote server and local search results. At operation **356**, the computed features of remote server and local search results are fed to one of the ML ranking models. At operation **358**, a score is generated from one of the ML ranking models. At operation **360**, the generated scores are saved. At operation **362**, a determination is made if saving all the generated scores is finished. At operation **363**, the operation refeeds generated scores as features if not finished to compute additional features at operation **354**. At operation **370**, if finished, all of the saved scores can be combined to rank the search results. At operation **372**, the ranked search results by category are displayed based on the combined scores.

User Query and Improved Search Result Ranking Example

[0103] FIGS. **8**A-**8**D are example flow diagrams of processing an example user query to provide improved search results by category based on the operations **300** and **320** disclosed in FIGS. **3**A and **3**B.

[0104] Referring to FIG. **8**A, filtering and ranking phase **800** is shown. At block **802**, a user of client device **102** can input a user query **802**, e.g., "HELLO" into a local search interface **110** (e.g., operation **302**). In one example, at block **804**, local query service **114** can pull or identify indexed items **1** through N for the user query "HELLO" from local database **111**. Indexed items **804** can initially contain hundreds or thousands of items such as, e.g., documents, files, apps, texts, etc. At block **806**, the indexed items **804** are filtered by category or rule, e.g., using local ranking rule category examples **402** shown in FIG. **4**A (e.g., operation **304** in FIG. **3**A), to obtain a smaller set of filtered items **808** ranked per category as filtered ranked results **809**. Categories of filtered items **808** can include PDF files, TXT files, and APP files in which the categories can be ranked. For the PDF category, Hello1.pdf can have a result vector count value (e.g., result vector **404** in FIG. **4**B) higher than Hello2.pdf and displayed at the top in the PDF category based on this count value indicating the number of categories the item can be found. Likewise, Helloworld1.txt can have a higher count value than Helloworld2.txt in the TXT category, and Hello1.app can have a higher count value than Hello2.app in the APP category and displayed at the top of respective categories as shown in FIG. **8**A.

[0105] Referring to FIG. **8**B, ranking local results phase **810** is shown. At block **812-1** and block **812-2** two ML models (I and II) receive or are fed computed features **814** for filtered ranked results **809** and subset of computed features **816** to ML model I and ML model II respectively (e.g., operation **306**, **308**, and **310** of FIG. **3**A). Computed features **814** and subset of computed features **816** can be transformed as described in FIGS. **6**, **7**A-**7**B. In one example, subset of computed features **816** contains a smaller set of computed features in computed features **814** in which ML model II focuses on a smaller set of computed features. Each of the ML models I and II generates score **1** and **2** which are combined (e.g., operation **312** of FIG. **3**A). The combined score can be used to rank items in local ranked results **819** by category, e.g., PDF, TXT, and APP. In local ranked results **819**, for the PDF category, Hello2.pdf had a higher score than Hello1.pdf, and for TXT category, Helloworld2.txt had a higher score than Helloworld1.txt, and, for the APP category, Hello2.app had a higher score than Hello1.app in with the higher score items are displayed on top.

[0106] Referring to FIG. **8**C, pipeline path **1** phase **820** is shown (e.g., operations **324** through **332**) At blocks **819** and **820**, local and remote search results are obtained. In one example, local results **819** are local ranked results **819** from FIG. **8**B. Server results **820** can include initially ranked items in categories, e.g., Music, Movies, Website. For example, for the Music category, remote search results can include Hello by Adele, Hello song, etc. For Movies, remote search results can include Hello NYC, Hello Stranger, etc. For Website, remote results can include hello.com. At block **827**, in one example, a blended ML model A receives or is fed computed local computed features **814** and remote computed features **815**. Blended ML model A can generate a score for each category from local results **819** and server results **820** and the categories can be ranked and displayed accordingly in ranked category of search results **837**. As shown, e.g., the ranking of categories from highest to lowest is App, PDF, Music, Website, Txt, and Movies with ranked items accordingly in each category.

[0107] Referring to FIG. **8**D, pipeline path **2** phase **830** is shown (e.g., operations **324** through **342**). At blocks **819** and **820**, the same local and remote search results are obtained as shown in FIG. **8**C. At block **847**, in one example, a blended ML model B receives or is fed computed features of top local results **824** and server features and search results **825**. Blended ML model B can generate a score for each category from local results **819** and server results **820** and the categories can be ranked and displayed accordingly in ranked category of search results **857**. As shown, e.g., the ranking of categories from highest to lowest is App, PDF, Music, Website, Txt, and Movies with ranked items accordingly in each category. Blended ML model B can generate different scores providing different ranked categories in ranked category of search results **837** than blended ML model A of FIG. **8**C.

