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(54) **SYSTEMS AND METHODS FOR INCREASING CUSTOMER REVIEWS**

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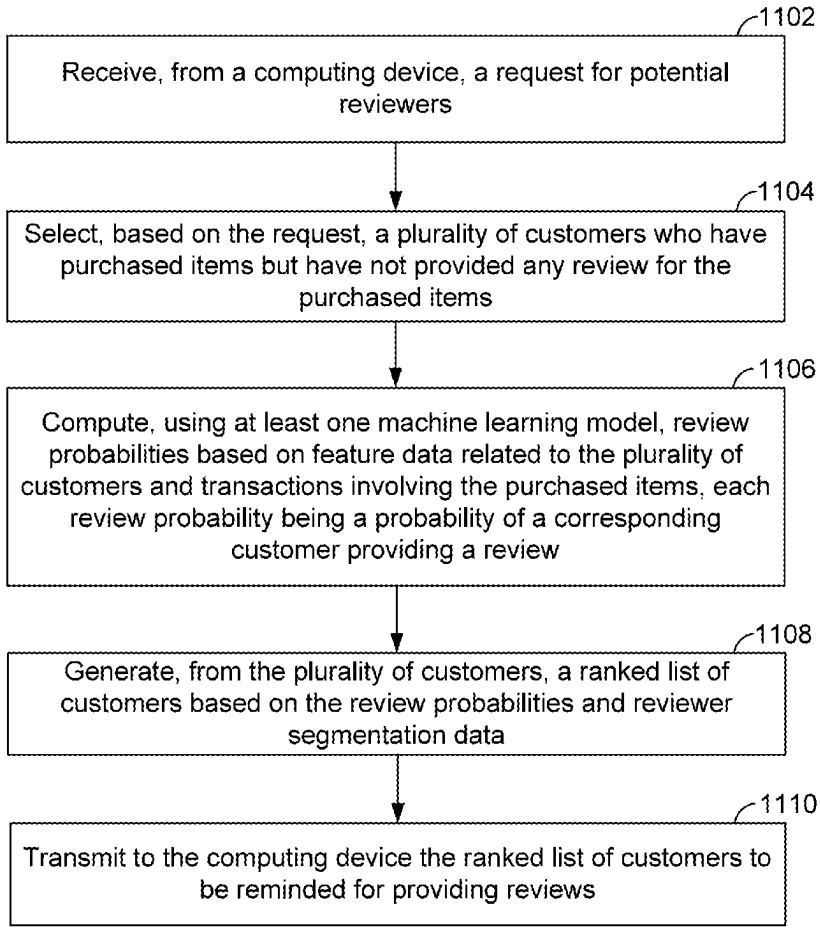
(57) **ABSTRACT**

Systems and methods for predicting and motivating customers to provide reviews are disclosed. In some embodiments, a disclosed method includes: receiving, from a computing device, a request for potential reviewers; selecting, based on the request, a plurality of customers who have purchased items but have not provided any review for the purchased items; computing, using at least one machine learning model, review probabilities based on feature data related to the plurality of customers and transactions involving the purchased items, wherein each review probability is a probability of a corresponding customer providing a review; generating, from the plurality of customers, a ranked list of customers based on the review probabilities and reviewer segmentation data; and transmitting to the computing device the ranked list of customers to be reminded for providing reviews.



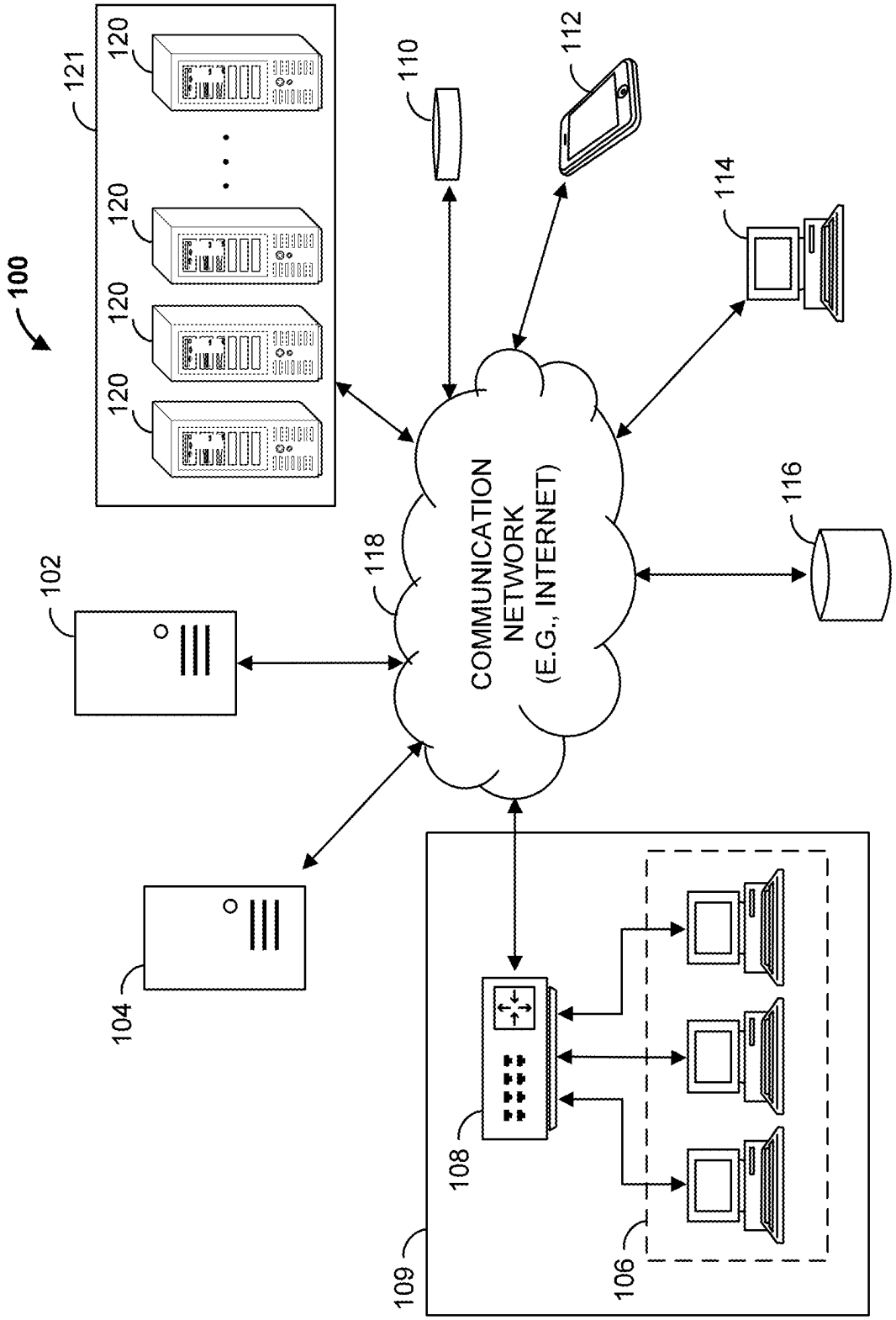

100
121
120
120
120
120
110
112
114
116
COMMUNICATION NETWORK (E.G., INTERNET)
118
102
104
108
109
106

FIG. 1

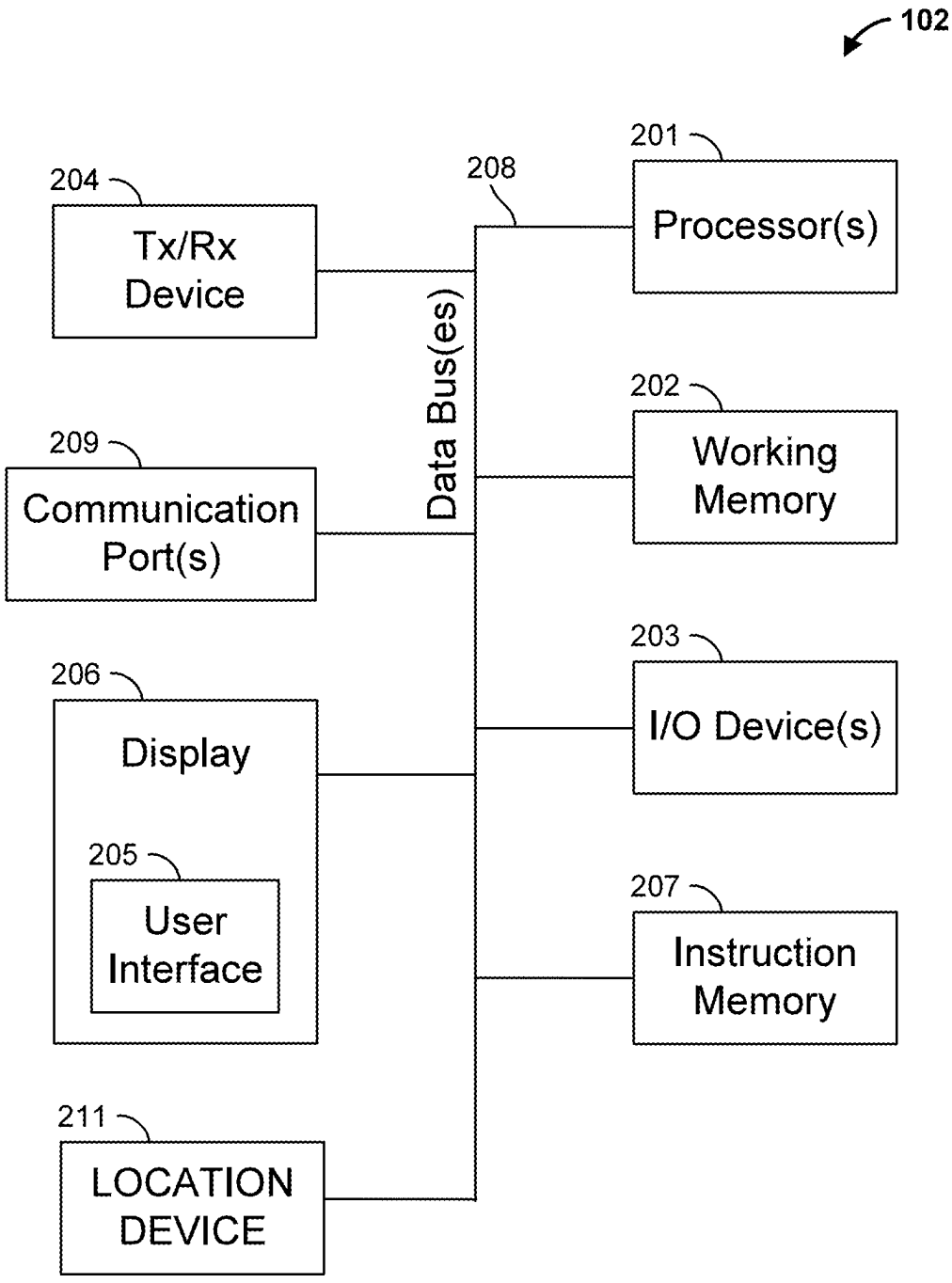

102
201
Processor(s)
208
204
Tx/Rx Device
Data Bus(es)
202
Working Memory
209
Communication Port(s)
203
I/O Device(s)
206
Display
205
User Interface
207
Instruction Memory
211
LOCATION DEVICE

