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(54) **FUTURE USER DEVICE PREFERENCE PREDICTION BASED ON TELECOM DATA**

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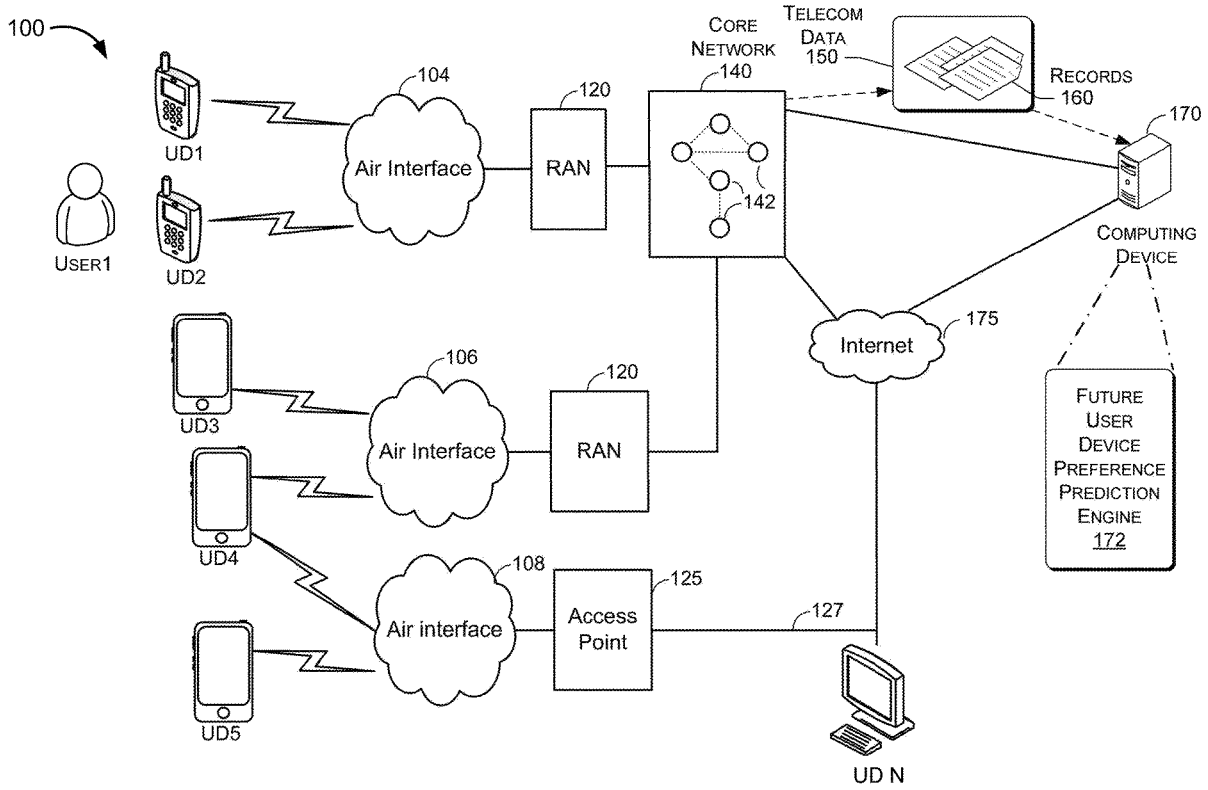
CPC ***G06N 5/04*** (2013.01); ***H04W 8/18*** (2013.01); ***G06N 20/00*** (2019.01)

(57) **ABSTRACT**

Aspects of the present disclosure provide for future user device preference prediction based on telecom data. In one aspect, a computer-implemented method includes collecting the telecom data from at least one node of a wireless communication network, where the telecom data includes records for a plurality of occurrences of user interaction with the wireless communication network via a respective current user device. The telecom data is then applied to a predictive model to obtain a prediction of future user device preferences. The prediction of the future user device preferences may include an indication that a user will switch from the respective current user device to another user device for future use with the wireless communication network. The method further includes performing an action with respect to the wireless communication network in response to the prediction of future user device preferences.



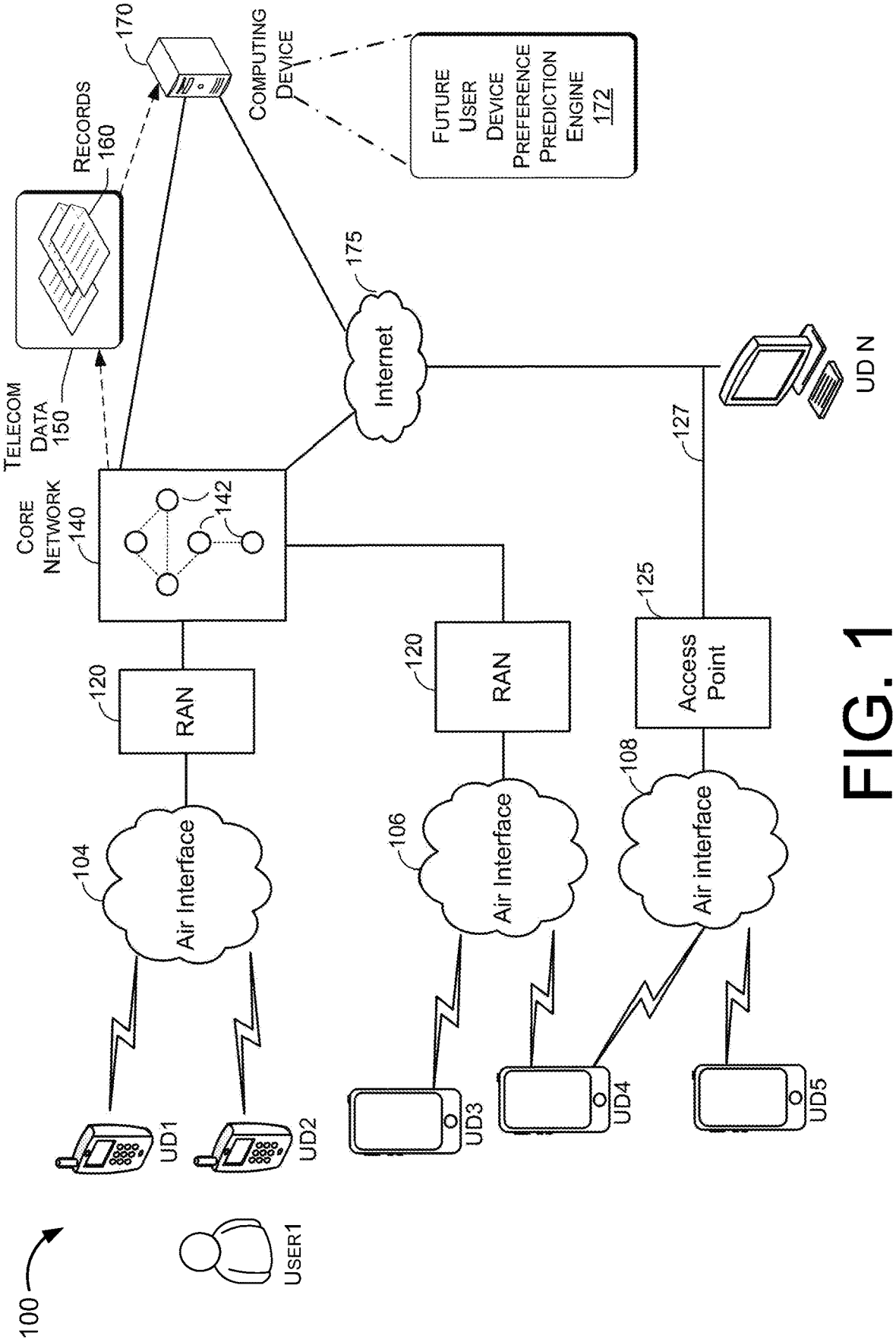

100
USER1
UD1
UD2
UD3
UD4
UD5
UD N
Air Interface
Air Interface
Air interface
RAN
RAN
Access Point
104
106
108
120
120
125
127
Internet
175
CORE NETWORK 140
142
TELECOM DATA 150
RECORDS 160
170
COMPUTING DEVICE
FUTURE USER DEVICE PREFERENCE PREDICTION ENGINE 172

