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(54) **SYSTEMS AND METHODS FOR AUTOMATED CLUSTERING OF MULTI-DIMENSIONAL AI/ML TRAINING DATA**

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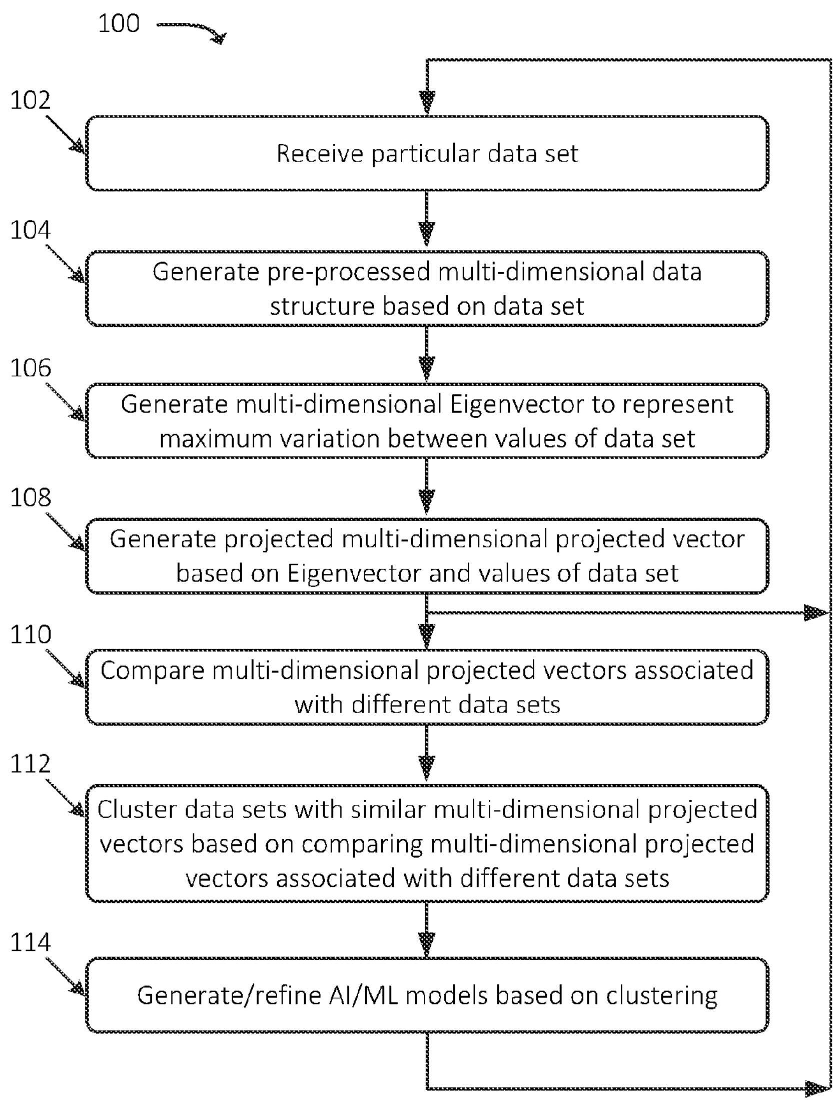
(57) **ABSTRACT**

A system described herein may receive a plurality of data sets; generate, for each data set, an Eigenvector representing a maximum variance of the data set; generate, for each data set, a projected vector, wherein generating a particular projected vector includes identifying a lowest distance between respective values of the particular data set and the particular Eigenvector, wherein the particular projected vector includes values along the Eigenvector that are each a lowest distance from a corresponding value of the particular data set; compare respective projected vectors, associated with one or more data sets, with one or more other data sets of the plurality of data sets; generate a plurality of clusters based on the comparing, wherein each cluster includes one or more data sets of the plurality of data sets; and train one or more artificial intelligence/machine learning ("AI/ML") models based on the plurality of clusters.



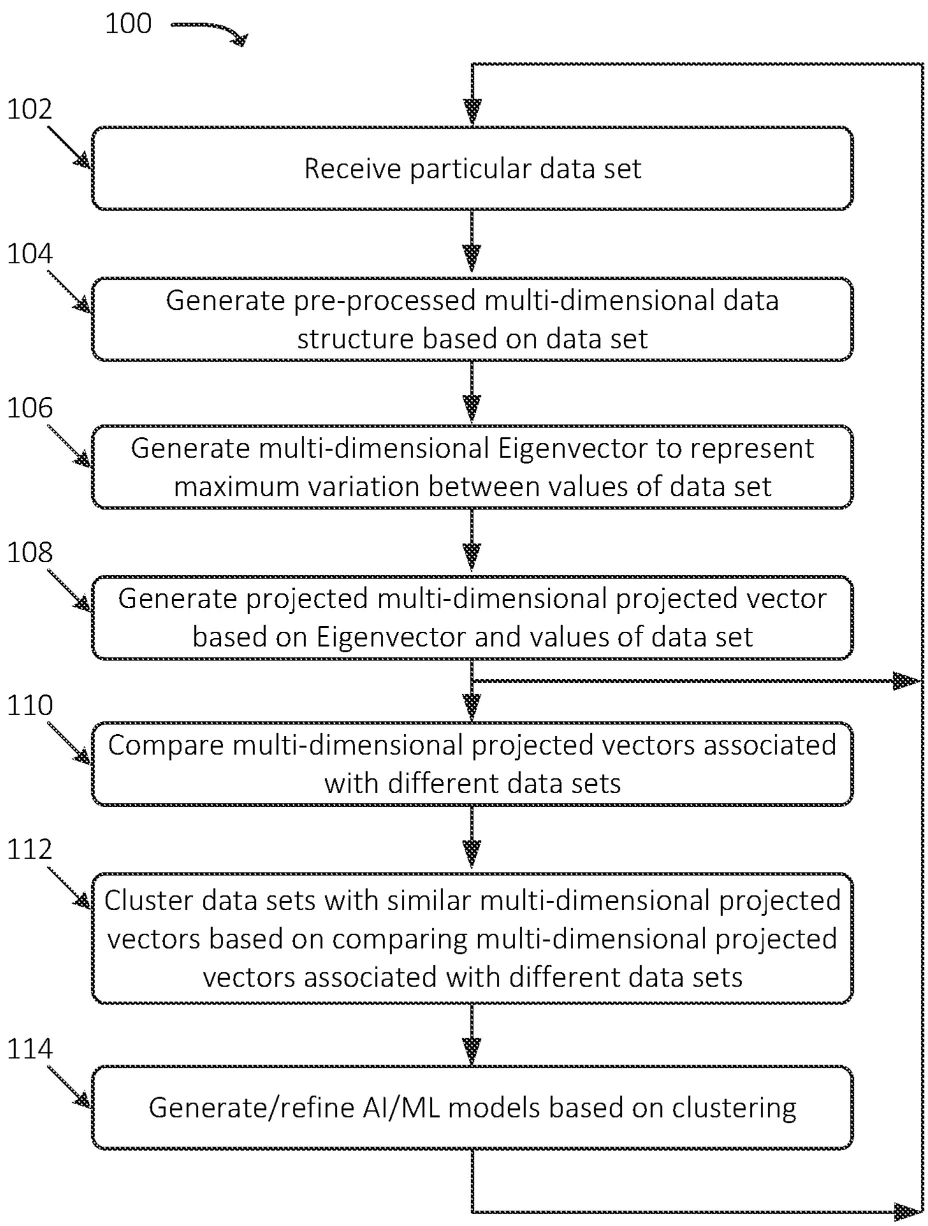
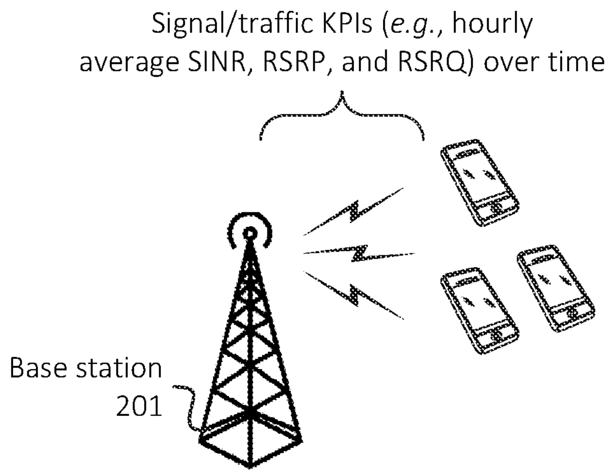

100
102
Receive particular data set
104
Generate pre-processed multi-dimensional data structure based on data set
106
Generate multi-dimensional Eigenvector to represent maximum variation between values of data set
108
Generate projected multi-dimensional projected vector based on Eigenvector and values of data set
110
Compare multi-dimensional projected vectors associated with different data sets
112
Cluster data sets with similar multi-dimensional projected vectors based on comparing multi-dimensional projected vectors associated with different data sets
114
Generate/refine AI/ML models based on clustering

FIG. 1

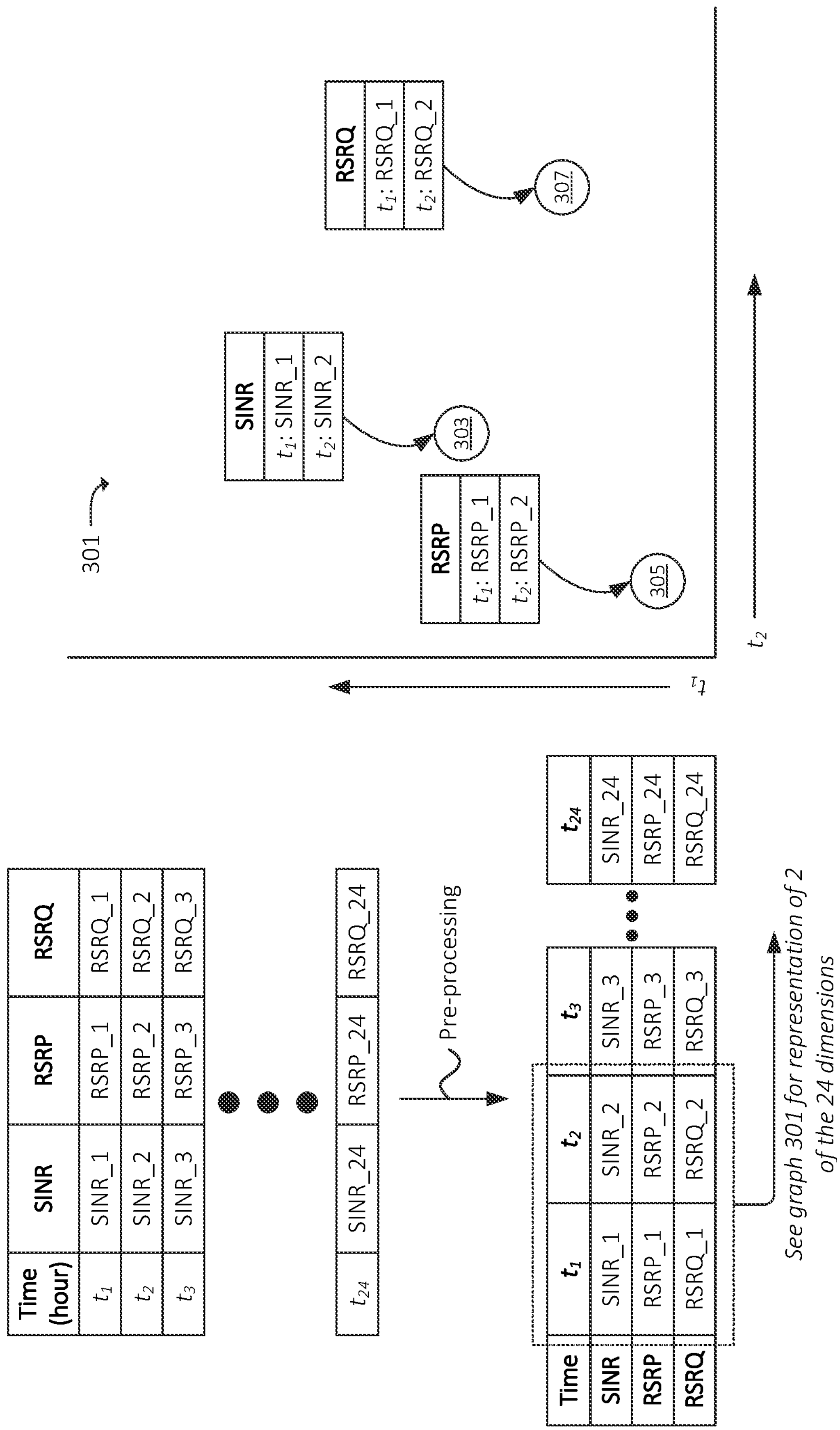


Time (hour)	SINR	RSRP	RSRQ
t_1	SINR_1	RSRP_1	RSRQ_1
t_2	SINR_2	RSRP_2	RSRQ_2
t_3	SINR_3	RSRP_3	RSRQ_3
	⋮		
t_{24}	SINR_24	RSRP_24	RSRQ_24
t_{25}	SINR_25	RSRP_25	RSRQ_25
t_{26}	SINR_26	RSRP_26	RSRQ_26
t_{27}	SINR_27	RSRP_27	RSRQ_27
	⋮		
t_{48}	SINR_48	RSRP_48	RSRQ_48

