US 20250259083A1

(19) United States

(12) Patent Application Publication

(10) Pub. No.: US 2025/0259083 A1

(43) Pub. Date: Aug. 14, 2025

Anand et al.

(54) **DATA DIVERSITY VISUALIZATION AND QUANTIFICATION FOR MACHINE LEARNING MODELS**

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(21) Appl. No.: **19/192,076**

(22) Filed: **Apr. 28, 2025**

Related U.S. Application Data

(63) Continuation of application No. 17/243,046, filed on Apr. 28, 2021, now Pat. No. 12,321,866.

Publication Classification

(51) **Int. Cl.**

G06N 5/04 (2023.01)

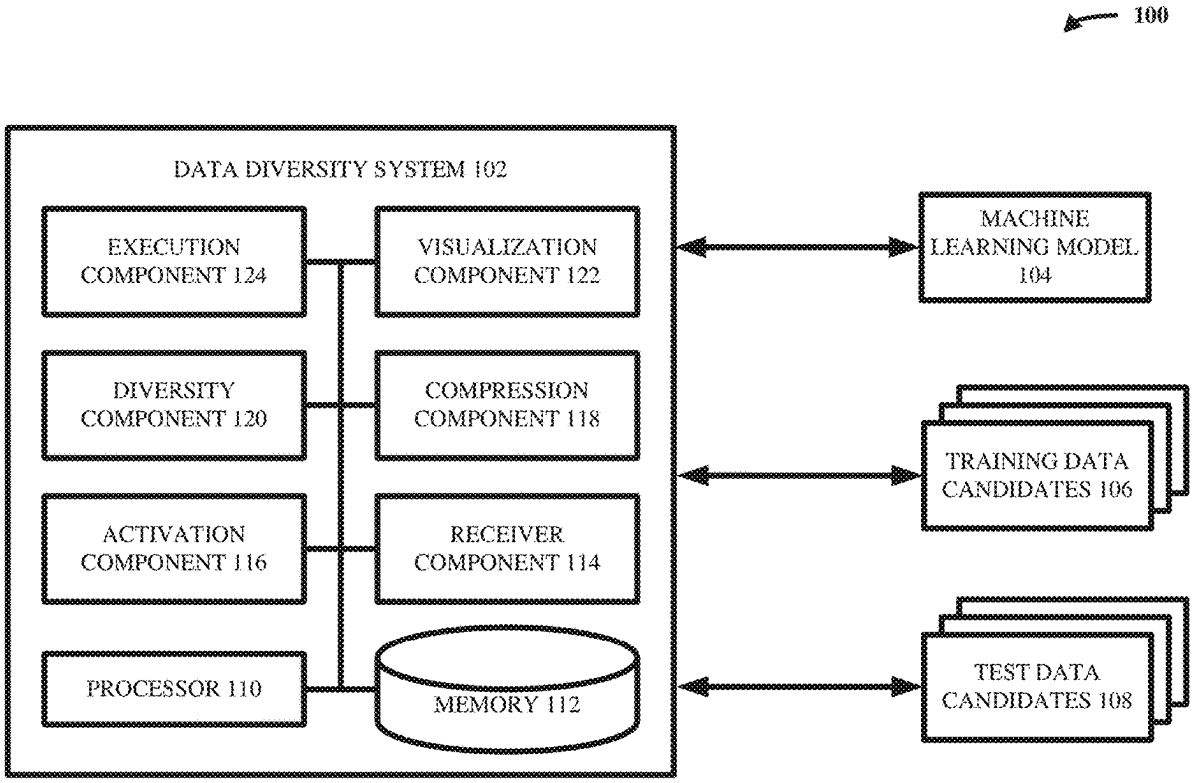
G06N 20/00 (2019.01)

(52) **U.S. Cl.**

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

(57) **ABSTRACT**

Systems and techniques that facilitate data diversity visualization and/or quantification for machine learning models are provided. In various embodiments, a processor can access a first dataset and a second dataset, where a machine learning (ML) model is trained on the first dataset. In various instances, the processor can obtain a first set of latent activations generated by the ML model based on the first dataset, and a second set of latent activations generated by the ML model based on the second dataset. In various aspects, the processor can generate a first set of compressed data points based on the first set of latent activations, and a second set of compressed data points based on the second set of latent activations, via dimensionality reduction. In various instances, a diversity component can compute a diversity score based on the first set of compressed data points and second set of compressed data points.