FIG. 1

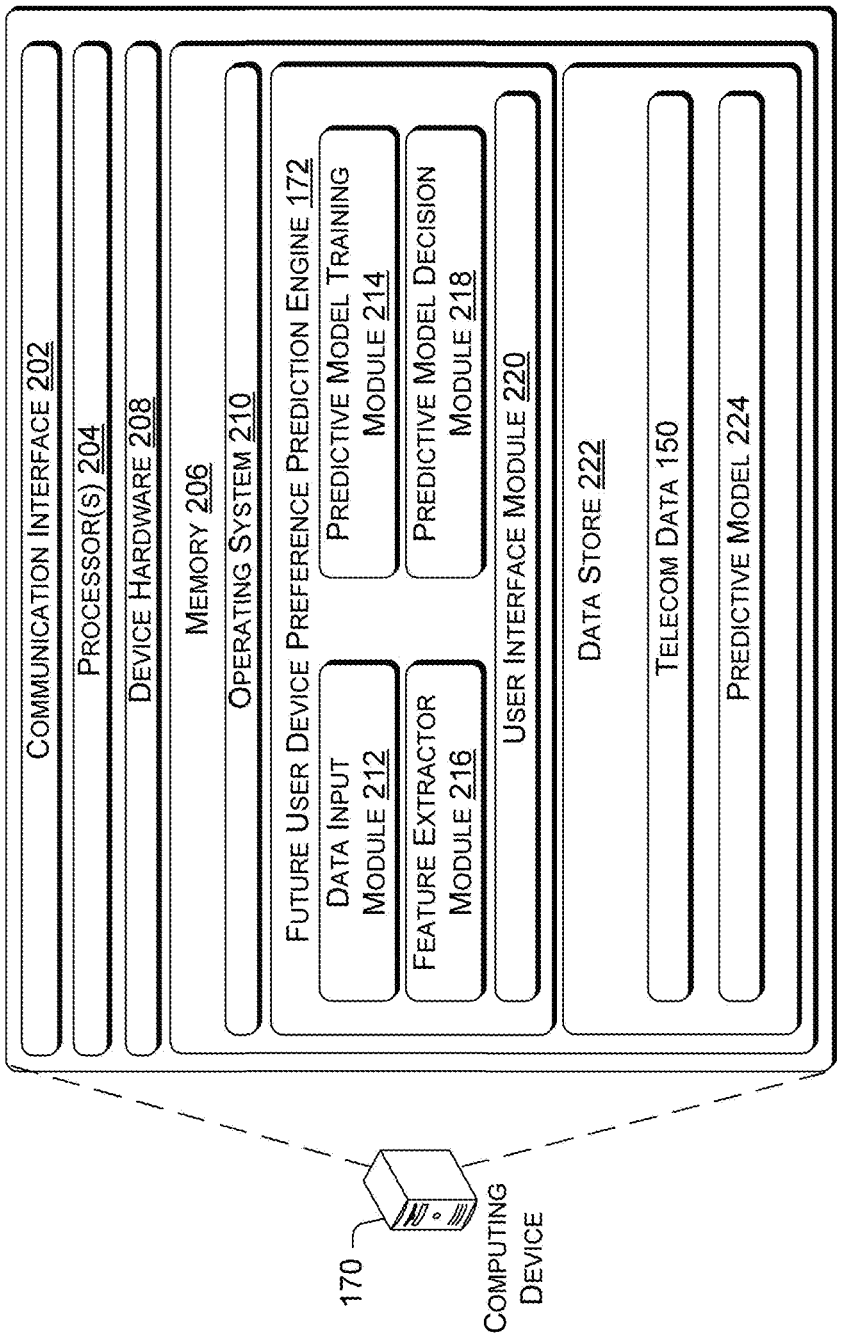

COMMUNICATION INTERFACE 202
PROCESSOR(S) 204
DEVICE HARDWARE 208
MEMORY 206
OPERATING SYSTEM 210
FUTURE USER DEVICE PREFERENCE PREDICTION ENGINE 172
DATA INPUT MODULE 212
PREDICTIVE MODEL TRAINING MODULE 214
FEATURE EXTRACTOR MODULE 216
PREDICTIVE MODEL DECISION MODULE 218
USER INTERFACE MODULE 220
DATA STORE 222
TELECOM DATA 150
PREDICTIVE MODEL 224
170
COMPUTING DEVICE

FIG. 2

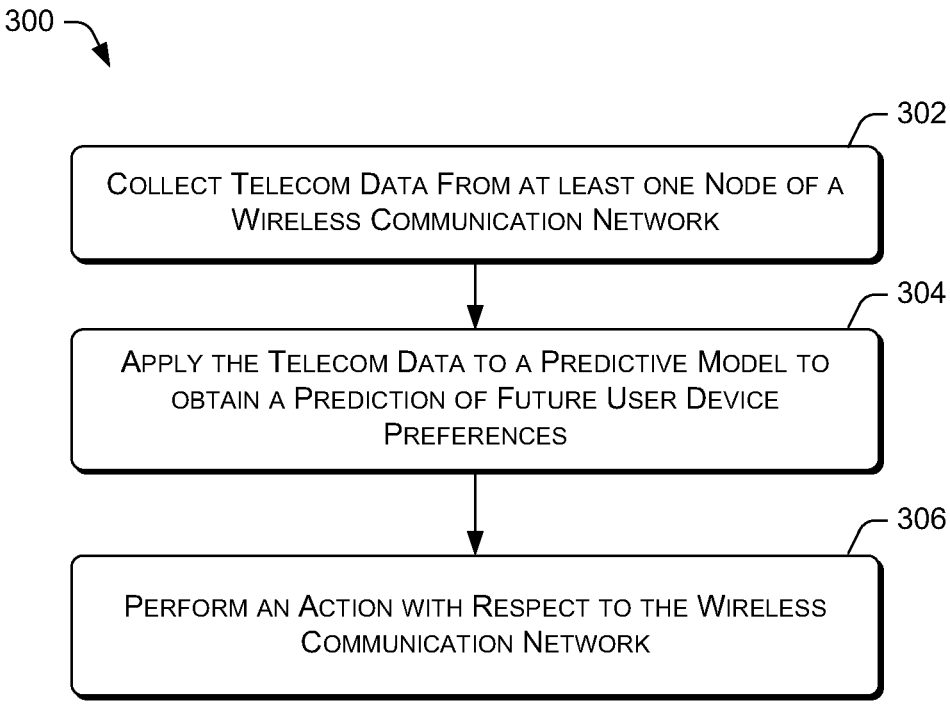

300
302
COLLECT TELECOM DATA FROM AT LEAST ONE NODE OF A WIRELESS COMMUNICATION NETWORK
304
APPLY THE TELECOM DATA TO A PREDICTIVE MODEL TO OBTAIN A PREDICTION OF FUTURE USER DEVICE PREFERENCES
306
PERFORM AN ACTION WITH RESPECT TO THE WIRELESS COMMUNICATION NETWORK