FIG. 2

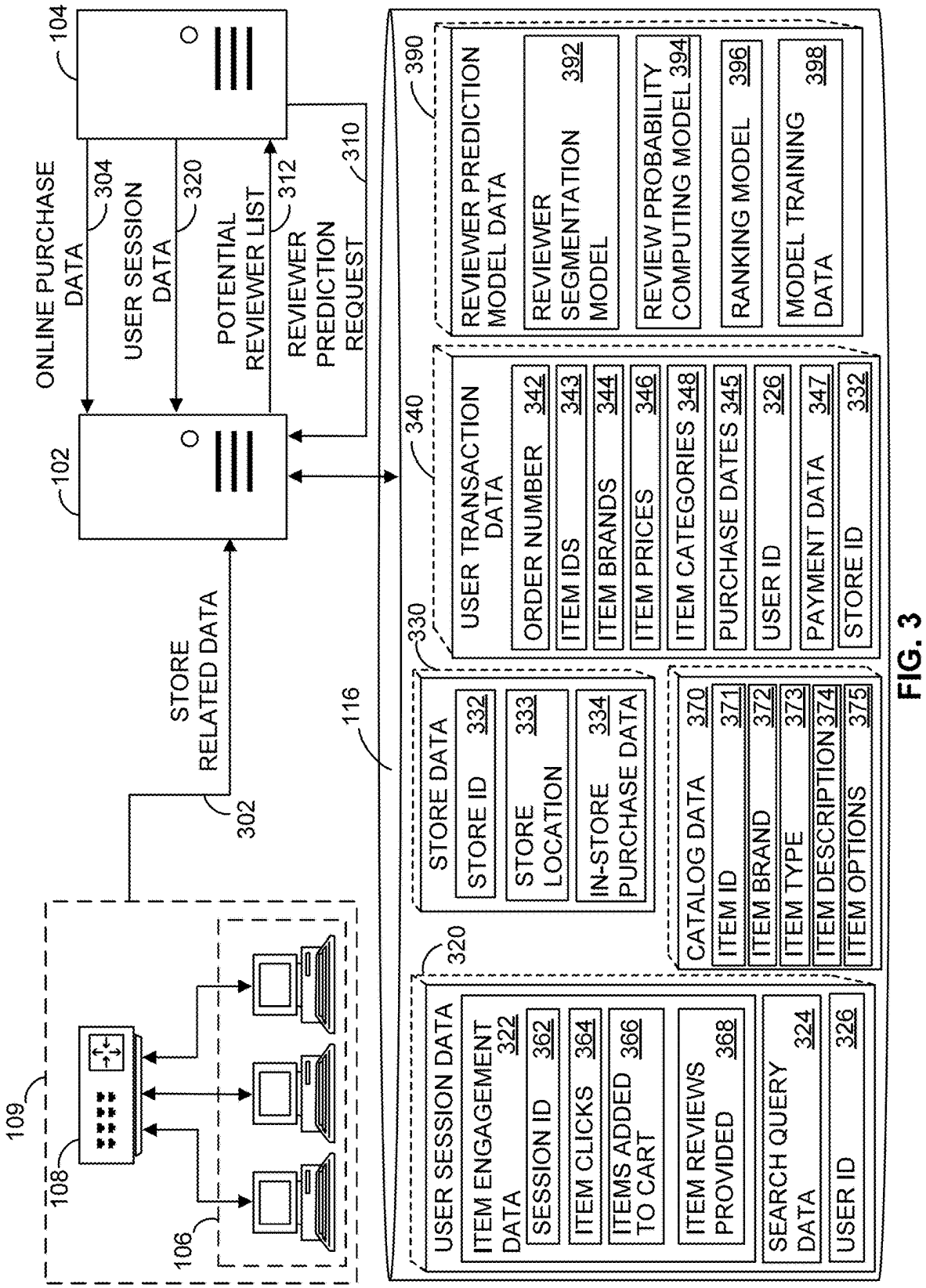

104
ONLINE PURCHASE DATA
304
USER SESSION DATA
320
POTENTIAL REVIEWER LIST
312
REVIEWER PREDICTION REQUEST
310
102
STORE RELATED DATA
302
109
108
106
116
340
330
390
USER TRANSACTION DATA
ORDER NUMBER 342
ITEM IDS 343
ITEM BRANDS 344
ITEM PRICES 346
ITEM CATEGORIES 348
PURCHASE DATES 345
USER ID 326
PAYMENT DATA 347
STORE ID 332
REVIEWER PREDICTION MODEL DATA
REVIEWER SEGMENTATION MODEL 392
REVIEW PROBABILITY COMPUTING MODEL 394
RANKING MODEL 396
MODEL TRAINING DATA 398
STORE DATA
STORE ID 332
STORE LOCATION 333
IN-STORE PURCHASE DATA 334
CATALOG DATA 370
ITEM ID 371
ITEM BRAND 372
ITEM TYPE 373
ITEM DESCRIPTION 374
ITEM OPTIONS 375
320
USER SESSION DATA
ITEM ENGAGEMENT DATA 322
SESSION ID 362
ITEM CLICKS 364
ITEMS ADDED TO CART 366
ITEM REVIEWS PROVIDED 368
SEARCH QUERY DATA 324
USER ID 326

FIG. 3

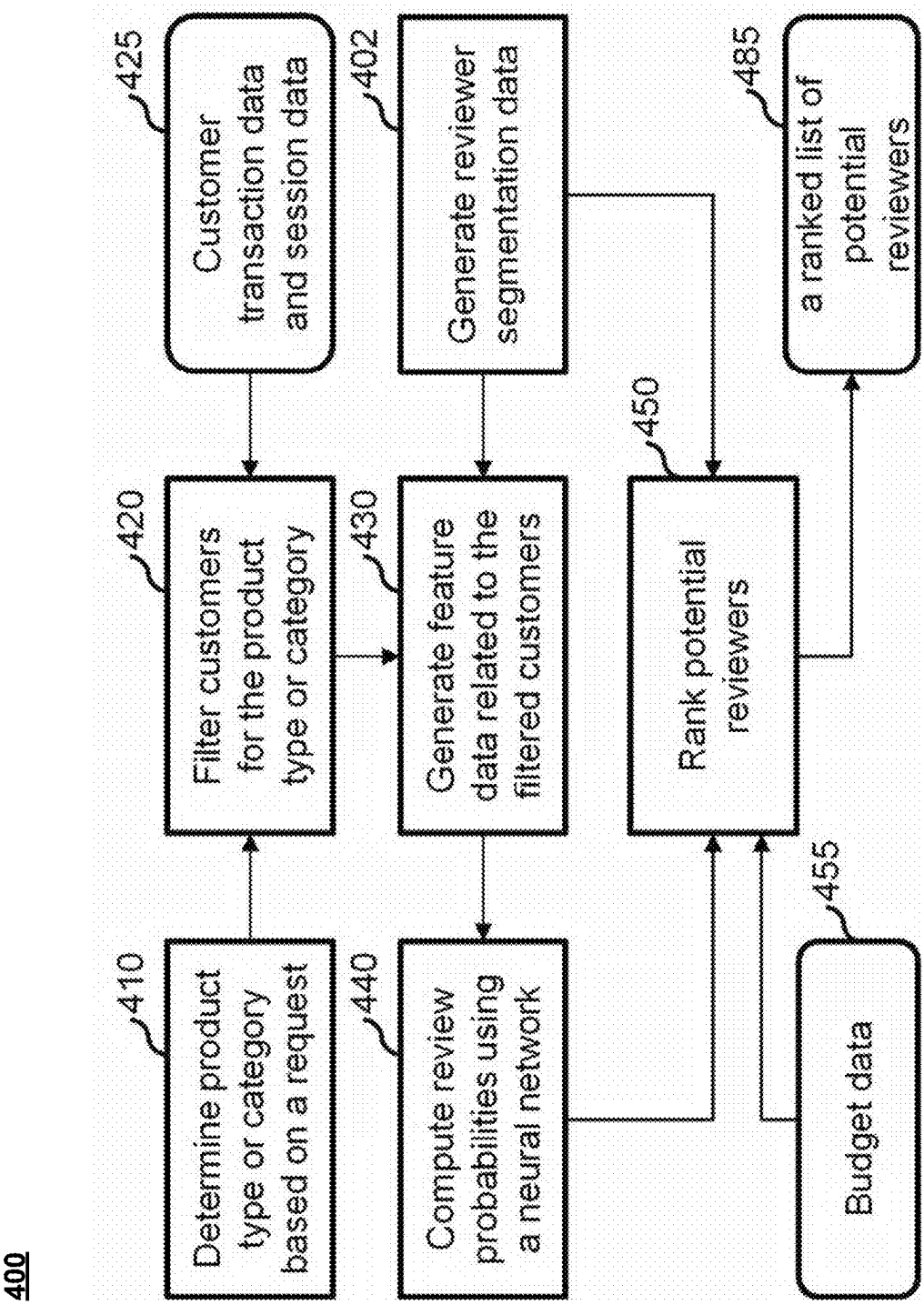

400
410
Determine product type or category based on a request
420
Filter customers for the product type or category
425
Customer transaction data and session data
402
Generate reviewer segmentation data
430
Generate feature data related to the filtered customers
440
Compute review probabilities using a neural network
450
Rank potential reviewers
455
Budget data
485
a ranked list of potential reviewers

FIG. 4

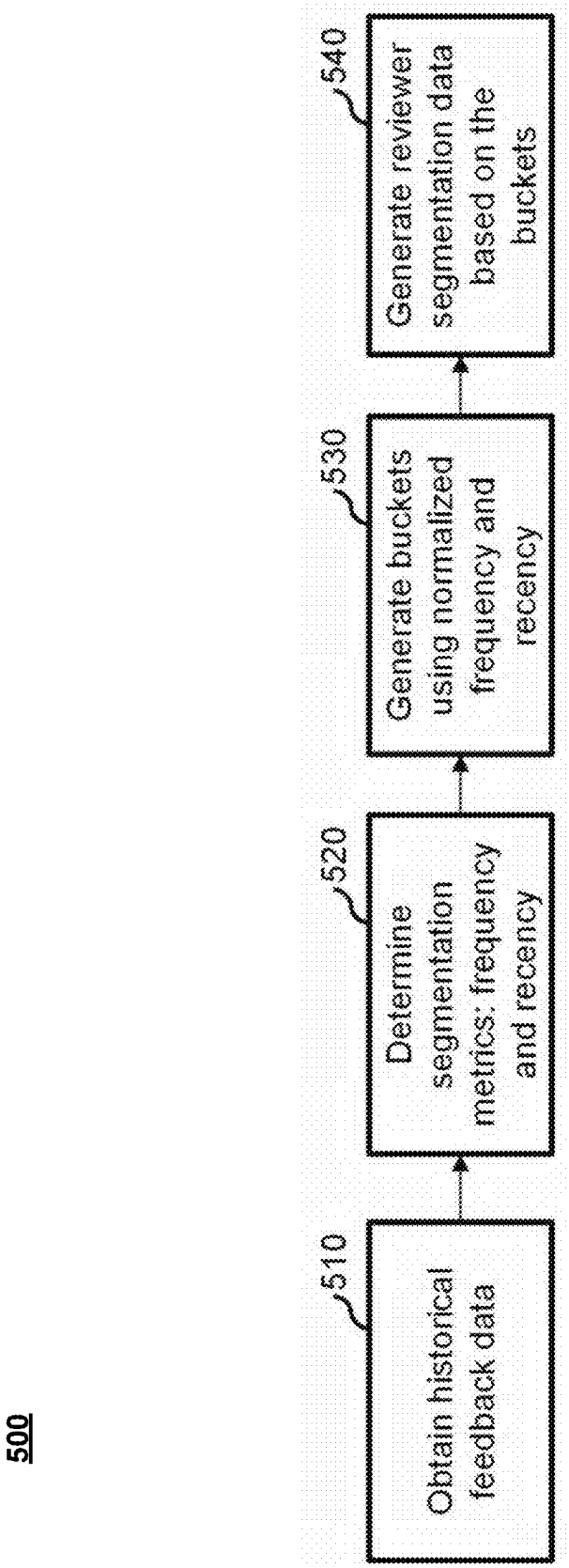

500
510
Obtain historical feedback data
520
Determine segmentation metrics: frequency and recency
530
Generate buckets using normalized frequency and recency
540
Generate reviewer segmentation data based on the buckets

FIG. 5

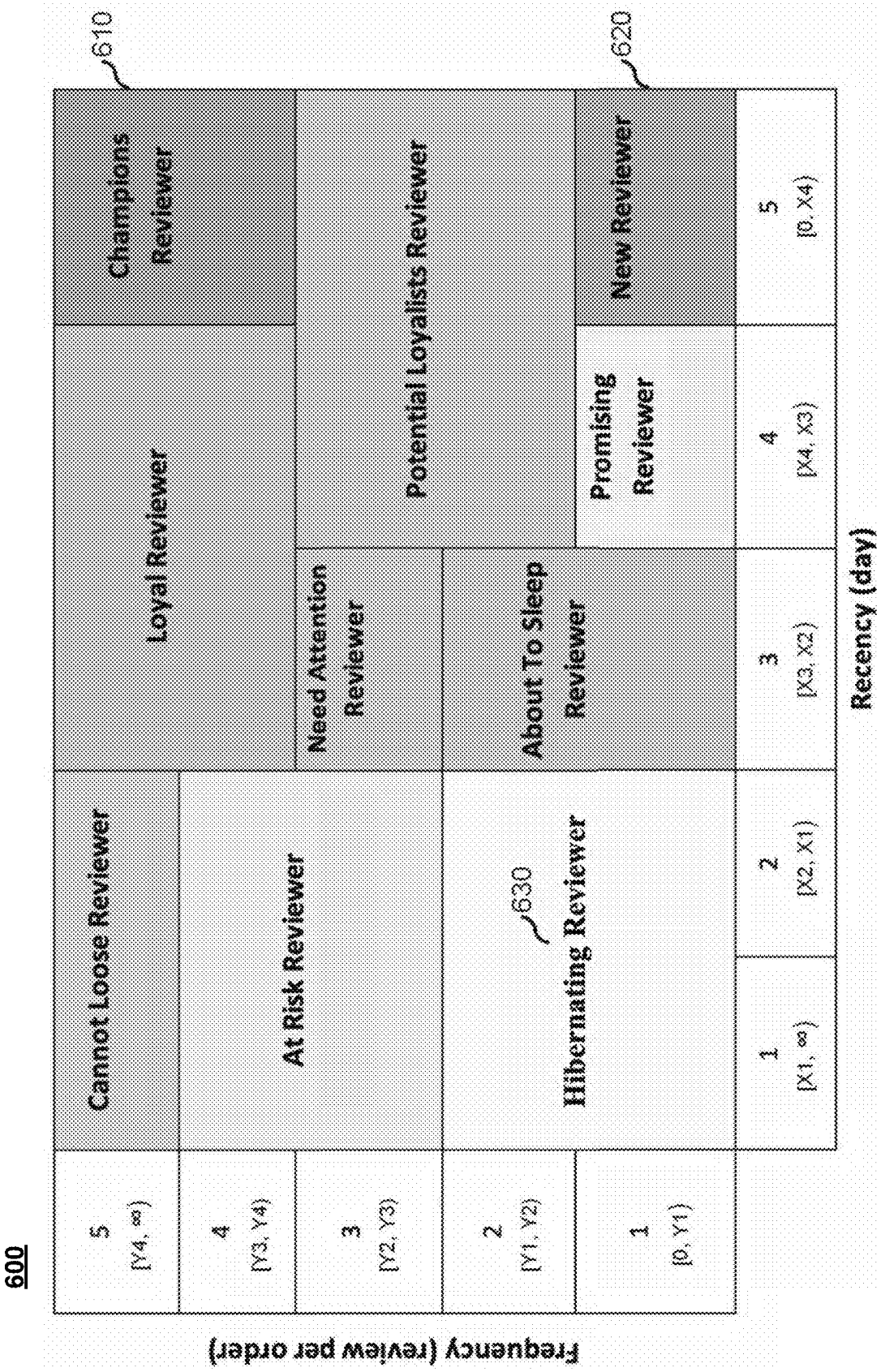

600
610
620
630
Champions Reviewer
Loyal Reviewer
Potential Loyalists Reviewer
New Reviewer
Cannot Loose Reviewer
Need Attention Reviewer
Promising Reviewer
At Risk Reviewer
About To Sleep Reviewer
Hibernating Reviewer
5 [Y4, ∞)
4 [Y3, Y4)
3 [Y2, Y3)
2 [Y1, Y2)
1 [0, Y1)
1 [X1, ∞)
2 [X2, X1)
3 [X3, X2)
4 [X4, X3)
5 [0, X4)
Frequency (review per order)
Recency (day)