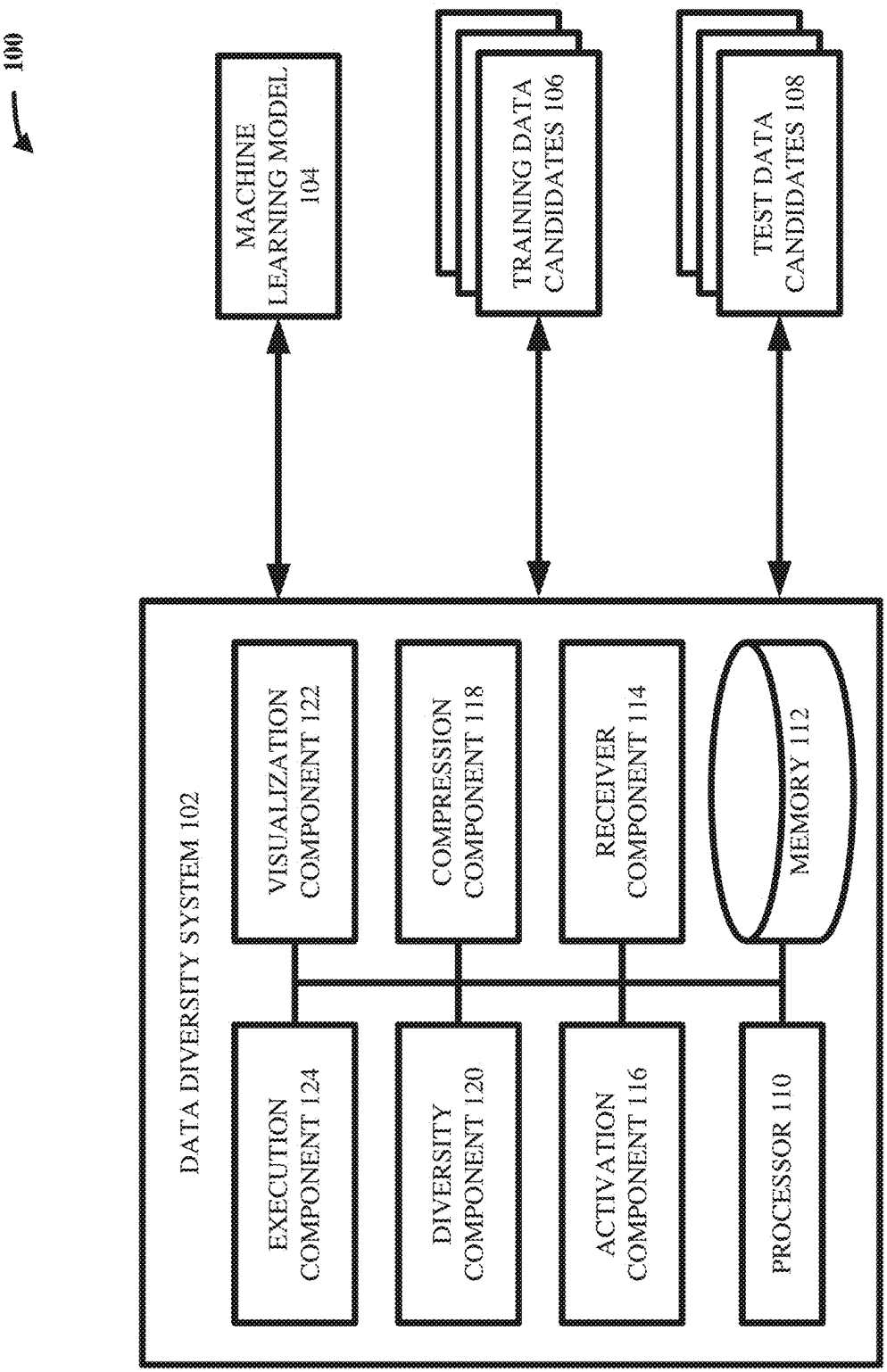

100
MACHINE LEARNING MODEL 104
TRAINING DATA CANDIDATES 106
TEST DATA CANDIDATES 108
DATA DIVERSITY SYSTEM 102
VISUALIZATION COMPONENT 122
COMPRESSION COMPONENT 118
RECEIVER COMPONENT 114
MEMORY 112
EXECUTION COMPONENT 124
DIVERSITY COMPONENT 120
ACTIVATION COMPONENT 116
PROCESSOR 110