FIG. 3

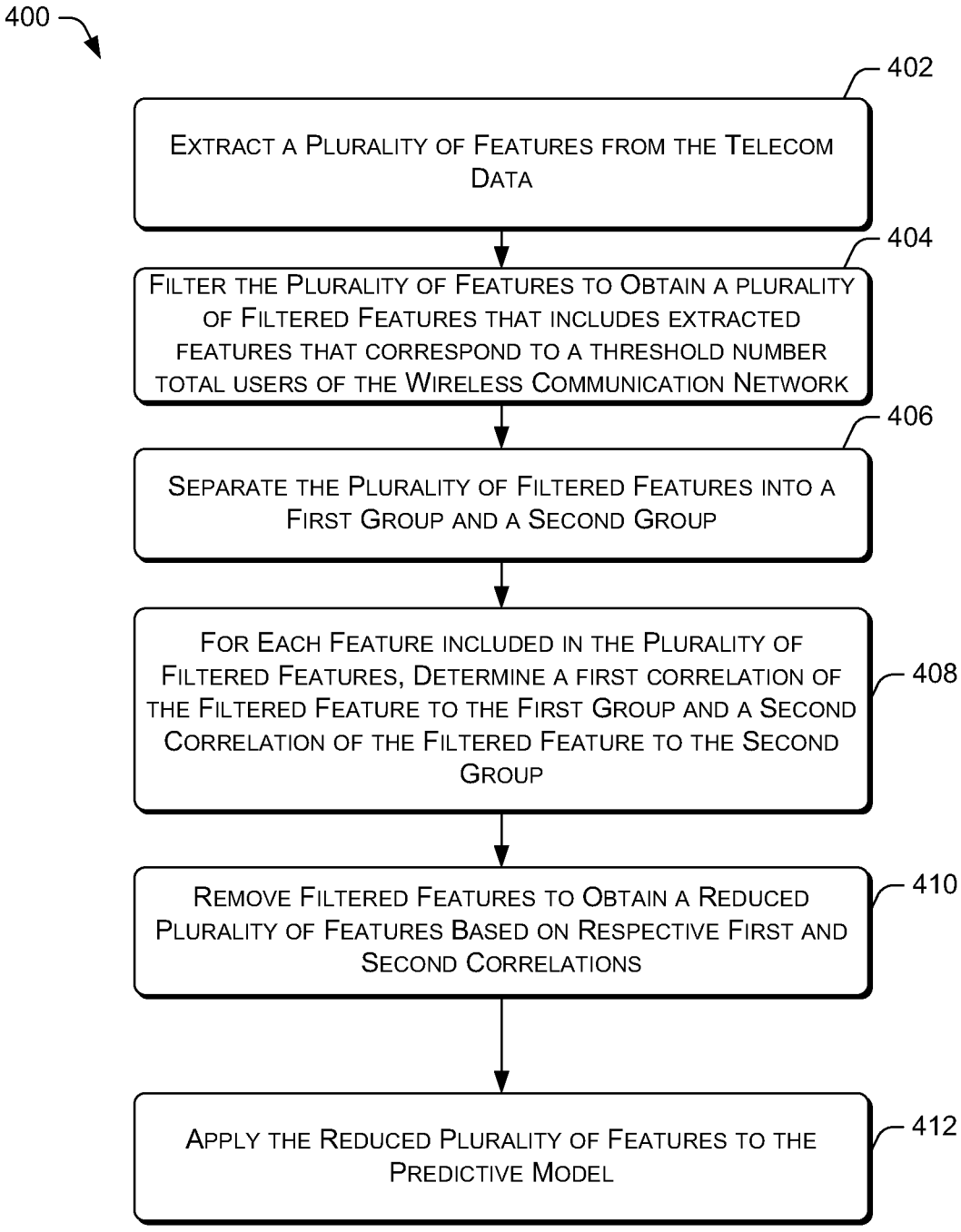

400
402
EXTRACT A PLURALITY OF FEATURES FROM THE TELECOM DATA
404
FILTER THE PLURALITY OF FEATURES TO OBTAIN A PLURALITY OF FILTERED FEATURES THAT INCLUDES EXTRACTED FEATURES THAT CORRESPOND TO A THRESHOLD NUMBER TOTAL USERS OF THE WIRELESS COMMUNICATION NETWORK
406
SEPARATE THE PLURALITY OF FILTERED FEATURES INTO A FIRST GROUP AND A SECOND GROUP
FOR EACH FEATURE INCLUDED IN THE PLURALITY OF FILTERED FEATURES, DETERMINE A FIRST CORRELATION OF THE FILTERED FEATURE TO THE FIRST GROUP AND A SECOND CORRELATION OF THE FILTERED FEATURE TO THE SECOND GROUP
408
REMOVE FILTERED FEATURES TO OBTAIN A REDUCED PLURALITY OF FEATURES BASED ON RESPECTIVE FIRST AND SECOND CORRELATIONS
410
APPLY THE REDUCED PLURALITY OF FEATURES TO THE PREDICTIVE MODEL
412