[0108] In the foregoing specification, specific examples and exemplary embodiments have been disclosed and described. It will be evident that various modifications may be made to those examples and embodiments without departing from the broader spirit and scope set forth in the following claims. The specification and drawings are, accordingly, to be regarded in an illustrative sense rather than a restrictive sense.

1-32. (canceled)

33. A computer-implemented method comprising:

receiving a search query from a user on a client device;

filtering local search results based on the received search query and one or more local ranking rules;

computing features for each filtered local search result, wherein computing features for the filtered local search results includes computing values for the computed features to anonymize user data;

inputting the computed features of each filtered local search result to one or more machine learning (ML) models, each ML model generating a score for each filtered local search result;

ranking the filtered local search results based on the generated score within a category; and

ranking a plurality of categories for the filtered local search results based on at least one generated score of the filtered local search results within each category from the plurality.

34. The method of claim **33**, wherein filtering the local search results comprises:

applying the one or more ranking rules to each local search result to generate a bit vector including individual bits representing applicable ranking rules and one or more fixed combination of bits representing one or more count values;

comparing the one or more count values of each bit vector to rank the local search results based on the comparison; and

identifying a set of top ranked local search results as the filtered local search results.

35. The method of claim **34**, wherein the one or more count values in each bit vector of at least indicates a number of ranking rules applicable to each local search result.

36. The method of claim **35**, wherein identifying the set of top ranked local search results as the filtered local search results includes ranking higher local search results with bit vectors having count values with higher numbers than local search results with bit vectors having count values with lower numbers.

37. The method of claim **36**, wherein identifying the set of top ranked local search results includes selecting a subset of higher ranked local search results.

38. The method of claim **33**, further comprising:

transforming the computed features of the filtered local search results for processing by the one or more ML models; and

inputting the transformed computed features of the filtered local search results to the one or more machine learning (ML) models, each ML model generating a score for each filtered local search result.

39. The method of claim **38**, wherein transforming the computed features uses feature dependent transformation operations.

40. The method of claim **38**, wherein inputting the transformed computed features of the filtered local search results including inputting a first set of transformed computed features to a first ML model and a second set of computed features to a second ML model, the first ML model generating a first score and the second ML model generating a second score, and combining the first score with the second score to rank the filtered local search results.

41. The method of claim **40**, wherein the first set and second set include different computed features.

42. The method of claim **33**, further comprising:

obtaining local search results and remote server search results;

ranking the obtained local search results and remote server search results using at least one machine learning (ML) ranking model; and

displaying the ranked local search results and remote server search results on the client device by category.

43. The method of claim **42**, further comprising:

selecting a first processing path or a second processing path to rank the obtained local search results and remote server search results.

44. The method of claim **42**, wherein if the first processing path is selected, the method further comprises:

computing additional features for the remote server search results;

inputting the additional computed features for the remote server search results and computed features of top ranked local search results to a first machine learning (ML) ranking model;

generating a score for each of the local search results and remote server search results by the first ML ranking model; and

displaying the ranked local search results and remote server search results by category.

45. The method of claim **42**, wherein if the second processing path is selected, the method further comprises:

computing a subset of features for top ranked local search results;

obtaining features of remote server search results;

inputting computed subset of features for top ranked local search results and features of remote server search results to a second machine learning (ML) ranking model;

generating a score for each of the local search results and remote server search results by the second ML ranking model;

ranking the local search results and remote server search based on the generated score; and

displaying the ranked local search results and remote server search results by category.

46. The method of claim **43**, further comprising:

computing additional features for the remote server search results;

inputting the additional computed features for the remote server search results and computed features of top ranked local search results to a third machine learning (ML) ranking model;

generating a score for each of the local search results and remote server search results by the third ML ranking model;

computing a subset of features for top ranked local search results;

obtaining features of remote server search results;

inputting computed subset of features for top ranked local search results and features of remote server search results to a fourth machine learning (ML) ranking model;

generating a score for each of the local search results and remote server search results by the fourth ML ranking model;

combining the scores of the third and fourth ML ranking models; and

ranking the local search results and remote server search based on the combined scores; and

displaying the ranked local search results and remote server search results by category.