First 24-hour time window (t_1 – t_{24})

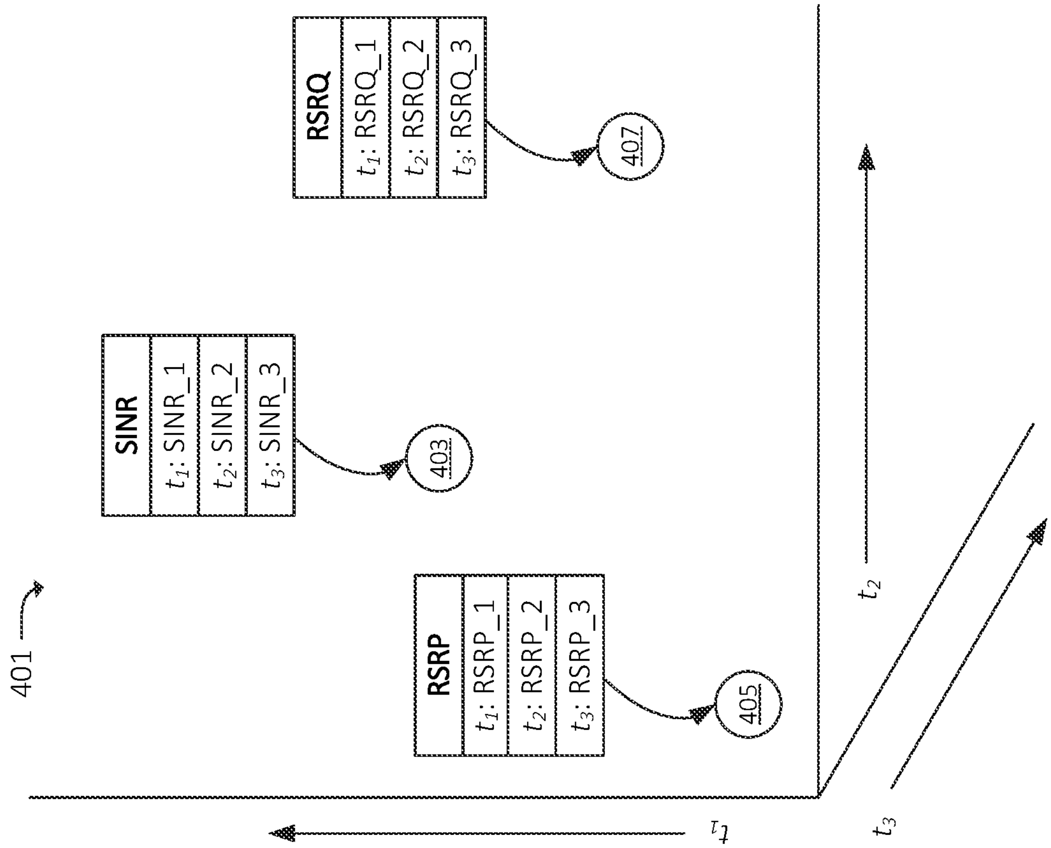
Second 24-hour time window (t_{25} – t_{48})

FIG. 2



Time (hour)
SINR
RSRP
RSRQ
t_1 SINR_1 RSRP_1 RSRQ_1
t_2 SINR_2 RSRP_2 RSRQ_2
t_3 SINR_3 RSRP_3 RSRQ_3
t_{24} SINR_24 RSRP_24 RSRQ_24
Pre-processing
Time t_1 t_2 t_3 t_{24}
SINR SINR_1 SINR_2 SINR_3 SINR_24
RSRP RSRP_1 RSRP_2 RSRP_3 RSRP_24
RSRQ RSRQ_1 RSRQ_2 RSRQ_3 RSRQ_24
See graph 301 for representation of 2 of the 24 dimensions
301
SINR
t_1: SINR_1
t_2: SINR_2
303
RSRP
t_1: RSRP_1
t_2: RSRP_2
305
RSRQ
t_1: RSRQ_1
t_2: RSRQ_2
307
t_1
t_2

FIG. 3



Time	t_1	t_2	t_3	...	t_{24}
SINR	SINR_1	SINR_2	SINR_3	...	SINR_24
RSRP	RSRP_1	RSRP_2	RSRP_3	...	RSRP_24
RSRQ	RSRQ_1	RSRQ_2	RSRQ_3	...	RSRQ_24

See graph 401 for representation of 3 of the 24 dimensions

FIG. 4

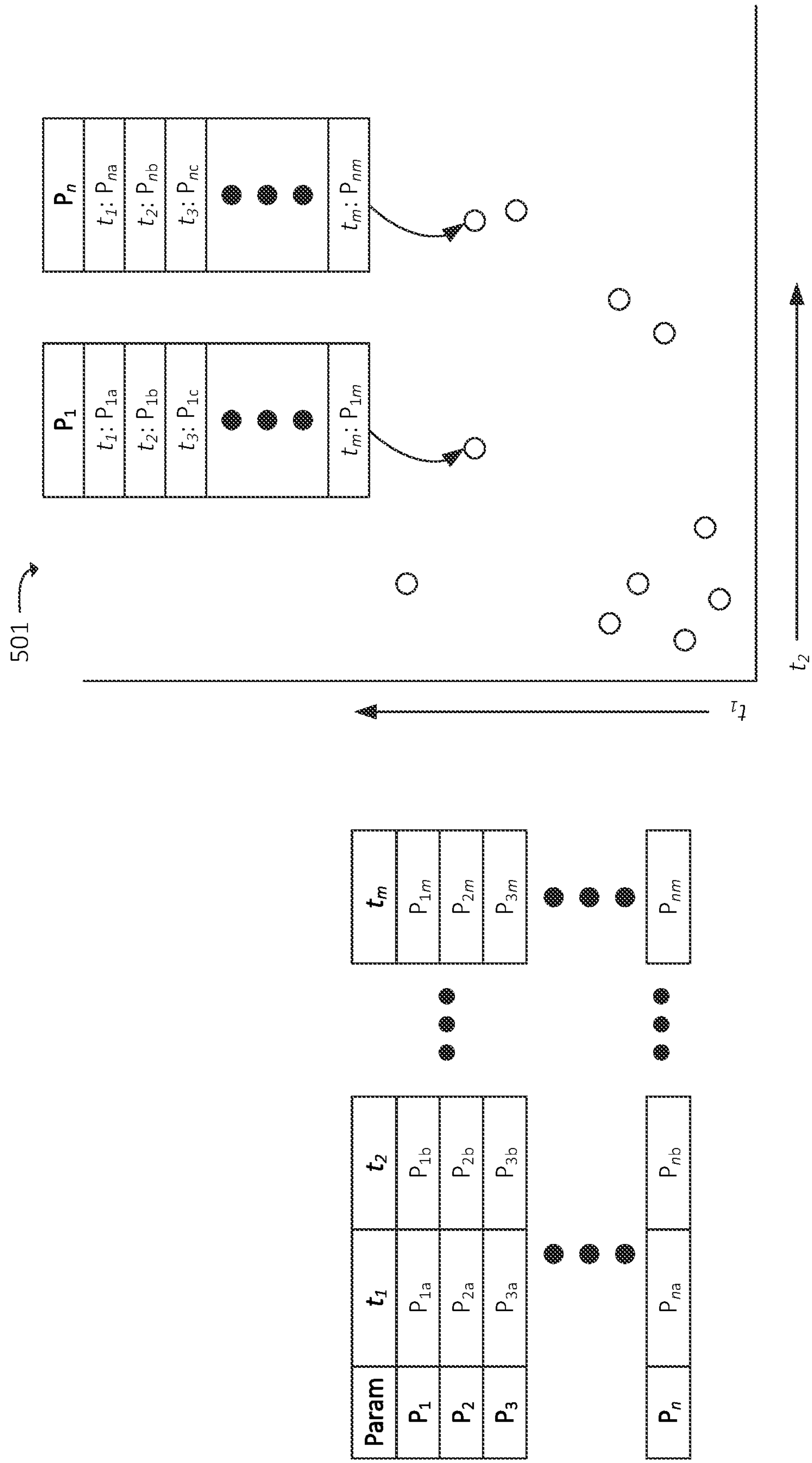
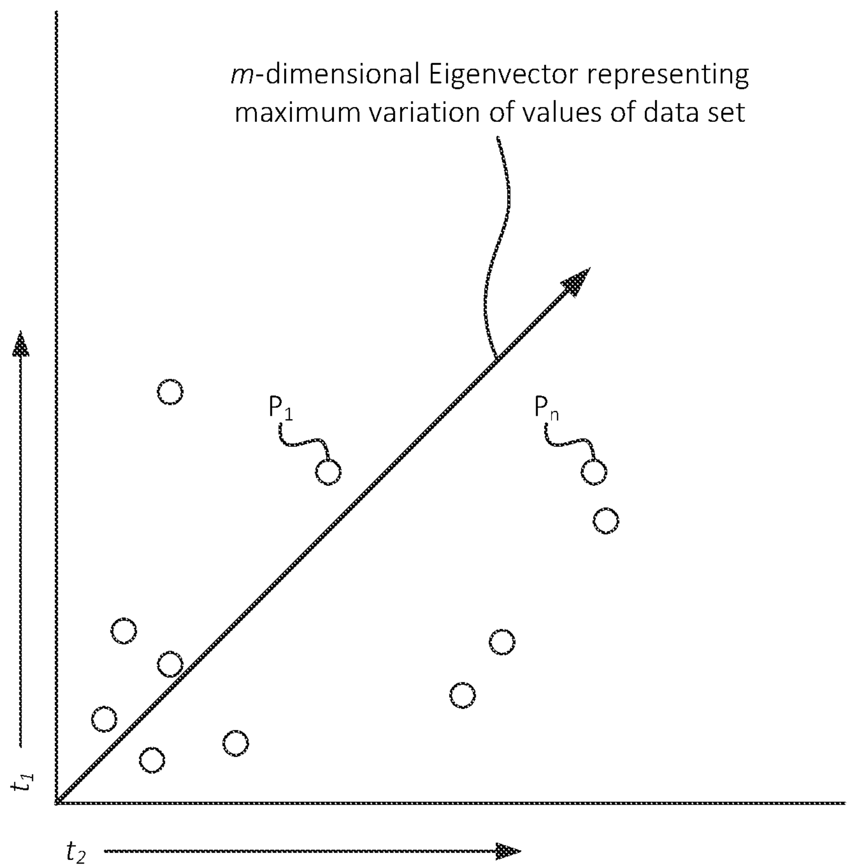

501
P1
t1: P1a
t2: P1b
t3: P1c
tm: P1m
Pn
t1: Pna
t2: Pnb
t3: Pnc
tm: Pnm
t1
t2
Param
P1
P2
P3
Pn
P1a
P2a
P3a
Pna
P1b
P2b
P3b
Pnb
tm
P1m
P2m
P3m
Pnm

FIG. 5



m-dimensional Eigenvector representing maximum variation of values of data set
P_1
P_n
t_1
t_2