FIG. 4

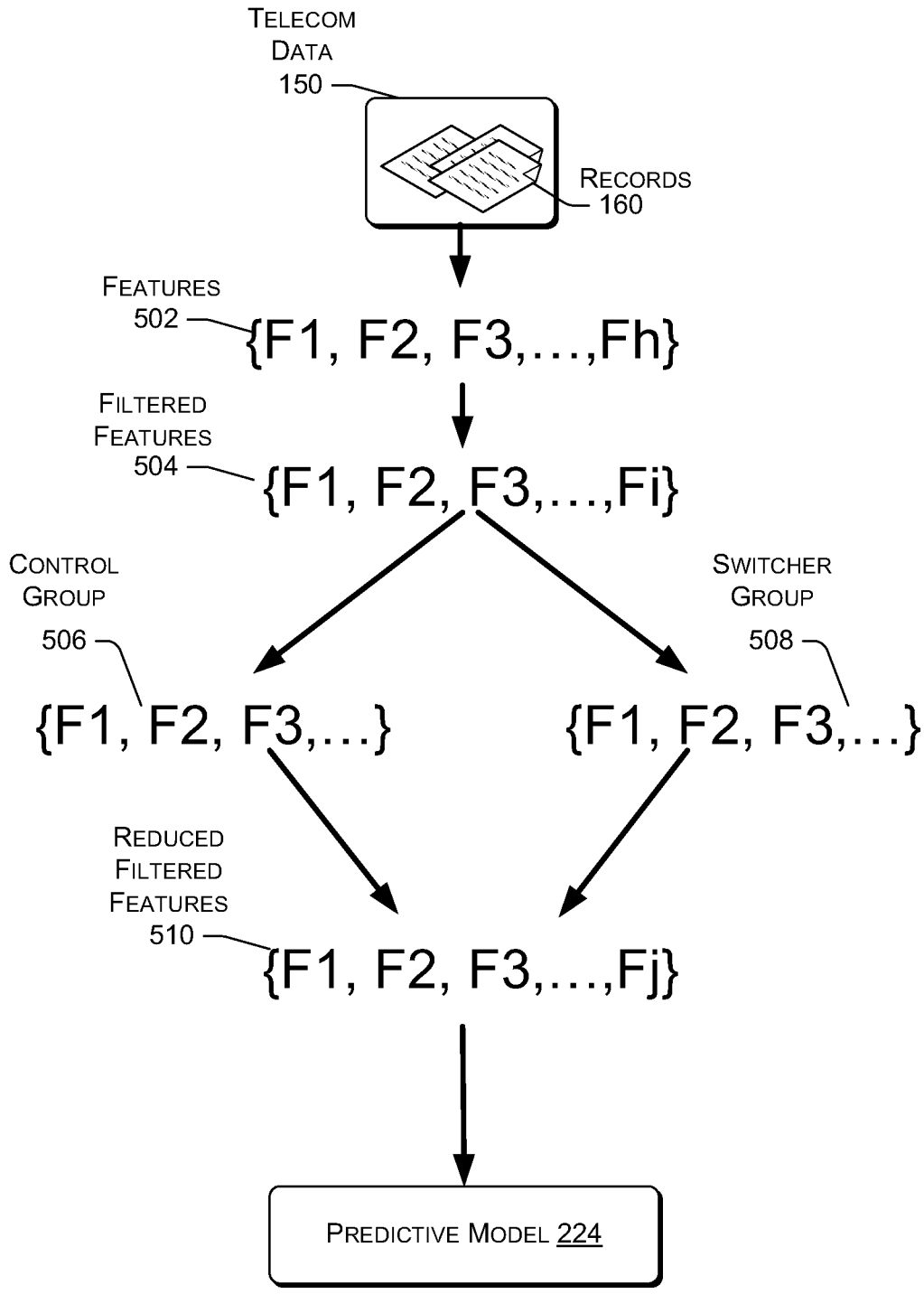

TELECOM DATA 150
RECORDS 160
FEATURES 502
{F1, F2, F3,…,Fh}
FILTERED FEATURES 504
{F1, F2, F3,…,Fi}
CONTROL GROUP 506
SWITCHER GROUP 508
{F1, F2, F3,…}
{F1, F2, F3,…}
REDUCED FILTERED FEATURES 510
{F1, F2, F3,…,Fj}
PREDICTIVE MODEL 224

FIG. 5

FUTURE USER DEVICE PREFERENCE PREDICTION BASED ON TELECOM DATA

BACKGROUND

[0001] Wireless communication devices are integral to the daily lives of most users. Wireless communication devices are used to make voice calls, check email and text messages, update social media pages, stream media, browse websites, and so forth. Accordingly, manufacturers of wireless communication devices are constantly developing new models in an attempt to provide users with new and improved capabilities. Thus, the users of wireless communication devices expect telecommunication carriers to have the latest models available for sale/use, and also for the carriers to provide constant and reliable telecommunication and data communication services that take advantage of these new capabilities.

BRIEF DESCRIPTION OF THE DRAWINGS

[0002] The detailed description is described with reference to the accompanying figures, in which the left-most digit(s) of a reference number identifies the figure in which the reference number first appears. The use of the same reference numbers in different figures indicates similar or identical items.

[0003] FIG. **1** illustrates a high-level system architecture of a wireless communication network that provides for future user device preference prediction.

[0004] FIG. **2** is a block diagram of a computing device that implements future user device preference prediction.

[0005] FIG. **3** is a flow diagram of an example process for future user device preference prediction based on telecom data.

[0006] FIG. **4** is a flow diagram of an example process for updating a predictive model for use with future user device preference prediction.

[0007] FIG. **5** is a diagram illustrating an example implementation of updating a predictive model for use with future user device preference prediction.

DETAILED DESCRIPTION

[0008] Aspects of the present disclosure are directed to predicting if/when a user (e.g., customer of a mobile network operator (MNO)) will switch (e.g., upgrade) a user device that the user utilizes to access a wireless communication network operated by the MNO. In addition to predicting if/when the customer will switch user devices, aspects may also include predicting the type, brand, and/or model of the user device that the user will switch to.

[0009] The determination of how many and when customers will switch user devices may be applied to forecasting device supply, for correctly fulfilling telecom needs related to customer preferences, and/or for optimizing cost and supply distribution in stores.

[0010] In some aspects a predictive model may be generated based on telecom data such as Event Data Records (EDRs). For example, click stream data such as domain and protocol data may be collected over a time period (e.g., 3 months). The domain data may include the domain name of websites/internet services that are visited by users, whereas the protocol data may include additional information such as: protocols utilized (e.g., http, https, etc.), a number of hits at a particular domain over a certain time period, an amount of data exchanged, a duration of a visit to the domain, a frequency with which that domain was visited, etc.

[0011] Features may then be identified from the collected click stream data, where a feature is an identifiable set of one or more data points that are comparable. The identified features are then filtered such that they represent a threshold number of users of the wireless communication network. For example, an identified feature that only represents a minor number (e.g., <50%) of users would be discarded, whereas a feature that corresponds to a majority (e.g., >50%) of users would be kept.

[0012] The identified and filtered features may then be separated into two groups: a control group (users that did not switch devices over the time period that the data was collected) and a switcher group (users who indeed switched devices during the time period that the data was collected).

[0013] The features may be further filtered to keep only those features that clearly indicate that a user has/will switch devices. For example, a feature that has a close correlation to both the control group and the switcher group may be discarded (e.g., an identified feature has a 50% chance of indicating that a user will switch devices and a 50% chance of indicating that a user will not switch devices). Conversely, if a feature is closely correlated to one of the groups, then the feature may be retained and applied to the predictive model (e.g., in 90% of the occurrences that this feature appears, the user ends up switching devices, or in 90% of the occurrences that this feature appears, the user ends up not switching devices).

[0014] The generated predictive model may then be applied to further incoming telecom data (e.g., click-stream data) to identify and/or quantify users that will be likely switching devices in the future. As mentioned above, this prediction may be used to adjust supply chains and/or optimize the wireless communication network for future use.

[0015] In some examples, the prediction of future user device preferences may be supplemented with additional data such as a user location to identify future supply issues and/or network issues that are specific to a certain geographic region.

[0016] In addition, the collection of telecom data may be done on a sliding window basis where the predictive model may be continuously updated (e.g., every month, collect previous 3 months of telecom data to update the predictive model). The techniques described herein may be implemented in a number of ways. Example implementations are provided below with reference to the following figures.

