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Gibson et al.

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(54) **SYSTEMS AND METHODS BASED ON ANONYMIZED DATA**

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This patent is subject to a terminal disclaimer.

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Related U.S. Application Data

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(51) **Int. Cl.**

G06Q 20/40	(2012.01)
G06F 18/2413	(2023.01)
G06F 21/62	(2013.01)
G06N 20/00	(2019.01)

(52) **U.S. Cl.**
CPC ... ***G06Q 20/4016*** (2013.01); ***G06F 18/24147*** (2023.01); ***G06F 21/6254*** (2013.01); ***G06N 20/00*** (2019.01); ***G06Q 20/4015*** (2020.05)

(58) **Field of Classification Search**
CPC G06Q 20/00–425; G06F 18/00–30
See application file for complete search history.

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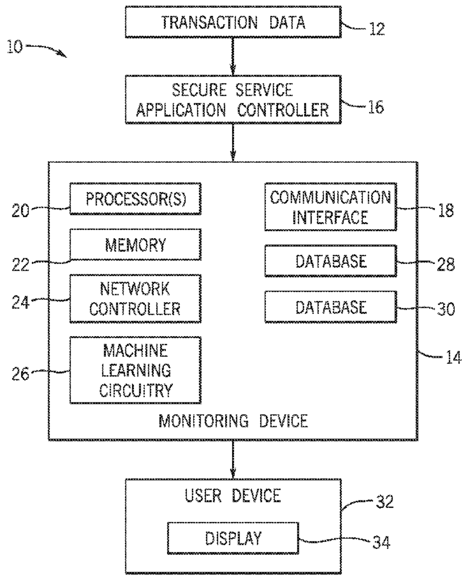
(57) **ABSTRACT**

The present disclosure relates to systems and methods to generate user or user group behavior similarities based on computing distances between individual users or user groups and without using demographic data, e.g., based on anonymized data. The methods include creating a multidimensional vector representation for each user in a group by summarizing user's behaviors across various categories. Based on the created vectors, distance calculation and nearest neighbor search are performed to locate users that are most similar to target users. The resulting distance metrics may be used to rank similarities. Additionally, dimensionality reduction may be performed to further distill the behavior information to make the disclosed methods suitable for a variety of analytics and modeling tasks.

14 Claims, 12 Drawing Sheets



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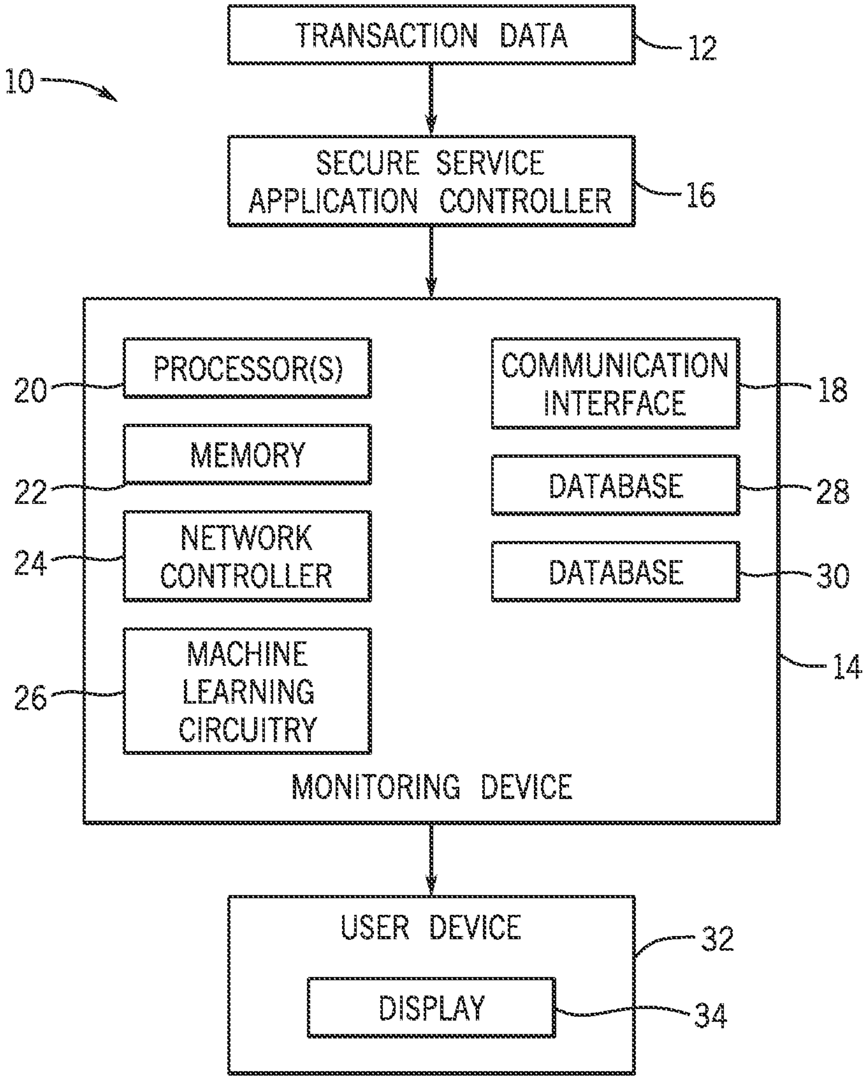

TRANSACTION DATA
12
10
SECURE SERVICE APPLICATION CONTROLLER
16
PROCESSOR(S)
20
MEMORY
22
NETWORK CONTROLLER
24
MACHINE LEARNING CIRCUITRY
26
COMMUNICATION INTERFACE
18
DATABASE
28
DATABASE
30
14
MONITORING DEVICE
USER DEVICE
32
DISPLAY
34

FIG. 1

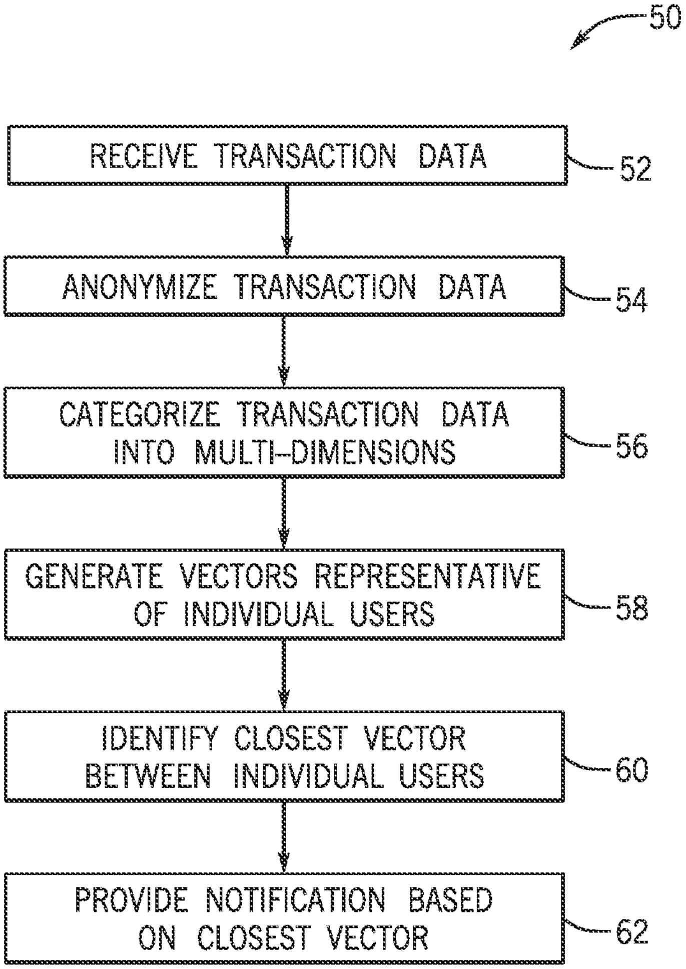

50
RECEIVE TRANSACTION DATA
52
ANONYMIZE TRANSACTION DATA
54
CATEGORIZE TRANSACTION DATA INTO MULTI-DIMENSIONS
56
GENERATE VECTORS REPRESENTATIVE OF INDIVIDUAL USERS
58
IDENTIFY CLOSEST VECTOR BETWEEN INDIVIDUAL USERS
60
PROVIDE NOTIFICATION BASED ON CLOSEST VECTOR
62

FIG. 2

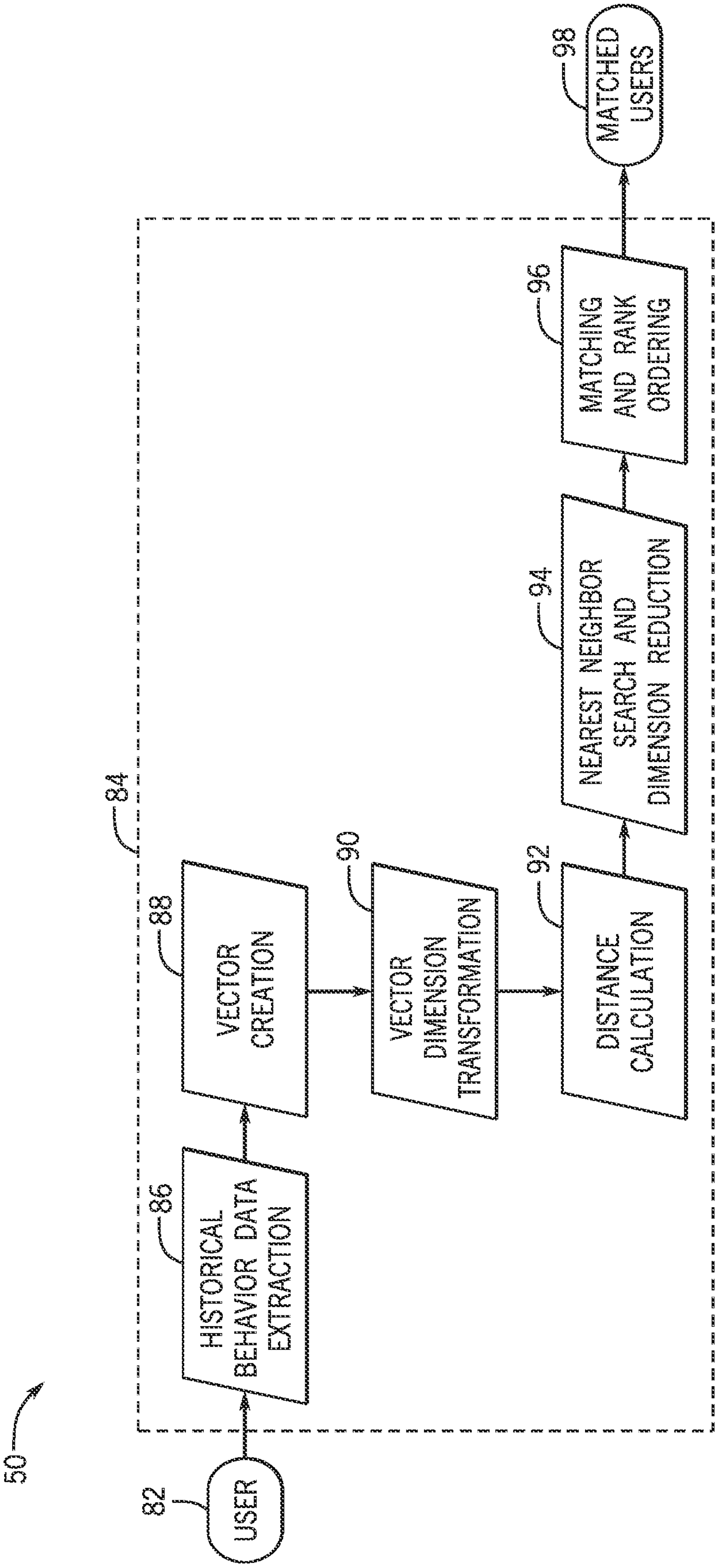
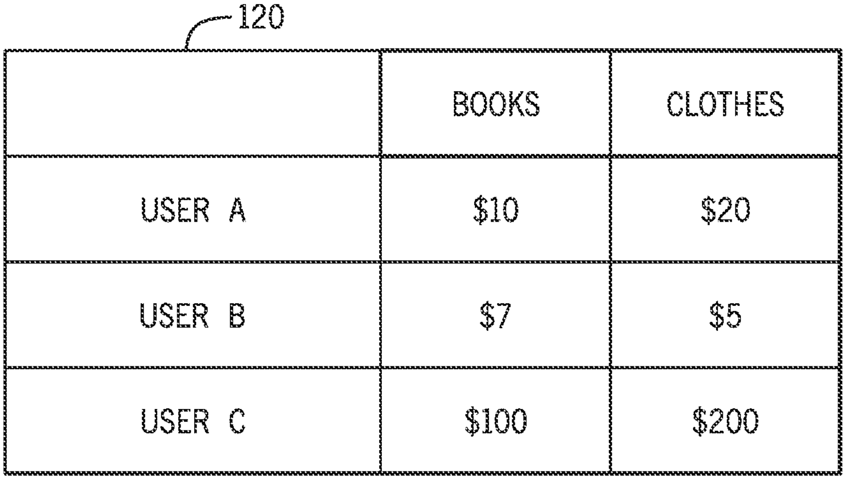
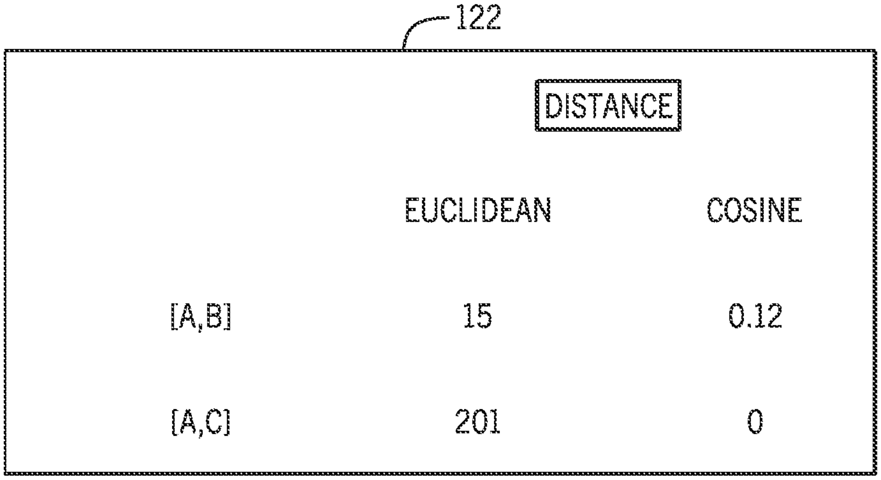