FIG. 6

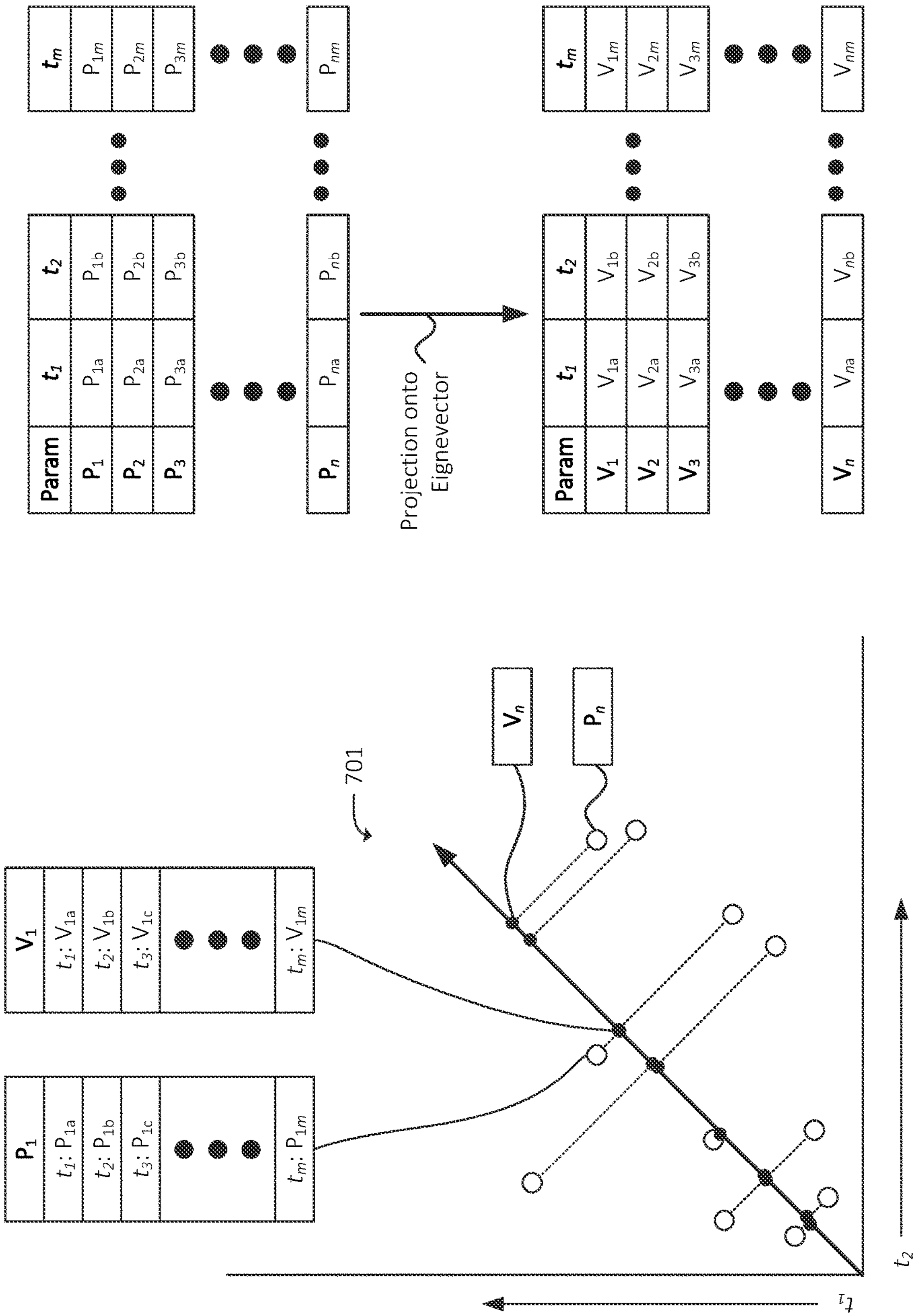

Param
t_1
t_2
t_m
P_1
P_{1a}
P_{1b}
P_{1m}
P_2
P_{2a}
P_{2b}
P_{2m}
P_3
P_{3a}
P_{3b}
P_{3m}
P_n
P_{na}
P_{nb}
P_{nm}
Projection onto Eignevector
V_1
V_{1a}
V_{1b}
V_{1m}
V_2
V_{2a}
V_{2b}
V_{2m}
V_3
V_{3a}
V_{3b}
V_{3m}
V_n
V_{na}
V_{nb}
V_{nm}
P_1
t_1: P_{1a}
t_2: P_{1b}
t_3: P_{1c}
t_m: P_{1m}
V_1
t_1: V_{1a}
t_2: V_{1b}
t_3: V_{1c}
t_m: V_{1m}
701
V_n
P_n
t_1
t_2

FIG. 7

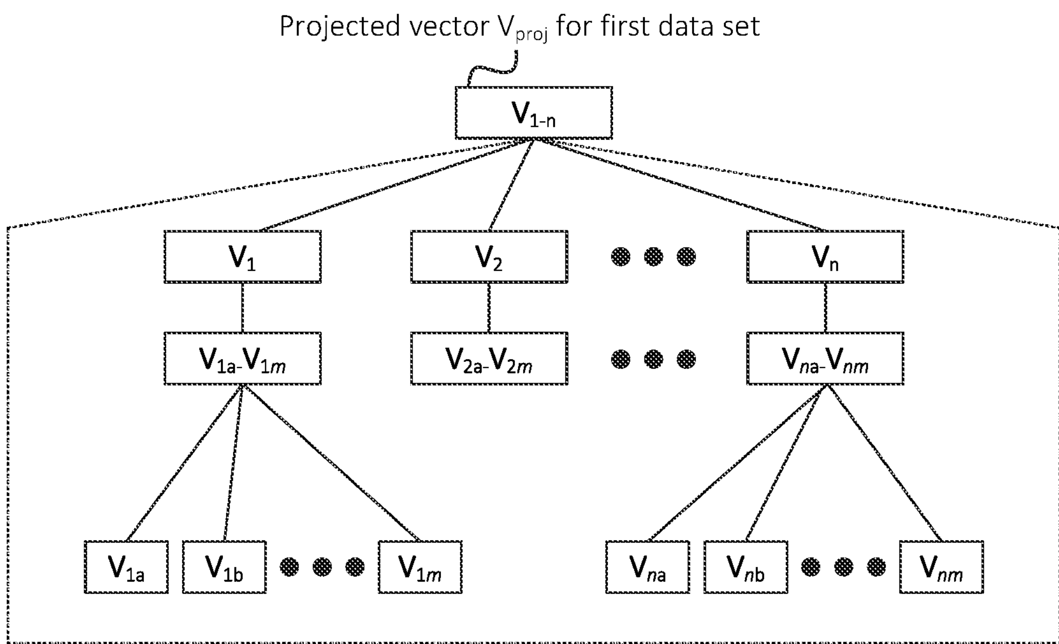

Projected vector V_{proj} for first data set
V_{1-n}
V_1
V_2
V_n
V_{1a}-V_{1m}
V_{2a}-V_{2m}
V_{na}-V_{nm}
V_{1a}
V_{1b}
V_{1m}
V_{na}
V_{nb}
V_{nm}

FIG. 8

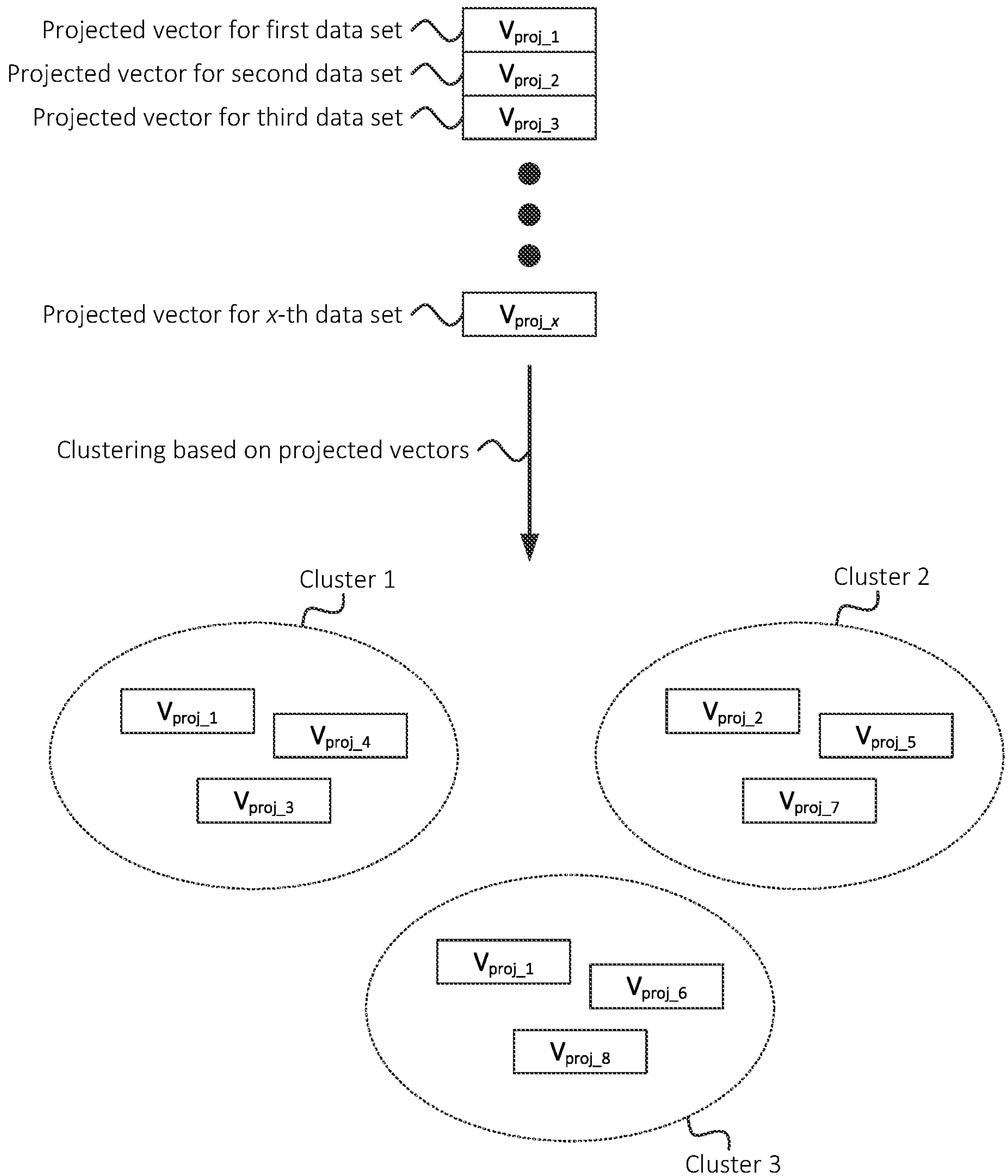

Projected vector for first data set
V_{proj_1}
Projected vector for second data set
V_{proj_2}
Projected vector for third data set
V_{proj_3}
Projected vector for *x*-th data set
V_{proj_x}
Clustering based on projected vectors
Cluster 1
V_{proj_1}
V_{proj_4}
V_{proj_3}
Cluster 2
V_{proj_2}
V_{proj_5}
V_{proj_7}
V_{proj_1}
V_{proj_6}
V_{proj_8}
Cluster 3