FIG. 6

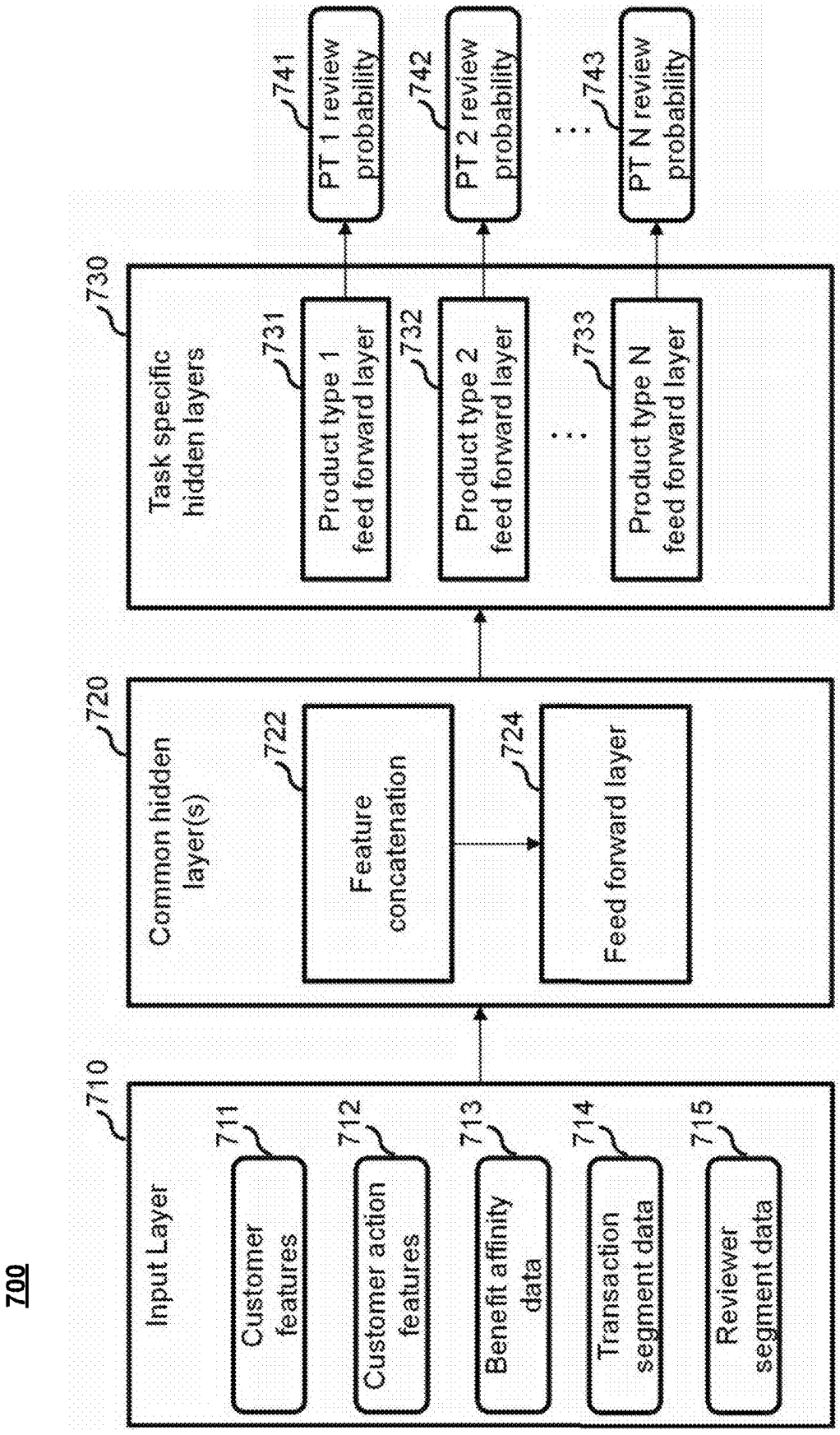

700
710
Input Layer
711
Customer features
712
Customer action features
713
Benefit affinity data
714
Transaction segment data
715
Reviewer segment data
720
Common hidden layer(s)
722
Feature concatenation
724
Feed forward layer
730
Task specific hidden layers
731
Product type 1 feed forward layer
732
Product type 2 feed forward layer
733
Product type N feed forward layer
741
PT 1 review probability
742
PT 2 review probability
743
PT N review probability

FIG. 7

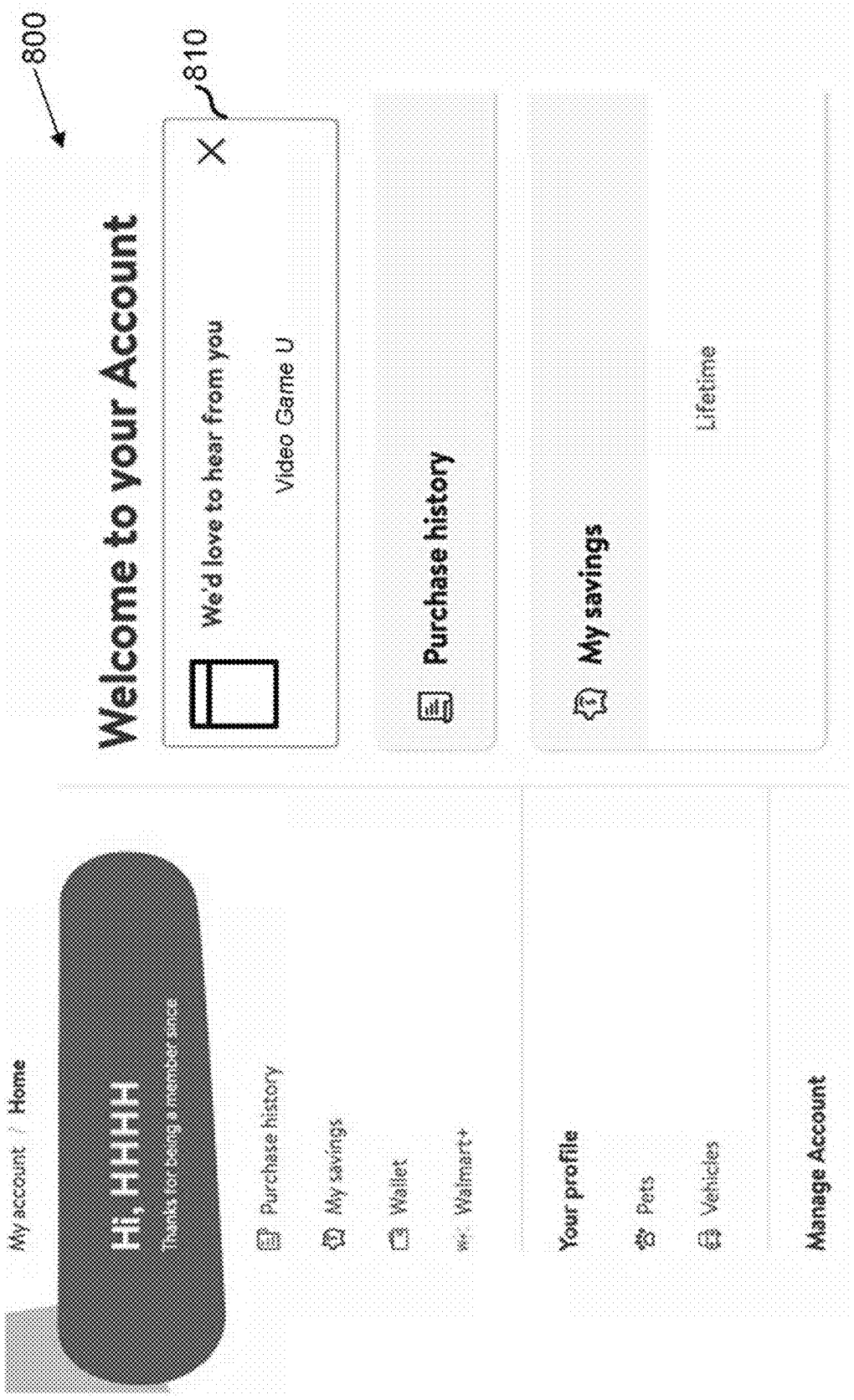

800
810
Welcome to your Account
We'd love to hear from you
Video Game U
Purchase history
My savings
Lifetime
My account / Home
Hi, HHHH
Purchase history
My savings
Wallet
Walmart+
Your profile
Pets
Vehicles
Manage Account

FIG. 8

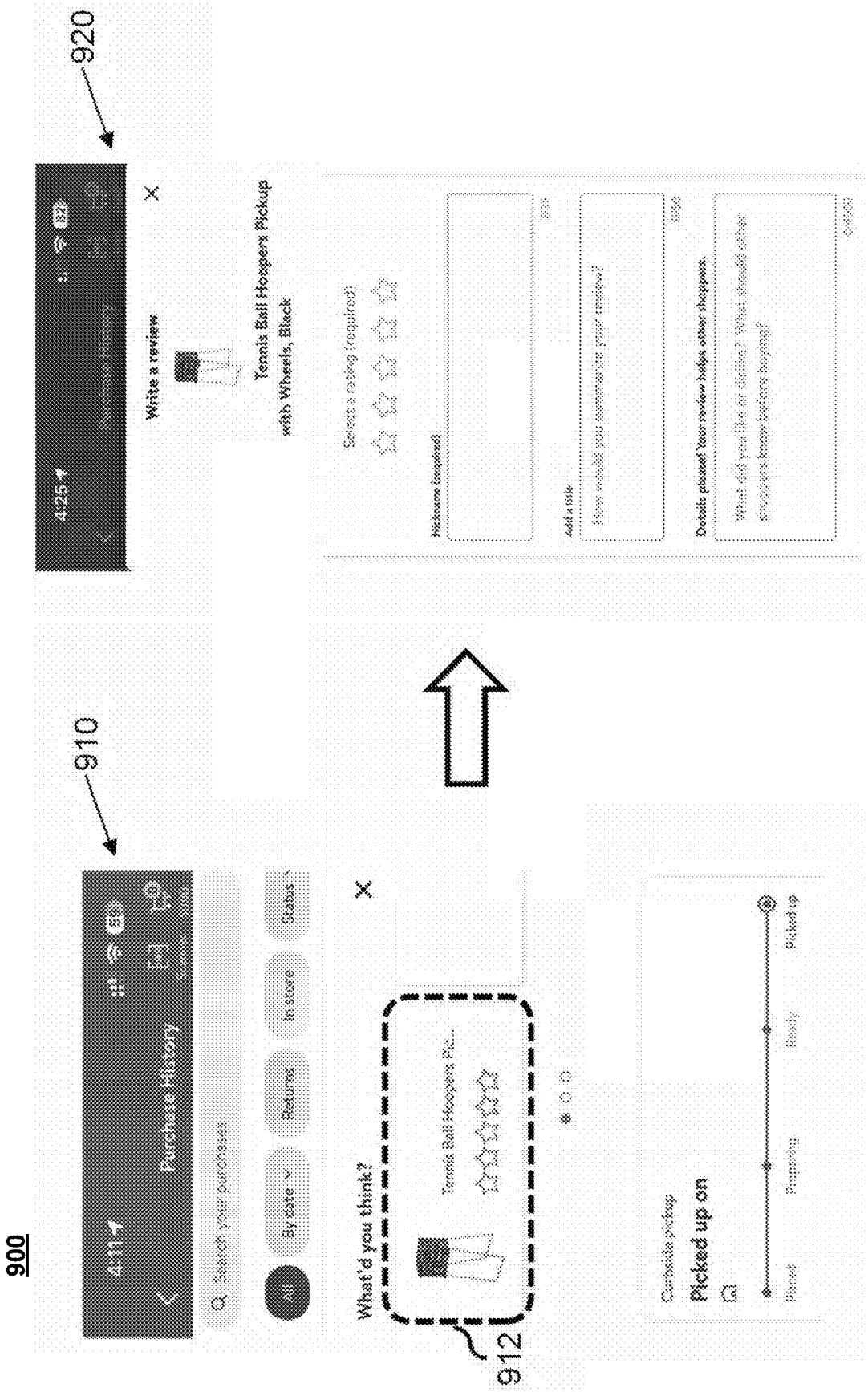

900
910
920
912
Purchase History
Search your purchases
By date
Returns
In store
Status
What'd you think?
Tennis Ball Hoppers Pic...
Curbside pickup
Picked up on
Placed
Preparing
Ready
Picked up
Write a review
Tennis Ball Hoppers Pickup with Wheels, Black
Select a rating (required)
Nickname (required)
Add a title
How would you summarize your review?
Details please! Your review helps other shoppers.
What do you like or dislike? What should other shoppers know before buying?