50
82
USER
84
86
HISTORICAL BEHAVIOR DATA EXTRACTION
88
VECTOR CREATION
90
VECTOR DIMENSION TRANSFORMATION
92
DISTANCE CALCULATION
94
NEAREST NEIGHBOR SEARCH AND DIMENSION REDUCTION
96
MATCHING AND RANK ORDERING
98
MATCHED USERS

FIG. 3



	BOOKS	CLOTHES
USER A	$10	$20
USER B	$7	$5
USER C	$100	$200

FIG. 4A



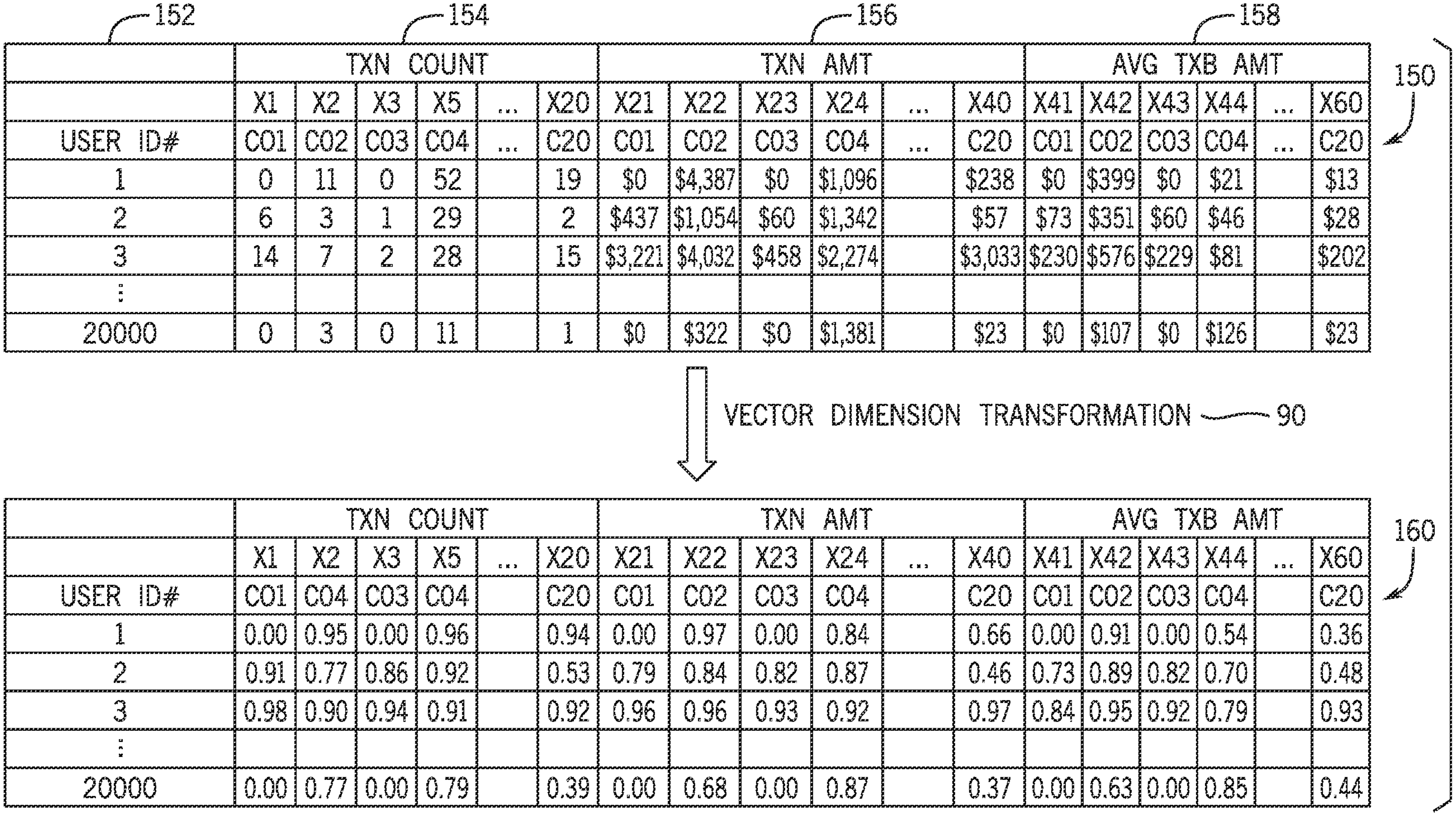
	DISTANCE	
	EUCLIDEAN	COSINE
[A,B]	15	0.12
[A,C]	201	0

FIG. 4B

140 142

CATEGORY DESCRIPTION	EXAMPLES
AIRLINES, AIR CARRIERS	AIRLINES
LODGING–HOTELS, MOTELS, RESORTS	LODGING
CAR RENTAL AGENCIES	CAR RENTAL
GROUND TRANSPORTATION	TAXI, BUS, PARKING, TOLLS
GAS / FUEL	GAS, FUEL
DINING	DINING
DINING – FAST FOOD	FAST FOOD
GROCERY STORES / PHARMACIES / FOOD SERVICES /	GROCERY, FOOD, PHARMACY
CLOTHING / SHOES / ACCESSORIES / UNIFORMS / RETAIL STORES	CLOTHES, SHOES, BOOKS, LUGGAGE
FURNISHINGS / APPLIANCES / MAINTENANCE / HOME	FURNITURE, APPLIANCE
FINANCIAL SERVICES	BT, INSURANCE ETC
HEALTHCARE / CHILDCARE SERVICES	MEDICAL, DENTAL, HOSPITAL
PERSONAL SERVICES	COUNSELING, TAX, FUNERAL SERVICES
ASSOCIATIONS / ORGANIZATIONS	CHARITABLE, ACCOUNTING, FINES
BUSINESS / PROFESSIONAL / MISCELLANEOUS SERVICES	MARKETING, LAUNDRY, BARBER, PHOTOGRAPHIC STUDIOS
EDUCATIONAL SERVICES	SCHOOLS, EDUCATION SERVICES
ELECTRONIC AND TECHNICAL SERVICES	ELECTRONIC STORES, CABLE, TV SERVICES
DIGITAL GOODS	EBOOK, MOVIE, GAME
ENTERTAINMENT / THEATER / DANCE STUDIOS	BOWLING, THEATRE, GOLF, PARK
RETURN	RETURNS

FIG. 5



	TXN COUNT						TXN AMT						AVG TXB AMT					
	X1	X2	X3	X5	...	X20	X21	X22	X23	X24	...	X40	X41	X42	X43	X44	...	X60
USER ID#	C01	C02	C03	C04	...	C20	C01	C02	C03	C04	...	C20	C01	C02	C03	C04	...	C20
1	0	11	0	52		19	$0	$4,387	$0	$1,096		$238	$0	$399	$0	$21		$13
2	6	3	1	29		2	$437	$1,054	$60	$1,342		$57	$73	$351	$60	$46		$28
3	14	7	2	28		15	$3,221	$4,032	$458	$2,274		$3,033	$230	$576	$229	$81		$202
⋮																		
20000	0	3	0	11		1	$0	$322	$0	$1,381		$23	$0	$107	$0	$126		$23

	TXN COUNT						TXN AMT						AVG TXB AMT					
	X1	X2	X3	X5	...	X20	X21	X22	X23	X24	...	X40	X41	X42	X43	X44	...	X60
USER ID#	C01	C04	C03	C04		C20	C01	C02	C03	C04		C20	C01	C02	C03	C04		C20
1	0.00	0.95	0.00	0.96		0.94	0.00	0.97	0.00	0.84		0.66	0.00	0.91	0.00	0.54		0.36
2	0.91	0.77	0.86	0.92		0.53	0.79	0.84	0.82	0.87		0.46	0.73	0.89	0.82	0.70		0.48
3	0.98	0.90	0.94	0.91		0.92	0.96	0.96	0.93	0.92		0.97	0.84	0.95	0.92	0.79		0.93
⋮																		
20000	0.00	0.77	0.00	0.79		0.39	0.00	0.68	0.00	0.87		0.37	0.00	0.63	0.00	0.85		0.44