FIG. 9

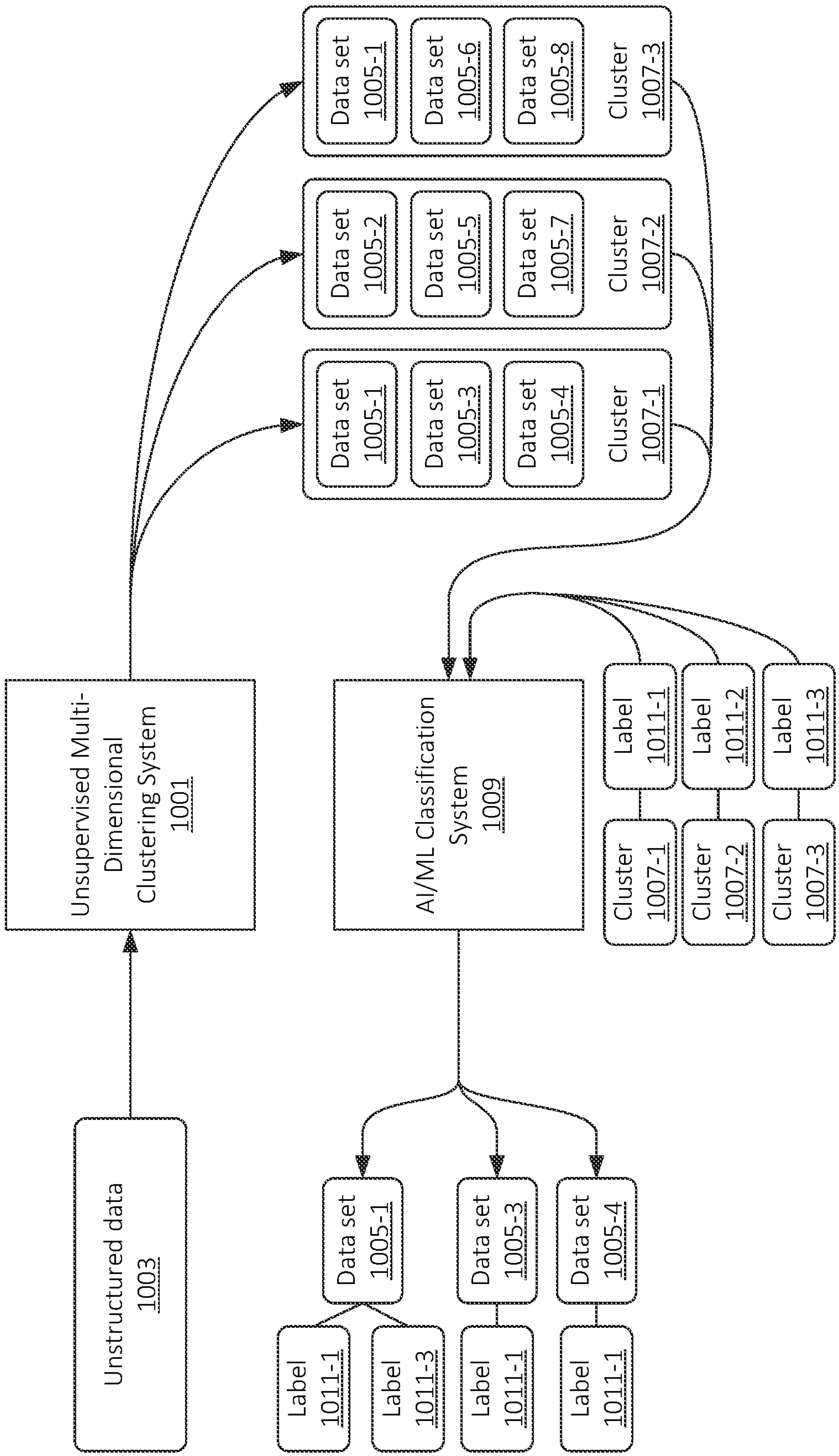
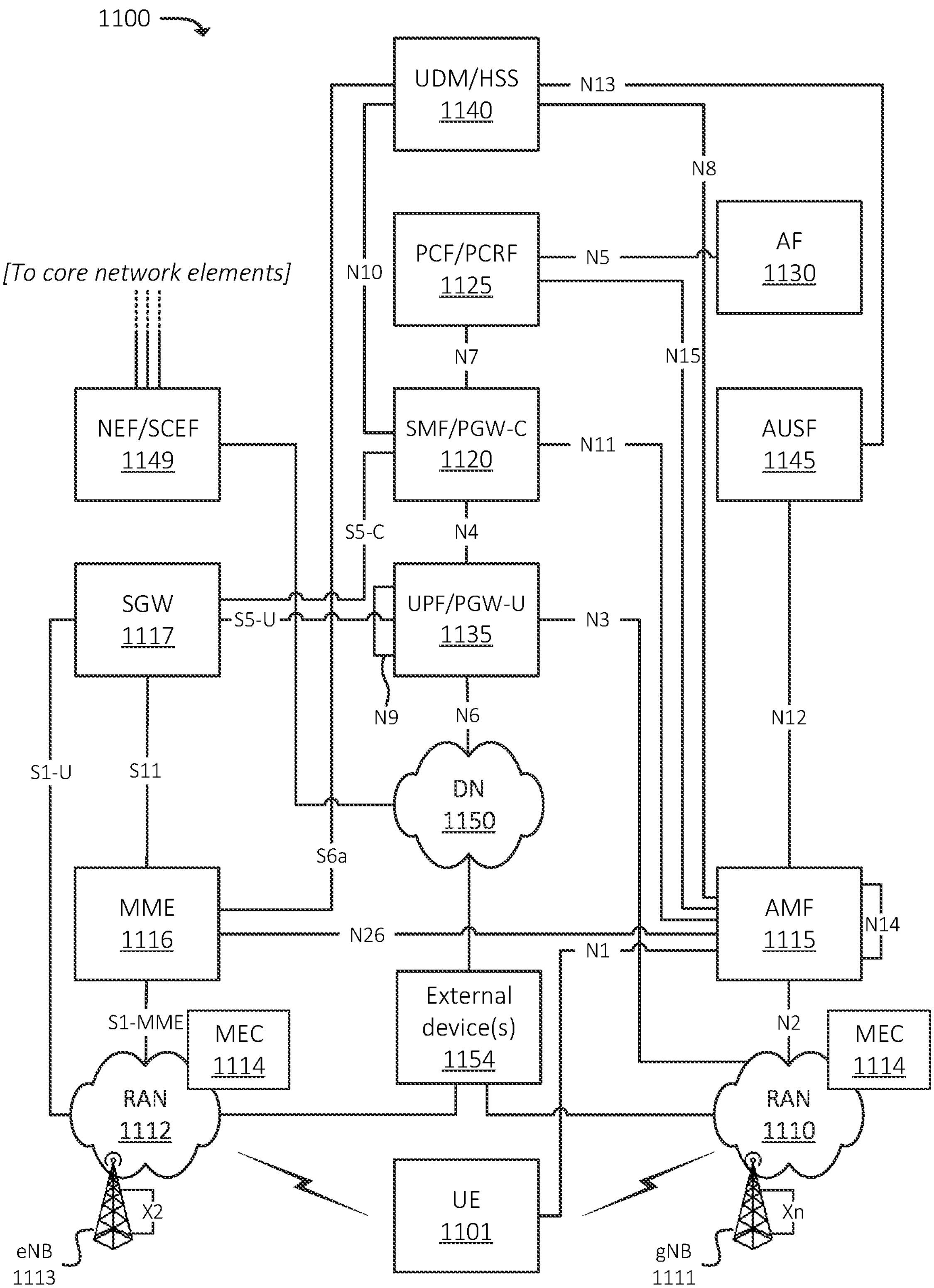

Unstructured data 1003
Unsupervised Multi-Dimensional Clustering System 1001
Data set 1005-1
Data set 1005-3
Data set 1005-4
Cluster 1007-1
Data set 1005-2
Data set 1005-5
Data set 1005-7
Cluster 1007-2
Data set 1005-1
Data set 1005-6
Data set 1005-8
Cluster 1007-3
AI/ML Classification System 1009
Label 1011-1
Label 1011-2
Label 1011-3
Cluster 1007-1
Cluster 1007-2
Cluster 1007-3
Data set 1005-1
Data set 1005-3
Data set 1005-4
Label 1011-1
Label 1011-3
Label 1011-1
Label 1011-1

FIG. 10



1100
UDM/HSS
1140
N13
N8
N10
PCF/PCRF
1125
N5
AF
1130
[To core network elements]
N7
N15
NEF/SCEF
1149
SMF/PGW-C
1120
N11
AUSF
1145
S5-C
N4
SGW
1117
S5-U
UPF/PGW-U
1135
N3
N9
N6
N12
S1-U
S11
DN
1150
S6a
MME
1116
N26
AMF
1115
N14
N1
S1-MME
MEC
1114
External
device(s)
1154
N2
MEC
1114
RAN
1112
RAN
1110
X2
UE
1101
Xn
eNB
1113
gNB
1111

FIG. 11

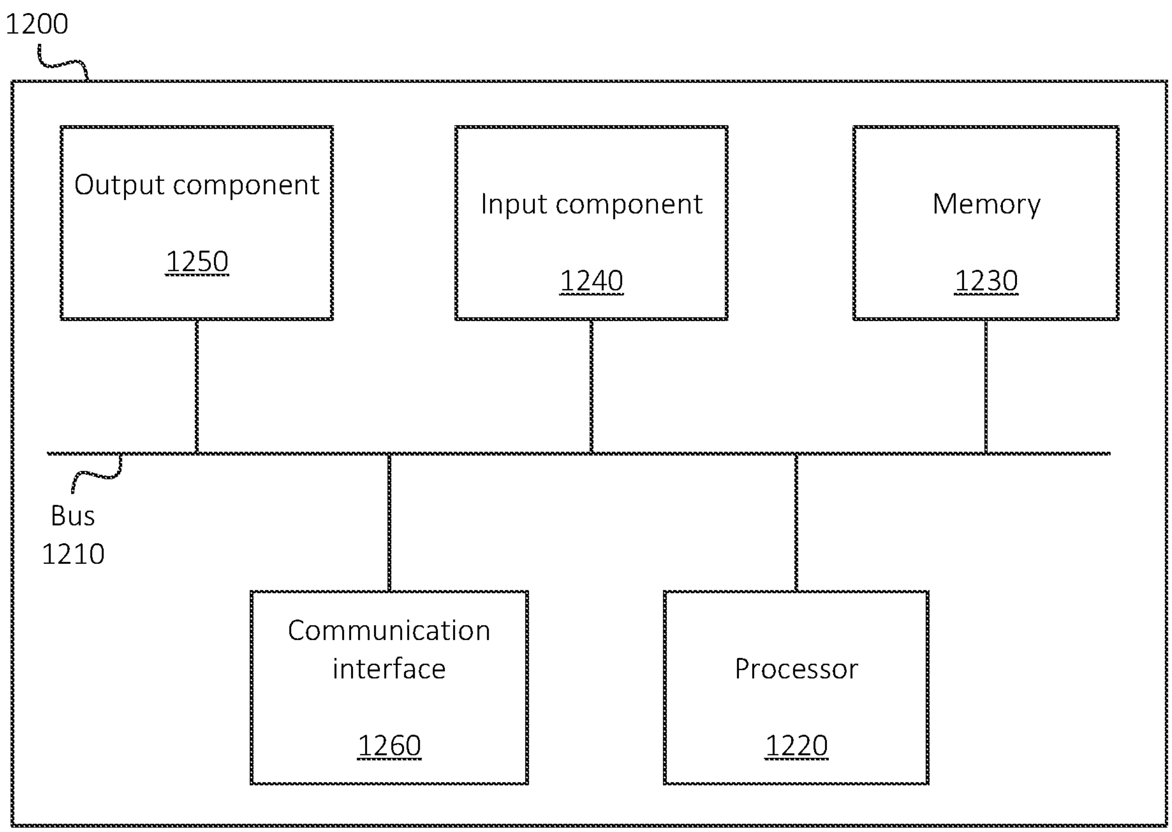

1200
Output component
1250
Input component
1240
Memory
1230
Bus
1210
Communication interface
1260
Processor
1220

FIG. 12

SYSTEMS AND METHODS FOR AUTOMATED CLUSTERING OF MULTI-DIMENSIONAL AI/ML TRAINING DATA

BACKGROUND

[0001] Artificial intelligence/machine learning ("AI/ML") techniques may be used to categorize or classify data sets, such as wireless network Key Performance Indicators ("KPIs"), time series data, features of images or other types of content, autonomous vehicle control data, etc. AI/ML techniques may make use of models to generate output parameters such as categories, classifications, actions, etc. based on input parameters such as wireless network KPIs, images, autonomous vehicle sensor data, etc. The AI/ML models may, for example, be trained or configured based on training data. For example, training data may be provided as input to a model, and the model may be "trained" to generate a particular set of output parameters (e.g., a known or desired set of output parameters) based on the training data. Once trained (e.g., at "run time"), the model may provide the same (or similar) output parameters when receiving the same (or similar) input parameters at run time.

BRIEF DESCRIPTION OF THE DRAWINGS

[0002] FIG. **1** illustrates an example overview of one or more embodiments described herein;

[0003] FIGS. **2-5** illustrate examples of pre-processing one or more multi-dimensional data sets, in accordance with some embodiments;

[0004] FIG. **6** illustrates an example of generating a multi-dimensional Eigenvector to represent a maximum variation in values of a multi-dimensional data set, in accordance with some embodiments;

[0005] FIG. **7** illustrates an example of generating a multi-dimensional projected vector based on a multi-dimensional Eigenvector associated with a data set, in accordance with some embodiments;

[0006] FIG. **8** illustrates values of an example multi-dimensional projected vector, in accordance with some embodiments;

[0007] FIG. **9** illustrates an example of clustering multi-dimensional data sets based on multi-dimensional projected vector associated with each of the multi-dimensional data sets, in accordance with some embodiments;

[0008] FIG. **10** illustrates an example of generating or refining an AI/ML model based on the clustered multi-dimensional data sets, in accordance with some embodiments;

[0009] FIG. **11** illustrates an example environment in which one or more embodiments, described herein, may be implemented; and

[0010] FIG. **12** illustrates example components of one or more devices, in accordance with one or more embodiments described herein.