FIG. 1

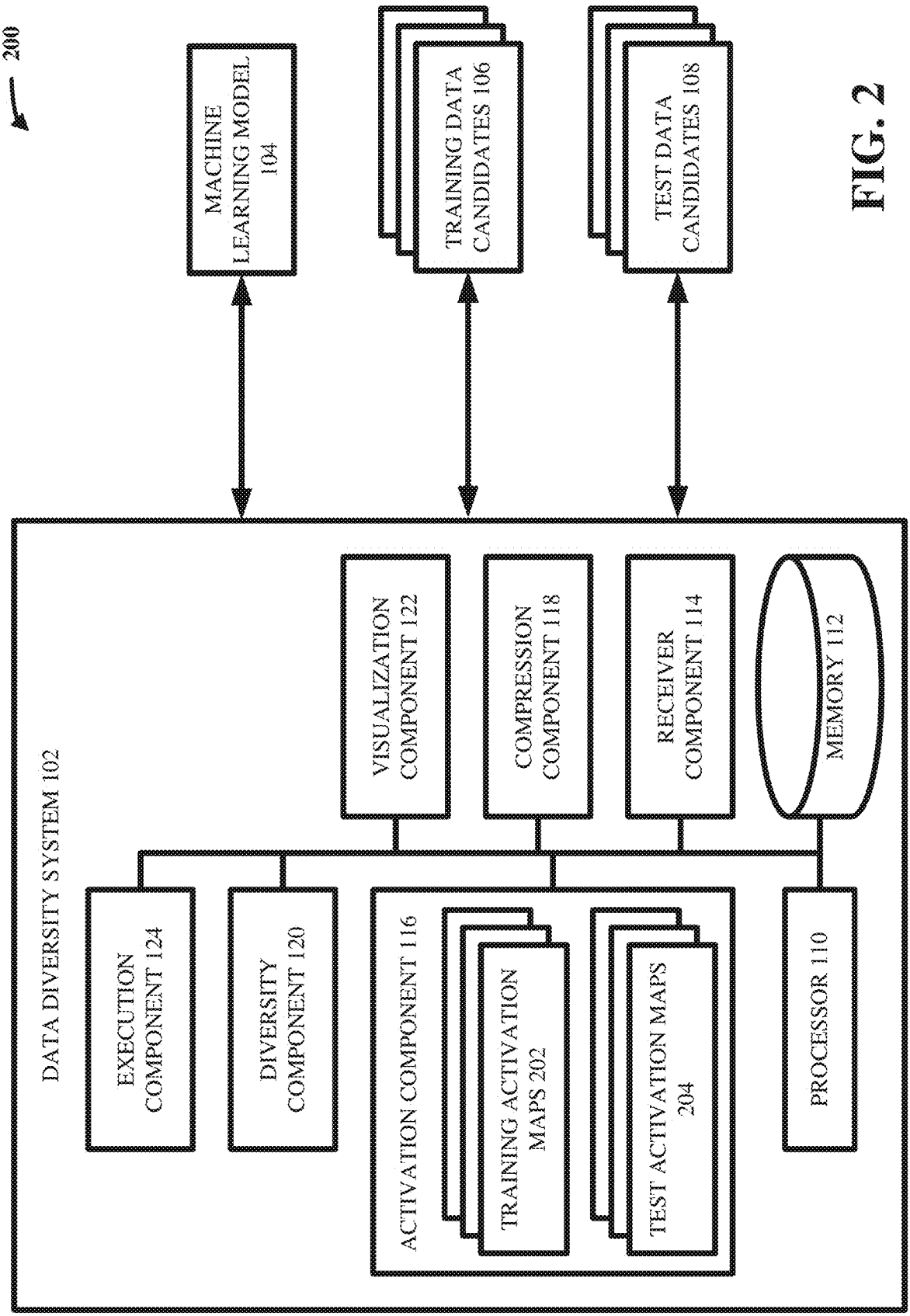

200
MACHINE LEARNING MODEL 104
TRAINING DATA CANDIDATES 106
TEST DATA CANDIDATES 108
DATA DIVERSITY SYSTEM 102
EXECUTION COMPONENT 124
DIVERSITY COMPONENT 120
ACTIVATION COMPONENT 116
TRAINING ACTIVATION MAPS 202
TEST ACTIVATION MAPS 204
VISUALIZATION COMPONENT 122
COMPRESSION COMPONENT 118
RECEIVER COMPONENT 114
MEMORY 112
PROCESSOR 110