FIG. 6

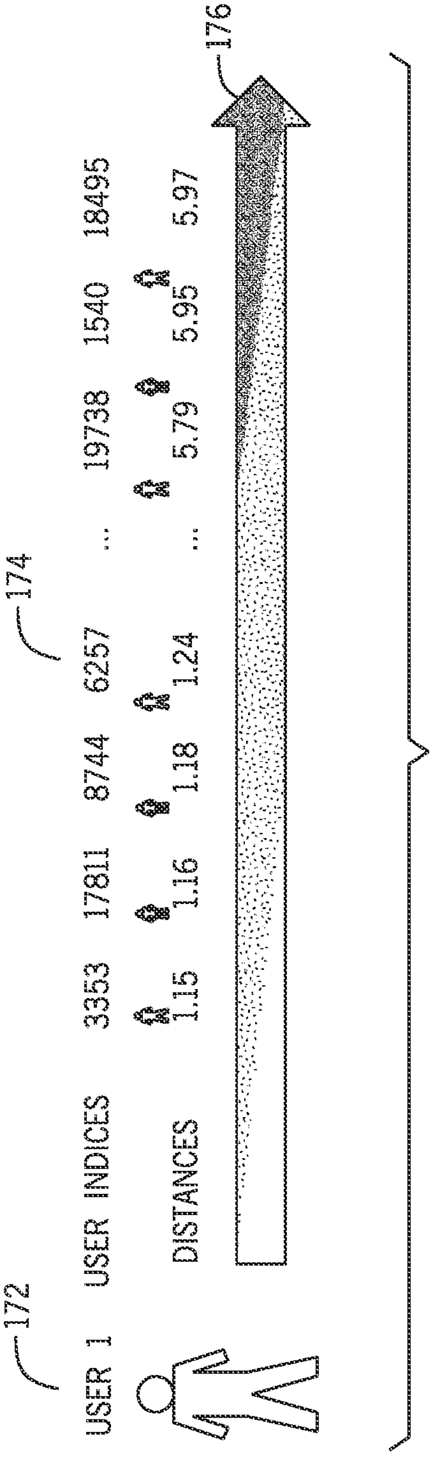
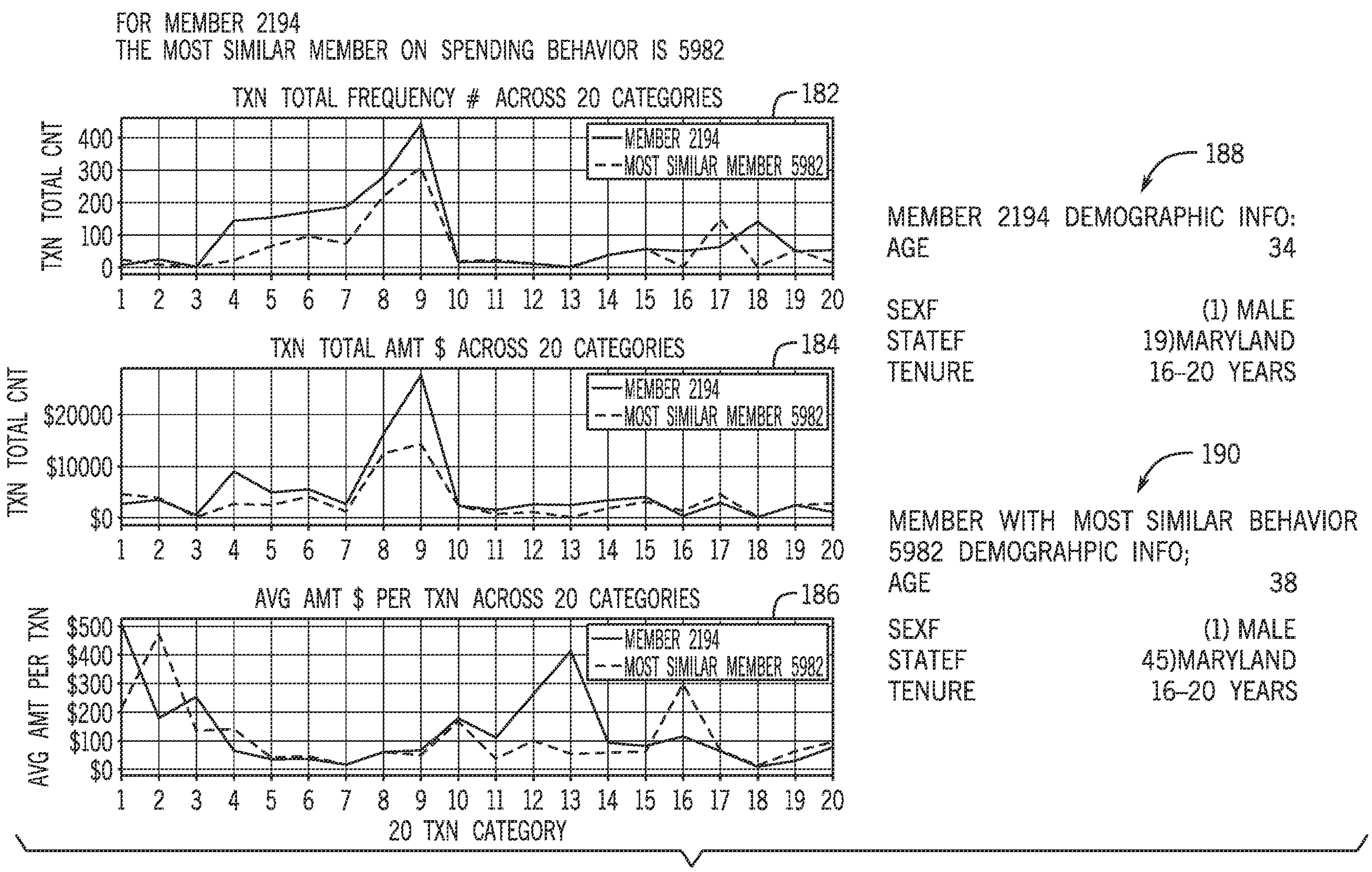

USER 1
172
USER INDICES
3353
17811
8744
6257
...
19738
1540
18495
174
DISTANCES
1.15
1.16
1.18
1.24
...
5.79
5.95
5.97
176

FIG. 7



MEMBER 2194 DEMOGRAPHIC INFO:
AGE 34

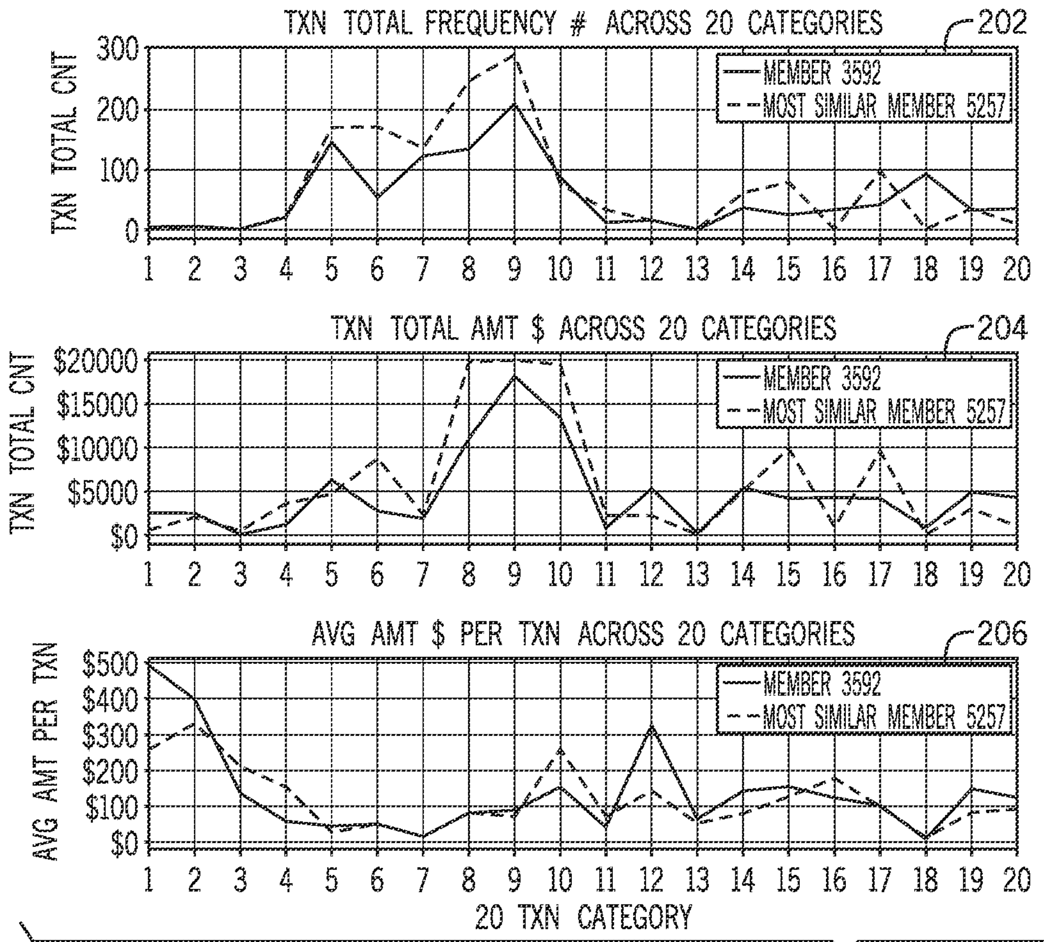
SEXF (1) MALE
STATEF 19)MARYLAND
TENURE 16–20 YEARS

MEMBER WITH MOST SIMILAR BEHAVIOR
5982 DEMOGRAHPIC INFO;
AGE 38

SEXF (1) MALE
STATEF 45)MARYLAND
TENURE 16–20 YEARS

FIG. 8

FOR MEMBER 3592
THE MOST SIMILAR MEMBER ON SPENDING BEHAVIOR IS 5257



208

MEMBER 3592 DEMOGRAPHIC INFO:
AGE 45

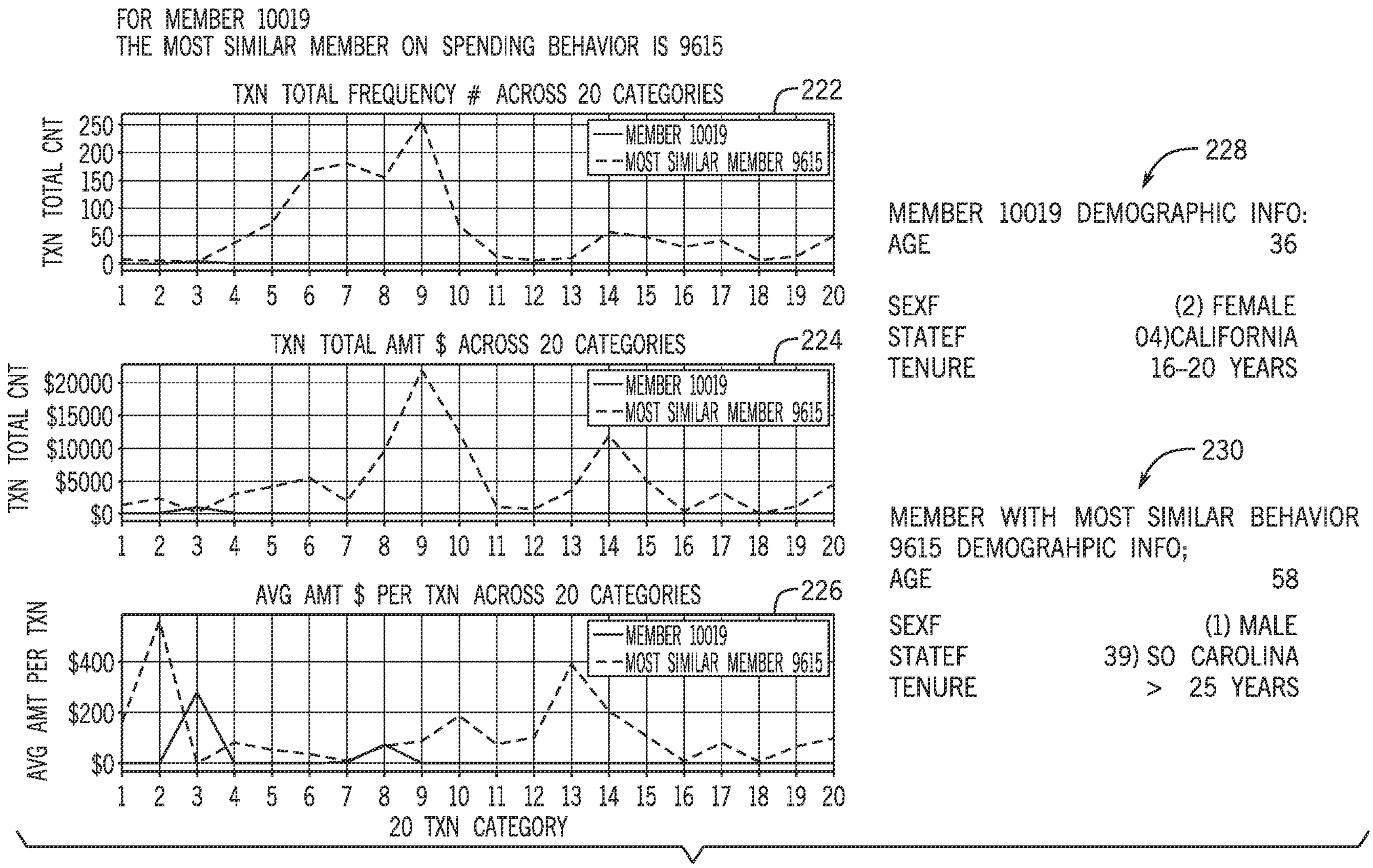
SEXF (2) FEMALE
STATEF 15KANSAS
TENURE 16-20 YEARS