DETAILED DESCRIPTION OF EXAMPLE EMBODIMENTS

[0011] The following detailed description refers to the accompanying drawings. The same reference numbers in different drawings may identify the same or similar elements.

[0012] Embodiments described herein provide for an automated clustering and/or classification procedure to facilitate a training stage of one or more AI/ML models. The automated clustering and/or classification procedure described herein may remove the need for manual review of training data sets to group similar data sets (e.g., supervised machine learning training techniques), thus enhancing the overall efficiency and speed of the training process for AI/ML modeling systems.

[0013] FIG. **1** illustrates an example process **100** for training one or more AI/ML models using an automated clustering technique as described herein. In some embodiments, some or all of process **100** may be performed by one or more computing devices that generate or refine AI/ML models and/or training data used in the training of AI/ML models. Process **100** is described in conjunction with subsequent figures, which illustrate some or all of the operations of process **100**.

[0014] As shown, process **100** may include receiving (at **102**) a particular data set. The particular data set may include values associated with wireless network KPIs (e.g., interference, noise, latency, throughput, etc.), sensor readings (e.g., readings measured or reported by Internet of Things ("IoT") devices, automated guided vehicles ("AGVs"), autonomous factory robots, etc.), content files (e.g., images, videos, audio, etc.), and/or other suitable data. In some embodiments, the data set may include time series data, where values for particular parameters or variables may differ over time.

[0015] FIG. **2** illustrates an example of one or more data sets that may be the subject of operations described herein with respect to the automatic clustering and/or classification of such data. In this example, time series data may reflect signal and/or traffic KPIs associated with a radio access network ("RAN") of a wireless network, such as signal and/or traffic KPIs associated with a particular base station **201** of the RAN. In the examples discussed herein, multiple different KPIs may be reflected in the data, such as Signal-to-Interference-and-Noise-Ratio ("SINR"), Reference Signal Received Power ("RSRP"), and Reference Signal Received Quality ("RSRQ"). In these examples, each value for each KPI may be associated with a particular time or time period. For example, a first SINR value (represented as "SINR_1") may be associated with a first time period t_1, a second SINR value (e.g., SINR_2) may be associated with a second time period t_2, and so on. Similarly, a first RSRP value (e.g., RSRP_1) may be associated with the first time period t_1, a second RSRP value (e.g., RSRP_2) may be associated with the second time period t_2, and so on.

[0016] In the examples described herein, the time periods are delineated on an hourly basis. For example, t_1 may refer to a first hour, t_2 may refer to a second hour (e.g., an hour that is immediately subsequent to the hour represented by t_1), and so on. Each respective value may be "associated with" a particular time period inasmuch as the values may include readings or measurements determined at specific times or offsets for each time period. For example, SINR_1 may reflect one or more SINR measurements (e.g., between base station **201** and one or more User Equipment ("UEs"), such as mobile telephones, that are wirelessly connected to base station **201**) that are determined at the beginning of the first hour, SINR_2 may reflect one or more SINR measurements that are determined at the beginning of the second hour, and so on. Additionally, or alternatively, the values may reflect average values. For example, SINR_1 may reflect an average SINR between base station **201** and one or more UEs over the entire first hour, SINR_2 may reflect an average SINR between base station **201** and one or more UEs over the entire second hour, and so on. Additionally, or alternatively, the values may otherwise reflect readings or measurements associated with particular time periods in some other way. For example, SINR_1 may refer to the highest SINR value associated with t_1(e.g., the highest SINR value determined during the hour represented by t_1), the lowest SINR value associated with t_1, the average of SINR values that are between the 25th and 75th percentile of SINR values associated with t_1, and so on.

[0017] In some embodiments, discrete data sets may be identified or extracted from received data. The discrete data sets may be identified based on parameters of an AI/ML model to be trained, and/or based on input parameters of training data used to train an AI/ML model. In this example, the training data is specified to include hourly KPIs on separate 24-hour windows. In this sense, the hourly KPIs associated with the first 24 hours (i.e., t_1 through t_{24}) may be identified as a first data set, the hourly KPIs associated with the next 24 hours (i.e., t_{25} through t_{48}) may be identified as a second data set, and so on. Accordingly, one or more operations described herein (e.g., operations **102-108**) may be performed with respect to each data set (e.g., RAN KPIs for each 24-hour window, in this example).

[0018] Process **100** may further include generating (at **104**) a pre-processed multi-dimensional data structure based on the particular data set. Pre-processing the data set may include normalizing the data to a particular quantity of dimensions, quantity or types of values, etc. In the example above, 24 SINR values are received, 24 RSRP values are received, and 24 RSRQ values are received (e.g., where each value is associated with a particular hourly time period). In such embodiments, each hourly value may be considered as a "dimension" for such value. For example, the 24 SINR values for the dataset may be represented as a first 24-dimensional point on a graph with 24 axes (e.g., dimensions), the 24 RSRQ values may be represented as a second 24-dimensional point on the graph, etc.

[0019] In some embodiments, normalizing the data set may include assigning scores, weights, values, etc. in a same value range or space for the different types of values. For example, SINR values may be converted, translated, etc. from a range of values between 0 dB and 40 dB to a normalized range of values of 1 through 100, RSRP values may be converted from a range of values between −100 dbm through −80 dbm to the same normalized range of values of 1 through 100, RSRQ values may be converted from a range of values between −20 dB through −10 dB to the same normalized range of values of 1 through 100, and so on.

[0020] In some scenarios, values may not necessarily be keyed to a specific dimensionality. For example, the received data set may include eight SINR values received over a first hour, twelve SINR values received over a second hour, etc. Normalizing the data may include aggregating, combining, etc. such values to a single SINR value for the first hour, a single SINR value for the second hour, etc.

[0021] In some embodiments, pre-processing the data set may include transposing the data, in which rows of the data are represented as columns, and in which columns of the data are represented as rows. The transposing may be used to represent each parameter of the data set in multiple dimensions, where each dimension is associated with a particular instance of the parameter. For example, as noted above, as a result of transposing the data, the SINR parameter may be represented as 24 dimensions, where each dimension represents a separate instance of the SINR parameter (e.g., separate hourly measurements of the SINR parameter).

[0022] Graph **301** may be a graphical representation of the pre-processed data set (e.g., the transposed and/or normalized data set). Each parameter may be plotted as a multi-dimensional point, and the axes of graph **301** may each represent the different dimensions. In FIG. **3**, graph **301** represents two of the 24 example dimensions, similar to how a two-dimensional image may be used to represent a three-dimensional object (e.g., a picture of a pumpkin may be a two-dimensional image, while the pumpkin itself exists in three dimensions). The axes may each be in the same normalized value range, such as 1 through 100, as discussed above (e.g., a value at the bottom of the t_1 axis may be 1 while a value at the top of the t_1 axis may be 100, and a value at the left of the t_2 axis may be 1 while a value at the right of the t_2 axis may be 100).

[0023] Point **303** represents two dimensions of the SINR parameter. For example, the position on the t_1 axis represents the normalized SINR value at time t_1, and the position on the t_2 axis represents the normalized SINR value at time t_2. Similarly, point **305** represents two dimensions of the RSRP parameter, and point **307** represents two dimensions of the RSRQ parameter.

[0024] FIG. **4** includes graph **401**, in which three of the dimensions of each parameter are represented in graphical form. Point **403** represents three dimensions of the SINR parameter, point **405** represents three dimensions of the RSRP parameter, and point **407** represents three dimensions of the RSRQ parameter. In this vein, multiple (e.g., more than three) dimensions may be represented by multi-dimensional points for each parameter.

[0025] For example, as shown in FIG. **5**, n parameters may each be associated with m dimensions. To provide context to the parameters and dimensions shown in FIG. **5**, note that SINR is an example of a first parameter (e.g., parameter P_1 may refer to SINR values or normalized values based on SINR values), RSRP is an example of a second parameter (e.g., parameter P_2 may refer to RSRP values), and RSRQ is an example of a third parameter (e.g., parameter P_3 may refer to RSRQ values). Similarly, a first dimension may refer to a first hourly measurement or reading, a second dimension may refer to a second hourly measurement or reading, and an m-th dimension may refer to an m-th hourly measurement or reading. For example, referring to example values shown in FIG. **5**, P_{1a} may be a value for the first parameter P_1 at time t_1, P_{1b} may be a value for the first parameter P_1 at time t_2, P_{2a} may be a value for a second parameter P_2 at time t_1, P_{2b} may be a value for the second parameter P_2 at time t_2, and P_{nm} may be a value for the n-th parameter P_n at time t_m.

[0026] Graph **501** illustrates a plotting of multi-dimensional points that each represent all values for a particular parameter. For example, point P_1 represents all m values for parameter P_1 (i.e., P_{1a} through P_{1m}), point P_2 represents all m values for parameter P_2 (i.e., P_{12} through P_{2m}), point P_n represents all values for parameter P_n (i.e., P_{na} through P_{nm}), and so on. As similarly noted above, a two-dimensional graph **501** is shown to represent the plotting of these points in m dimensions, where m may be an integer that is equal to or greater than 2 (e.g., 3, 24, 50, etc.).

[0027] Returning to FIG. **1**, process **100** may additionally include generating (at **106**) a multi-dimensional Eigenvector to represent the maximum variance, variation, difference, etc. between the values of the particular data set included in the transposed and/or normalized data set. FIG. **6** includes a two-dimensional representation of the m-dimensional Eigenvector that represents the maximum variance of the values of the data set. Since the Eigenvector is an m-dimensional vector, any given point along the Eigenvector would also be an m-dimensional point. In some embodiments, the generated Eigenvector may be defined in terms of an m-dimensional endpoint and/or one or more angles or directions (e.g., originating from a value of 0 or other suitable originating value in each of the m dimensions). The length of the Eigenvector may, in some implements, be a static or pre-set length, and the Eigenvector itself may be defined, denoted, etc. in terms of the m-dimensional endpoint of the Eigenvector and/or the one or more angles or directions from the origin(s) of each dimension, as noted above.

[0028] Process **100** may also include generating (at **108**) a projected multi-dimensional vector based on the Eigenvector and the values of the data set. For example, as shown in FIG. **7**, graph **701** represents the m-dimensional points P_1 through P_n, the Eigenvector shown in FIG. **6**, as well as points V_1 through V_n that represent a projection of each value of the data set (e.g., each "P" point such as points P_1 through P_n) onto the Eigenvector. For example, point P_1 may be projected onto the Eigenvector by determining which point (i.e., which m-dimensional point) on the Eigenvector is closest, in m dimensions, to point P_1 (e.g., the lowest distance in m dimensions). In FIG. **7**, the closest point on the Eigenvector to point P_1 is represented as point V_1 (e.g., v_1 is the m-dimensional point on the Eigenvector that is the lowest distance, in m dimensions, from point P_1). Similarly, point P_n may be projected onto the Eigenvector by determining which point on the Eigenvector is closest to point P_n. In FIG. **7**, the closest point on the Eigenvector to point P_1 is represented as point V_1, and the closest point on the Eigenvector to point $P_n$is represented as point $V_{n.}$

[0029] As noted above, each point projected onto the Eigenvector may be an m-dimensional point. For example, as point P_1 includes m values P_{1a} through P_{1m}, the corresponding point v_1 on the Eigenvector also includes m values V_{1a} through V_{1m}. That is, the dimensionality of the projected "V" points on the Eigenvector may be the same as the dimensionality of the corresponding "P" points that represent the data set. In this manner, the vector formed by the "V" points (e.g., referred to as the "projected vector" herein) may represent the entire data set (e.g., the normalized data set). Since the projected vector is further based on the Eigenvector that represents the maximum variation of the data included in the data set, the projected vector may be thought of as a "signature" of the original data set.

[0030] FIG. **8** illustrates a representation of a particular multi-dimensional projected vector V_{proj}, which may be generated using techniques described above with respect to the particular data set. As noted above, projected vector V_{proj} may include n points of m dimensions each (e.g., points V_1 through V_n). For example, as shown in FIG. **8** and as discussed above, point v_1 may include values V_{1a} through V_{1m}, and point V_n may include values V_{na} through V_{nm}.