FIG. 9

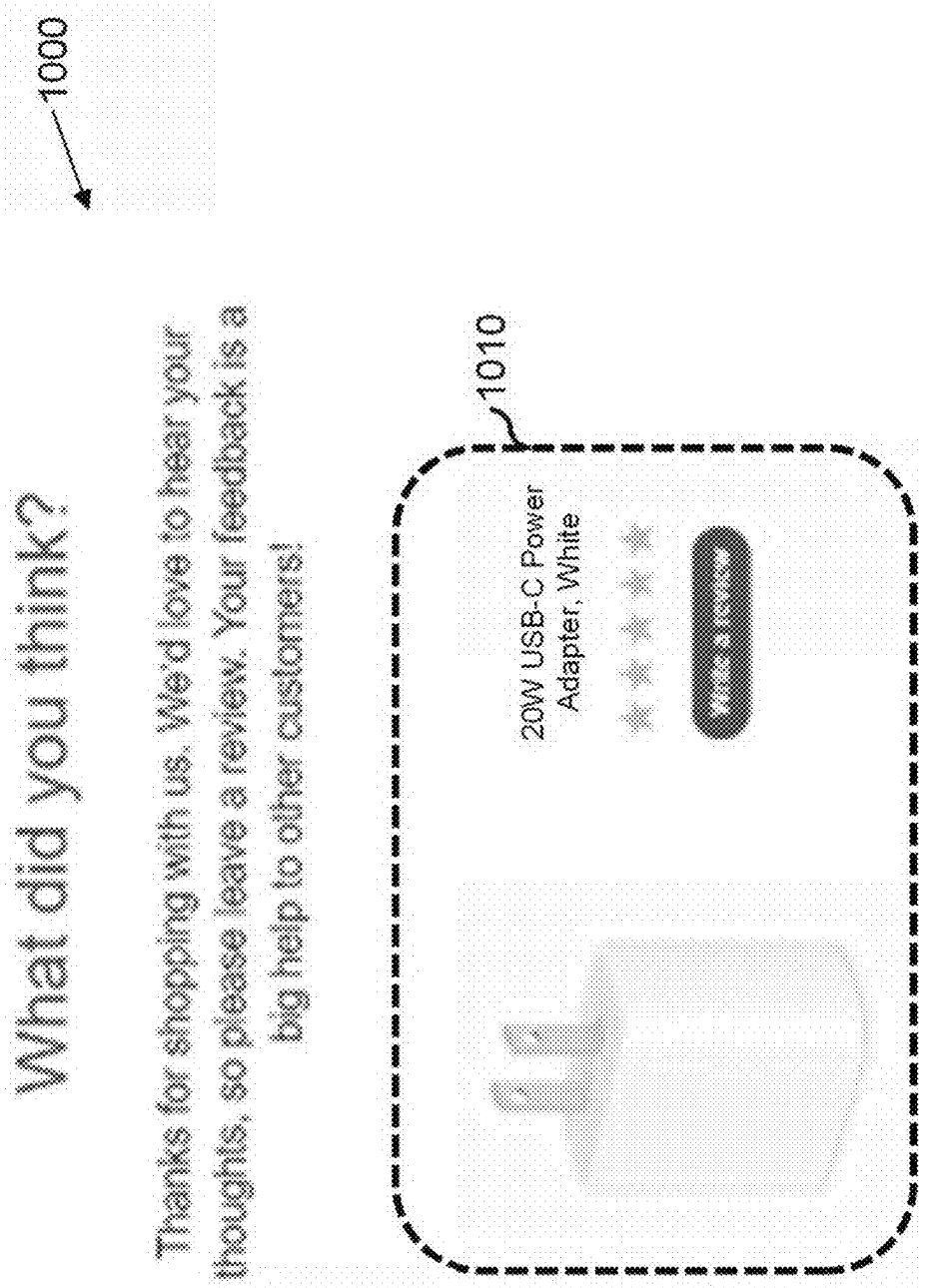

1000
What did you think?
Thanks for shopping with us. We'd love to hear your thoughts, so please leave a review. Your feedback is a big help to other customers!
1010
20W USB-C Power Adapter, White

FIG. 10

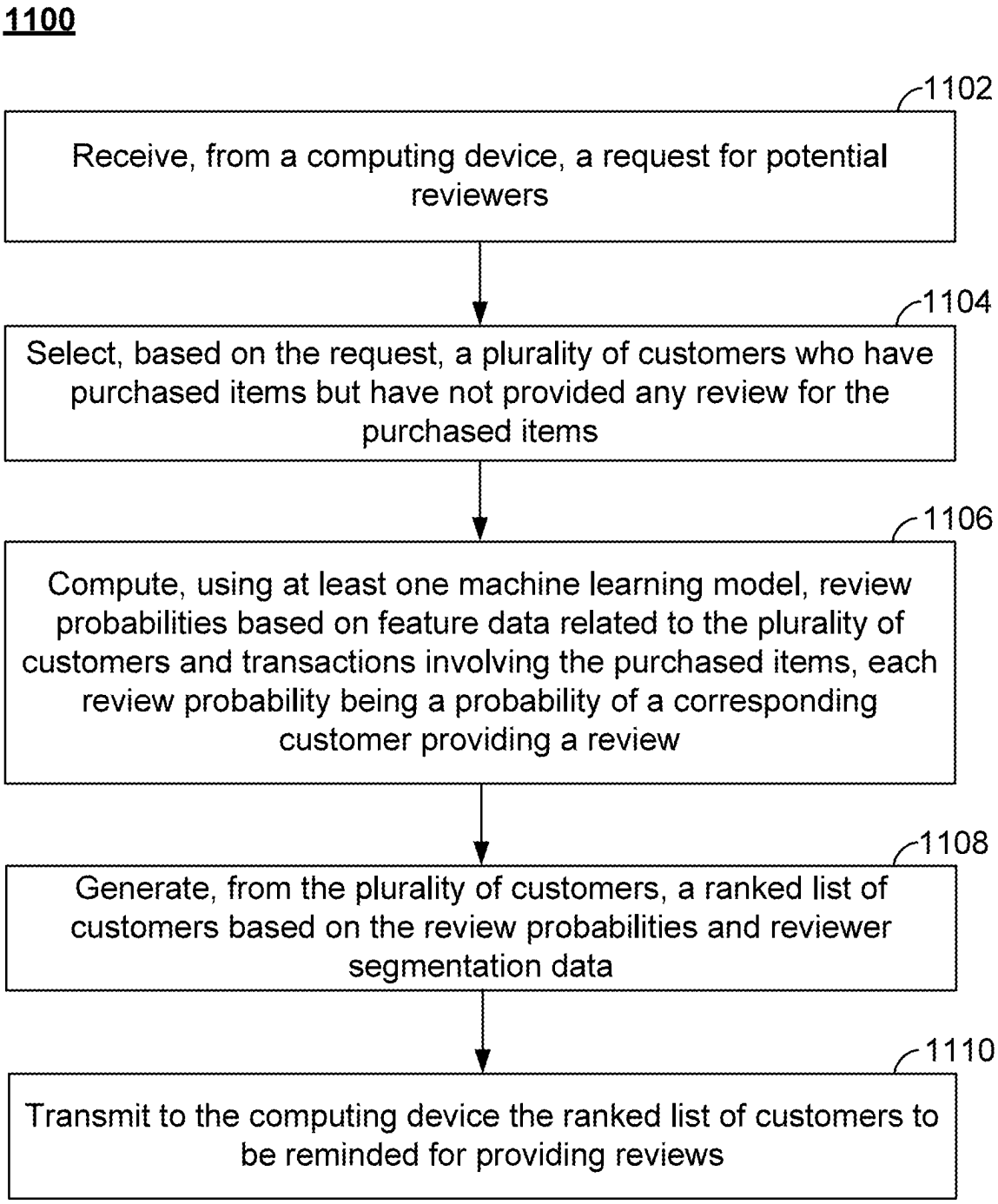

1100
1102
Receive, from a computing device, a request for potential reviewers
1104
Select, based on the request, a plurality of customers who have purchased items but have not provided any review for the purchased items
1106
Compute, using at least one machine learning model, review probabilities based on feature data related to the plurality of customers and transactions involving the purchased items, each review probability being a probability of a corresponding customer providing a review
1108
Generate, from the plurality of customers, a ranked list of customers based on the review probabilities and reviewer segmentation data
1110
Transmit to the computing device the ranked list of customers to be reminded for providing reviews

FIG. 11

SYSTEMS AND METHODS FOR INCREASING CUSTOMER REVIEWS

CROSS-REFERENCE TO RELATED APPLICATION

[0001] This application claims benefit to U.S. Provisional Application Ser. No. 63/552,853, entitled "SYSTEMS AND METHODS FOR INCREASING CUSTOMER REVIEWS," filed on Feb. 13, 2024, the disclosure of which is incorporated herein by reference in its entirety.

TECHNICAL FIELD

[0002] This application relates generally to customer engagement and, more particularly, to systems and methods for predicting and motivating customers to provide reviews of purchased items.

BACKGROUND

[0003] An e-commerce platform of a retailer may provide a large number of products for sale to customers over the Internet. In order to enhance the online shopping experience and to allow customers to fully research a particular product, the retailer can provide various product information, which might include a detailed description of the product, a list of features, technical specifications, as well as reviews of the product provided by other customers. The product reviews allow a potential purchaser to evaluate what other customers think about the product. The reviews may include a quantitative rating for a product, comments regarding another customer's experience and satisfaction with the product, and potentially other information.

[0004] Some study results have shown that an increase in product rating leads to an increase in product sales. In accordance with other study results, an increase in the number of reviews for an item leads to an increase in sales of the item. That is, customers have a propensity to purchase products with a greater number of reviews. It is with respect to these and other considerations that the disclosure made herein is presented.

SUMMARY

[0005] The embodiments described herein are directed to systems and methods for predicting and motivating customers to provide reviews of purchased items.

[0006] In various embodiments, a system including a non-transitory memory configured to store instructions thereon and at least one processor is disclosed. The at least one processor is operatively coupled to the non-transitory memory and configured to read the instructions to: receive, from a computing device, a request for potential reviewers; select, based on the request, a plurality of customers who have purchased items but have not provided any review for the purchased items; compute, using at least one machine learning model, review probabilities based on feature data related to the plurality of customers and transactions involving the purchased items, wherein each review probability is a probability of a corresponding customer providing a review; generate, from the plurality of customers, a ranked list of customers based on the review probabilities and reviewer segmentation data; and transmit to the computing device the ranked list of customers to be reminded for providing reviews

[0007] In various embodiments, a computer-implemented method is disclosed. The computer-implemented method includes: receiving, from a computing device, a request for potential reviewers; selecting, based on the request, a plurality of customers who have purchased items but have not provided any review for the purchased items; computing, using at least one machine learning model, review probabilities based on feature data related to the plurality of customers and transactions involving the purchased items, wherein each review probability is a probability of a corresponding customer providing a review; generating, from the plurality of customers, a ranked list of customers based on the review probabilities and reviewer segmentation data; and transmitting to the computing device the ranked list of customers to be reminded for providing reviews.

[0008] In various embodiments, a non-transitory computer readable medium having instructions stored thereon is disclosed. The instructions, when executed by at least one processor, cause at least one device to perform operations including: receiving, from a computing device, a request for potential reviewers; selecting, based on the request, a plurality of customers who have purchased items but have not provided any review for the purchased items; computing, using at least one machine learning model, review probabilities based on feature data related to the plurality of customers and transactions involving the purchased items, wherein each review probability is a probability of a corresponding customer providing a review; generating, from the plurality of customers, a ranked list of customers based on the review probabilities and reviewer segmentation data; and transmitting to the computing device the ranked list of customers to be reminded for providing reviews.

BRIEF DESCRIPTION OF THE DRAWINGS

[0009] The features and advantages of the present invention will be more fully disclosed in, or rendered obvious by the following detailed description of the preferred embodiments, which are to be considered together with the accompanying drawings wherein like numbers refer to like parts and further wherein:

[0010] FIG. **1** is a network environment configured for predicting and motivating customers to provide item reviews, in accordance with some embodiments of the present teaching;

[0011] FIG. **2** is a block diagram of a reviewer prediction computing device, in accordance with some embodiments of the present teaching;

[0012] FIG. **3** is a block diagram illustrating various portions of a system for predicting and motivating customers to provide item reviews, in accordance with some embodiments of the present teaching;

[0013] FIG. **4** illustrates an exemplary process for generating a list of potential reviewers, in accordance with some embodiments of the present teaching;

[0014] FIG. **5** illustrates an exemplary process for generating reviewer segmentation data, in accordance with some embodiments of the present teaching;

[0015] FIG. **6** illustrates an exemplary reviewer segmentation result, in accordance with some embodiments of the present teaching;

[0016] FIG. **7** illustrates an exemplary structure of a multi-task neural network for computing review probabilities, in accordance with some embodiments of the present teaching;

[0017] FIG. **8** illustrates an exemplary user interface via a website for reminding a customer to provide item review, in accordance with some embodiments of the present teaching;

[0018] FIG. **9** illustrates exemplary user interfaces via an app for reminding a customer to provide item review, in accordance with some embodiments of the present teaching;

[0019] FIG. **10** illustrates an exemplary user interface via an email for reminding a customer to provide item review, in accordance with some embodiments of the present teaching;

[0020] FIG. **11** is a flowchart illustrating an exemplary method for predicting and motivating customers to provide item reviews, in accordance with some embodiments of the present teaching.

DETAILED DESCRIPTION

[0021] This description of the exemplary embodiments is intended to be read in connection with the accompanying drawings, which are to be considered part of the entire written description. Terms concerning data connections, coupling and the like, such as "connected" and "interconnected," and/or "in signal communication with" refer to a relationship wherein systems or elements are electrically and/or wirelessly connected to one another either directly or indirectly through intervening systems, as well as both moveable or rigid attachments or relationships, unless expressly described otherwise. The term "operatively coupled" is such a coupling or connection that allows the pertinent structures to operate as intended by virtue of that relationship.

[0022] In the following, various embodiments are described with respect to the claimed systems as well as with respect to the claimed methods. Features, advantages or alternative embodiments herein can be assigned to the other claimed objects and vice versa. In other words, claims for the systems can be improved with features described or claimed in the context of the methods. In this case, the functional features of the method are embodied by objective units of the systems.

[0023] It is important for a retailer to motivate more customers to write more product reviews, because an increase of reviews leads to an increase of sales. Objectives of the present teaching include but not limited to: predicting customers who are likely to be reviewers, motivating these customers to write reviews with personalized nudges, and enabling data-driven decision-making by leveraging the personalized nudges.

[0024] In some embodiments, a system can predict a set of customers who have a higher affinity to write reviews for one or more product types. The prediction may be based on a machine learning model (e.g. a multi-task neural network) that can predict multiple review probabilities simultaneously for a customer regarding multiple product types, based on features related to customers and/or transactions. Each of the review probabilities is a probability of the customer providing a review in a respect product type.

[0025] In some embodiments, the system generates a ranked list of customers to be reminded for providing reviews, based on the review probabilities predicted for the customers. In some embodiments, both the review probability prediction and the customer ranking can be performed based on a customer segmentation (or reviewer segmentation), which categorizes customers based on their recency and frequency of reviews, allowing for tailored review motivation strategies. Nudges or review reminders can be sent to the ranked list of customers via various user interfaces, e.g. website, app, email. In some embodiments, the nudges may be sent with priority according to the ranking of the customers in consideration of any given budget.