47. A computing device comprising:

a memory programmed with executable instructions; and

a processing system coupled to the memory to execute the executable instructions and to receive a search query from a user on a client device;

filter local search results based on the received search query and one or more local ranking rules;

compute features for each filtered local search result, wherein computing features for the filtered local search results includes computing values for the computed features to anonymize user data;

input the computed features of each filtered local search result to one or more machine learning (ML) models, each ML model generating a score for each filtered local search result;

rank the filtered local search results based on the generated score within a category; and

rank a plurality of categories for of the filtered local search results based on at least one generated score of the filtered local search results within each category from the plurality.

48. The computing device of claim **47**, wherein the processing system is to

apply the one or more ranking rules to each local search result to generate a bit vector including individual bits representing applicable ranking rules and one or more fixed combination of bits representing one or more count values;

compare the one or more count values of each bit vector to rank the local search results based on the comparison; and

identify a set of top ranked local search results as the filtered local search results.

49. The computing device of claim **48**, wherein the one or more count values in each bit vector at least indicates a number of ranking rules applicable to each local search result.

50. The computing device of claim **47**, wherein the processing system is to rank higher local search results with bit vectors having count values with higher numbers than local search results with bit vectors having count values with lower numbers.

51. The computing device of claim **49**, wherein the processing system is to identify the set of top ranked local search results includes selecting a subset of higher ranked local search results.

52. The computing device of claim **47**, wherein the processing system is to transform the computed features of the filtered local search results for processing by the one or more ML models, and input the transformed computed features of the filtered local search results to the one or more machine learning (ML) models, each ML model generating a score for each filtered local search result of each category.

53. The computing device of claim **47**, wherein the processing system is to use feature dependent transformation operations to transform the computed features.

54. The computing device of claim **47**, wherein the processing system is to input a first set of transformed computed features to a first ML model and second set of computed features to a second ML model, the first ML model generating a first score and the second ML model generating a second score, and combine the first score and the second score to rank the filtered local search results, and wherein the first set and second set include different computed features.

55. The computing device of claim **47**, wherein the processing system is to obtain local search results and remote server search results, rank the obtained local search results and remote server search results using at least one machine learning (ML) ranking model, display the ranked local search results and remote server search results on the client device by category.

56. A non-transitory machine-readable medium programmed with instructions that, when executed by a computing device, cause the computing device to perform operations comprising:

receiving a search query from a user on a client device;

filtering local search results based on the received search query and one or more local ranking rules;

computing features for each filtered local search result, wherein computing features for the filtered local search results includes computing values for the computed features to anonymize user data;

inputting the computed features of each filtered local search result to one or more machine learning (ML) models, each ML model generating a score for each filtered local search result;

ranking the filtered local search results based on the generated score within a category; and

ranking a plurality of categories for of the filtered local search results based on at least one generated score of the filtered local search results within each category from the plurality.

57. The non-transitory machine-readable medium of claim **56**, to cause the computing device to perform operations comprising:

applying the one or more ranking rules to each local search result to generate a bit vector including individual bits representing applicable ranking rules and one or more fixed combination of bits representing one or more count values;

comparing the one or more count values of each bit vector to rank the local search results based on the comparison; and

identifying a set of top ranked local search results as the filtered local search results.

58. The non-transitory machine-readable medium of claim **57**, to cause the computing device to perform operations comprising:

ranking higher local search results with bit vectors having count values with higher numbers than local search results with bit vectors having count values with lower numbers; and

selecting a subset of higher ranked local search results.

59. The non-transitory machine-readable medium of claim **57**, to cause the computing device to perform operations comprising:

transforming the computed features of the filtered local search results for processing by the one or more ML models; and

inputting the transformed computed features of the filtered local search results to the one or more machine learning (ML) models, each ML model generating a score for each filtered local search result.

60. The non-transitory machine-readable medium of claim **58**, to cause the computing device to perform operations comprising:

inputting a first set of transformed computed features to a first ML model and a second set of computed features to a second ML model, the first ML model generating a first score and the second ML model generating a second score; and

combining the first score with the second score to rank the filtered local search results.

61. The non-transitory machine-readable medium of claim **59**, to cause the computing device to perform operations comprising:

obtaining local search results and remote server search results;

ranking the obtained local search results and remote server search results using at least one machine learning (ML) ranking model; and

displaying the ranked local search results and remote server search results on the client device by category.

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