[0031] Returning to FIG. **1**, some or all of the above-described operations (e.g., operations **102** through **108**) may be performed on multiple data sets. For example, a first data set may refer to RAN KPIs measured over a first 24-hour window, a second data set may refer to RAN KPIs measured over a second 24-hour window, and so on. As another example, a first data set may refer to a first image (e.g., may be generated based on a file or set of files with encoded data that represents a first image), a second data set may refer to a second image, and so on. As yet another example, a first data set may refer to first video or audio data (e.g., a file or set of files with encoded data that represents video or audio content), and a second data set may refer to second video or audio data. In some embodiments, the data sets may be or may include other types of data, with applicability to a wide range of technical applications (e.g., image-based autonomous vehicle control, wireless network interference and/or Quality of Service ("QoS") modeling, audio processing, image recognition, etc.). Generating (e.g., (at **108**) multi-dimensional projected vectors for each data set, in accordance with some embodiments, may generate a representation that significantly captures a "signature" or otherwise captures features of each distinct data set.

[0032] In some embodiments, the dimensionality of each pre-processed data set may be the same. In this manner, each respective multi-dimensional projected vector V_{proj} may be compared (at **110**), in order to cluster (at **112**) data sets with similar multi-dimensional projected vectors. For example, one or more clustering techniques, such as K-means clustering, density-based clustering, hierarchical clustering, and/or other suitable clustering techniques may be used to identify multi-dimensional projected vectors that exhibit at least a threshold measure of similarity. Process **100** may also include generating and/or refining (at **114**) one or more AI/ML models based on the clustering.

[0033] For example, as shown in FIG. **9**, multi-dimensional projected vectors V_{proj_1} through V_{proj_x} may have been generated (e.g., based on multiple iterations of operations **102-108**) for x different data sets. As discussed above, multi-dimensional projected vectors V_{proj_1} through V_{proj_x} may be made up of m-dimensional points that represent respective original data sets, and may therefore be able to be compared and clustered on the basis of the m-dimensional points. For example, in this example, a first cluster may include respective data sets associated with multi-dimensional projected vectors V_{proj_1}, V_{proj_3}, and V_{proj_4}; a second cluster may include respective data sets associated with multi-dimensional projected vectors V_{proj_2},V_{proj_5}, and V_{proj_7}; and a third cluster may include respective data sets associated with multi-dimensional projected vectors V_{proj_1}, V_{proj_6}, and V_{proj_8}.

[0034] In some embodiments, some or all of the operations described above may be performed by Unsupervised Multi-Dimensional Clustering System **1001**. For example, as shown in FIG. **10**, Unsupervised Multi-Dimensional Clustering System **1001** may receive a set of unstructured data **1003**. The unstructured data may include, as discussed above, KPIs of a wireless network, one or more content files (e.g., image, audio, text, video, etc.), time series data, and/or other suitable types of data. Unsupervised Multi-Dimensional Clustering System **1001** may, for example, receive wireless network KPIs from a Service Capability Exposure Function ("SCEF") or Network Exposure Function ("NEF") of a wireless network, a RAN controller, or other suitable type of device or system that reports or otherwise provides wireless network KPIs. In some embodiments, Unsupervised Multi-Dimensional Clustering System **1001** may receive image or video data from one or more autonomous vehicles or from a central repository that aggregates such data as collected by such autonomous vehicles. In some embodiments, unstructured data **1003** may be received from some other suitable source.

[0035] Unsupervised Multi-Dimensional Clustering System **1001** may perform some or all of operations **102**-**112** in order to generate distinct data sets **1005** (e.g., example data sets **1005-1** through **1005-8**) and associate such data sets **1005** with respective clusters **1007**. For example, as discussed above, Unsupervised Multi-Dimensional Clustering System **1001** may generate respective Eigenvectors to represent the maximum variation for each data set **1005**, and may generate multi-dimensional projected vectors based on the values of each data set **1005** and the respective Eigenvector for each data set **1005**. Clusters **1007** may be determined by performing a similarity analysis and/or clustering technique on each data set **1005**, to identify data sets **1005** with matching or similar (e.g., within a threshold measure of similarity) multi-dimensional projected vectors.

[0036] In some embodiments, clusters **1007** may further be used to generate or refine one or more AI/ML models or other suitable models (e.g., which may be used to identify particular labels, categories, classifications, etc. for a respective set of input data). As shown in FIG. **10**, AI/ML Classification System **1009** may receive or identify clusters **1007** (e.g., which indicate respective data sets **1005** that are associated with each cluster **1007**). AI/ML Classification System **1009** may also receive one or more models, definitions, mappings, etc. that associate respective clusters **1007** with particular labels, categories, classifications, etc. (referred to herein simply as "labels **1011**" for brevity). Such models, associations, etc. may have been generated or refined using AI/ML techniques (e.g., by AI/ML Classification System **1009** or some other suitable device or system) or using other suitable techniques. In some embodiments, the associations between clusters **1007** and respective labels **1011** may be determined using a supervised machine learning procedure, an unsupervised machine learning procedure, and/or other suitable procedure.

[0037] In the example where data sets **1005** include wireless network KPI information (e.g., interference information, signal quality information, traffic performance metrics, etc.), a particular label **1011** associated with a particular cluster **1007** may include a descriptor such as "high interference," "good signal quality," "overloaded," etc. In an example where data sets **1005** include image or video data used for autonomous vehicle control applications, a particular label **1011** associated with a particular cluster **1007** may include a descriptor of prominent features depicted in the image or video data, such as "school bus," "crosswalk," "bridge," etc.

[0038] AI/ML Classification System **1009** may further refine one or more models associating particular data sets **1005** with particular labels **1011**. For example, based on the association of data set **1005-1** with clusters **1007-1** and **1007-3**, and further based on the respective associations between clusters **1007-1** and **1007-2** with labels **1011-1** and **1011-3**, AI/ML Classification System **1009** may generate or modify such models to associate data set **1005-1** with labels **1011-1** and **1011-3**. AI/ML Classification System **1009** may similarly associate data sets **1005-3** and **1005-4** with label **1011-1**, and so on. The models may be used to classify, categorize, etc. input data in order to identify particular labels **1011** associated with such input data. For example, a wireless network operator may utilize the models, that have been generated based on clustering performed by Unsupervised Multi-Dimensional Clustering System **1001**, to identify particular network conditions (e.g., network overload conditions, poor radio quality conditions, etc.) and perform automated remedial measures (e.g., e.g., actions such as modifying radio resource allocations, modifying beamforming parameters of the wireless network, etc.) in response to such network conditions.

[0039] FIG. **11** illustrates an example environment **1100**, in which one or more embodiments may be implemented. In some embodiments, environment **1100** may correspond to a Fifth Generation ("5G") network, and/or may include elements of a 5G network. In some embodiments, environment **1100** may correspond to a 5G Non-Standalone ("NSA") architecture, in which a 5G radio access technology ("RAT") may be used in conjunction with one or more other RATs (e.g., a Long-Term Evolution ("LTE") RAT), and/or in which elements of a 5G core network may be implemented by, may be communicatively coupled with, and/or may include elements of another type of core network (e.g., an evolved packet core ("EPC")). In some embodiments, portions of environment **1100** may represent or may include a 5G core ("5GC"). As shown, environment **1100** may include UE **1101**, RAN **1110** (which may include one or more Next Generation Node Bs ("gNBs") **1111**), RAN **1112** (which may include one or more evolved Node Bs ("eNBs") **1113**), and various network functions such as Access and Mobility Management Function ("AMF") **1115**, Mobility Management Entity ("MME") **1116**, Serving Gateway ("SGW") **1117**, Session Management Function ("SMF")/Packet Data Network ("PDN") Gateway ("PGW")—Control plane function ("PGW-C") **1120**, Policy Control Function ("PCF")/Policy Charging and Rules Function ("PCRF") **1125**, Application Function ("AF") **1130**, User Plane Function ("UPF")/PGW-User plane function ("PGW-U") **1135**, Unified Data Management ("UDM")/Home Subscriber Server ("HSS") **1140**, Authentication Server Function ("AUSF") **1145**, and Network Exposure Function NEF/SCEF **1149**. Environment **1100** may also include one or more networks, such as Data Network ("DN") **1150**. Environment **1100** may include one or more additional devices or systems communicatively coupled to one or more networks (e.g., DN **1150**), such as one or more external devices **1154**.

[0040] The example shown in FIG. **11** illustrates one instance of each network component or function (e.g., one instance of SMF/PGW-C **1120**, PCF/PCRF **1125**, UPF/PGW-U **1135**, UDM/HSS **1140**, and/or AUSF **1145**). In practice, environment **1100** may include multiple instances of such components or functions. For example, in some embodiments, environment **1100** may include multiple "slices" of a core network, where each slice includes a discrete and/or logical set of network functions (e.g., one slice may include a first instance of AMF **1115**, SMF/PGW-C **1120**, PCF/PCRF **1125**, and/or UPF/PGW-U **1135**, while another slice may include a second instance of AMF **1115**, SMF/PGW-C **1120**, PCF/PCRF **1125**, and/or UPF/PGW-U **1135**). The different slices may provide differentiated levels of service, such as service in accordance with different Quality of Service ("QoS") parameters.

[0041] The quantity of devices and/or networks, illustrated in FIG. **11**, is provided for explanatory purposes only. In practice, environment **1100** may include additional devices and/or networks, fewer devices and/or networks, different devices and/or networks, or differently arranged devices and/or networks than illustrated in FIG. **11**. For example, while not shown, environment **1100** may include devices that facilitate or enable communication between various components shown in environment **1100**, such as routers, modems, gateways, switches, hubs, etc. In some implementations, one or more devices of environment **1100** may be physically integrated in, and/or may be physically attached to, one or more other devices of environment **1100**. Alternatively, or additionally, one or more of the devices of environment **1100** may perform one or more network functions described as being performed by another one or more of the devices of environment **1100**.

[0042] Additionally, one or more elements of environment **1100** may be implemented in a virtualized and/or containerized manner. For example, one or more of the elements of environment **1100** may be implemented by one or more Virtualized Network Functions ("VNFs"), Cloud-Native Network Functions ("CNFs"), etc. In such embodiments, environment **1100** may include, may implement, and/or may be communicatively coupled to an orchestration platform that provisions hardware resources, installs containers or applications, performs load balancing, and/or otherwise manages the deployment of such elements of environment **1100**. In some embodiments, such orchestration and/or management of such elements of environment **1100** may be performed by, or in conjunction with, the open-source Kubernetes® application programming interface ("API") or some other suitable virtualization, containerization, and/or orchestration system.

[0043] Elements of environment **1100** may interconnect with each other and/or other devices via wired connections, wireless connections, or a combination of wired and wireless connections. Examples of interfaces or communication pathways between the elements of environment **1100**, as shown in FIG. **11**, may include an N**1** interface, an N**2** interface, an N**3** interface, an N**4** interface, an N**5** interface, an N**6** interface, an N**7** interface, an N**8** interface, an N**9** interface, an N**10** interface, an N**11** interface, an N**12** interface, an N**13** interface, an N**14** interface, an N**15** interface, an N**26** interface, an S**1**-C interface, an S**1**-U interface, an S**5**-C interface, an S**5**-U interface, an S**6***a* interface, an S**11** interface, and/or one or more other interfaces. Such interfaces may include interfaces not explicitly shown in FIG. **11**, such as Service-Based Interfaces ("SBIs"), including an Namf interface, an Nudm interface, an Npcf interface, an Nupf interface, an Nnef interface, an Nsmf interface, and/or one or more other SBIs.

[0044] UE **1101** may include a computation and communication device, such as a wireless mobile communication device that is capable of communicating with RAN **1110**, RAN **1112**, and/or DN **1150**. UE **1101** may be, or may include, a radiotelephone, a personal communications system ("PCS") terminal (e.g., a device that combines a cellular radiotelephone with data processing and data communications capabilities), a personal digital assistant ("PDA") (e.g., a device that may include a radiotelephone, a pager, Internet/intranet access, etc.), a smart phone, a laptop computer, a tablet computer, a camera, a personal gaming system, an Internet of Things ("IoT") device (e.g., a sensor, a smart home appliance, a wearable device, a Machine-to-Machine ("M2M") device, or the like), a Fixed Wireless Access ("FWA") device, or another type of mobile computation and communication device. UE **1101** may send traffic to and/or receive traffic (e.g., user plane traffic) from DN **1150** via RAN **1110**, RAN **1112**, and/or UPF/PGW-U **1135**.