210

MEMBER WITH MOST SIMILAR BEHAVIOR
5257 DEMOGRAHPIC INFO;
AGE 59

SEXF (1) MALE
STATEF 04)CALIFORNIA
TENURE > 25 YEARS

FIG. 9



MEMBER 10019 DEMOGRAPHIC INFO:

AGE	36
SEXF	(2) FEMALE
STATEF	04)CALIFORNIA
TENURE	16-20 YEARS

MEMBER WITH MOST SIMILAR BEHAVIOR 9615 DEMOGRAHPIC INFO;

AGE	58
SEXF	(1) MALE
STATEF	39) SO CAROLINA
TENURE	> 25 YEARS

FIG. 10

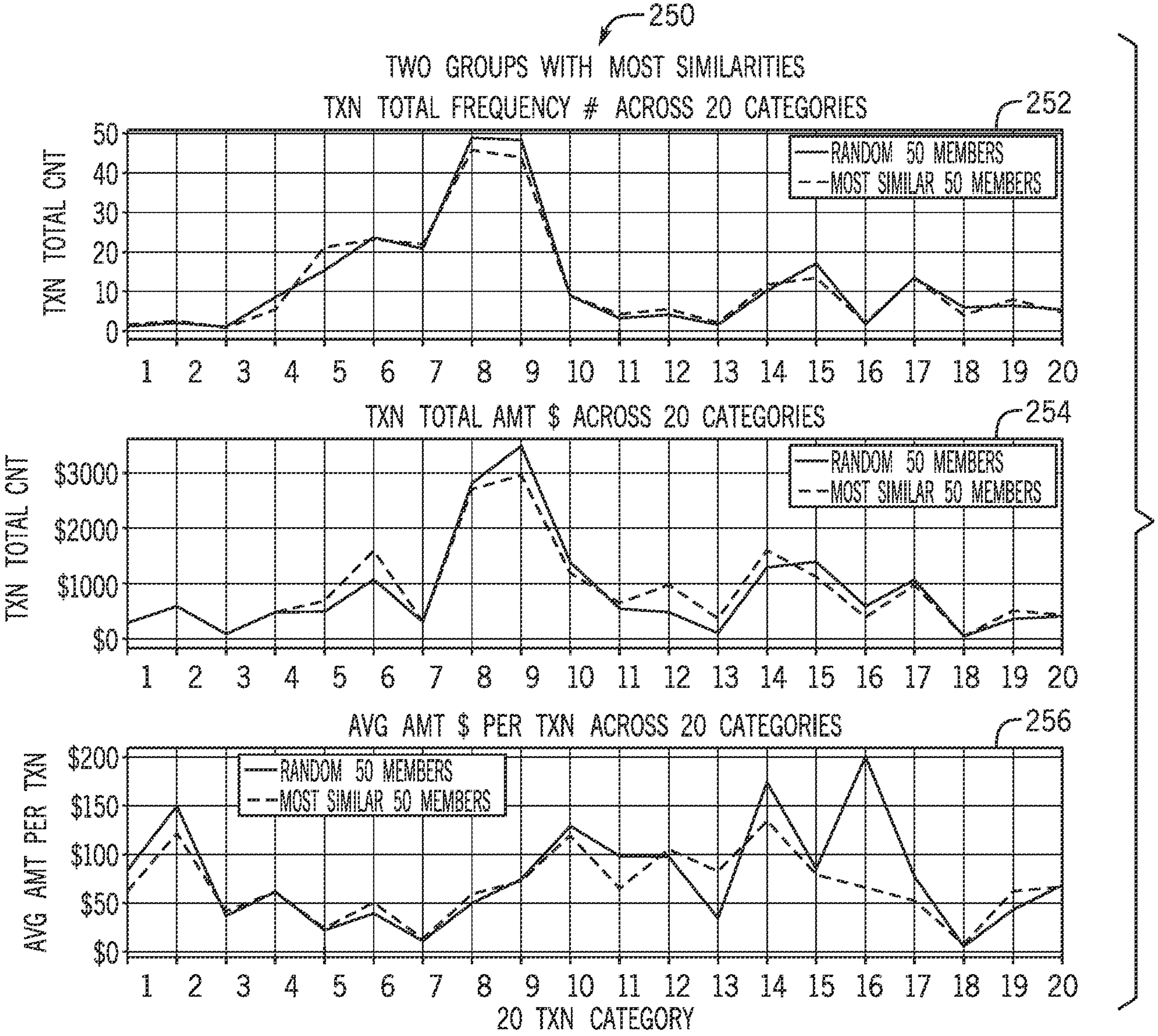
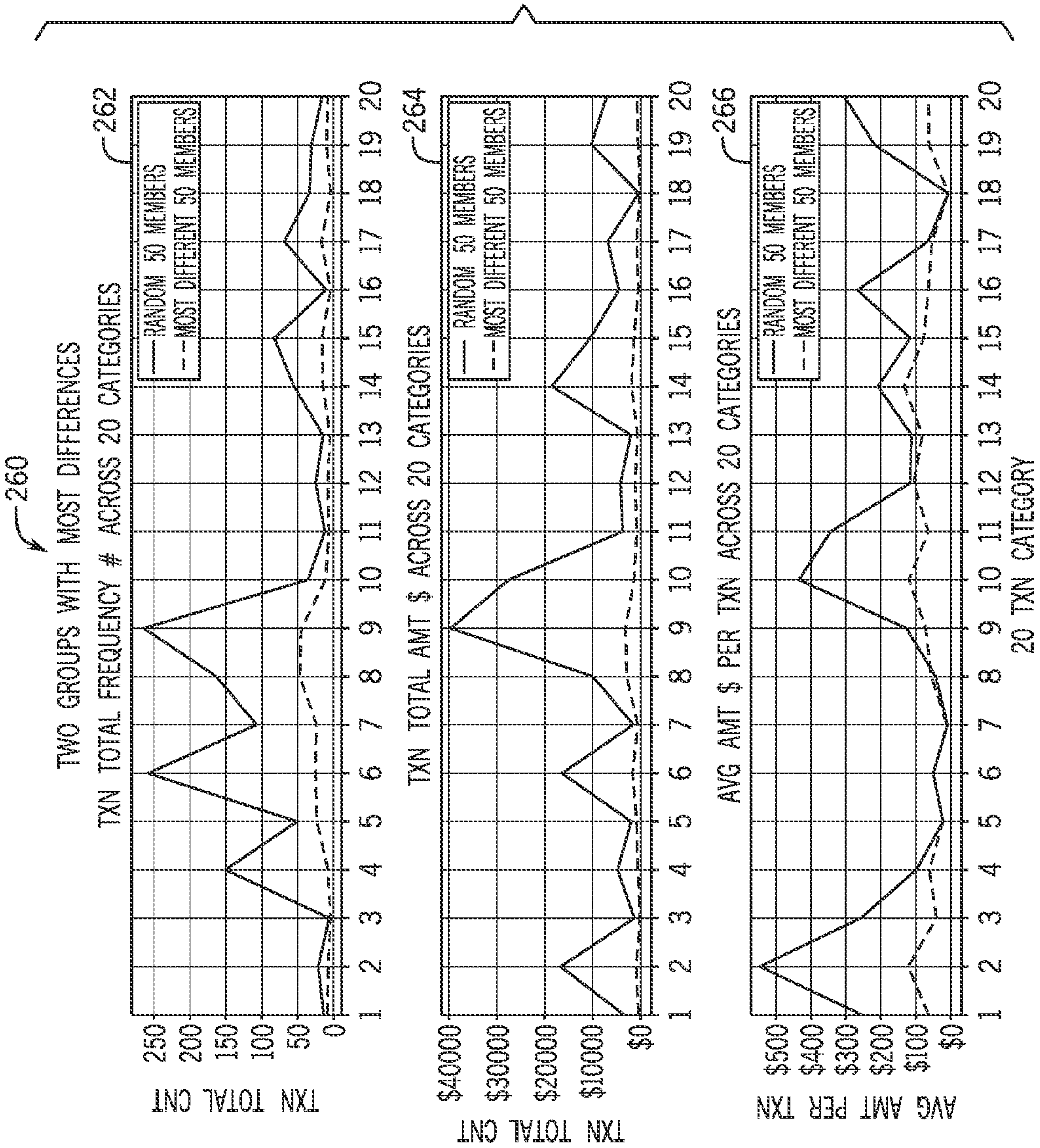

250
TWO GROUPS WITH MOST SIMILARITIES
TXN TOTAL FREQUENCY # ACROSS 20 CATEGORIES
252
TXN TOTAL CNT
50
40
30
20
10
0
RANDOM 50 MEMBERS
MOST SIMILAR 50 MEMBERS
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
TXN TOTAL AMT $ ACROSS 20 CATEGORIES
254
TXN TOTAL CNT
$3000
$2000
$1000
$0
RANDOM 50 MEMBERS
MOST SIMILAR 50 MEMBERS
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
AVG AMT $ PER TXN ACROSS 20 CATEGORIES
256
AVG AMT PER TXN
$200
$150
$100
$50
$0
RANDOM 50 MEMBERS
MOST SIMILAR 50 MEMBERS
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
20 TXN CATEGORY

FIG. 11A

FIG. 11B


260
TWO GROUPS WITH MOST DIFFERENCES
TXN TOTAL FREQUENCY # ACROSS 20 CATEGORIES
262
RANDOM 50 MEMBERS
MOST DIFFERENT 50 MEMBERS
TXN TOTAL CNT
250
200
150
100
50
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
TXN TOTAL AMT $ ACROSS 20 CATEGORIES
264
RANDOM 50 MEMBERS
MOST DIFFERENT 50 MEMBERS
TXN TOTAL CNT
$40000
$30000
$20000
$10000
$0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
AVG AMT $ PER TXN ACROSS 20 CATEGORIES
266
RANDOM 50 MEMBERS
MOST DIFFERENT 50 MEMBERS
AVG AMT PER TXN
$500
$400
$300
$200
$100
$0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
20 TXN CATEGORY

SYSTEMS AND METHODS BASED ON ANONYMIZED DATA

CROSS-REFERENCE TO RELATED APPLICATIONS

The present application is a divisional of U.S. patent application Ser. No. 16/917,296, filed on Jun. 30, 2020, the disclosure of which is hereby incorporated by reference in its entirety herein.

BACKGROUND

The present disclosure relates generally to analyzing user data while adhering to data privacy. More particularly, the present disclosure relates to systems and methods for identifying a valid transaction of a user based on look-alike users or groups of users based on anonymized data.