Example Network Architecture

[0017] FIG. **1** illustrates a high-level system architecture of a wireless communication network **100** in accordance with aspects of the present disclosure. As shown in FIG. **1**, a user (e.g., USER1) may access one or more services provided by the wireless communication network **100** via one or more respective current user devices (UDs **1** . . . N). The UDs **1** . . . N can include cellular telephones, personal digital assistant (PDAs), pagers, a laptop computer, a desktop computer, and so on. For example, in FIG. **1**, UDs **1** . . . **2** are illustrated as cellular calling phones, UDs **3** . . . **5** are illustrated as cellular touchscreen phones or smart phones, and UD N is illustrated as a desktop computer or PC.

[0018] Referring to FIG. **1**, UDs **1** . . . N are configured to communicate with an access network (e.g., the radio access

network (RAN) **120**, an access point **125**, etc.) over a physical communications interface or layer, shown in FIG. **1** as air interfaces **104**, **106**, **108** and/or a direct connection **127**. The air interfaces **104** and **106** can comply with a given cellular communications protocol, such as, Code Division Multiple Access (CDMA), Evolution Data-Optimized (EVDO), evolved High Rate Packet Data (eHRPD), Global System for Mobile communications (GSM), Enhanced Data rates for GSM Evolution (EDGE), Wideband CDMA (W-CDMA), Long Term Evolution (LTE), etc., while the air interface **108** can comply with a wireless IP protocol (e.g., IEEE 802.11). The RAN **120** includes a plurality of access points that serve UDs over air interfaces, such as the air interfaces **104** and **106**. The access points in the RAN **120** can be referred to as access nodes or ANs, access points or APs, base stations or BSs, Node Bs, eNode Bs, and so on. These access points can be terrestrial access points (or ground stations), or satellite access points. The RAN **120** is configured to connect to a core network **140** that can perform a variety of functions, including bridging circuit switched (CS) calls between UDs served by the RAN **120** and other UDs served by the RAN **120** or a different RAN altogether, and can also mediate an exchange of packet-switched (PS) data with external networks such as Internet **175**. The Internet **175** includes a number of routing agents and processing agents (not shown in FIG. **1** for the sake of convenience). In FIG. **1**, UD N is shown as connecting to the Internet **175** directly (i.e., separate from the core network **140**, such as over a direct connection **127** that may include an Ethernet connection, Wi-Fi, or 802.11-based network). The Internet **175** can thereby function to bridge packet-switched data communications between UD N and UDs **1** . . . N via the core network **140**. Also shown in FIG. **1** is the access point **125** that is separate from the RAN **120**. The access point **125** may be connected to the Internet **175** independent of the core network **140** (e.g., via an optical communication system such as FiOS, a cable modem, etc.). The air interface **108** may serve UD **4** or UD **5** over a local wireless connection, such as IEEE 802.11 in an example. UD N is shown as a desktop computer with a wired connection to the Internet **175**, such as direct connection **127** to a modem or router, which can correspond to the access point **125** itself in an example (e.g., for a Wi-Fi router with both wired and wireless connectivity).

[0019] Referring to FIG. **1**, computing device **170** is shown as connected to the Internet **175**, the core network **140**, or both. The computing device **170** may be implemented as a plurality of structurally separate servers, or alternately may correspond to a single server. As will be described below in more detail, the computing device **170** includes a future user device preference prediction engine **172** that is configured to generate a prediction of future user device preferences based on telecom data **150**. In one example, the telecom data **150** includes records **160** (e.g., event data records (EDRs)) for a plurality of occurrences of user interaction with the wireless communication network **100** via a respective current user device (e.g., UD**1**, UD**2**, . . . , UDN). In some aspects, the telecom data **150** is collected (e.g., received) from one or more nodes **142** of the core network **140**. The one or more nodes **142** of the core network **140** may correspond to one or more servers and/or functions provided by the core network **140**, such as a gateway, an IP multimedia subsystem (IMS), a Call Session Control Function (CSCF), a Mobility Management Entity (MME), a Home Subscriber Server (HSS), an event data recorder (EDR), a Telephone Application Server (TAS), and the like.

[0020] The future user device preference prediction engine **172** may collect the telecom data **150** and apply the telecom data **150** to a predictive model to obtain a prediction of future user device preferences that includes at least an indication that a user (e.g., USER1) will switch from a respective current user device (e.g., UD**1**) to another user device (e.g., UD**2**) for future use with the wireless communication network **100**. The future user device preference prediction engine **172** may then perform one or more actions with respect to the wireless communication network **100** based on the obtained prediction. For example, the future user device preference prediction engine **172** may communicate with one or more nodes **142** of the core network **140** to change one or more parameters and/or may generate a report for one or more user device distributors (e.g., stores, manufacturers, etc.) that indicates the future user device preferences.

Example Computing Device Components

[0021] FIG. **2** is a block diagram of a computing device **170** that implements future user device preference prediction. The future user device preference prediction engine **172** may be implemented on one or more computing devices that are a part of the core network **140**. The computing device **170** may include general purpose computers, such as desktop computers, tablet computers, laptop computers, servers, or other electronic devices that are capable of receive inputs, process the inputs, and generate output data. In other embodiments, the computing device **170** may be a virtual computing device in the form of virtual machines or software containers that are hosted in a cloud. The computing device **170** may be equipped with a communication interface **202**, one or more processors **204**, memory **206**, and device hardware **208**. The communication interface **202** may include wireless and/or wired communication components that enable the computing device **170** to transmit data to and receive data from other networked devices via a communication network. The device hardware **208** may include additional hardware that performs user interface, data display, data communication, data storage, and/or other server functions.

[0022] The memory **206** may be implemented using computer-readable media, such as computer storage media. Computer-readable media includes, at least, two types of computer-readable media, namely computer storage media and communications media. Computer storage media includes volatile and non-volatile, removable and non-removable media implemented in any method or technology for storage of information such as computer-readable instructions, data structures, program modules, or other data. Computer storage media includes, but is not limited to, RAM, ROM, EEPROM, flash memory or other memory technology, CD-ROM, digital versatile disks (DVD) or other optical storage, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, or any other non-transmission medium that can be used to store information for access by a computing device. In contrast, communication media may embody computer-readable instructions, data structures, program modules, or other data in a modulated data signal, such as a carrier wave, or other transmission mechanisms.

[0023] The processors **204** and the memory **206** of the computing device **170** may implement an operating system **210** and the future user device preference prediction engine **172**. The operating system **210** may include components that enable the computing device **170** to receive and transmit data via various interfaces (e.g., user controls, communication interface, and/or memory input/output devices), as well as process data using the processors **204** to generate output. The operating system **210** may include a presentation component that presents the output (e.g., display the data on an electronic display, store the data in memory, transmit the data to another electronic device, etc.). Additionally, the operating system **210** may include other components that perform various additional functions generally associated with an operating system.

[0024] The future user device preference prediction engine **172** may include a data input module **212**, a predictive model training module **214**, a feature extractor module **216**, a predictive model decision module **218**, and a user interface module **220**. The predictive model training module **214** and predictive model decision module **218** may also interact with a data store **222**. These modules may include routines, program instructions, objects, and/or data structures that perform particular tasks or implement particular abstract data types.