[0045] RAN **1110** may be, or may include, a 5G RAN that implements a 5G RAT and that includes one or more base stations (e.g., one or more gNBs **1111**), via which UE **1101** may communicate with one or more other elements of environment **1100**. UE **1101** may communicate with RAN **1110** via an air interface (e.g., as provided by gNB **1111**). For instance, RAN **1110** may receive traffic (e.g., user plane traffic such as voice call traffic, data traffic, messaging traffic, etc.) from UE **1101** via the air interface, and may communicate the traffic to UPF/PGW-U **1135** and/or one or more other devices or networks. Further, RAN **1110** may receive signaling traffic, control plane traffic, etc. from UE **1101** via the air interface, and may communicate such signaling traffic, control plane traffic, etc. to AMF **1115** and/or one or more other devices or networks. Additionally, RAN **1110** may receive traffic intended for UE **1101** (e.g., from UPF/PGW-U **1135**, AMF **1115**, and/or one or more other devices or networks) and may communicate the traffic to UE **1101** via the air interface.

[0046] RAN **1112** may be, or may include, an LTE RAN that implements an LTE RAT and that includes one or more base stations (e.g., one or more eNBs **1113**), via which UE **1101** may communicate with one or more other elements of environment **1100**. UE **1101** may communicate with RAN **1112** via an air interface (e.g., as provided by eNB **1113**). For instance, RAN **1112** may receive traffic (e.g., user plane traffic such as voice call traffic, data traffic, messaging traffic, signaling traffic, etc.) from UE **1101** via the air interface, and may communicate the traffic to UPF/PGW-U **1135** (e.g., via SGW **1117**) and/or one or more other devices or networks. Further, RAN **1112** may receive signaling traffic, control plane traffic, etc. from UE **1101** via the air interface, and may communicate such signaling traffic, control plane traffic, etc. to MME **1116** and/or one or more other devices or networks. Additionally, RAN **1112** may receive traffic intended for UE **1101** (e.g., from UPF/PGW-U **1135**, MME **1116**, SGW **1117**, and/or one or more other devices or networks) and may communicate the traffic to UE **1101** via the air interface.

[0047] One or more RANs of environment **1100** (e.g., RAN **1110** and/or RAN **1112**) may include, may implement, and/or may otherwise be communicatively coupled to one or more edge computing devices, such as one or more Multi-Access/Mobile Edge Computing ("MEC") devices (referred to sometimes herein simply as a "MECs") **1114**. MECs **1114** may be co-located with wireless network infrastructure equipment of RANs **1110** and/or **1112** (e.g., one or more gNBs **1111** and/or one or more eNBs **1113**, respectively). Additionally, or alternatively, MECs **1114** may otherwise be associated with geographical regions (e.g., coverage areas) of wireless network infrastructure equipment of RANs **1110** and/or **1112**. In some embodiments, one or more MECs **1114** may be implemented by the same set of hardware resources, the same set of devices, etc. that implement wireless network infrastructure equipment of RANs **1110** and/or **1112**. In some embodiments, one or more MECs **1114** may be implemented by different hardware resources, a different set of devices, etc. from hardware resources or devices that implement wireless network infrastructure equipment of

RANs **1110** and/or **1112**. In some embodiments, MECs **1114** may be communicatively coupled to wireless network infrastructure equipment of RANs **1110** and/or **1112** (e.g., via a high-speed and/or low-latency link such as a physical wired interface, a high-speed and/or low-latency wireless interface, or some other suitable communication pathway).

[0048] MECs **1114** may include hardware resources (e.g., configurable or provisionable hardware resources) that may be configured to provide services and/or otherwise process traffic to and/or from UE **1101**, via RAN **1110** and/or **1112**. For example, RAN **1110** and/or **1112** may route some traffic from UE **1101** (e.g., traffic associated with one or more particular services, applications, application types, etc.) to a respective MEC **1114** instead of to core network elements of **1100** (e.g., UPF/PGW-U **1135**). MEC **1114** may accordingly provide services to UE **1101** by processing such traffic, performing one or more computations based on the received traffic, and providing traffic to UE **1101** via RAN **1110** and/or **1112**. MEC **1114** may include, and/or may implement, some or all of the functionality described above with respect to UPF/PGW-U **1135**, AF **1130**, one or more application servers, and/or one or more other devices, systems, VNFs, CNFs, etc. In this manner, ultra-low latency services may be provided to UE **1101**, as traffic does not need to traverse links (e.g., backhaul links) between RAN **1110** and/or **1112** and the core network.

[0049] AMF **1115** may include one or more devices, systems, VNFs, CNFs, etc., that perform operations to register UE **1101** with the 5G network, to establish bearer channels associated with a session with UE **1101**, to hand off UE **1101** from the 5G network to another network, to hand off UE **1101** from the other network to the 5G network, manage mobility of UE **1101** between RANs **1110** and/or gNBs **1111**, and/or to perform other operations. In some embodiments, the 5G network may include multiple AMFs **1115**, which communicate with each other via the N**14** interface (denoted in FIG. **11** by the line marked "N**14**" originating and terminating at AMF **1115**).

[0050] MME **1116** may include one or more devices, systems, VNFs, CNFs, etc., that perform operations to register UE **1101** with the EPC, to establish bearer channels associated with a session with UE **1101**, to hand off UE **1101** from the EPC to another network, to hand off UE **1101** from another network to the EPC, manage mobility of UE **1101** between RANs **1112** and/or eNBs **1113**, and/or to perform other operations.

[0051] SGW **1117** may include one or more devices, systems, VNFs, CNFs, etc., that aggregate traffic received from one or more eNBs **1113** and send the aggregated traffic to an external network or device via UPF/PGW-U **1135**. Additionally, SGW **1117** may aggregate traffic received from one or more UPF/PGW-Us **1135** and may send the aggregated traffic to one or more eNBs **1113**. SGW **1117** may operate as an anchor for the user plane during inter-eNB handovers and as an anchor for mobility between different telecommunication networks or RANs (e.g., RANs **1110** and **1112**).

[0052] SMF/PGW-C **1120** may include one or more devices, systems, VNFs, CNFs, etc., that gather, process, store, and/or provide information in a manner described herein. SMF/PGW-C **1120** may, for example, facilitate the establishment of communication sessions on behalf of UE **1101**. In some embodiments, the establishment of communications sessions may be performed in accordance with one or more policies provided by PCF/PCRF **1125**.

[0053] PCF/PCRF **1125** may include one or more devices, systems, VNFs, CNFs, etc., that aggregate information to and from the 5G network and/or other sources. PCF/PCRF **1125** may receive information regarding policies and/or subscriptions from one or more sources, such as subscriber databases and/or from one or more users (such as, for example, an administrator associated with PCF/PCRF **1125**).

[0054] AF **1130** may include one or more devices, systems, VNFs, CNFs, etc., that receive, store, and/or provide information that may be used in determining parameters (e.g., quality of service parameters, charging parameters, or the like) for certain applications.

[0055] UPF/PGW-U **1135** may include one or more devices, systems, VNFs, CNFs, etc., that receive, store, and/or provide data (e.g., user plane data). For example, UPF/PGW-U **1135** may receive user plane data (e.g., voice call traffic, data traffic, etc.), destined for UE **1101**, from DN **1150**, and may forward the user plane data toward UE **1101** (e.g., via RAN **1110**, SMF/PGW-C **1120**, and/or one or more other devices). In some embodiments, multiple instances of UPF/PGW-U **1135** may be deployed (e.g., in different geographical locations), and the delivery of content to UE **1101** may be coordinated via the N**9** interface (e.g., as denoted in FIG. **11** by the line marked "N**9**" originating and terminating at UPF/PGW-U **1135**). Similarly, UPF/PGW-U **1135** may receive traffic from UE **1101** (e.g., via RAN **1110**, RAN **1112**, SMF/PGW-C **1120**, and/or one or more other devices), and may forward the traffic toward DN **1150**. In some embodiments, UPF/PGW-U **1135** may communicate (e.g., via the N**4** interface) with SMF/PGW-C **1120**, regarding user plane data processed by UPF/PGW-U **1135**.

[0056] UDM/HSS **1140** and AUSF **1145** may include one or more devices, systems, VNFs, CNFs, etc., that manage, update, and/or store, in one or more memory devices associated with AUSF **1145** and/or UDM/HSS **1140**, profile information associated with a subscriber. In some embodiments, UDM/HSS **1140** may include, may implement, may be communicatively coupled to, and/or may otherwise be associated with some other type of repository or database, such as a Unified Data Repository ("UDR"). AUSF **1145** and/or UDM/HSS **1140** may perform authentication, authorization, and/or accounting operations associated with one or more UEs **1101** and/or one or more communication sessions associated with one or more UEs **1101**.

[0057] DN **1150** may include one or more wired and/or wireless networks. For example, DN **1150** may include an Internet Protocol ("IP")-based PDN, a wide area network ("WAN") such as the Internet, a private enterprise network, and/or one or more other networks. UE **1101** may communicate, through DN **1150**, with data servers, other UEs **1101**, and/or to other servers or applications that are coupled to DN **1150**. DN **1150** may be connected to one or more other networks, such as a public switched telephone network ("PSTN"), a public land mobile network ("PLMN"), and/or another network. DN **1150** may be connected to one or more devices, such as content providers, applications, web servers, and/or other devices, with which UE **1101** may communicate.

[0058] External devices **1154** may include one or more devices or systems that communicate with UE **1101** via DN **1150** and one or more elements of **1100** (e.g., via UPF/

PGW-U **1135**). In some embodiments, external devices **1154** may include, may implement, and/or may otherwise be associated with Unsupervised Multi-Dimensional Clustering System **1001** and/or AI/ML Classification System **1009**. External devices **1154** may include, for example, one or more application servers, content provider systems, web servers, or the like. External devices **1154** may, for example, implement "server-side" applications that communicate with "client-side" applications executed by UE **1101**. External devices **1154** may provide services to UE **1101** such as gaming services, videoconferencing services, messaging services, email services, web services, and/or other types of services.

[0059] In some embodiments, external devices **1154** may communicate with one or more elements of environment **1100** (e.g., core network elements) via NEF/SCEF **1149**. NEF/SCEF **1149** include one or more devices, systems, VNFs, CNFs, etc. that provide access to information, APIs, and/or other operations or mechanisms of one or more core network elements to devices or systems that are external to the core network (e.g., to external device **1154** via DN **1150**). NEF/SCEF **1149** may maintain authorization and/or authentication information associated with such external devices or systems, such that NEF/SCEF **1149** is able to provide information, that is authorized to be provided, to the external devices or systems. For example, a given external device **1154** may request particular information associated with one or more core network elements. NEF/SCEF **1149** may authenticate the request and/or otherwise verify that external device **1154** is authorized to receive the information, and may request, obtain, or otherwise receive the information from the one or more core network elements. In some embodiments, NEF/SCEF **1149** may include, may implement, may be implemented by, may be communicatively coupled to, and/or may otherwise be associated with a Security Edge Protection Proxy ("SEPP"), which may perform some or all of the functions discussed above. External device **1154** may, in some situations, subscribe to particular types of requested information provided by the one or more core network elements, and the one or more core network elements may provide (e.g., "push") the requested information to NEF/SCEF **1149** (e.g., in a periodic or otherwise ongoing basis).

[0060] In some embodiments, external devices **1154** may communicate with one or more elements of RAN **1110** and/or **1112** via an API or other suitable interface. For example, a given external device **1154** may provide instructions, requests, etc. to RAN **1110** and/or **1112** to provide one or more services via one or more respective MECs **1114**. In some embodiments, such instructions, requests, etc. may include QoS parameters, Service Level Agreements ("SLAs"), etc. (e.g., maximum latency thresholds, minimum throughput thresholds, etc.) associated with the services.

[0061] FIG. **12** illustrates example components of device **1200**. One or more of the devices described above may include one or more devices **1200**. Device **1200** may include bus **1210**, processor **1220**, memory **1230**, input component **1240**, output component **1250**, and communication interface **1260**. In another implementation, device **1200** may include additional, fewer, different, or differently arranged components.

[0062] Bus **1210** may include one or more communication paths that permit communication among the components of device **1200**. Processor **1220** may include a processor, microprocessor, a set of provisioned hardware resources of a cloud computing system, or other suitable type of hardware that interprets and/or executes instructions (e.g., processor-executable instructions). In some embodiments, processor **1220** may be or may include one or more hardware processors. Memory **1230** may include any type of dynamic storage device that may store information and instructions for execution by processor **1220**, and/or any type of non-volatile storage device that may store information for use by processor **1220**.