[0026] As such, the disclosed system can provide a novel nudging and review reminding approach based on individual user behavior and preferences, ensuring a higher response rate. The customer segmentation enables the system to target precise potential reviewers, ensuring that nudges are directed at the most relevant customer segments. In addition, the disclosed system can leverage personalized nudging and customer segmentation to motivate customers to write reviews, drive exponential growth in review quantity, enhance user engagement, and empower a retailer to amplify customer voices. Furthermore, the framework of the system is flexible and adaptive to balance between exploration and exploitation, which can optimize the selection of potential reviewers by maximizing both diversity and authenticity of potential reviewers. Leveraging the unique insights gained from nudging data, potential reviewer data and realized reviewer data, the retailer can perform better data-driven decision-makings.

[0027] Furthermore, in the following, various embodiments are described with respect to systems and methods for predicting and motivating customers to provide reviews of purchased items are disclosed. In some embodiments, a disclosed method includes: receiving, from a computing device, a request for potential reviewers; selecting, based on the request, a plurality of customers who have purchased items but have not provided any review for the purchased items; computing, using at least one machine learning model, review probabilities based on feature data related to the plurality of customers and transactions involving the purchased items, wherein each review probability is a probability of a corresponding customer providing a review; generating, from the plurality of customers, a ranked list of customers based on the review probabilities and reviewer segmentation data; and transmitting to the computing device the ranked list of customers to be reminded for providing reviews.

[0028] Turning to the drawings, FIG. **1** is a network environment **100** configured for predicting and motivating customers to provide item reviews, in accordance with some embodiments of the present teaching. The network environment **100** includes a plurality of devices or systems configured to communicate over one or more network channels, illustrated as a network cloud **118**. For example, in various embodiments, the network environment **100** can include, but not limited to, a reviewer prediction computing device **102**, a server **104** (e.g., a web server or an application server), a cloud-based engine **121** including one or more processing devices **120**, workstation(s) **106**, a database **116**, and one or more user computing devices **110**, **112**, **114** operatively coupled over the network **118**. The reviewer prediction computing device **102**, the server **104**, the workstation(s) **106**, the processing device(s) **120**, and the multiple user computing devices **110**, **112**, **114** can each be any suitable computing device that includes any hardware or hardware and software combination for processing and handling information. For example, each can include one or more processors, one or more field-programmable gate arrays (FPGAs), one or more application-specific integrated circuits (ASICs), one or more state machines, digital circuitry, or any other

suitable circuitry. In addition, each can transmit and receive data over the communication network **118**.

[0029] In some examples, each of the reviewer prediction computing device **102** and the processing device(s) **120** can be a computer, a workstation, a laptop, a server such as a cloud-based server, or any other suitable device. In some examples, each of the processing devices **120** is a server that includes one or more processing units, such as one or more graphical processing units (GPUs), one or more central processing units (CPUs), and/or one or more processing cores. Each processing device **120** may, in some examples, execute one or more virtual machines. In some examples, processing resources (e.g., capabilities) of the one or more processing devices **120** are offered as a cloud-based service (e.g., cloud computing). For example, the cloud-based engine **121** may offer computing and storage resources of the one or more processing devices **120** to the reviewer prediction computing device **102**.

[0030] In some examples, each of the multiple user computing devices **110**, **112**, **114** can be a cellular phone, a smart phone, a tablet, a personal assistant device, a voice assistant device, a digital assistant, a laptop, a computer, a laser-based code scanner, or any other suitable device. In some examples, the server **104** hosts one or more websites or apps providing one or more products or services. In some examples, the reviewer prediction computing device **102**, the processing devices **120**, and/or the server **104** are operated by a retailer, and the multiple user computing devices **110**, **112**, **114** are operated by customers, associates and/or managers of the retailer. In some examples, the processing devices **120** are operated by a third party (e.g., a cloud-computing provider).

[0031] The workstation(s) **106** are operably coupled to the communication network **118** via a router (or switch) **108**. The workstation(s) **106** and/or the router **108** may be located at a store **109** of a retailer, for example. The workstation(s) **106** can communicate with the reviewer prediction computing device **102** over the communication network **118**. The workstation(s) **106** may send data to, and receive data from, the reviewer prediction computing device **102**. For example, the workstation(s) **106** may transmit data identifying items purchased by a customer at the store **109** to the reviewer prediction computing device **102**. The workstation(s) **106** may also transmit other data related to the store **109** to the reviewer prediction computing device **102**.

[0032] Although FIG. **1** illustrates three user computing devices **110**, **112**, **114**, the network environment **100** can include any number of user computing devices **110**, **112**, **114**. Similarly, the network environment **100** can include any number of the reviewer prediction computing devices **102**, the processing devices **120**, the workstations **106**, the servers **104**, and the databases **116**.

[0033] The communication network **118** can be a WiFi® network, a cellular network such as a 3GPP® network, a Bluetooth® network, a satellite network, a wireless local area network (LAN), a network utilizing radio-frequency (RF) communication protocols, a Near Field Communication (NFC) network, a wireless Metropolitan Area Network (MAN) connecting multiple wireless LANs, a wide area network (WAN), or any other suitable network. The communication network **118** can provide access to, for example, the Internet.

[0034] In some embodiments, each of the first user computing device **110**, the second user computing device **112**, and the Nth user computing device **114** may communicate with the server **104** over the communication network **118**. For example, each of the multiple user computing devices **110**, **112**, **114** may be operable to view, access, and interact with a website, such as a retailer's website, hosted by the server **104**. The server **104** may capture user session data related to a customer's activity (e.g., interactions) on the website.

[0035] In some examples, a customer may operate one of the user computing devices **110**, **112**, **114** to initiate a web browser that is directed to the website hosted by the server **104**. The customer may, via the web browser, view item advertisements for items displayed on the website, may click on item advertisements, and may leave a review for an item, for example. The website may capture these activities as user session data, and transmit the user session data to the reviewer prediction computing device **102** over the communication network **118**. The website may also allow the customer to add one or more of the items to an online shopping cart, and allow the customer to perform a "check-out" of the shopping cart to purchase the items. In some examples, the server **104** transmits purchase data identifying items the customer has purchased from the website to the reviewer prediction computing device **102**.

[0036] In some examples, a customer may go to a store, e.g. the store **109** for purchasing items. The customer may use some payment method, e.g. a credit card or a payment app, at the store **109** to purchase one or more items. The workstation(s) **106** in the store **109** may capture these activities as in-store purchase data, and transmit the in-store purchase data to the reviewer prediction computing device **102** over the communication network **118**, together with other store related data.

[0037] In some examples, the reviewer prediction computing device **102** may receive a reviewer prediction request for predicting potential reviewers from the server **104**. The reviewer prediction request may be sent standalone or together with data associated with a product type or category. In response, the reviewer prediction computing device **102** generates a ranked list of customers as potential reviewers to be reminded for providing reviews under the product type. The ranked list of customers may be generated based on some review probabilities, budget data and reviewer segmentation data.

[0038] In some examples, the reviewer prediction computing device **102** may execute one or more models (e.g., programs or algorithms), such as a machine learning model, deep learning model, statistical model, etc., to generate a ranked list of customers to be reminded for providing reviews. The reviewer prediction computing device **102** may generate and transmit the ranked list of customers to the server **104** over the communication network **118**, and the server **104** may send nudges or review reminders to these customers via a website, an app or emails.

[0039] In one example, a customer purchases an item on a website hosted by the server **104**, without providing any review of the purchased item. The server **104** may treat the customer as a candidate customer to be evaluated. In response to receiving a request from the server **104**, the reviewer prediction computing device **102** may execute the one or more processors to select a subset of candidate customers who have purchased items under a concerned product type but have not provided any review for the purchased items, compute review probabilities that the cus-

tomers will leave reviews for the items, and generate a ranked list of customers from the selected candidate customers based on the review probabilities, a budget and reviewer segmentation data. The reviewer prediction computing device **102** then transmits to the server **104** the ranked list of customers to be reminded for providing reviews.

[0040] In some embodiments, the reviewer prediction computing device **102** is further operable to communicate with the database **116** over the communication network **118**. For example, the reviewer prediction computing device **102** can store data to, and read data from, the database **116**. The database **116** can be a remote storage device, such as a cloud-based server, a disk (e.g., a hard disk), a memory device on another application server, a networked computer, or any other suitable remote storage. Although shown remote to the reviewer prediction computing device **102**, in some examples, the database **116** can be a local storage device, such as a hard drive, a non-volatile memory, or a USB stick. The reviewer prediction computing device **102** may store online purchase data received from the server **104** in the database **116**. The reviewer prediction computing device **102** may receive in-store purchase data and store related data from the store **109** and store them in the database **116**. The reviewer prediction computing device **102** may also receive from the server **104** user session data identifying events associated with browsing sessions, and may store the user session data in the database **116**. The reviewer prediction computing device **102** may also compute a potential reviewer list, and may store the potential reviewer list in the database **116**.

[0041] In some examples, the reviewer prediction computing device **102** generates and/or updates different models (e.g., machine learning models, deep learning models, statistical models, algorithms, etc.) for predicting and motivating customers to provide item reviews. The reviewer prediction computing device **102** may generate training data for the models based on historical user session data, purchase data, customer features and review labels. The reviewer prediction computing device **102** trains the models based on their corresponding training data, and stores the models in a database, such as in the database **116** (e.g., a cloud storage). The models, when executed by the reviewer prediction computing device **102**, allow the reviewer prediction computing device **102** to determine potential reviewers for nudging or reminding.

[0042] In some examples, the reviewer prediction computing device **102** assigns the models (or parts thereof) for execution to one or more processing devices **120**. For example, each model may be assigned to a virtual machine hosted by a processing device **120**. The virtual machine may cause the models or parts thereof to execute on one or more processing units such as GPUs. In some examples, the virtual machines assign each model (or part thereof) among a plurality of processing units. Based on the output of the models, the reviewer prediction computing device **102** may generate a ranked list of customers to be reminded for providing reviews.

[0043] FIG. **2** illustrates a block diagram of a reviewer prediction computing device, e.g. the reviewer prediction computing device **102** of FIG. **1**, in accordance with some embodiments of the present teaching. In some embodiments, each of the reviewer prediction computing device **102**, the server **104**, the workstation(s) **106**, the multiple user computing devices **110**, **112**, **114**, and the one or more processing devices **120** in FIG. **1** may include the features shown in FIG. **2**. Although FIG. **2** is described with respect to certain components shown therein, it will be appreciated that the elements of the reviewer prediction computing device **102** can be combined, omitted, and/or replicated. In addition, it will be appreciated that additional elements other than those illustrated in FIG. **2** can be added to the reviewer prediction computing device **102**.

[0044] As shown in FIG. **2**, the reviewer prediction computing device **102** can include one or more processors **201**, an instruction memory **207**, a working memory **202**, one or more input/output devices **203**, one or more communication ports **209**, a transceiver **204**, a display **206** with a user interface **205**, and an optional location device **211**, all operatively coupled to one or more data buses **208**. The data buses **208** allow for communication among the various components. The data buses **208** can include wired, or wireless, communication channels.

[0045] The one or more processors **201** can include any processing circuitry operable to control operations of the reviewer prediction computing device **102**. In some embodiments, the one or more processors **201** include one or more distinct processors, each having one or more cores (e.g., processing circuits). Each of the distinct processors can have the same or different structure. The one or more processors **201** can include one or more central processing units (CPUs), one or more graphics processing units (GPUs), application specific integrated circuits (ASICs), digital signal processors (DSPs), a chip multiprocessor (CMP), a network processor, an input/output (I/O) processor, a media access control (MAC) processor, a radio baseband processor, a co-processor, a microprocessor such as a complex instruction set computer (CISC) microprocessor, a reduced instruction set computing (RISC) microprocessor, and/or a very long instruction word (VLIW) microprocessor, or other processing device. The one or more processors **201** may also be implemented by a controller, a microcontroller, an application specific integrated circuit (ASIC), a field programmable gate array (FPGA), a programmable logic device (PLD), etc.

[0046] In some embodiments, the one or more processors **201** are configured to implement an operating system (OS) and/or various applications. Examples of an OS include, for example, operating systems generally known under various trade names such as Apple macOS™, Microsoft Windows™, Android™, Linux™, and/or any other proprietary or open-source OS. Examples of applications include, for example, network applications, local applications, data input/output applications, user interaction applications, etc.

[0047] The instruction memory **207** can store instructions that can be accessed (e.g., read) and executed by at least one of the one or more processors **201**. For example, the instruction memory **207** can be a non-transitory, computer-readable storage medium such as a read-only memory (ROM), an electrically erasable programmable read-only memory (EEPROM), flash memory (e.g. NOR and/or NAND flash memory), content addressable memory (CAM), polymer memory (e.g., ferroelectric polymer memory), phase-change memory (e.g., ovonic memory), ferroelectric memory, silicon-oxide-nitride-oxide-silicon (SONOS) memory, a removable disk, CD-ROM, any non-volatile memory, or any other suitable memory. The one or more processors **201** can be configured to perform a certain function or operation by executing code, stored on the instruction memory **207**,

embodying the function or operation. For example, the one or more processors **201** can be configured to execute code stored in the instruction memory **207** to perform one or more of any function, method, or operation disclosed herein.

[0048] Additionally, the one or more processors **201** can store data to, and read data from, the working memory **202**. For example, the one or more processors **201** can store a working set of instructions to the working memory **202**, such as instructions loaded from the instruction memory **207**. The one or more processors **201** can also use the working memory **202** to store dynamic data created during one or more operations. The working memory **202** can include, for example, random access memory (RAM) such as a static random access memory (SRAM) or dynamic random access memory (DRAM), Double-Data-Rate DRAM (DDR-RAM), synchronous DRAM (SDRAM), an EEPROM, flash memory (e.g. NOR and/or NAND flash memory), content addressable memory (CAM), polymer memory (e.g., ferroelectric polymer memory), phase-change memory (e.g., ovonic memory), ferroelectric memory, silicon-oxide-nitride-oxide-silicon (SONOS) memory, a removable disk, CD-ROM, any non-volatile memory, or any other suitable memory. Although embodiments are illustrated herein including separate instruction memory **207** and working memory **202**, it will be appreciated that the reviewer prediction computing device **102** can include a single memory unit configured to operate as both instruction memory and working memory. Further, although embodiments are discussed herein including non-volatile memory, it will be appreciated that the reviewer prediction computing device **102** can include volatile memory components in addition to at least one non-volatile memory component.