[0025] The data input module **212** may receive the telecom data **150** from one or more nodes **142** of the wireless communication network **100**. The data input module **212** may store the telecom data **150** in the data store **222**.

[0026] In some aspects, the telecom data **150** includes records **160** for a plurality of occurrences of user interaction with the wireless communication network **100**. For example, the records **160** may include several event data records (EDRs), where each EDR corresponds to one occurrence of a user's (e.g., USER1's) interaction with the wireless communication network **100** via a respective current user device (e.g., UD**1**). In some examples, the EDRs comprise click-stream data corresponding to a navigation of the Internet **175** by the user. In some aspects, the click-stream data may include a time-ordered sequence of hyperlinks, websites, and/or other internet services that a user navigates utilizing their respective current user device via wireless communication network **100**. By way of example, an EDR that includes click-stream data may indicate that a user starts their navigation of Internet **175** within a website or at a separate 3rd party website, such as a search engine results page, followed by a sequence of successive webpages visited by the user.

[0027] In some examples, the click-stream data included in the records **160** may include both domain data and protocol data. The domain data may indicate at least one domain name of an internet service or website visited by the user via their respective current user device. The protocol data may provide other information related to the user's navigation of the Internet **175**, such as a protocol (e.g., HTTP, HTTPS, FTP, etc.) utilized by the current user device when accessing the internet service or website, a frequency with which the current user device accessed the internet service or website, an amount of data exchanged between the current user device and the internet service or website, and/or a duration of at least one occurrence (e.g., session) of the user accessing the internet service or website.

[0028] The predictive model decision module **218** may apply the telecom data **150** to a predictive model **224** to obtain an indication that a user will switch from a respective current user device (e.g., UD**1**) to another user device (e.g., UD**2**) for future use with the wireless communication network **100**. In some examples, the prediction of future user device preferences may further include an indication of when the user will switch from their current user device to another user device. In further examples, the prediction may include an indication of a type, brand, and/or model of the other user device (i.e., the user device that the user is predicted to switch to). Even still, the prediction may include an indication of how many users will switch from their respective current user devices to another user device.

[0029] The Predictive model decision module **218** may also perform one or more actions based on the prediction of future user device preferences. For example, as discussed above, the predictive model decision module **218** may communicate with one or more nodes **142** of the core network **140** to change one or more parameters of the one or more nodes **142** based on the prediction. In another example, the action performed by the predictive model decision module **218** may include generating a report for one or more user device distributors (e.g., stores, manufacturers, etc.) that indicates the future user device preferences.

[0030] The predictive model training module **214**, in conjunction with the feature extractor module **216**, may perform operations related to updating the predictive model **224** based on the telecom data **150**. As mentioned above, the collection of telecom data **150** may be done on a sliding window basis where the predictive model **224** may be updated at regular intervals (e.g., every month, collect previous 3 months of telecom data to update the predictive model **224**). Particular details regarding the updating of the predictive model **224** will be discussed below with reference to process **400** of FIG. **4**. However, in general, the process of updating the predictive model **224** may include, first, the extraction of features from the telecom data **150** performed by the feature extractor module **216**. In some aspects, a feature is an identifiable set of one or more data points that are comparable. In the context of click-stream data, an extracted feature may correspond to a particular time-ordered series of domain data as well as protocol data. For example, the feature extractor module **216** may identify a first feature that corresponds to a user visiting a particular domain for a certain duration, where a particular amount of data was exchanged between the domain and the user's current user device. In another example, an identified feature may correspond to a user visiting a first domain, followed by a visit to a second domain, where this pattern of visiting the first domain and second domain was repeated by the user multiple times over a certain time period (e.g., every day for 4 days in a row).

[0031] Once the features are identified by the feature extractor module **216**, the predictive model training module **214** may further process the features to ensure that the extracted features represent a threshold number of users of the wireless communication network **100** and to ensure that the extracted features have a strong correlation to users who have/will switch user devices and/or a strong correlation to users who have/will not switch user devices. The predictive model training module **214** may then update the predictive model **224** based on the extracted and processed features. In some examples, the predictive model **224** is stored in the data store **222**.

[0032] The user interface module **220** may enable an administrator to interact with the modules of the future user device preference prediction engine **172** via data input devices and data output devices. For example, the user interface module **220** may enable the administrator to select the type, the amount, or the source of telecom data **150** that are analyzed by the future user device preference prediction engine **172**. In another example, the administrator may also use the user interface module **220** to select a particular type of machine-learning algorithm to apply by the predictive model training module **214** and/or the predictive model decision module **218**. In other examples, the administrator may also use the user interface module **220** to input or modify the specific response or action to be performed by the computing device **170** in response to a determined prediction of future user device preferences.

[0033] In some examples, the predictive model training module **214** and/or the predictive model decision module **218** may implement one or more machine learning techniques that are supervised, unsupervised, or include reinforcement learning techniques. Examples of supervised learning techniques include K-nearest neighbor (KNN), Naive Bayes, logistic regression, support vector machine (SVM), and others. Other supervised learning analysis techniques include linear or polynomial regression analysis, decision tress analysis, and random forests analysis. Examples of unsupervised learning analysis techniques include association analysis, clustering analysis, dimensionality reduction analysis, hidden Markov model analysis techniques, and others. Examples of clustering analysis techniques include K-means, principal component analysis (PCA), singular value decomposition (SVD), incremental clustering, and probability-based clustering techniques. The reinforcement learning technique may be, for example, a Q-learning analysis technique. The techniques described above are some examples of machine learning techniques that may be utilized by the computing device **170** to generate clustered features and/or to identify a particular future user device preference. These are not intended to be limiting.

[0034] In some aspects, the predictive model decision module **218** may also be configured to determine (e.g., calculate) a confidence level, mapping the telecom data **150** to a particular future user device preference.

[0035] The data store **222** may store data that are used by the various modules of the future user device preference prediction engine **172**. The data store **222** may include one or more databases, such as relational databases, object databases, object-relational databases, and/or key-value databases. In various embodiments, the data store **222** may store the telecom data **150** that are collected from one or more nodes of the wireless communication network **100**. The data store **222** may also store the predictive model **224**.

[0036] In some embodiments, the future user device preference prediction engine **172** may be implemented using a distributed-computing framework that distributes the analysis of the telecom data **150** to multiple computing nodes. In such embodiments, a centralized cluster manager may control how each computing node executes tasks for different parts of the root cause analysis. For example, one driver program may store the context of the analysis job and distribute processing tasks to multiple worker nodes. Each worker node may have its own cache and tasks to finish, which corresponds to processing a subset of the telecom data **150**. The framework can be deployed by organizing the worker nodes in a cloud service with the system scripts running on the worker nodes.

Example Processes

[0037] FIG. **3** is a flow diagram of an example process **300** for future user device preference prediction based on telecom data. Process **300** is illustrated as a collection of blocks in a logical flow chart, which represents a sequence of operations that can be implemented in hardware, software, or a combination thereof. In the context of software, the blocks represent computer-executable instructions that, when executed by one or more processors, perform the recited operations. Generally, computer-executable instructions may include routines, programs, objects, components, data structures, and the like that perform particular functions or implement particular abstract data types. The order in which the operations are described is not intended to be construed as a limitation, and any number of the described blocks can be combined in any order and/or in parallel to implement the process. Process **300** is one example process that may be performed by future user device preference prediction engine **172** and thus, is described with reference to FIGS. **1**, **2**, and **3**.