[0063] Input component **1240** may include a mechanism that permits an operator to input information to device **1200** and/or other receives or detects input from a source external to input component **1240**, such as a touchpad, a touchscreen, a keyboard, a keypad, a button, a switch, a microphone or other audio input component, etc. In some embodiments, input component **1240** may include, or may be communicatively coupled to, one or more sensors, such as a motion sensor (e.g., which may be or may include a gyroscope, accelerometer, or the like), a location sensor (e.g., a Global Positioning System ("GPS")-based location sensor or some other suitable type of location sensor or location determination component), a thermometer, a barometer, and/or some other type of sensor. Output component **1250** may include a mechanism that outputs information to the operator, such as a display, a speaker, one or more light emitting diodes ("LEDs"), etc.

[0064] Communication interface **1260** may include any transceiver-like mechanism that enables device **1200** to communicate with other devices and/or systems (e.g., via RAN **1110**, RAN **1112**, DN **1150**, etc.). For example, communication interface **1260** may include an Ethernet interface, an optical interface, a coaxial interface, or the like. Communication interface **1260** may include a wireless communication device, such as an infrared ("IR") receiver, a Bluetooth® radio, or the like. The wireless communication device may be coupled to an external device, such as a cellular radio, a remote control, a wireless keyboard, a mobile telephone, etc. In some embodiments, device **1200** may include more than one communication interface **1260**. For instance, device **1200** may include an optical interface, a wireless interface, an Ethernet interface, and/or one or more other interfaces.

[0065] Device **1200** may perform certain operations relating to one or more processes described above. Device **1200** may perform these operations in response to processor **1220** executing instructions, such as software instructions, processor-executable instructions, etc. stored in a computer-readable medium, such as memory **1230**. A computer-readable medium may be defined as a non-transitory memory device. A memory device may include space within a single physical memory device or spread across multiple physical memory devices. The instructions may be read into memory **1230** from another computer-readable medium or from another device. The instructions stored in memory **1230** may be processor-executable instructions that cause processor **1220** to perform processes described herein. Alternatively, hardwired circuitry may be used in place of or in combination with software instructions to implement processes described herein. Thus, implementations described herein are not limited to any specific combination of hardware circuitry and software.

[0066] The foregoing description of implementations provides illustration and description, but is not intended to be exhaustive or to limit the possible implementations to the precise form disclosed. Modifications and variations are possible in light of the above disclosure or may be acquired from practice of the implementations.

[0067] For example, while series of blocks and/or signals have been described above (e.g., with regard to FIGS. **1-10**), the order of the blocks and/or signals may be modified in other implementations. Further, non-dependent blocks and/or signals may be performed in parallel. Additionally, while the figures have been described in the context of particular devices performing particular acts, in practice, one or more other devices may perform some or all of these acts in lieu of, or in addition to, the above- mentioned devices.

[0068] The actual software code or specialized control hardware used to implement an embodiment is not limiting of the embodiment. Thus, the operation and behavior of the embodiment has been described without reference to the specific software code, it being understood that software and control hardware may be designed based on the description herein.

[0069] In the preceding specification, various example embodiments have been described with reference to the accompanying drawings. It will, however, be evident that various modifications and changes may be made thereto, and additional embodiments may be implemented, without departing from the broader scope of the invention as set forth in the claims that follow. The specification and drawings are accordingly to be regarded in an illustrative rather than restrictive sense.

[0070] Even though particular combinations of features are recited in the claims and/or disclosed in the specification, these combinations are not intended to limit the disclosure of the possible implementations. In fact, many of these features may be combined in ways not specifically recited in the claims and/or disclosed in the specification. Although each dependent claim listed below may directly depend on only one other claim, the disclosure of the possible implementations includes each dependent claim in combination with every other claim in the claim set.

[0071] Further, while certain connections or devices are shown, in practice, additional, fewer, or different, connections or devices may be used. Furthermore, while various devices and networks are shown separately, in practice, the functionality of multiple devices may be performed by a single device, or the functionality of one device may be performed by multiple devices. Further, multiple ones of the illustrated networks may be included in a single network, or a particular network may include multiple networks. Further, while some devices are shown as communicating with a network, some such devices may be incorporated, in whole or in part, as a part of the network.

[0072] To the extent the aforementioned implementations collect, store, or employ personal information of individuals, groups or other entities, it should be understood that such information shall be used in accordance with all applicable laws concerning protection of personal information. Additionally, the collection, storage, and use of such information can be subject to consent of the individual to such activity, for example, through well known "opt-in" or "opt-out" processes as can be appropriate for the situation and type of information. Storage and use of personal information can be in an appropriately secure manner reflective of the type of information, for example, through various access control, encryption and anonymization techniques for particularly sensitive information. No element, act, or instruction used in the present application should be construed as critical or essential unless explicitly described as such. An instance of the use of the term "and," as used herein, does not necessarily preclude the interpretation that the phrase "and/or" was intended in that instance. Similarly, an instance of the use of the term "or," as used herein, does not necessarily preclude the interpretation that the phrase "and/or" was intended in that instance. Also, as used herein, the article "a" is intended to include one or more items, and may be used interchangeably with the phrase "one or more." Where only one item is intended, the terms "one," "single," "only," or similar language is used. Further, the phrase "based on" is intended to mean "based, at least in part, on" unless explicitly stated otherwise.

What is claimed is:

1. A device, comprising:

one or more processors configured to:

receive a plurality of multi-dimensional data sets;

generate, for each multi-dimensional data set, an Eigenvector, wherein a particular Eigenvector for a particular multi-dimensional data set represents a maximum variance of the particular multi-dimensional data set;

generate, for each multi-dimensional data set, a projected vector, wherein generating a particular projected vector includes identifying a lowest distance between respective multi-dimensional values of the particular data set and the particular Eigenvector, wherein the particular projected vector includes multi-dimensional values along the Eigenvector that are each a lowest distance from a corresponding multi-dimensional value of the particular data set;

compare respective projected vectors, associated with one or more multi-dimensional data sets, with one or more other multi-dimensional data sets of the plurality of multi-dimensional data sets;

generate a plurality of clusters based on the comparing, wherein each cluster includes one or more multi-dimensional data sets of the plurality of multi-dimensional data sets; and

train one or more artificial intelligence/machine learning ("AI/ML") models based on the plurality of clusters.

2. The device of claim **1**, wherein the plurality of multi-dimensional data sets include wireless network Key Performance Indicators ("KPIs"), wherein training the one or more AI/ML models includes identifying one or more network conditions associated with respective clusters.

3. The device of claim **2**, wherein the one or more processors are further configured to:

receive KPIs of a particular wireless network;

determine, based on the one or more AI/ML models, that the received KPIs are associated with a particular cluster that is further associated with a particular network condition;

identify one or more remedial actions associated with the particular network condition; and

modify configuration parameters of the wireless network based on the identified one or more remedial actions.

4. The device of claim **1**, wherein the particular multi-dimensional data set includes a particular quantity of instances of a plurality of parameters, wherein a dimensionality of the particular multi-dimensional data set is based on the particular quantity of instances.

5. The device of claim **4**, wherein a dimensionality of the Eigenvector is based on the particular quantity of instances.

6. The device of claim **1**, wherein the particular projected vector represents a signature of the particular data set.

7. The device of claim **1**, wherein a particular cluster includes a first multi-dimensional data set and a second multi-dimensional data set of the plurality of multi-dimensional data sets, wherein generating the particular cluster includes:

determining a measure of similarity between a first projected vector, associated with the first multi-dimensional data set, and a second first projected vector associated with the second multi-dimensional data set; and

determining that the measure of similarity exceeds a threshold measure of similarity.

8. A non-transitory computer-readable medium, storing a plurality of processor-executable instructions to:

receive a plurality of multi-dimensional data sets;

generate, for each multi-dimensional data set, an Eigenvector, wherein a particular Eigenvector for a particular multi-dimensional data set represents a maximum variance of the particular multi-dimensional data set;

generate, for each multi-dimensional data set, a projected vector, wherein generating a particular projected vector includes identifying a lowest distance between respective multi-dimensional values of the particular data set and the particular Eigenvector, wherein the particular projected vector includes multi-dimensional values along the Eigenvector that are each a lowest distance from a corresponding multi-dimensional value of the particular data set;

compare respective projected vectors, associated with one or more multi-dimensional data sets, with one or more other multi-dimensional data sets of the plurality of multi-dimensional data sets;

generate a plurality of clusters based on the comparing, wherein each cluster includes one or more multi-dimensional data sets of the plurality of multi-dimensional data sets; and

train one or more artificial intelligence/machine learning ("AI/ML") models based on the plurality of clusters.

9. The non-transitory computer-readable medium of claim **8**, wherein the plurality of multi-dimensional data sets include wireless network Key Performance Indicators ("KPIs"), wherein training the one or more AI/ML models includes identifying one or more network conditions associated with respective clusters.

10. The non-transitory computer-readable medium of claim **9**, wherein the plurality of processor-executable instructions further include processor-executable instructions to:

receive KPIs of a particular wireless network;

determine, based on the one or more AI/ML models, that the received KPIs are associated with a particular cluster that is further associated with a particular network condition;

identify one or more remedial actions associated with the particular network condition; and

modify configuration parameters of the wireless network based on the identified one or more remedial actions.

11. The non-transitory computer-readable medium of claim **8**, wherein the particular multi-dimensional data set includes a particular quantity of instances of a plurality of parameters, wherein a dimensionality of the particular multi-dimensional data set is based on the particular quantity of instances.

12. The non-transitory computer-readable medium of claim **11**, wherein a dimensionality of the Eigenvector is based on the particular quantity of instances.

13. The non-transitory computer-readable medium of claim **8**, wherein the particular projected vector represents a signature of the particular data set.

14. The non-transitory computer-readable medium of claim **8**, wherein a particular cluster includes a first multi-dimensional data set and a second multi-dimensional data set of the plurality of multi-dimensional data sets, wherein generating the particular cluster includes:

determining a measure of similarity between a first projected vector, associated with the first multi-dimensional data set, and a second first projected vector associated with the second multi-dimensional data set; and

determining that the measure of similarity exceeds a threshold measure of similarity.

15. A method, comprising:

receiving a plurality of multi-dimensional data sets;

generating, for each multi-dimensional data set, an Eigenvector, wherein a particular Eigenvector for a particular multi-dimensional data set represents a maximum variance of the particular multi-dimensional data set;

generating, for each multi-dimensional data set, a projected vector, wherein generating a particular projected vector includes identifying a lowest distance between respective multi-dimensional values of the particular data set and the particular Eigenvector, wherein the particular projected vector includes multi-dimensional values along the Eigenvector that are each a lowest distance from a corresponding multi-dimensional value of the particular data set;

comparing respective projected vectors, associated with one or more multi-dimensional data sets, with one or more other multi-dimensional data sets of the plurality of multi-dimensional data sets;

generating a plurality of clusters based on the comparing, wherein each cluster includes one or more multi-dimensional data sets of the plurality of multi-dimensional data sets; and

training one or more artificial intelligence/machine learning ("AI/ML") models based on the plurality of clusters.

16. The method of claim **15**, wherein the plurality of multi-dimensional data sets include wireless network Key Performance Indicators ("KPIs"), wherein training the one or more AI/ML models includes identifying one or more network conditions associated with respective clusters, wherein the method comprises:

receiving KPIs of a particular wireless network;

determining, based on the one or more AI/ML models, that the received KPIs are associated with a particular cluster that is further associated with a particular network condition;

identifying one or more remedial actions associated with the particular network condition; and modifying configuration parameters of the wireless network based on the identified one or more remedial actions.

17. The method of claim **15**, wherein the particular multi-dimensional data set includes a particular quantity of instances of a plurality of parameters, wherein a dimensionality of the particular multi-dimensional data set is based on the particular quantity of instances.

18. The method of claim **17**, wherein a dimensionality of the Eigenvector is based on the particular quantity of instances.

19. The method of claim **15**, wherein the particular projected vector represents a signature of the particular data set.

20. The method of claim **15**, wherein a particular cluster includes a first multi-dimensional data set and a second multi-dimensional data set of the plurality of multi-dimensional data sets, wherein generating the particular cluster includes:

determining a measure of similarity between a first projected vector, associated with the first multi-dimensional data set. and a second first projected vector associated with the second multi-dimensional data set; and

determining that the measure of similarity exceeds a threshold measure of similarity.

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