This section is intended to introduce the reader to various aspects of art that may be related to various aspects of the present disclosure, which are described and/or claimed below. This discussion is believed to help provide the reader with background information to facilitate a better understanding of the various aspects of the present disclosure. Accordingly, it is understood that these statements are to be read in this light, and not as admissions of prior art.

Services that handle user data may wish to analyze the data for the purposes of transaction validation, user authentication, other security purposes, or to identify patterns in user behavior. Such analysis may include identifying groups of users that are predicted to behave in a similar manner based on collected demographic information (e.g., location, age, race, and gender) related to the users or user groups. For example, a service provider may identify a group of clients in a particular age range that live in a particular city. The service provider may extrapolate behavior from individual members to the entire group and make decisions based on the extrapolation.

SUMMARY

A summary of certain embodiments disclosed herein is set forth below. It should be understood that these aspects are presented merely to provide the reader with a brief summary of these certain embodiments and that these aspects are not intended to limit the scope of this disclosure. Indeed, this disclosure may encompass a variety of aspects that may not be set forth below.

Embodiments of the present disclosure relate to systems and methods to quantify user or user group behavior similarities by computing distances between users or user groups. The methods include creating a multidimensional vector representation for each user in a group by summarizing user's behaviors across various categories. Based on the created vectors, distance calculation and nearest neighbor search are performed to locate users that are most similar to target users. The resulting distance metrics may be used to rank similarities. Additionally, dimensionality reduction may be performed to further distill the behavior information to make the disclosed methods suitable for a variety of analytics and modeling tasks.

In an embodiment, a system is provided that includes a monitoring device. The monitoring device includes a communication interface; and one or more processors coupled to the communication interface, wherein the one or more processors are configured to receive, via the communication interface, transaction data of a plurality of users; categorize

the transaction data into a plurality of dimensions for each of the plurality of users; generate a plurality of vectors, the plurality of vectors comprising a vector for each of the plurality of users based on the plurality of dimensions; identify one or more closest vectors for each user from the plurality of vectors; determine, based on updated transaction data for an individual user of the plurality of users, a change in the one or more closest vectors for an individual user; and generate a notification of a potential fraudulent transaction in the updated transaction data based on the change.

In an embodiment, a method is provided that includes the steps of receiving, via a communication interface, transaction data of a user, wherein the transaction data is anonymized to exclude demographic information of the user; categorizing the transaction data into a plurality of dimensions; generating a user vector associated with the user based on the plurality of dimensions; identifying one or more closest vectors to the user vector, the one or more closest vectors comprising a first subset of vectors from a plurality of vectors stored in a database; receiving additional information indicative of a life event of the user; identifying a second subset of vectors from a plurality of vectors stored in the database based on the life event, the second subset being a predicted closest match associated with the life event; and generating one or more notifications to the user based on transaction data of a group of users associated with the second subset.

In an embodiment, a system is provided that includes a secure service application controller configured to receive transaction data of a user and to anonymize the user transaction data; a communication interface in communication with the secure service application controller and that receives the anonymized transaction data of the user; a data analysis application, comprising: a memory; and one or more processors coupled to the communication interface, wherein the one or more processors are configured access instructions from the memory to cause the one or more processors to receive, via the communication interface, the anonymized transaction data of the user; categorize the anonymized transaction data into a plurality of dimensions for the user; generate a user vector based on the plurality of dimensions; identify one or more closest vectors for the user from a plurality of vectors stored in the memory; and generate a notification to the user based on the one or more closest vectors, wherein the communication interface provides the notification to the secure service application controller, and wherein the secure service application controller associates the notification with the user and communicates or pushes the notification to a device of the user.

Various refinements of the features noted above may exist in relation to various aspects of the present disclosure. Further features may also be incorporated in these various aspects as well. These refinements and additional features may exist individually or in any combination. For instance, various features discussed below in relation to one or more of the illustrated embodiments may be incorporated into any of the above-described aspects of the present disclosure alone or in any combination. The brief summary presented above is intended only to familiarize the reader with certain aspects and contexts of embodiments of the present disclosure without limitation to the claimed subject matter.

DRAWINGS

These and other features, aspects, and advantages of the present disclosure will become better understood when the following detailed description is read with reference to the accompanying drawings in which like characters represent like parts throughout the drawings, wherein:

FIG. **1** illustrates a block diagram of a transaction monitoring system, in accordance with an embodiment of the present disclosure;

FIG. **2** depicts a flow chart for identifying a closest vector based on analyzing transaction data using the transaction monitoring system of FIG. **1**, in accordance with an embodiment of the present disclosure;

FIG. **3** depicts a flow chart for analyzing behavior data (e.g., transaction data) of a group of users and identifying a matched user for each user in the group, in accordance with an embodiment of the present disclosure;

FIG. **4**A illustrates an example user group with vectors representative of user behaviors, in accordance with an embodiment of the present disclosure;

FIG. **4**B illustrates the example user group of FIG. **4**A with calculated distances between the corresponding vectors, in accordance with an embodiment of the present disclosure;

FIG. **5** illustrates examples of different categories for classifying the transaction data, in accordance with an embodiment of the present disclosure;

FIG. **6** illustrates an example of vector dimension transformation, in accordance with an embodiment of the present disclosure;

FIG. **7** illustrates examples of calculated distances between a user and the other users in a user group, in accordance with an embodiment of the present disclosure;

FIG. **8** illustrates an example of two users with similar behaviors and demographics, in accordance with an embodiment of the present disclosure;

FIG. **9** illustrates an example of two users with similar behaviors but different demographics, in accordance with an embodiment of the present disclosure;

FIG. **10** illustrates an example of two users with different behaviors, in accordance with an embodiment of the present disclosure;

FIG. **11**A illustrates an example of two user groups with similar behaviors, in accordance with an embodiment of the present disclosure; and

FIG. **11**B illustrates another example of two user groups with different behaviors, in accordance with an embodiment of the present disclosure.

DETAILED DESCRIPTION

One or more specific embodiments of the present disclosure are described above. In an effort to provide a concise description of these embodiments, all features of an actual implementation may not be described in the specification. It should be appreciated that in the development of any such actual implementation, as in any engineering or design project, numerous implementation-specific decisions must be made to achieve the developers' specific goals, such as compliance with system-related and business-related constraints, which may vary from one implementation to another. Moreover, it should be appreciated that such a development effort might be complex and time consuming, but would nevertheless be a routine undertaking of design, fabrication, and manufacture for those of ordinary skill having the benefit of this disclosure.

When introducing elements of various embodiments of the present disclosure, the articles "a," "an," "the," and "said" are intended to mean that there are one or more of the elements. The terms "comprising," "including," and "having" are intended to be inclusive and mean that there may be additional elements other than the listed elements. It should be noted that the term "multimedia" and "media" may be used interchangeably herein.

The disclosed techniques provide improvements in analyzing, validating, or authenticating user interactions using similarity analysis of anonymized user data to find look-alike users or user groups (or, conversely, least similar users). For example, using look-alike analysis or modeling, an organization (e.g., a service provider) may be able to identify users (e.g., members or clients) who may behave similarly to existing users. As such, the organization may analyze the user data relative to their identified look-alike user or users to validate a user transaction or authenticate the user, in one example. In another example, the techniques may flag a user transaction as likely to be invalid if the transaction moves the user data towards a least similar user and away from look-alike users.

The disclosed techniques are in contrast to other validation techniques that use demographic profiles of users (e.g., members or clients) as part of data analysis. The demographic profiles are collections of characteristics about individual users, such as age, race, gender, employment, tenure, marital status, location, education, and the like. For example, users may be grouped based on age and education bands, and the service provider may flag certain groups to receive special offers or to be pushed news or notifications of interest, However, while service providers collect such demographic data, providing this data to analysis applications controlled by agents of the service provider or third parties may introduce potential breaches of privacy for their clients, because the demographic information may be potentially identifying for users. Using the demographic profiles may impose compliance risks by using potential protected user information (such as age and gender). Accordingly, providing and/or analyzing user data that includes potentially identifying demographic information for a user may introduce additional complexities in secure communication, data encryption, and requirements for reporting for any parties sending or receiving the data.

Further, in some cases, however, using the demographic profiles to find look-alike groups may not be accurate or reliable. For instance, two users with similar demographic background may behave very differently.

The disclosed embodiments provide the advantage of more accurate identification of similar users or user groups that does not involve using demographic information and that may be performed on anonymized data. Thus, the present techniques reduce communication computing complexity by permitting lower data security protocols to be enacted for the sending and receiving parties or any party that handles the data to perform the techniques disclosed herein.

In some embodiments, the techniques disclosed herein may enable a service provider to identify potential users or user groups who may who may behave similarly to existing users or user groups. For example, the service provider may use identifications based on similarity analysis to identify potential users or user groups for new product offers, and/or existing product promotional offers. Such product offers, when presented to the potential users or user groups, may increase response rates from the potential users or user groups.

As discussed in greater detail below, the present embodiments described herein provide methods to identify look-alike users or user groups based on user behavior data (e.g., user transaction data) using anonymized data, e.g., data without demographic or potentially identifying information.

The methods include receiving user transaction data and categorizing the data into multiple dimensions. The methods also include generating individual vectors for each user based on the multiple dimensions of the data and identifying closest vectors for each user or user groups. Identifying the closest vectors may be based on quantifying behavior similarities of the users or user groups by computing distances between the users or user groups. Based on the created vectors, distance calculation and nearest neighbor search may be performed to locate users that are most similar to target users. The resulting distance metrics may be used to rank similarities. Additionally, dimensionality reduction may be performed to further distill the behavior information to make the disclosed methods suitable for a variety of analytics and modeling tasks. In some embodiments, the methods further include determining a change in the closest vectors based on updated user behavior data and generating a notification of a potential fraudulent behavior in the updated behavior data.

With the forgoing in mind, turning now to the figures, FIG. **1** illustrates a block diagram of a transaction monitoring system **10**, according to implementations of the present disclosure. As shown in the example of FIG. **1**, a secure service application controller **16** receives transaction data **12** of a user. The transaction data **12** may include information recorded from various transactional events, including but not limited to financial, logistical or service-related data. For example, the transaction data may include banking activities, purchases, invoices, payments, debits and credits, hotel reservations, interest paid, insurance costs and claims, and the like.

The secure service application controller **16** may operate to anonymize the transaction data **12** to exclude demographic information of the user. A monitoring device **14** may receive, via a communication interface **18**, the anonymized transaction data of the user. The communication interface **18** may be in communication with the secure service application controller **16** to receive the anonymized transaction data of the user. The anonymized transaction data of the user may be analyzed by a data analysis application. The data analysis application may be executed by one or more processors **20** and may be stored on a memory **22**. In some embodiments, the data analysis application may include a machine learning circuitry **26**. The anonymized transaction data and analyzed data output from the data analysis application may be stored in multiple databases including a database **28** and a database **30**. The processors **20** may generate a notification to the user based on the analyzed data. The communication interface **18** may provide the notification to the secure service application controller **16**, which may associate the notification with the user and communicates or pushes the notification to a user device **32**.

The monitoring device **14** may be any suitable type of computing device but is not limited to: a desktop computer, a laptop computer, a notebook computer, a distributed computing device (e.g., a cloud computing device), a microcomputer, a system on a chip (SoC), a system in a package (SiP), and so forth. Although examples herein may describe the monitoring device **14** as a physical device, implementations are not so limited. In some examples, the monitoring device **14** may include one or more of a virtual computing environment, a hypervisor, an emulation, or a virtual machine executing on one or more physical computing devices. In some examples, two or more computing devices may include a cluster, cloud, farm, or other grouping of multiple devices that coordinate operations to provide load balancing, failover support, parallel processing capabilities, shared storage resources, shared networking capabilities, or other aspects.