[0038] In process block **302**, the data input module **212** collects (e.g., receives, queries, etc.) the telecom data **150** from at least one node (e.g., one or more nodes **142**) of the wireless communication network **100**. In some examples, the data input module **212** may be configured to periodically collect the telecom data **150** (e.g., every month, collect previous 3-months' worth of telecom data **150**). Next, in a process block **304**, the predictive model decision module **218** applies the telecom data **150** to the predictive model **224** to obtain a prediction of future user device preferences. As mentioned above, the prediction may include an indication that a user will switch from a respective current user device to another user device for future use with the wireless communication network **100**. The prediction may include other information such as the number of users who are expected to switch user devices, a model, brand, and/or type of the user device that a user is expected to switch to, as well as when the user(s) are expected to switch user devices. Next, in process block **306**, the predictive model decision module **218** performs at least one action with respect to the wireless communication network **100** based on the prediction of future user device preferences. For example, the action may include communicating with one or more nodes **142** of the core network **140** to change a parameter of the one or more nodes **142** (e.g., update a node to prepare for increased data traffic). In other examples, the action performed by the predictive model decision module **218** may include generating a report that indicates one or more metrics about the prediction of future user device preferences (e.g., how many users are expected to switch user devices, the type, brand, and/or model that users are expected to switch to, when the users are expected to switch user devices, etc.). In some examples, the report may be communicated (e.g., sent) to one or more user device distributors, such as a manufacturer, retail store, etc.

[0039] In some aspects, the telecom data **150** received at the computing device **170** may further include an indication of a user location of the user (e.g., USER1) associated with a respective current user device. If so, the prediction of future user device preferences may be generated by the predictive model decision module **218** with respect to a

geographic region that includes the user location. For example, a record **160** included in the telecom data **150** may indicate that user is located in Bellevue, Wash. (e.g., based on billing address associated with the user). Thus, the prediction of future user device preferences may be generated with respect to all users located in the Bellevue area, such that suppliers and/or user device distributers may adjust and/or update their supplies of user devices for specific geographic locations.

[0040] FIG. **4** is a flow diagram of an example process **400** for updating the predictive model **224** for use with future user device preference prediction. Process **400** is one possible process performed by the feature extractor module **216** and predictive model training module **214** of FIG. **2**. Process **400** is described with reference to FIG. **5** which illustrates an example implementation of updating the predictive model **224**.

[0041] In a process block **402**, the feature extractor module **216** extracts a plurality of features **502**. As discussed above, a feature is an identifiable set of one or more data points that are comparable. In some aspects, an extracted feature may be referred to as an "interesting" part of the telecom data **150** as represented by the records **160**. A desirable property for feature detection is repeatability: whether or not the same feature may be detected in two or more different records **160**.

[0042] In some examples, feature detection is a low-level processing operation. That is, it is usually performed as the first operation on the telecom data **150**, and includes examining record **160** to see if there is a feature present. Occasionally, when feature detection is computationally expensive and there are time constraints, a higher-level algorithm may be used to guide the feature detection stage, so that only certain parts of the telecom data **150** are searched for features.

[0043] Next, in process block **404**, the plurality of features **502** are filtered to obtain a plurality of filtered features **504**. The Filtered features **504** may be generated such that only extracted features which represent a threshold number of total users of the wireless communication network **100** are retained. For example, an identified feature that only represents a minor number (e.g., <50%) of users would be discarded, whereas a feature that corresponds to a majority (e.g., >50%) of users would be kept. In some examples, the threshold number is higher, such as 90%. Thus, only features that correspond to 90% of the total number of users in the wireless communication network **100** may be retained in the plurality of filtered features **504**. By way of example, an identified feature, such as a user visiting a particular website, may only be detected as being performed by a small number (e.g., 10%) of the total users. In this case, the identified feature may be discarded as it would not be a reliable predictor of future user device preferences if applied to other users of the wireless communication network **100**.

[0044] In process block **406**, the plurality of filtered features **504** are then separated into two groups: a first group (i.e., control group **506**), and a second group (i.e., switcher group **508**). The control group **506** may include filtered features corresponding to users who did not switch from a respective current user device to another user device over a time period that the telecom data **150** was collected (e.g., previous 3-months). The switcher group **508** may include filtered features corresponding to users who did indeed switch from a respective current user device to another user device over the time period. In some examples, the control group **506** may be larger than the switcher group **508** (i.e., more instances of features in the control group **506** as compared to the number of instances of features included in the switcher group **508**). Accordingly, the predictive model training module **214** may undersample the control group **506** and/or oversample the switcher group **508**. In some examples, undersampling and oversampling may involve one or more data analysis techniques to adjust the class distribution of the control group **506** and/or switcher group **508**. The undersampling and/or oversampling may involve using a bias to select more or less instances of features from one of the groups than from the other. Example techniques for undersampling and oversampling the control group **506** and switcher group **508** may include the synthetic minority over-sampling technique (SMOTE) and the adaptive synthetic sampling approach (ADASYN).

[0045] In some examples, one or more of the same features may appear in both the control group **506** as appear in the switcher group **508**. Accordingly, in process block **408**, the predictive model training module **214** may determine a correlation between each particular feature and the two groups **506** and **508**. That is, the features may be further filtered to keep only those features that clearly indicate that a user has/will switch devices. For example, a feature that has a close correlation to both the control group **506** and the switcher group **508** may be discarded (e.g., an identified feature has a 50% chance of indicating that a user will switch devices and a 50% chance of indicating that a user will not switch devices). Conversely, if a feature is closely correlated to one of the groups, then the feature may be retained (e.g., in 90% of the occurrences that this feature appears, the user ends up switching devices, or in 90% of the occurrences that this feature appears, the user ends up not switching devices).

[0046] Accordingly, process block **410** includes removing filtered features to obtain a plurality of reduced filtered features **510**, where the plurality of reduced filtered features **510** includes only those features which have a strong correlation to one of the two groups **506** and **508**. By way of example, for each feature included in the plurality of filtered features **504**, the predictive model training module **214** may determine a first correlation of the filtered feature to the control group **506** and a second correlation of the filtered feature to the switcher group **508**. If a difference between the first correlation and the second correlation is less than a minimum correlation threshold, then the filtered feature may be removed such that it does not appear in the plurality of reduced filtered features **510**. If, however, the difference between the first correlation and the second correlation is greater than the minimum correlation threshold, then the filtered feature may be kept such that it is retained in the plurality of reduced filtered features **510**.

[0047] By way of example, consider a first feature that has a 10% correlation to the control group **506** (i.e., 10% of occurrences of the first feature are in the control group **506**) and a 90% correlation to the switcher group **508** (i.e., 90% of the occurrences of the first feature are in the switcher group **508**). In this case, assuming a minimum correlation threshold of 75%, the first feature would be retained (e.g., 90%−10%=80%, which is greater than the 75% minimum correlation threshold). However, if the first feature's correlation to the first group is determined to be 40% and the first feature's correlation to the second group is 60%, then the first feature may be removed and not included in the

plurality of reduced filtered features **510** (e.g., 60%–40%=20%, which is less than the 75% minimum correlation threshold).