[0049] In some embodiments, the instruction memory **207** and/or the working memory **202** includes an instruction set, in the form of a file for executing various methods, e.g. any method as described herein. The instruction set can be stored in any acceptable form of machine-readable instructions, including source code or various appropriate programming languages. Some examples of programming languages that can be used to store the instruction set include, but are not limited to: Java, JavaScript, C, C++, C #, Python, Objective-C, Visual Basic, .NET, HTML, CSS, SQL, NoSQL, Rust, Perl, etc. In some embodiments a compiler or interpreter is configured to convert the instruction set into machine executable code for execution by the one or more processors **201**.

[0050] The input-output devices **203** can include any suitable device that allows for data input or output. For example, the input-output devices **203** can include one or more of a keyboard, a touchpad, a mouse, a stylus, a touchscreen, a physical button, a speaker, a microphone, a keypad, a click wheel, a motion sensor, a camera, and/or any other suitable input or output device.

[0051] The transceiver **204** and/or the communication port(s) **209** allow for communication with a network, such as the communication network **118** of FIG. **1**. For example, if the communication network **118** of FIG. **1** is a cellular network, the transceiver **204** is configured to allow communications with the cellular network. In some embodiments, the transceiver **204** is selected based on the type of the communication network **118** the reviewer prediction computing device **102** will be operating in. The one or more processors **201** are operable to receive data from, or send data to, a network, such as the communication network **118** of FIG. **1**, via the transceiver **204**.

[0052] The communication port(s) **209** may include any suitable hardware, software, and/or combination of hardware and software that is capable of coupling the reviewer prediction computing device **102** to one or more networks and/or additional devices. The communication port(s) **209** can be arranged to operate with any suitable technique for controlling information signals using a desired set of communications protocols, services, or operating procedures. The communication port(s) **209** can include the appropriate physical connectors to connect with a corresponding communications medium, whether wired or wireless, for example, a serial port such as a universal asynchronous receiver/transmitter (UART) connection, a Universal Serial Bus (USB) connection, or any other suitable communication port or connection. In some embodiments, the communication port(s) **209** allows for the programming of executable instructions in the instruction memory **207**. In some embodiments, the communication port(s) **209** allow for the transfer (e.g., uploading or downloading) of data, such as machine learning model training data.

[0053] In some embodiments, the communication port(s) **209** are configured to couple the reviewer prediction computing device **102** to a network. The network can include local area networks (LAN) as well as wide area networks (WAN) including without limitation Internet, wired channels, wireless channels, communication devices including telephones, computers, wire, radio, optical and/or other electromagnetic channels, and combinations thereof, including other devices and/or components capable of/associated with communicating data. For example, the communication environments can include in-body communications, various devices, and various modes of communications such as wireless communications, wired communications, and combinations of the same.

[0054] In some embodiments, the transceiver **204** and/or the communication port(s) **209** are configured to utilize one or more communication protocols. Examples of wired protocols can include, but are not limited to, Universal Serial Bus (USB) communication, RS-232, RS-422, RS-423, RS-485 serial protocols, FireWire, Ethernet, Fibre Channel, MIDI, ATA, Serial ATA, PCI Express, T-1 (and variants), Industry Standard Architecture (ISA) parallel communication, Small Computer System Interface (SCSI) communication, or Peripheral Component Interconnect (PCI) communication, etc. Examples of wireless protocols can include, but are not limited to, the Institute of Electrical and Electronics Engineers (IEEE) 802.xx series of protocols, such as IEEE 802.11a/b/g/n/ac/ag/ax/be, IEEE 802.16, IEEE 802.20, GSM cellular radiotelephone system protocols with GPRS, CDMA cellular radiotelephone communication systems with 1×RTT, EDGE systems, EV-DO systems, EV-DV systems, HSDPA systems, Wi-Fi Legacy, Wi-Fi 1/2/3/4/5/6/6E, wireless personal area network (PAN) protocols, Bluetooth Specification versions 5.0, 6, 7, legacy Bluetooth protocols, passive or active radio-frequency identification (RFID) protocols, Ultra-Wide Band (UWB), Digital Office (DO), Digital Home, Trusted Platform Module (TPM), ZigBee, etc.

[0055] The display **206** can be any suitable display, and may display the user interface **205**. For example, the user interfaces **205** can enable user interaction with the reviewer prediction computing device **102** and/or the server **104**. For

example, the user interface **205** can be a user interface for an application of a network environment operator that allows a customer to view and interact with the operator's website. In some embodiments, a user can interact with the user interface **205** by engaging the input-output devices **203**. In some embodiments, the display **206** can be a touchscreen, where the user interface **205** is displayed on the touchscreen.

[0056] The display **206** can include a screen such as, for example, a Liquid Crystal Display (LCD) screen, a light-emitting diode (LED) screen, an organic LED (OLED) screen, a movable display, a projection, etc. In some embodiments, the display **206** can include a coder/decoder, also known as Codecs, to convert digital media data into analog signals. For example, the visual peripheral output device can include video Codecs, audio Codecs, or any other suitable type of Codec.

[0057] The optional location device **211** may be communicatively coupled to a location network and operable to receive position data from the location network. For example, in some embodiments, the location device **211** includes a GPS device configured to receive position data identifying a latitude and longitude from one or more satellites of a GPS constellation. As another example, in some embodiments, the location device **211** is a cellular device configured to receive location data from one or more localized cellular towers. Based on the position data, the reviewer prediction computing device **102** may determine a local geographical area (e.g., town, city, state, etc.) of its position.

[0058] In some embodiments, the reviewer prediction computing device **102** is configured to implement one or more modules or engines, each of which is constructed, programmed, configured, or otherwise adapted, to autonomously carry out a function or set of functions. A module/engine can include a component or arrangement of components implemented using hardware, such as by an application specific integrated circuit (ASIC) or field-programmable gate array (FPGA), for example, or as a combination of hardware and software, such as by a microprocessor system and a set of program instructions that adapt the module/engine to implement the particular functionality, which (while being executed) transform the microprocessor system into a special-purpose device. A module/engine can also be implemented as a combination of the two, with certain functions facilitated by hardware alone, and other functions facilitated by a combination of hardware and software. In certain implementations, at least a portion, and in some cases, all, of a module/engine can be executed on the processor(s) of one or more computing platforms that are made up of hardware (e.g., one or more processors, data storage devices such as memory or drive storage, input/output facilities such as network interface devices, video devices, keyboard, mouse or touchscreen devices, etc.) that execute an operating system, system programs, and application programs, while also implementing the engine using multitasking, multithreading, distributed (e.g., cluster, peer-peer, cloud, etc.) processing where appropriate, or other such techniques. Accordingly, each module/engine can be realized in a variety of physically realizable configurations, and should generally not be limited to any particular implementation exemplified herein, unless such limitations are expressly called out. In addition, a module/engine can itself be composed of more than one sub-modules or sub-engines, each of which can be regarded as a module/engine in its own right. Moreover, in the embodiments described herein, each of the various modules/engines corresponds to a defined autonomous functionality; however, it should be understood that in other contemplated embodiments, each functionality can be distributed to more than one module/engine. Likewise, in other contemplated embodiments, multiple defined functionalities may be implemented by a single module/engine that performs those multiple functions, possibly alongside other functions, or distributed differently among a set of modules/engines than specifically illustrated in the embodiments herein.

[0059] FIG. **3** is a block diagram illustrating various portions of a system for predicting and motivating customers to provide item reviews, e.g. the system shown in the network environment **100** of FIG. **1**, in accordance with some embodiments of the present teaching. As indicated in FIG. **3**, the reviewer prediction computing device **102** may receive user session data **320** from the server **104**, and store the user session data **320** in the database **116**. The user session data **320** may identify, for each user (e.g., customer), data related to that user's browsing session, such as when browsing a retailer's webpage hosted by the server **104**.

[0060] In some examples, the user session data **320** may include item engagement data **322**, search query data **324**, and user ID **326** (e.g., a customer ID, retailer website login ID, a cookie ID, etc.). The item engagement data **322** may include one or more of a session ID **362** (i.e., a website browsing session identifier), item clicks **364** identifying items which a user clicked (e.g., images of items for purchase, keywords to filter reviews for an item), items added-to-cart **366** identifying items added to the user's online shopping cart, and item reviews provided **368** identifying item reviews a user provided on the website. The search query data **324** may identify one or more searches conducted by a user during a browsing session (e.g., a current browsing session).

[0061] The reviewer prediction computing device **102** may also receive online purchase data **304** from the server **104**, which identifies and characterizes one or more online purchases, such as purchases made by the user and other users via a retailer's website hosted by the server **104**. The reviewer prediction computing device **102** may also receive store related data **302** from the store **109**, which identifies and characterizes one or more in-store purchases. In some embodiments, the store related data **302** may also indicate other information about the store **109**.

[0062] The reviewer prediction computing device **102** may parse the store related data **302** and the online purchase data **304** to generate user transaction data **340**. In this example, the user transaction data **340** may include, for each purchase, one or more of: an order number **342** identifying a purchase order, item IDs **343** identifying one or more items purchased in the purchase order, item brands **344** identifying a brand for each item purchased, item prices **346** identifying the price of each item purchased, item categories **348** identifying a product type (or category) of each item purchased, purchase dates **345** identifying the purchase dates of the purchase orders, a user ID **326** for the user making the corresponding purchase, payment data **347** indicating payment methods and related information (e.g. emails associated with payment) for corresponding online orders, and store ID **332** for the corresponding in-store purchase, or for the pickup store or shipping-from store associated with the corresponding online purchase.

[0063] In some embodiments, the database **116** may parse the store related data **302** to generate store data **330**. In this example, the store data **330** may include, for each store, one or more of: a store ID **332** of the store, a store location **333** of the store, and in-store purchase data **334** of the store.

[0064] In some embodiments, the database **116** may further store catalog data **370**, which may identify one or more attributes of a plurality of items, such as a portion of or all items a retailer carries in stores and/or at e-commerce platforms. The catalog data **370** may identify, for each of the plurality of items, an item ID **371** (e.g., an SKU number), item brand **372**, item type **373** (e.g., grocery item such as milk, clothing item), item description **374** (e.g., a description of the product including product features, such as ingredients, benefits, use or consumption instructions, or any other suitable description), and item options **375** (e.g., item colors, sizes, flavors, etc.).

[0065] The database **116** may also store reviewer prediction model data **390** identifying and characterizing one or more models and related data for predicting and motivating customers to provide item reviews. For example, the reviewer prediction model data **390** may include: a reviewer segmentation model **392**, a review probability computing model **394**, a ranking model **396**, and model training data **398**.

[0066] The reviewer segmentation model **392** may be used to divide customers of a retailer into different segments based on some metrics related to product review. In some embodiments, the reviewer segmentation model **392** utilizes two metrics: review frequency and review recency, at the same time. The review frequency indicates how many reviews a customer provided per order during a past time period, e.g. the last year. The review recency indicates a time period or days passed since the last review provided by a customer. Customers of a retailer can be assigned, using the reviewer segmentation model **392**, to different buckets based on their review frequencies and review recencies after normalization. Each bucket corresponds to a segment of customers or reviewers with shared features. These shared features will be learned and utilized by machine learning to compute review probability and rank potential reviewers.

[0067] The review probability computing model **394** may be used to compute review probabilities based on feature data related to customers and transactions. In some embodiments, the review probability computing model **394** includes a neural network configured to predict a review probability that a customer will provide a review for an item in a product type. For example, the neural network may take input features related to: the customer, the customer's interaction with a retailer website or retailer app, transactions performed by the customer, and previous reviews given by the customer. In some embodiments, the neural network is a multi-task neural network configured to predict multiple review probabilities each being a probability that the customer will provide a review for an item in a respective product type.

[0068] The ranking model **396** may be used to rank potential reviewers based on the reviewer segmentation data and the review probabilities, which are computed based on the reviewer segmentation model **392** and the review probability computing model **394**, respectively. In some examples, the ranking model **396** also considers a budget, e.g. predetermined based on business requirement, to rank the potential reviewers. For example, given a reviewer segment and review probabilities for candidate reviewers (or customers) in the reviewer segment, the ranking model **396** may be used to generate a ranked list of customers in the reviewer segment, without breaking the budget requirement. This ranked list of customers includes potential reviewers ranked according to their likelihood of leaving reviews in a given product type.

[0069] The model training data **398** may include training data utilized for training one or more of the reviewer segmentation model **392**, the review probability computing model **394** and the ranking model **396**. In some examples, the model training data **398** may include, but not limited to, data related to a plurality of customers, their historical transaction data, their historical user session data, and review label data. The review label data may be determined based on historical reviews provided by the plurality of customers. For example, given a product type, a customer who has provided a review in this product type is labelled +1, and a customer who has not provided any review in this product type is labelled −1. In some examples, the model training data **398** may be used to train a machine learning model to optimize an objective function based on optimized hyperparameters. The optimized hyperparameters can enable a first ranking of potential reviewers generated by the machine learning model during a test stage to be closest to a second ranking of the potential reviewers based on the review label data. In the second ranking, a customer having a larger label value is ranked higher than a customer having a smaller label value.

[0070] In some examples, the reviewer prediction computing device **102** receives a reviewer prediction request **310** from the server **104**. The reviewer prediction request **310** may be associated with one or more product types, or one or more product categories. In some embodiments, the reviewer prediction computing device **102** may determine a plurality of customers who have purchased items in an associated product type but have not provided any review for the purchased items. Based on feature data related to the plurality of customers and transactions involving the purchased items, the reviewer prediction computing device **102** may compute, using at least one machine learning model, review probabilities each being a probability of a corresponding customer providing a review in the associated product type. The at least one machine learning model may include any model in the reviewer prediction model data **390**. Among or from the plurality of customers, a potential reviewer list **312** including ranked customers or potential reviewers is generated by the reviewer prediction computing device **102** based on the review probabilities, budget data and reviewer segmentation data. In response to the reviewer prediction request **310**, the reviewer prediction computing device **102** transmits the potential reviewer list **312** to the server **104**.