While in the depicted embodiment, the secure service application controller **16** is separate from the monitor **14**, in other applications, the secure service application controller **16** may be integrated with or part of the monitor **14**. However, the secure service application controller **16** operates to receive data including user identification information, while data analysis operations of the monitor **14** as provided herein do not receive the identification information of the user, i.e., these operations receive anonymized data. Accordingly, the secure service application controller **16**, whether integrated with or separate from the monitor **14**, may communicate with a first, relatively more secure, communication protocol to receive the user transaction information that includes the identification information relative to a second, relatively less secure, communication protocol with the monitor **14** (or within the monitor **14**) to provide anonymized data to the data analysis operations performed by the processor **20**. In one embodiment, the secure service application controller **16** communicates the anonymized data to a third party or to an application operating third party software on the monitor **14**.

In an embodiment, the secure service application controller **16** may operate or include a service layer that supports functions such as, for example, data collection, device management, security, billing, location Tracking/geo-fencing, device/service discovery, and legacy systems integration, and provides these functions as services to system **10**.

In general, the monitoring device **14** may capture a variety of transaction data **12** associated with the user using the communication interface **18**. The communication interface **18** may be any suitable type of electronic circuitry designed to a specific standard that may enable the monitoring device **14** to communicate with other computing devices (e.g., computers or mobile phones). The communication interface **18** may also enable intercommunications between internal components (such as the processors **20**, machine learning circuitry **26**, and databases **28** and **30**). The communications may use various communication protocols, including but not limited to Open Database Connectivity (ODBC), TCP/IP Protocol, Distributed Relational Database Architecture (DRDA) protocol, Database Change Protocol (DCP), HTTP protocol, other suitable current or future protocols, or combinations thereof.

The processors **20** may be configured to process instructions for execution within the monitoring device **14**. The processors **20** may include single-threaded processor(s), multi-threaded processor(s), or both. The processors **20** may be configured to process instructions stored in the memory **22**. The processors **20** may include hardware-based processor(s) each including one or more cores. The processors **20** may include general purpose processor(s), special purpose processor(s), or both. The processors **20** may be communicatively coupled to other internal components (such as the communication interface **18**, the machine learning circuitry **26**, the databases **28** and **30**). Based on the anonymized transaction data, the processors **20** may identify one or more closest vectors for the user from a group of vectors representative of a group of users.

The memory **22** may be integral or attachable. For example, the memory **22** may be inserted into and ejected from the monitoring device **14** to facilitate transfer of the transaction data **12** by moving the memory **22** between systems (e.g., the memory **22** may be shipped from a user to an organization via mail and used to transfer data to the organization's system on a periodic basis). The memory **22** may enable the user and/or the organization to store and review aspects of the transaction data **12**. In some embodiments, the user and/or the organization may be permitted access to all transaction-related data stored in the memory **22**. In some embodiments, the user and/or the organization may not be permitted access to certain data (e.g., privacy of the user or confidential information associated with the organization) stored in the memory **22**.

The processor **20** may analyze the anonymized transaction data and generate the notification to the user based on the analyzed data. The notification may be sent to the user device **32** associated with the user via a network controller **24**. The notifications may be presented to the user via a display **34**. The processors **20** and the communication interface **18** may be communicatively coupled to the network controller **24**.

The processors **20** may execute processing instructions stored in the memory **22**. The processing instructions may instruct the processors **20** to receive anonymized transaction data of the user, using the communication interface **18** and the protocols described above. The anonymized transaction data may exclude demographic information of the user. Additionally or alternatively, the processing instructions may instruct the processors **20** to categorize the anonymized transaction data into multi-dimensional data for individual users. Based on the categorized multi-dimensional data, the processors **20** may generate vectors representative of the individual users. In some embodiments, the processors **20** may normalize the generated vectors based on certain vector dimension transformations (e.g., quantile grouping). By calculating distances between each pair of vectors, the processors **20** may identify one or more closest vectors for each user. The distance calculation may be based on Euclidean distance calculation, cosine distance calculation, other suitable distance calculations, or combinations thereof. In some embodiments, identifying the closest vectors may use a nearest neighbor search.

In some embodiments, the processing instructions may instruct the processors **20** to determine a change in the one or more closest vectors for the user, based on updated transaction data for the user. Accordingly, a notification, such as a notification of a potential fraudulent transaction in the updated transaction data based on the change may be generated by the processors **20**. For example, the updated transaction data may include an abnormal transaction (e.g., purchasing order), which may be related to a potential fraudulent transaction.

In some embodiments, the processors **20** may use the communication interface **18** to communicate with a source that provides the updated transaction data to stop the potential fraudulent transaction. In some embodiments, the monitoring device **16** may use the communication interface **18** to communicate with the source to request additional information from the individual users before permitting the potential fraudulent transaction.

In some embodiments, the processors **20** may receive additional information indicative of a life event of a user, such as getting married, having a baby, losing health coverage, or being enlisted for a military service. Accordingly, the processors **20** may identify a second subset of vectors from the vectors stored in a database (e.g., database **28** or **30**) based on the life event of the user. The second subset may be a predicted closest match associated with the life event of the user. The processors **20** may further generate one or more notifications to the user based on transaction data of a group of users associated with the second subset.

Some behavior analysis processes (e.g., predicting closest match associated with the life event of the user) described above may be performed by the machine learning circuitry **26** using the anonymized transaction data and additional information (e.g., information related to a life event of the user) associate with the user. The machine learning circuitry **26** (e.g., circuitry used to implement machine learning algorithms or logic) may access the anonymized transaction data and additional information to identify patterns, correlations, or trends associated with behavior related to the user. The transaction data **12** may be sourced from a multitude of diverse online services and databases, new data patterns not previously attainable based on behavior analysis without machine learning may emerge. As used herein, machine learning may refer to algorithms and statistical models that computer systems use to perform a specific task with or without using explicit instructions. For example, a machine learning process may generate a mathematical model based on a sample of the clean data, known as "training data," in order to make predictions or decisions without being explicitly programmed to perform the task.

Depending on the inferences to be made, the machine learning circuitry **26** may implement different forms of machine learning. In some embodiments, a supervised machine learning may be implemented. In supervised machine learning, the mathematical model of a set of transaction data contains both the inputs and the desired outputs. The set of transaction data is referred to as "training data" and is essentially a set of training examples. Each training example has one or more inputs and the desired output, also known as a supervisory signal. In a mathematical model, each training example is represented by an array or vector, sometimes called a feature vector, and the training data is represented by a matrix. Through iterative optimization of an objective function, supervised learning algorithms learn a function that can be used to predict the output associated with new inputs. An optimal function will allow the algorithm to correctly determine the output for inputs that were not a part of the training data. An algorithm that improves the accuracy of its outputs or predictions over time is said to have learned to perform that task.

Supervised learning algorithms may include classification and regression. Classification algorithms are used when the outputs are restricted to a limited set of values, and regression algorithms are used when the outputs may have any numerical value within a range. Similarity learning is an area of supervised machine learning closely related to regression and classification, but the goal is to learn from examples using a similarity function that measures how similar or related two objects (e.g. two behaviors from different users) are. It has applications in fraud detection, ranking, recommendation systems, visual identity tracking, face verification, and speaker verification.

Additionally and/or alternatively, in some situations, it may be beneficial for the machine-learning circuitry **24** to utilize unsupervised learning (e.g., when particular output types are not known). Unsupervised learning algorithms take a set of transaction data that contains only inputs, and find structure in the data, like grouping or clustering of transaction data. The algorithms, therefore, learn from test data that has not been labeled, classified or categorized. Instead of responding to feedback, unsupervised learning algorithms identify commonalities in the transaction data and react based on the presence or absence of such commonalities in each new piece of transaction data.

Cluster analysis is the assignment of a set of observations (e.g., transaction datasets) into subsets (called clusters) so that observations within the same cluster are similar according to one or more predesignated criteria, while observations drawn from different clusters are dissimilar. Different clustering techniques make different assumptions on the structure of the transaction data, often defined by some similarity metric and evaluated, for example, by internal compactness, or the similarity between users of the same cluster, and separation, the difference between clusters. Predictions or correlations may be derived by the machine learning circuitry **26**. For example, groupings and/or other classifications of the transaction data may be used to predict user behaviors. The predictions may be provided to downstream applications, which may perform actions based upon the predictions. The actions that are performed may be mediated through the secure service application controller **16**, either directly or through a coupled secure system, that has access to the user identification associated with the anonymized user data, to facilitate secure communication with the user or other party that is authorized by the user.

For example, the actions may include automatically pushing news or information related to the specific life event to the user device **32**, whereby the news or information is selected based on the news or information in transaction data of closest match users. In this manner, the individual user having the life event is automatically presented with information that was of interest to closest match users. However, this information is pushed to the individual user without tracking cookies and in a manner that protects the data privacy of the closest matcher users by keeping the identities associated with their transaction data at arm's length from that of the individual user. In this manner, certain types of health information may be provided, or predicted, while complying with health privacy regulations.

The user device **32** may include any suitable type of computing device. In some instances, the user device **32** is a portable computing device such as a smartphone, tablet computer, wearable device, implanted computer, automotive computer, portable gaming platform, and so forth, the location of which may change throughout the course of a day or other period of time as the user moves about. In some embodiments, the user device **32** may also be a less portable type of computing device, such as a desktop computer, laptop computer, game console, smart appliance, and so forth.

In particular, the user device **32** and the monitoring device **16** may communicate with one another, or with other computing devices, using one or more networks. Such networks may include public networks such as the internet, private networks such as an institutional or personal intranet, or any combination of private and public networks. The networks may include any type of wired or wireless network, including but not limited to local area networks (LANs), wide area networks (WANs), wireless WANs (WWANs), wireless LANs (WLANs), mobile communications networks (e.g., 3G, 4G, 5G, Edge, etc.), and so forth. In some implementations, the communications between computing devices may be encrypted or otherwise secured. For example, communications may employ one or more public or private cryptographic keys, ciphers, digital certificates, or other credentials supported by a security protocol, such as any version of the Secure Sockets Layer (SSL) or the Transport Layer Security (TLS) protocol.

Additional details with regard to analyzing user behavior similarities, along with other technologies for consolidating behavior analytics associated with users or user groups, will be discussed in detail below with reference to FIGS. **2-11**. With the preceding in mind, FIG. **2** depicts a flow chart for identifying a closest vector based on analyzing transaction data using the transaction monitoring system **10** of FIG. **1**, according to implementations of the present disclosure.

At block **52**, the transaction monitoring system **10** may receive transaction data (e.g., the transaction data **12**). As provided herein, the transaction data may be associated with an individual user (e.g., a member or client) of a service provider. For example, the transaction data may be associated with a user identification number that is associated with a user profile, and the user profile includes stored demographic information of the user. The stored demographic information may be stored in a database that is integrated with or accessible through the secure service application controller **16**. However, the stored demographic information may not be generally accessible to the processor **20** performing the data analysis operations. In turn, the transaction monitoring system **10** may anonymize the transaction data (block **54**) to exclude demographic information of the user and/or user identification information. That is, the anonymized data does not include or is not linked to user identification information, including the demographic information.

However, it should be understood that the transaction data for an individual user, while anonymized, is nevertheless retained as data of a single anonymous user. That is, in an embodiment, data for different users is not mixed in the data analysis. After transaction data anonymization, the transaction monitoring system **10** may categorize the transaction data into multi-dimensions (block **56**).

In some embodiments, the transaction data, the anonymized transaction data, and the categorized transaction data may be stored into different databases. For example, the transaction data **12** and the categorized transaction data associated with existing users may be stored into the database **28**, and the transaction data **12** and the categorized transaction data associated with new or potential users may be stored into the database **30** respectively.