[0048] Accordingly, the plurality of reduced filtered features **510** may include only those features which have a strong correlation (i.e., greater than the minimum correlation threshold) to either control group **506** or to switcher group **508**.

[0049] Next, in process block **412**, the predictive model training module **214** updates the predictive model **224** based on the plurality of reduced filtered features **510**. In some examples, the updated predictive model **224** may be stored to data store **222** and for application to subsequently acquired telecom data **150**.

CONCLUSION

[0050] Although the subject matter has been described in language specific to structural features and/or methodological acts, it is to be understood that the subject matter defined in the appended claims is not necessarily limited to the specific features or acts described. Rather, the specific features and acts are disclosed as exemplary forms of implementing the claims.

What is claimed is:

1. A computer-implemented method, comprising:

collecting telecom data from at least one node of a wireless communication network, wherein the telecom data includes records for a plurality of occurrences of user interaction with the wireless communication network via a respective current user device;

applying the telecom data to a predictive model to obtain a prediction of future user device preferences, wherein the prediction of future user device preferences comprises an indication that a user will switch from the respective current user device to another user device for future use with the wireless communication network; and

performing an action with respect to the wireless communication network in response to the prediction of future user device preferences.

2. The computer-implemented method of claim **1**, wherein the prediction of future user device preferences further comprises at least one additional indication selected from the group consisting of: an indication of when the user will switch from the respective current user device to another user device for the future use with the wireless communication network, an indication of a type, brand, or model of the other user device, and an indication of a number of users that will switch from the respective current user device to another user device for future use with the wireless communication network.

3. The computer-implemented method of claim **1**, wherein the records included in the telecom data comprise at least one event data record (EDR) corresponding to a user's interaction with the wireless communication network via the respective current user device.

4. The computer-implemented method of claim **3**, wherein the at least one EDR comprises click-stream data corresponding to a navigation of the Internet by the user.

5. The computer-implemented method of claim **4**, wherein the click-stream data comprises domain data and protocol data, the domain data indicating at least one domain name of an internet service or website visited by the user, the protocol data indicating at least one additional information selected from the group consisting of: a protocol utilized by the respective current user device when accessing the internet service or website, a frequency with which the respective current user device accessed the internet service or website, an amount of data exchanged between the respective current user device and the internet service or website, and a duration of at least one occurrence of the user accessing the internet service or website via the respective current user device.

6. The computer-implemented method of claim **1**, further comprising:

updating the predictive model based on the telecom data.

7. The computer-implemented method of claim **6**, wherein updating the predictive model comprises:

extracting a plurality of features from the telecom data; and

filtering the plurality of features to obtain a plurality of filtered features that includes extracted features corresponding to a threshold number of total users of the wireless communication network.

8. The computer-implemented method of claim **7**, wherein the threshold number represents a majority of the total users of the wireless communication network.

9. The computer-implemented method of claim **7**, further comprising:

separating the plurality of filtered features into a first group and a second group, the first group including filtered features corresponding to users who did not switch from the respective current user device to another user device over a time period that the telecom data was collected, the second group including filtered features corresponding to users who did switch from the respective current user device to the another user device during the time period that the telecom data was collected.

10. The computer-implemented method of claim **9**, further comprising:

for each filtered feature included in the plurality of filtered features, determining a first correlation of the filtered feature to the first group and a second correlation of the filtered feature to the second group; and

removing the filtered feature from the plurality of filtered features to obtain a reduced plurality of filtered features based on the first and second correlations.

11. The computer-implemented method of claim **10**, wherein removing the filtered feature comprises:

removing the filtered feature from the plurality of filtered features in response to determining that a difference between the first correlation and the second correlation is less than a minimum correlation threshold.

12. The computer-implemented method of claim **10**, further comprising:

keeping the filtered feature in the plurality of filtered features in response to determining that a difference between the first correlation and the second correlation is greater than a minimum correlation threshold.

13. The computer-implemented method of claim **1**, wherein the telecom data further includes an indication of a user location of the user associated with the respective current user device, and wherein the prediction of future user device preferences is with respect to a geographic region that includes the user location.

14. The computer-implemented method of claim **1**, wherein performing the action with respect to the wireless

communication network comprises performing at least one action selected from the group consisting of: changing a parameter of at least one node of the wireless communication network and generating a report for one or more user device distributors indicating the prediction of future user device preferences.

15. One or more non-transitory computer-readable media storing computer-executable instructions, which when executed by the at least one processor, direct the at least one processor to:

collect telecom data from at least one node of a wireless communication network, wherein the telecom data includes records for a plurality of occurrences of user interaction with the wireless communication network via a respective current user device;

apply the telecom data to a predictive model to obtain a prediction of future user device preferences, wherein the prediction of the future user device preferences comprises an indication that a user will switch from the respective current user device to another user device for future use with the wireless communication network; and

perform an action with respect to the wireless communication network in response to the prediction of future user device preferences, wherein the action comprises at least one action selected from the group consisting of: changing a parameter of at least one node of the wireless communication network and generating a report for one or more user device distributors indicating the prediction of future user device preferences.

16. The one or more non-transitory computer-readable media of claim **15**, wherein the records included in the telecom data comprise at least one event data record (EDR) corresponding to a user's interaction with the wireless communication network via the respective current user device, wherein the at least one EDR comprises click-stream data corresponding to a navigation of the Internet by the user.

17. The one or more non-transitory computer-readable media of claim **16**, wherein the click-stream data comprises domain data and protocol data, the domain data indicating at least one domain name of an internet service or website visited by the user, the protocol data indicating at least one additional information selected from the group consisting of: a protocol utilized by the respective current user device when accessing the internet service or website, a frequency with which the respective current user device accessed the internet service or website, an amount of data exchanged between the respective current user device and the internet service or website, and a duration of at least one occurrence of the user accessing the internet service or website via the respective current user device.

18. The one or more non-transitory computer-readable media of claim **15**, further comprising updating the predictive model based on the telecom data.

19. A computing device, comprising:

at least one processor; and

at least one memory coupled to the at least one processor, the at least one memory having instructions stored therein, which when executed by the at least one processor, direct the computing device to:

collect telecom data from at least one node of a wireless communication network, wherein the telecom data includes records for a plurality of occurrences of user interaction with the wireless communication network via a respective current user device;

apply the telecom data to a predictive model to obtain a prediction of future user device preferences, wherein the prediction of future user device preferences comprises an indication that a user will switch from the respective current user device to another user device for future use with the wireless communication network; and

perform an action with respect to the wireless communication network in response to the prediction of future user device preferences.

20. The computing device of claim **19**, wherein the records included in the telecom data comprise at least one event data record (EDR) corresponding to a user's interaction with the wireless communication network via the respective current user device, wherein the at least one EDR comprises click-stream data corresponding to a navigation of the Internet by the user, and wherein the at least one memory further comprises instructions to direct the computing device to:

update the predictive model based on the telecom data.

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