[0071] In some embodiments, the reviewer prediction computing device **102** may assign one or more of the above described operations to a different processing unit or virtual machine hosted by one or more processing devices **120**. Further, the reviewer prediction computing device **102** may obtain the outputs of the these assigned operations from the processing units, and generate the ranked potential reviewers based on the outputs.

[0072] FIG. **4** illustrates an exemplary process **400** for generating a list of potential reviewers, in accordance with some embodiments of the present teaching. In some embodi-

ments, the process **400** can be carried out by one or more computing devices, such as the reviewer prediction computing device **102** and/or the cloud-based engine **121** of FIG. **1**.

[0073] As shown in FIG. **4**, the process **400** starts from operation **410**, where a product type (or category) is determined based on a request, e.g. the reviewer prediction request **310** in FIG. **3**. The product type (or category) is sent to operation **420** for filtering customers. In some embodiments, the process **400** can handle multiple product types at the same time. In various embodiments, the product type can be replaced by a product category, a product family, a product group, or any other granularity of products. For simplicity, the following descriptions will use product type as an exemplary granularity.

[0074] At the operation **420**, customers of a retailer are filtered based on the product type. In this example, customer transaction data and session data **425** are obtained and utilized to filter the customers. For example, at the operation **420**, a subset of the entire customers of the retailer is selected as candidate customers (or candidate reviewers) who have purchased items in the product type but have not provided any review for the purchased items yet. This selection may be based on the customer transaction data and session data **425** of customers of the retailer. The selected list of candidate customers may be sent to operation **430** for feature generation.

[0075] At the operation **430**, feature data related to the selected list of candidate customers is generated. In some embodiments, the feature data includes but not limited to: customer features, customer action features, benefit affinity data, transaction segment data, and reviewer segment data. In some examples, the customer features include features about: retailer membership, purchase history, demographic data and persona of each customer. In some examples, the customer action features include interaction features like click, add-to-cart, impression, etc. of each customer. In some examples, the benefit affinity data includes data about transaction related benefits likely to be used by each customer. The transaction related benefits may include benefits like free shipping or free delivery from store. The benefit affinity data may indicate a tendency of each customer to use these benefits. In some examples, the transaction segment data indicates a transaction-based segment each customer belongs to. A transaction-based segment for a customer may be determined based on monetary and payment information of the customer's past transactions weighted according to transaction frequency and recency of the customer. In some examples, the reviewer segment data indicates a reviewer segment each customer belongs to.

[0076] In some embodiments, the reviewer segment data is generated at operation **402**, which can be performed offline before the request is received or in real-time after the request is received. In some embodiments, the operation **402** is performed based on the reviewer segmentation model **392** in FIG. **3**. An exemplary detailed process for the operation **402** is shown in FIG. **5**.

[0077] FIG. **5** illustrates an exemplary process **500** for generating reviewer segmentation data, in accordance with some embodiments of the present teaching. In some embodiments, the process **500** can be carried out by one or more computing devices, such as the reviewer prediction computing device **102** and/or the cloud-based engine **121** of FIG. **1**. In some embodiments, the process **500** is a detailed process of the operation **402** in FIG. **4**.

[0078] As shown in FIG. **5**, the process **500** starts from operation **510**, where historical feedback data or review data are obtained for customers of a retailer. In some embodiments, the review data are collected at the operation **510** for a past time period, e.g. the past one year or two years.

[0079] As shown in FIG. **5**, the historical review data is provided to operation **520**, where segmentation metrics are determined based on the historical review data. In some examples, two segmentation metrics are determined: review frequency and review recency. The review frequency of a customer indicates how many reviews the customer provided per order during a past time period, e.g. the last year. The review recency of a customer indicates a time period or days passed since the last review provided by the customer.

[0080] At operation **530**, the review frequency and review recency of the historical review data are normalized to generate different buckets. The buckets of the review frequency and review recency may be utilized at the same time to generate reviewer segmentation data at operation **540**. The reviewer segmentation data may include a plurality of reviewer segments, each of which corresponds to one or more buckets generated at the operation **530**.

[0081] FIG. **6** illustrates an exemplary reviewer segmentation result **600**, in accordance with some embodiments of the present teaching. In some embodiments, the reviewer segmentation result **600** is a result generated by the process **500** in FIG. **5**. As shown in FIG. **6**, the reviewer segmentation result **600** includes review recency buckets 1~5 on the X axis, and review frequency buckets 1~5 on the Y axis. In the example shown in FIG. **6**, the range numbers associated with each recency bucket represent a range of days passed since the last review of a customer; the range numbers associated with each frequency bucket represent a range of "review per order" for a customer.

[0082] In some embodiments, the exact numbers or values of these ranges can vary and be optimized based on historical review data across different shopping seasons or events. For example, during a Black Friday shopping season, the number of orders placed by customers increases dramatically compared to other seasons. As such, the review frequency values tend to be reduced for all customers during the Black Friday shopping season. To keep a relatively even distribution of customers into the buckets of the review frequency, either a larger number of review frequency buckets or a redetermination of values of bucket ranges can be applied.

[0083] In the example shown in FIG. **6**, there are 5 review recency buckets and 5 review frequency buckets. As such, there are in total 25 recency-frequency segments. But since a reviewer segment may occupy one or more recency-frequency segments, the reviewer segmentation result **600** in this example includes in total 10 reviewer segments: cannot lose reviewer, loyal reviewer, champions reviewer, at risk reviewer, need attention reviewer, potential loyalists reviewer, hibernating reviewer, about to sleep reviewer, promising reviewer, and new reviewer.

[0084] In one example, if a customer provided the last review within the past X4 days (within the recency bucket 5) and provided on average more than Y3 review(s) per order (within the frequency buckets 4 and 5) during the last year, the customer is assigned to the champions reviewer segment **610** and treated as a champions reviewer who frequently provided item reviews till now.

[0085] In another example, if a customer provided the last review within the past X4 days (within the recency bucket 5) but provided on average less than Y1 review(s) per order (within the frequency bucket 1) during the last year, the customer is assigned to the new reviewer segment **620** and treated as a new reviewer who seldom provided item reviews before and just started to provide item review.

[0086] In yet another example, if a customer provided the last review more than X2 days ago (within the recency buckets 1 and 2) and provided on average less than Y2 review(s) per order (within the frequency buckets 1 and 2) during the last year, the customer is assigned to the hibernating reviewer segment **630** and treated as a hibernating reviewer who seldom provided item reviews before and has not provided item reviews for a long time.

[0087] In some embodiments, the reviewer segmentation result **600** may be generated by the process **500** in FIG. **5** or the operation **402** in FIG. **4**, as reviewer segmentation data. Referring back to FIG. **4**, the reviewer segmentation data generated at the operation **402** can be utilized by the operation **430** for generating feature data and by operation **450** for ranking potential reviewers.

[0088] As discussed above, the feature data generated at the operation **430** is related to the selected list of candidate customers and transactions involving the purchased items of the candidate customers. At operation **440**, review probabilities are computed based on the feature data, e.g. using a neural network. In some embodiments, the neural network is a multi-task neural network having a structure shown in FIG. **7**. In some embodiments, the operation **440** is performed based on the review probability computing model **394** in FIG. **3**. In some embodiments, a multi-task neural network is better than a multi-class classification model for the operation **440**, because one customer can provide reviews for multiple product types.

[0089] FIG. **7** illustrates an exemplary structure of a multi-task neural network **700** for computing review probabilities, in accordance with some embodiments of the present teaching. In some embodiments, the multi-task neural network **700** is operated by one or more computing devices, such as the reviewer prediction computing device **102** and/or the cloud-based engine **121** of FIG. **1**. In some embodiments, the multi-task neural network **700** can be implemented as the neural network used at the operation **440** in FIG. **4**.

[0090] As shown in FIG. **7**, the multi-task neural network **700** includes an input layer **710**, one or more common hidden layer(s) **720** and a plurality of task specific hidden layers **730**. The input layer **710** in this example includes various input features to be fed into a serving layer, e.g. the common hidden layer(s) **720**. As shown in FIG. **7**, the input layer **710** includes: customer features **711**, customer action features **712**, benefit affinity data **713**, transaction segment data **714**, and reviewer segment data **715**. During a training stage of the multi-task neural network **700**, the features in the input layer **710** are features related to a training group of customers with known historical review data. During a real-time inference stage of the multi-task neural network **700**, the features in the input layer **710** are features related to a selected group of customers whose review probabilities are to be predicted.

[0091] In some examples, the customer features **711** include features about: retailer membership, purchase history, demographic data and persona of each customer (in the training group during training or in the selected group during inference). In some examples, the customer action features **712** include interaction features like click, add-to-cart, impression, etc. of each customer. In some examples, the benefit affinity data **713** includes data about transaction related benefits likely to be used by each customer. In some examples, the transaction segment data **714** indicates a transaction-based segment each customer belongs to. A transaction-based segment for a customer may be determined based on monetary and payment information of the customer's past transactions weighted according to transaction frequency and recency of the customer. In some examples, the reviewer segment data **715** indicates a reviewer segment each customer belongs to. The reviewer segments may be predetermined based on the process **500** in FIG. **5** and/or as shown in the reviewer segmentation result **600** in FIG. **6**. In some embodiments, the input layer **710** may also include other features, e.g. features related to shopping seasons or holidays. For example, during a Halloween or Christmas shopping season, nudging customers who purchased home decoration products may be more efficient than nudging customer who purchased other product types.

[0092] The common hidden layer(s) **720** in FIG. **7** includes: a feature concatenation module **722** and a feed forward layer **724**. The feature concatenation module **722** in this example concatenates features from the input layer **710** to generate concatenated features. The feed forward layer **724** in this example may include multiple layers that can fit the concatenated features for each customer and convert them into one multi-dimensional vector for the customer.

[0093] In some embodiments, the output of the feed forward layer **724** is the input to all of the plurality of task specific hidden layers **730**, each of which corresponds to a specific task for a respective product type. In this example, each task of N tasks is performed by a specific fully connected neural network in a corresponding feed forward layer to predict review probability more accurately for a respective product type. As shown in FIG. **7**, the plurality of task specific hidden layers **730** include N feed forward layers: a product type 1 (PT 1) feed forward layer **731** configured to compute a PT 1 review probability **741** for each customer, a product type 2 (PT 2) feed forward layer **732** configured to compute a PT 2 review probability **742** for each customer . . . a product type N (PT N) feed forward layer **733** configured to compute a PT N review probability **743** for each customer. The number of tasks here is the same as the number of product types being processed simultaneously by the multi-task neural network **700**.

[0094] In some embodiments, the labels in the training data are generated based on historical behavior of the customers. For example, a customer who has purchased three items can be labelled as [1, 1, 0], if the customer provided reviews for the first two items, but did not provide a review for the third item. During the training stage, for each customer, the system can compute an error based on the predicted response of the multi-task neural network **700** and the labels of real review data. The error can be back propagated to the multi-task neural network **700** to update the network parameters iteratively until the error is smaller than a predetermined threshold.

[0095] In some embodiments, the common hidden layer(s) **720** is trained based on the error prediction and backpropagation across all product types. At each task specific hidden

layer, the system adjusts the model parameters based on the error prediction of the specific task. In some examples, the error prediction and backpropagation is performed and shared by the common hidden layer(s) **720** and the plurality of task specific hidden layers **730**. In some embodiments, the multi-task neural network **700** is re-trained weekly with updated reviewer segments and other updated training data.

[0096] In some embodiments, the multi-task neural network **700** can be used to find out which features in the input layer **710** are important or give a big contribution to the review probabilities. These important features can be used to generate insight data for making business decisions related to customer review and engagement.

[0097] In some embodiments, the review probabilities **741**, **742**, **743** are generated simultaneously by the multi-task neural network **700** for different product types, and may be the review probabilities computed at the operation **440** in FIG. **4**. Referring back to FIG. **4**, the review probabilities are provided to operation **450**, to rank potential reviewers and generate a ranked list of potential reviewers **485**. In some embodiments, the operation **450** is performed based on the ranking model **396** in FIG. **3**.

[0098] As shown in FIG. **4**, the potential reviewers are ranked at the operation **450** based on: the reviewer segmentation data generated at the operation **402**, the review probabilities computed at the operation **440**, and some budget data **455**. In some examples, the budget data **455** includes a budget predetermined based business requirement. In some embodiments, a quantity B of top customers to nudge can be determined based on the budget. In some embodiments, based on the budget, the system can also determine a maximum number of nudges to send to each customer and/or during each month.

[0099] In some examples, the review probabilities are used to sort and rank the customers according to their predicted probabilities of writing or providing the reviews, given a product type. The most probable customers or the top B ranked customers, among a plurality of candidate customers, may be selected to generate the ranked list of potential reviewers **485** for the given product type.

[0100] In some embodiments, multiple ranked lists of potential reviewers **485** are generated by the process **400** at the same time for multiple product types, respectively. In some examples, the review probabilities computed at the operation **440** are provided in form of a table of customers with their review probabilities for each product type. The system operates the ranking model for all product types or some specific product types based on the request.

[0101] In some examples, the reviewer segmentation data can be utilized at the operation **450** as a selection strategy. For example, based on a predetermined instruction for picking the champion reviewers, or picking potential reviewers having review probabilities higher than a threshold, a selection strategy may be determined at the operation **450** to select these types of reviewers first. Then these reviewers are sorted and ranked based on their respective review probabilities, and the top B potential candidates may be selected for nudging based on the budget, to generate the ranked list of potential reviewers **485**.