The transaction data may include many categories related to different types of user behaviors or user events, such as lodging, rental, transportation, dining, personal service, education, entertainment, insurance, and the like. For large group of users (e.g., millions of users), analyzing behavior based on large amount of transaction data may be difficult (e.g., due to limited computational resources or long turnaround time). The transaction data may be categorized into multi-dimensional data based on a number of categories (e.g., 20 categories). In some embodiments, the transaction data may be pre-selected based on certain criteria. Such categorization and/or pre-selection may simplify the structure of the transaction data, therefore improving efficiencies of downstream operations (e.g., data storage, data analysis, vector generation, distance calculation, nearest neighbor searching, matching and ranking) and/or reducing turnaround time.

Based on the categorized transaction data, the transaction monitoring system **10** may generate vectors representative of individual users (block **58**). Each vector may include a multi-dimensional array of transaction data. The dimension of each vector may depend on the number of categories used to categorize the anonymized transaction data. The vectors may be used to compare behavior similarities/differences between the individual users. Additional details with regard to categorizing the anonymized transaction data **2** and generating the vectors will be discussed below with reference to FIGS. **5-6**.

Utilizing the generated vectors representative of individual users, the transaction monitoring system **10** may identify a closest vector between individual users (block **60**). The closest vector may be determined based on distance calculation. The calculated distance may be used as a quantitative representation of the behavior similarities/differences between the users or user groups. The distance calculation may be based on Euclidean distance calculation, cosine distance calculation, other suitable distance calculations, or combinations thereof. In some embodiments, identifying the closest vectors may use a nearest neighbor search or other suitable search algorithms/methods.

Further, the transaction monitoring system **10** may provide a notification based on the closest vector (block **62**). The notifications may be sent to a user or a vendor as an indication that certain behavior analysis or fraudulent transaction may be available for review. For example, the transaction monitoring system **10** may provide visual, vibrational, and/or auditory displays/indications/alerts in response to the identified closest vector.

Turning to FIG. **3**, a flow chart for analyzing behavior data (e.g., transaction data) of a group of users and identifying a matched user for each user in the group, according to implementations of the present disclosure. As illustrated, behavior data of a user **82** may be input to a behavior analysis process **84**. The behavior analysis process **84** may include a series of processing blocks for performing the behavior analysis and identify matched users **98** based on the behavior analysis. The vectors representative of the matched users **98** have shortest distance with respect to the vector representative of the user **82**.

As illustrated, the behavior analysis process **84** may start with a historical behavior data extraction (block **84**). The historical behavior data may include historical behavior data of the user **82** and historical behavior data of other users selected for finding the matched users **98** among them. The historical behavior data extraction may include anonymizing the historical behavior data to exclude demographic information of each user and categorizing the anonymized historical behavior data into multi-dimensional data for each user. The historical behavior data may include many categories related to different types of user behaviors (e.g., lodging, rental, transportation, dining, education, and entertainment). The historical behavior data may be categorized into multi-dimensional data based on a limited number of categories (e.g., 20 categories). In some embodiments, the historical behavior data may be pre-selected based on certain criteria.

Based on the multi-dimensional data categorized from the historical behavior data, a vector creation (block **88**) may be performed to generate vectors representative of the user **82** and other users. Each vector may include a multi-dimensional array of behavior data. The dimension of each vector may depend on the number of categories used to categorize the behavior data. The vectors may be used to compare behavior similarities/differences between the user **82** and other users.

In some embodiments, the generated vectors may be normalized based on a vector dimension transformation (block **90**), such as a quantile grouping/encoding. The quantile encoding may be performed for each vector dimension before distance calculations. Transforming each vector dimension may normalize the vectors by removing certain differences (e.g., scaling difference) between different vectors and/or different vector components.

The quantile encoding may provide an automatic way to transform a numeric input variable to have a different data distribution, which in turn, may be used as input to a predictive modeling. In some embodiments, the quantile encoding may change the probability distribution by dividing a range of discrete data (e.g., the historical behavior data with many dimensions) into continuous intervals with equal probabilities.

After the vector dimension transformation, a distance calculation (block **92**) may be performed by calculating distances between the user **82** and each of the other users. The distance calculation may be based on Euclidean distance calculation, cosine distance calculation, other suitable distance calculations, or combinations thereof.

The Euclidean distance calculation measures absolute differences in distance including direction and magnitude. A Euclidean distance may be a straight-line distance between two non-zero vectors in Euclidean space. The Euclidean distance may be calculated using Formula 1 as shown below:

Formula 1

$$d(p, q) = \sqrt{(p_1 \ldots q_1)^2 + (p_2 \ldots q_2)^2 + \ldots + (p_n \ldots q_n)^2} = \sqrt{\sum_{i=1}^{n} (p_i \ldots q_i)^2}.$$

Based on the Formula 1, the Euclidean distance between two vectors, p and q, may be calculated by summing up the square of a difference between each pair of vector components (p_i–q_i, where i is vector component index ranging from 1 to n, n is the dimension number of the vector p and q) and then taking a square root of the summation.

The cosine distance calculation measures cosine similarity (or angular similarity) by angle distance (directional only). Cosine similarity may be a measure of similarity between two non-zero vectors in an inner product space. The cosine similarity and cosine distance may be calculated using Formula 2 as shown below:

Formula 2

$$\text{The cosine similiarity is defined as Cosine Similarity} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}}$$

$$\text{The cosine distance is defined as Cosine Distance} = 1 - \text{Cosine Similarity}$$

Based on the Formula 2, the cosine similarity between two vectors, x and y, may be calculated using vector components x_i and y_i, where i is vector component index ranging from 1 to n, n is the dimension number of the vector x and y.

A Nearest neighbor search (block **94**) may be performed for identifying one or more closest vectors for each user. The distance calculation may be based on Euclidean distance calculation, cosine distance calculation, other suitable distance calculations, or combinations thereof. In some embodiments, identifying the closest vectors may use a nearest neighbor search.

The nearest neighbor search herein is a type of proximity search used for optimization problems of finding a vector in a given space (e.g., Euclidean space or inner-product space) that is closest (or most similar) to a given vector. Various solutions to the nearest neighbor search problems may be used, including but not limited to exact methods such as linear search and space partitioning, and approximation methods such as greedy search in proximity neighborhood graphs, locality sensitive hashing, nearest neighbor search in spaces with small intrinsic dimension(s), projected radial search, vector approximation, compression or clustering based search, and other suitable neighbor search methods.

In some embodiments, the nearest neighbor search may use machine learning. For example, a supervised machine learning algorithms such as a k-nearest neighbors (KNN) algorithm may be used to identify closest vectors in a group of vectors. In some embodiments, certain computing devices or elements such as the machine learning circuitry **26** may be used to support the machine learning.

In some embodiments, the block **94** may include a dimensionality reduction. The dimensionality reduction may include processes of reducing the number of random variables under consideration by obtaining a set of principal variables. For example, a predictive model based on behavior analysis may be more sensitive to certain categories of the behavior data than other categories. The vector components associated with the categories with less sensitivities may be excluded from the vectors. The resulting vectors may have reduced dimensions. The dimensionality reduction may reduce the computational load due to a size of the vectors used in behavior analysis, limited computing resources, fast turnaround for specific purposes (e.g., identifying fraudulent transactions), or the like.

The dimensionality reduction may use a variety of techniques, including but not limited to Principal component analysis (PCA), Non-negative matrix factorization (NMF), Kernel PCA, Graph-based kernel PCA, Linear discriminant analysis (LDA), Generalized discriminant analysis (GDA), Autoencoder, T-distributed Stochastic Neighbor Embedding (t-SNE), Uniform manifold approximation and projection (UMAP), and the like.

After nearest neighbor search and dimensionality reduction, a matching and rank ordering (block **94**) may be performed to finding the matched users **98** and ranking the matched users **98** in a particular order (e.g., from a matched user with shortest distance with respect to the user **82** to a matched user with longest distance with respect to the user **82**, or vice versa.

In an embodiment, the rank ordering of the matched users may be used to activate various notifications or downstream actions. In one example, a particular user may be matched with one or more closest match users based on distance. As updated transaction data for the individual user is added to the analysis, the ranked list may change as a result of the change in the vector distance based on new dimension data. Changes generated by the updated transaction data that cause distance changes exceeding a preset threshold between closest match users (i.e., that increase the distance between two users that were previously closely matched) may be flagged as potentially fraudulent or not authorized. Accordingly, one or more transaction can be flagged, a notification to the user can be provided, and, in one example, a credit card can be frozen such that additional transactions are not authorized pending further review. In another example, transactions that move closest match users closer together or do not significantly change (e.g., less than a threshold distance) the distance between closest matched users may be validated or authorized. Accordingly, the disclosed techniques may be used to validate or authorize new transaction data based on conformance to the established set of closest match users. Because the closest match users are generated based on more accurate and efficient techniques, the identification of valid or invalid transaction is also improved. In another embodiment, the disclosed techniques may be used to validate migration of data from legacy systems via generation of new transaction data that conforms to or maintains the ranked list of closest match users.

FIG. **4** illustrates an example user group with vectors representative of user behaviors and calculated distances between the corresponding vectors, according to implementations of the present disclosure. FIG. **4**A shows a table **120** including a group of users (Users A, B, and C) and their spending on books and clothes. For example, User A may spend $10 on purchasing books and $20 on clothes, and User C may spend $100 on purchasing books and $200 on clothes. Accordingly, three vectors, A, B and C may be created to represent the spending of respective users on two different categories (books and clothes). For example, the vector A representative of the spending of the User A may include two vector components, **10** and **20**.

Based on the created vectors representative of the spending of the users, Euclidean and cosine distances between each pair of the users may be calculated using the Formula 1 and 2 described above. The calculated distances are presented in a table **122** of FIG. **4**B, as illustrated. For example, the Euclidean distance [A,B] between the vectors A and B is 15 and the cosine distance is 0.12.

FIG. **5** illustrates examples of different categories for classifying the transaction data, according to implementations of the present disclosure. In illustrated embodiment, user transactions (e.g., credit card spending) may be classified into 20 categories, as shown in a column **140**. These 20 categories may be used to categorize the transaction data. The 20 categories may include airline, lodging, car rental, ground transportation, gas, dinning, and so on. Examples of each category listed in the column **140** are shown in a column **142**. For example, a ground transportation category may include taxi, bus, parking, and tolls.

In some embodiments, categories (e.g., the 20 categories listed in the column **140**) may be based on certain standards. For example, A Merchant Category Code (MCC) code is used in present embodiment. The MCC code is listed in ISO 18245 for retail financial services. The MCC may be used to classify a business by the types of goods or services it provides.

With the forgoing in mind, FIG. **6** illustrates an example of vector dimension transformation, according to implementations of the present disclosure. In an embodiment, certain behavior data, such as credit card spending behavior of a group of users (e.g., over two million customers of an organization), may be analyzed to identify valid transactions of the user based on look-alike users or groups of users based on anonymized behavior data.

To reduce the computational load and/or turnaround time of the behavior analysis (e.g., due to the large number of the users), a pre-selection of behavior data may be implemented to reduce an amount of data to be analyzed in downstream operations (e.g., data storage, data analysis, vector generation, distance calculation, nearest neighbor searching, matching and ranking). The pre-selection of behavior data may use certain criteria or thresholds. For example, the pre-selection of behavior data may include identifying users that spend at least $50 each quarter in a given year on their credit cards. Furthermore, a smaller group of users (e.g., 20,000 customers among over two million customers) may be randomly selected (e.g., regardless of demographic information of the users). After the pre-selection, behavior data for the smaller group of users may be extracted. An anonymization of the extracted behavior data is implemented to exclude demographic information of the user.

The anonymized credit card spending behaviors of the 20,000 users may be categorized into 20 categories. For each user, three sets of dimension information across the 20 categories may be calculated, including a total number of transactions (TXN count), a total spending amount of transactions (TXN amt), and an average spending amount per transaction (Avg TXN amt). Resulting vector for each user may have 60 dimensions, as shown in a table **150**.