[0102] In some examples, a general instruction is received for exploration of new customers to nudge, to motivate them to write reviews in hope that they will become champions reviews later. Based on this instruction, the ranking at the operation **450** may give priority to new reviewer segment, promising reviewer segment and/or about to sleep reviewer segment (as shown in FIG. **6**), and rank the customers falling into these segments to generate top reviewer candidates to form the ranked list of potential reviewers **485**.

[0103] In some examples, a general instruction is received for exploitation to increase the total number of reviews. Based on this instruction, the ranking at the operation **450** may give priority to champions reviewer segment, loyal reviewer segment and/or potential loyalists reviewer segment (as shown in FIG. **6**), and rank the customers falling into these segments to generate top reviewer candidates to form the ranked list of potential reviewers **485**.

[0104] In some examples, a selection strategy is determined at the operation **450** to select across all reviewer segments. In some examples, a selection strategy is determined at the operation **450** to select one or more of the reviewer segments.

[0105] FIG. **8** illustrates an exemplary user interface via a website **800** for reminding a customer to provide item review, in accordance with some embodiments of the present teaching. As shown in FIG. **8**, a nudge or review reminder **810** is provided on the website **800** to a customer, to motivate the customer to provide a review of a video game purchased by the customer. The nudge **810** in this example is located on top of other sections like purchase history, my savings, etc., in an account webpage of the customer.

[0106] FIG. **9** illustrates exemplary user interfaces via an app **900** for reminding a customer to provide item review, in accordance with some embodiments of the present teaching. As shown in FIG. **9**, a nudge or review reminder **912** is provided on a user interface **910** of the app to a customer, to motivate the customer to provide a review of a tennis ball hopper purchased by the customer. The nudge **912** in this example is located on top of other sections like a pick up timeline in a purchase history webpage of the customer on the user interface **910**. Upon the customer's selection of or click on the nudge **912**, a user interface **920** of the app is shown to the customer for filling out review information (e.g. rating, reviewer nickname, review title, review details, etc.) of the tennis ball hopper.

[0107] FIG. **10** illustrates an exemplary user interface via an email **1000** for reminding a customer to provide item review, in accordance with some embodiments of the present teaching. As shown in FIG. **10**, a nudge or review reminder **1010** is provided in the email **1000** to a customer, to motivate the customer to provide a review of a power adapter purchased by the customer. The nudge **1010** in this example is located right below the email content.

[0108] As such, after determining a customer to be in a potential reviewer list, e.g. the potential reviewer list **312** or the ranked list of potential reviewers **485**, the system can nudge the customer in various manners with different nudging locations in the user interface, within a nudging time period from the customer's purchase. In some embodiments, the nudging manners, the nudging locations and/or the nudging time period may be part of the model parameters to be optimized during training of the machine learning model (s) used to generate the potential reviewer list. In some embodiments, the potential reviewer list generated based on the methods and systems disclosed above can automatically trigger nudge notification transmissions to the customers in the potential reviewer list.

[0109] FIG. **11** is a flowchart illustrating an exemplary method **1100** for predicting and motivating customers to

provide item reviews, in accordance with some embodiments of the present teaching. In some embodiments, the method **1100** can be carried out by one or more computing devices, such as the reviewer prediction computing device **102** and/or the cloud-based engine **121** of FIG. **1**. Beginning at operation **1102**, a reviewer prediction request for predicting potential reviewers is received from a computing device. At operation **1104**, a plurality of customers who have purchased items but have not provided any review for the purchased items are selected based on the reviewer prediction request. At operation **1106**, review probabilities are computed using at least one machine learning model based on feature data related to the plurality of customers and transactions involving the purchased items. Each review probability is a probability of a corresponding customer providing a review. At operation **1108**, a ranked list of customers is generated from the plurality of customers based on the review probabilities and reviewer segmentation data. At operation **1110**, the ranked list of customers is transmitted to the computing device to be reminded for providing reviews.

[0110] Although the methods described above are with reference to the illustrated flowcharts, it will be appreciated that many other ways of performing the acts associated with the methods can be used. For example, the order of some operations may be changed, and some of the operations described may be optional.

[0111] The methods and system described herein can be at least partially embodied in the form of computer-implemented processes and apparatus for practicing those processes. The disclosed methods may also be at least partially embodied in the form of tangible, non-transitory machine-readable storage media encoded with computer program code. For example, the steps of the methods can be embodied in hardware, in executable instructions executed by a processor (e.g., software), or a combination of the two. The media may include, for example, RAMs, ROMs, CD-ROMs, DVD-ROMs, BD-ROMs, hard disk drives, flash memories, or any other non-transitory machine-readable storage medium. When the computer program code is loaded into and executed by a computer, the computer becomes an apparatus for practicing the method. The methods may also be at least partially embodied in the form of a computer into which computer program code is loaded or executed, such that, the computer becomes a special purpose computer for practicing the methods. When implemented on a general-purpose processor, the computer program code segments configure the processor to create specific logic circuits. The methods may alternatively be at least partially embodied in application specific integrated circuits for performing the methods.

[0112] Each functional component described herein can be implemented in computer hardware, in program code, and/or in one or more computing systems executing such program code as is known in the art. As discussed above with respect to FIG. **2**, such a computing system can include one or more processing units which execute processor-executable program code stored in a memory system. Similarly, each of the disclosed methods and other processes described herein can be executed using any suitable combination of hardware and software. Software program code embodying these processes can be stored by any non-transitory tangible medium, as discussed above with respect to FIG. **2**.

[0113] The foregoing is provided for purposes of illustrating, explaining, and describing embodiments of these disclosures. Modifications and adaptations to these embodiments will be apparent to those skilled in the art and may be made without departing from the scope or spirit of these disclosures. Although the subject matter has been described in terms of exemplary embodiments, it is not limited thereto. Rather, the appended claims should be construed broadly, to include other variants and embodiments, which can be made by those skilled in the art.

What is claimed is:

1. A system, comprising:

a processor; and

a non-transitory memory storing instructions, that when executed, cause the processor to:

receive a request for potential reviewers,

select, based on the request, a plurality of customers who have purchased items but have not provided any review for the purchased items,

compute, using at least one machine learning model, review probabilities based on feature data related to the plurality of customers and transactions involving the purchased items, wherein each review probability is a probability of a corresponding customer providing a review,

generate, from the plurality of customers, a ranked list of customers based on the review probabilities and reviewer segmentation data, and

transmit to a computing device the ranked list of customers to be reminded for providing reviews.

2. The system of claim **1**, wherein the plurality of customers are selected based on:

determining, based on the request, at least one product type; and

selecting, from a customer pool, the plurality of customers who have purchased items in the at least one product type but have not provided any review for the purchased items, wherein the plurality of customers are selected based on transaction data and user session data associated with the customer pool.

3. The system of claim **2**, wherein the review probabilities are computed based on:

generating the feature data based on: customer features, customer action features, benefit affinity data, transaction segmentation data, and reviewer segmentation data; and

inputting the feature data into the at least one machine learning model to compute, for each of the plurality of customers, a review probability that the customer will provide a review within the at least one product type.

4. The system of claim **1**, wherein the reviewer segmentation data is generated based on:

obtaining historical review data of customers within a past time period;

determining segmentation metrics based on the historical review data, wherein the segmentation metrics comprise:

a review frequency indicating how many reviews a customer provided per order during the past time period, and

a review recency indicating a time period passed since a last review provided by a customer;

normalizing each of the segmentation metrics to generate normalized metrics;

generating buckets based on the normalized metrics; and

generating the reviewer segmentation data based on the buckets, wherein the reviewer segmentation data includes a plurality of reviewer segments, each of which corresponds to one or more of the buckets.

5. The system of claim **4**, wherein:

each bucket is associated with a range boundary; and

the range boundaries of the buckets and a total quantity of the buckets are determined based on seasonal data and event data during the past time period.

6. The system of claim **1**, wherein the at least one machine learning model comprises a multi-task neural network including:

an input layer configured to receive the feature data;

a feature concatenation layer configured to concatenate features of the feature data to generate concatenated features;

a feed forward layer configured to fit the concatenated features and convert them into a multi-dimensional vector for each of the plurality of customers; and

a plurality of task specific hidden layers each of which corresponds to a respective task for a respective product type, wherein each respective task is performed by a respective fully connected neural network in a corresponding feed forward layer to predict a review probability for a respective product type.

7. The system of claim **1**, wherein the ranked list of customers is generated based on:

selecting, from the plurality of customers, a list of customers whose review probabilities are higher than a predetermined threshold based on: (1) a product type determined based on the request and (2) a reviewer segment determined based on the request, wherein:

the review probabilities are computed with respect to the product type, and

the list of customers are selected from the reviewer segment; and

ranking the list of customers according to their respective review probabilities to generate the ranked list of customers based on budget data.

8. The system of claim **7**, wherein the reviewer segment is determined based on:

determining, based on the request, an instruction for selecting customers, wherein the instruction indicates an exploration of new customers or an exploitation to increase a total number of reviews; and

determining the reviewer segment based on the instruction.

9. The system of claim **7**, wherein the instructions, when executed, further cause the processor to:

send review reminders to customers in the ranked list, wherein:

the review reminders are sent via at least one of: an email, a text message, an app or a website, and

different review reminders are sent in different priorities according to rankings of the customers in the ranked list based on the budget data.

10. A computer-implemented method, comprising:

receiving a request for potential reviewers;

selecting, based on the request, a plurality of customers who have purchased items but have not provided any review for the purchased items;

computing, using at least one machine learning model, review probabilities based on feature data related to the plurality of customers and transactions involving the purchased items, wherein each review probability is a probability of a corresponding customer providing a review;

generating, from the plurality of customers, a ranked list of customers based on the review probabilities and reviewer segmentation data; and

transmitting to a computing device the ranked list of customers to be reminded for providing reviews.

11. The computer-implemented method of claim **10**, wherein selecting the plurality of customers comprises:

determining, based on the request, at least one product type; and

selecting, from a customer pool, the plurality of customers who have purchased items in the at least one product type but have not provided any review for the purchased items, wherein the plurality of customers are selected based on transaction data and user session data associated with the customer pool.

12. The computer-implemented method of claim **11**, wherein computing the review probabilities comprises:

generating the feature data based on: customer features, customer action features, benefit affinity data, transaction segmentation data, and reviewer segmentation data; and

inputting the feature data into the at least one machine learning model to compute, for each of the plurality of customers, a review probability that the customer will provide a review within the at least one product type.

13. The computer-implemented method of claim **10**, wherein generating the reviewer segmentation data comprises:

obtaining historical review data of customers within a past time period;

determining segmentation metrics based on the historical review data, wherein the segmentation metrics comprise:

a review frequency indicating how many reviews a customer provided per order during the past time period, and

a review recency indicating a time period passed since a last review provided by a customer;

normalizing each of the segmentation metrics to generate normalized metrics;

generating buckets based on the normalized metrics; and

generating the reviewer segmentation data based on the buckets, wherein the reviewer segmentation data includes a plurality of reviewer segments, each of which corresponds to one or more of the buckets.

14. The computer-implemented method of claim **13**, wherein:

each bucket is associated with a range boundary; and

the range boundaries of the buckets and a total quantity of the buckets are determined based on seasonal data and event data during the past time period.

15. The computer-implemented method of claim **10**, wherein the at least one machine learning model comprises a multi-task neural network including:

an input layer configured to receive the feature data;

a feature concatenation layer configured to concatenate features of the feature data to generate concatenated features;

a feed forward layer configured to fit the concatenated features and convert them into a multi-dimensional vector for each of the plurality of customers; and

a plurality of task specific hidden layers each of which corresponds to a respective task for a respective product type, wherein each respective task is performed by a respective fully connected neural network in a corresponding feed forward layer to predict a review probability for a respective product type.

16. The computer-implemented method of claim **10**, wherein generating the ranked list of customers comprises:

selecting, from the plurality of customers, a list of customers whose review probabilities are higher than a predetermined threshold based on: (1) a product type determined based on the request and (2) a reviewer segment determined based on the request, wherein:

the review probabilities are computed with respect to the product type, and

the list of customers are selected from the reviewer segment; and

ranking the list of customers according to their respective review probabilities to generate the ranked list of customers based on budget data.

17. A non-transitory computer readable medium having instructions stored thereon, wherein the instructions, when executed by at least one processor, cause at least one device to perform operations comprising:

receiving a request for potential reviewers;

selecting, based on the request, a plurality of customers who have purchased items but have not provided any review for the purchased items;

computing, using at least one machine learning model, review probabilities based on feature data related to the plurality of customers and transactions involving the purchased items, wherein each review probability is a probability of a corresponding customer providing a review;

generating, from the plurality of customers, a ranked list of customers based on the review probabilities and reviewer segmentation data; and

transmitting to a computing device the ranked list of customers to be reminded for providing reviews.

18. The non-transitory computer readable medium of claim **17**, wherein selecting the plurality of customers comprises:

determining, based on the request, at least one product type; and

selecting, from a customer pool, the plurality of customers who have purchased items in the at least one product type but have not provided any review for the purchased items, wherein the plurality of customers are selected based on transaction data and user session data associated with the customer pool.

19. The non-transitory computer readable medium of claim **18**, wherein computing the review probabilities comprises:

generating the feature data based on: customer features, customer action features, benefit affinity data, transaction segmentation data, and reviewer segmentation data; and

inputting the feature data into the at least one machine learning model to compute, for each of the plurality of customers, a review probability that the customer will provide a review within the at least one product type.

20. The non-transitory computer readable medium of claim **17**, wherein generating the reviewer segmentation data comprises:

obtaining historical review data of customers within a past time period;

determining segmentation metrics based on the historical review data, wherein the segmentation metrics comprise:

a review frequency indicating how many reviews a customer provided per order during the past time period, and

a review recency indicating a time period passed since a last review provided by a customer;

normalizing each of the segmentation metrics to generate normalized metrics;

generating buckets based on the normalized metrics; and

generating the reviewer segmentation data based on the buckets, wherein the reviewer segmentation data includes a plurality of reviewer segments, each of which corresponds to one or more of the buckets, wherein:

each bucket is associated with a range boundary; and

the range boundaries of the buckets and a total quantity of the buckets are determined based on seasonal data and event data during the past time period.

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