Table **150** shows some example vectors described above. Each row in the table **150** (except first two rows on top of the table **150**) represents a vector. Each vector mas be associated with a unique user identification number (User ID #) listed in column **152**. The user ID # ranges from 1 to 20,000 in present example. Each vector has 20 components (from X1 to X20) associated with the TXN count listed in column **154**, 20 components (from X21 to X40) associated with the TXN amount listed in column **156**, and 20 components (from X41 to X60) associated with the average TXN amount.

As mentioned previously, the vector dimension transformation (block **90**), such as the quantile grouping/encoding may be performed for each vector dimension before distance calculations. Transforming each vector dimension may normalize the vectors by removing certain differences (e.g., scaling difference) between different vectors and/or different vector components. The transformed vectors are shown in a table **160**.

Provided herein are certain examples of data analysis as provided herein to identify look-alike or least similar users. While the disclosed examples may reference user identification and/or demographic information, it should be understood that this is for the purposes of demonstrating that the disclosed techniques are as robust as, or in some cases more robust than, analysis using demographic features alone. Further, in certain embodiments, the data analysis may assign identification numbers to the anonymized data to facilitate comparisons between vectors of individual anonymous users (e.g., clients or members).

It should also be understood that, because the data is anonymized, updated calculations may be performed de novo upon receipt of updated transaction information by the secure service application controller **16**. That is, the monitoring device **14** may receive updated data for an anonymous individual user. However, in an embodiment, the monitoring device **14** may not be able to correlate previously received data with updated data for an individual user. In another embodiment, the secure service application controller **16** may assign an anonymous user ID, which may be transmitted with updated data so that the monitor **14** can correlate the updated data to previously received data. However, as disclosed, the data analysis is performed using anonymized data.

FIG. **7** illustrates examples of calculated distances between a user and the other users in a user group, according to implementations of the present disclosure. The calculated distances in this example are Euclidean distances calculated from the transformed vectors in table **160** of FIG. **6** based on the Formula 1. A pre-selected user **172** with a unique user ID # (e.g., user 1) is used as a reference point and a distance associated with the user **172** is zero. Distances between the user **172** and other users **174** (with unique ID # ranging from 2 to 20,000) are presented along an increased distance direction **176**. A shortest distance indicates most similar behavior, while a longest distance indicates most different behavior. For example, a user with user ID # **3353** is identified with a shortest distance with respect to the user **172**. As such, the vector associated with the user **3353** is identified as the closest vector in the group. The user **3353** may have the most similar behavior as the user **172** in the group. In contrast, a user with user ID # **18495** is identified with a longest distance with respect to the user **172**. As such, the vector associated with the user **18495** is identified as the farthest vector in the group. The user **18495** may have the least similar behavior as the user **172** in the group.

With the forgoing in mind, several examples of comparing behavior similarities or differences between users or user groups are illustrated in FIGS. **8-11**. These examples are generated using the implementations described above. It should be noted that these examples are based on Euclidean distance calculations measuring absolute differences in distance.

FIG. **8** illustrates an example of two users with similar behaviors and demographics, according to implementations of the present disclosure. For a given user, such as a user with user ID # **2194**, his/her TXN counts, TXN amount, and average TXN amount across the 20 categories described above are plotted in plots **182**, **184**, and **186**, respectively. Another user with user ID #**5982** is identified as the most similar user that has the closest vector with respect to the user **2194**. That is, the user **5982** has the most similar behavior (e.g., spending behavior) relative to the user **2194**. The user **5982**'s TXN counts, TXN amount, and average TXN amount across the 20 categories are plotted in plots **182**, **184**, and **186**, respectively.

As illustrated, plotted curves between the user **2194** and user **5982**, such as the plotted TXN count curves, TXN amount curves, and average TXN amount curves, show matches in magnitudes and trends between the two users. The result shows that a user having a closest vector with respect to a reference user may have the most similar behavior as the reference user.

Demographic information of the user **2194** and user **5982** are also presented as demographics **188** and demographic **190**, respectively. The demographics of the two users are similar in certain categories such as age, gender, and tenure.

FIG. **9** illustrates an example of two users with similar behaviors but different demographics, according to implementations of the present disclosure. For a given user, such as a user with user ID # **3592**, his/her TXN counts, TXN amount, and average TXN amount across the 20 categories are plotted in plots **202**, **204**, and **206**, respectively. Another user with user ID #**5257** is identified as the most similar user that has the closest vector with respect to the user **3592**. That is, the user **5257** has the most similar behavior (e.g., spending behavior) relative to the user **3592**. The user **5257**'s TXN counts, TXN amount, and average TXN amount across the 20 categories are plotted in plots **202**, **204**, and **206**, respectively.

As illustrated, plotted curves between the user **3592** and user **5257**, such as the plotted TXN count curves, TXN amount curves, and average TXN amount curves, show matches in magnitudes and trends between the two users. The result shows that a user having a closest vector with respect to a reference user may have the most similar behavior as the reference user.

Demographic information of the user **3592** and user **5257** are also presented as demographics **208** and demographic **210**, respectively. In contrast to previous example shown in FIG. **8**. The present example shows demographics of the two users are very different. As mentioned previously, using the demographic profiles to find look-alike groups may not be accurate or reliable in some cases. For instance, two users with very different demographics may behave similarly, while other two users with similar demographics may behave very differently.

FIG. **10** illustrates an example of two users with different behaviors, according to implementations of the present disclosure. For a given user, such as a user with user ID # **10019**, his/her TXN counts, TXN amount, and average TXN amount across the 20 categories are plotted in plots **222**, **224**, and **226**, respectively. Another user with user ID # **9615** is identified as the most different user that has the farthest vector with respect to the user **10019**. That is, the user **9615** has the most different behavior (e.g., spending behavior) relative to the user **10019**. The user **9615**'s TXN counts, TXN amount, and average TXN amount across the 20 categories are plotted in plots **222**, **224**, and **226**, respectively.

As illustrated, plotted curves between the user **10019** and user **9615**, such as the plotted TXN count curves, TXN amount curves, and average TXN amount curves, show no match in magnitudes and trends between the two users. The result shows that a user having a farthest vector with respect to a reference user may have the most different behavior as the reference user.

Demographic information of the user **2194** and user **5982** are also presented as demographics **188** and demographic **190**, respectively. The demographics of the two users are very different.

The technologies disclosed herein may be applied to analyzing behavior similarities/differences between two user groups each having different group members. For example, vectors representative of individual user groups are used to calculate distances between different user groups and identify closest vectors for each user group.

FIG. **11**A illustrates an example of two user groups **250** with most similar behaviors. Each group of the two user groups **250** includes 50 randomly selected users. The TXN counts, TXN amount, and average TXN amount of each group across the 20 categories are plotted in plots **252**, **254**, and **256**, respectively. As illustrated, plotted curves between the two groups, such as the plotted TXN count curves, TXN amount curves, and average TXN amount curves, show matches in magnitudes and trends between the two groups. The result shows that a user group having a closest vector with respect to a reference user group may have the most similar behavior as the reference user group.

In contrast, FIG. **11**B illustrates an example of two user groups **260** with most different behaviors. Each group of the two user groups **260** includes 50 randomly selected users. The TXN counts, TXN amount, and average TXN amount of each group across the 20 categories are plotted in plots **262**, **264**, and **266**, respectively. As illustrated, plotted curves between the two groups, such as the plotted TXN count curves, TXN amount curves, and average TXN amount curves, show no match in magnitudes and trends between the two groups. The result shows that a user group having a farthest vector with respect to a reference user group may have the most different behavior as the reference user group.

While this specification contains many specifics, these should not be construed as limitations on the scope of the disclosure or of what may be claimed, but rather as descriptions of features specific to particular implementations. Certain features that are described in this specification in the context of separate implementations may also be implemented in combination in a single implementation. Conversely, various features that are described in the context of a single implementation may also be implemented in multiple implementations separately or in any suitable subcombination. Moreover, although features may be described above as acting in certain combinations and even initially claimed as such, one or more features from a claimed combination may in some examples be excised from the combination, and the claimed combination may be directed to a sub-combination or variation of a sub-combination.

Similarly, while operations are depicted in the drawings in a particular order, this should not be understood as requiring that such operations be performed in the particular order shown or in sequential order, or that all illustrated operations be performed, to achieve desirable results. In certain circumstances, multitasking and parallel processing may be advantageous. Moreover, the separation of various system components in the implementations described above should not be understood as requiring such separation in all implementations, and it should be understood that the described program components and systems may generally be integrated together in a single software product or packaged into multiple software products.

While only certain features of the disclosure have been illustrated and described herein, many modifications and changes will occur to those skilled in the art. It is, therefore, to be understood that the appended claims are intended to cover all such modifications and changes as fall within the true spirit of the invention.

The invention claimed is:

1. A system comprising:

a monitoring device, comprising:

a memory storing a plurality of vectors, the plurality of vectors comprising a vector for each of a plurality of users based on the plurality of dimensions;

a communication interface;

a secure service application controller comprising a service layer, wherein the service layer is configured to receive user transaction information of a first user using a first communication protocol and to anonymize the user transaction information, wherein the user transaction data comprises merchant information;

one or more processors coupled to the communication interface;

wherein the memory stores instructions that, when executed by the one or more processors, cause the one or more processors to:

receive, via the communication interface, from the secure service application controller, anonymized transaction data of the plurality of users using a second communication protocol, wherein the anonymized user transaction data excludes demographic information of the plurality of users, and wherein the second communication protocol is different than the first communication protocol;

categorize the anonymized transaction data into a plurality of dimensions for each of the plurality of users, wherein the categorizing the anonymized transaction data further comprises categorizing the anonymized transaction data based on a merchant category code associated with merchant information;

generate, based on the plurality of dimensions, a user vector for the anonymized user transaction information of the first user;

identify one or more closest vectors for the first user from the plurality of vectors;

determine, based on updated transaction data for the first user, a change in the identified one or more closest vectors for the first user;

generate a notification of a potential fraudulent transaction based on the change;

provide, via the communication interface and to the secure service application controller, the notification; and

wherein the secure service application controller is configured to associate the notification with the first user and to communicate or push the notification to a device of the first user.

2. The system of claim **1**, wherein the one or more processors are configured to normalize the plurality of vectors based on quantile groupings.

3. The system of claim **1**, wherein the one or more processors are configured to calculate distances between each pair of vectors of the plurality of vectors and wherein identifying the one or more closest vectors is based on the calculated distances.

4. The system of claim **3**, wherein the calculated distances are cosine distances.

5. The system of claim **3**, wherein the calculated distances are Euclidean distances.

6. The system of claim **1**, wherein identifying the one or more closest vectors uses a nearest neighbor search.

7. The system of claim **1**, wherein the communication interface is configured to communicate with a source of the updated transaction data to stop the potential fraudulent transaction.

8. The system of claim **1**, wherein the communication interface is configured to communicate with a source of the updated transaction data to request additional information from the individual user before permitting the potential fraudulent transaction.

9. The system of claim **6**, wherein the nearest neighbor search uses machine learning.

10. The system of claim **6**, wherein the system comprises a dimensionality reduction to generate a set of principal variables.

11. The system of claim **10**, wherein the dimensionality reduction comprises Principal component analysis (PCA), Non-negative matrix factorization (NMF), Kernel PCA, Graph-based kernel PCA, Linear discriminant analysis (LDA), Generalized discriminant analysis (GDA), Autoencoder, T-distributed Stochastic Neighbor Embedding (tSNE), or Uniform manifold approximation and projection (UMAP).

12. The system of claim **1**, comprising rank ordering the identified one or more closest vectors of the plurality of vectors to identify matched users.

13. The system of claim **12**, wherein the notification of the potential fraudulent transaction is based on the change causing a distance change that exceeds a preset threshold between the identified one or more closest vectors.

14. The system of claim **1**, wherein the one or more processors are coupled to the communication interface via secure service application comprising a service.

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