FIG. 2

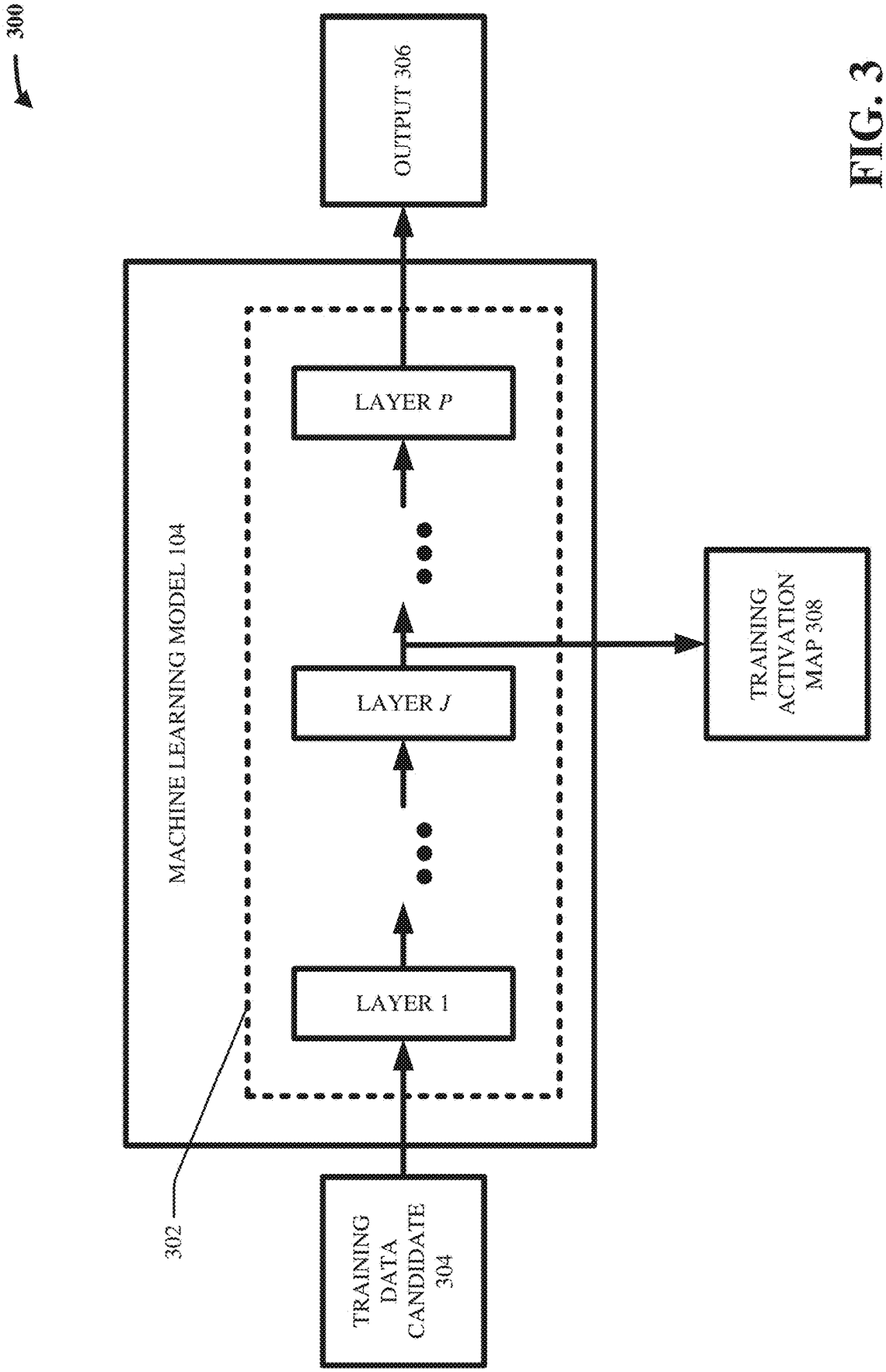

300
OUTPUT 306
MACHINE LEARNING MODEL 104
LAYER P
LAYER J
LAYER 1
TRAINING ACTIVATION MAP 308
302
TRAINING DATA CANDIDATE 304

FIG. 3

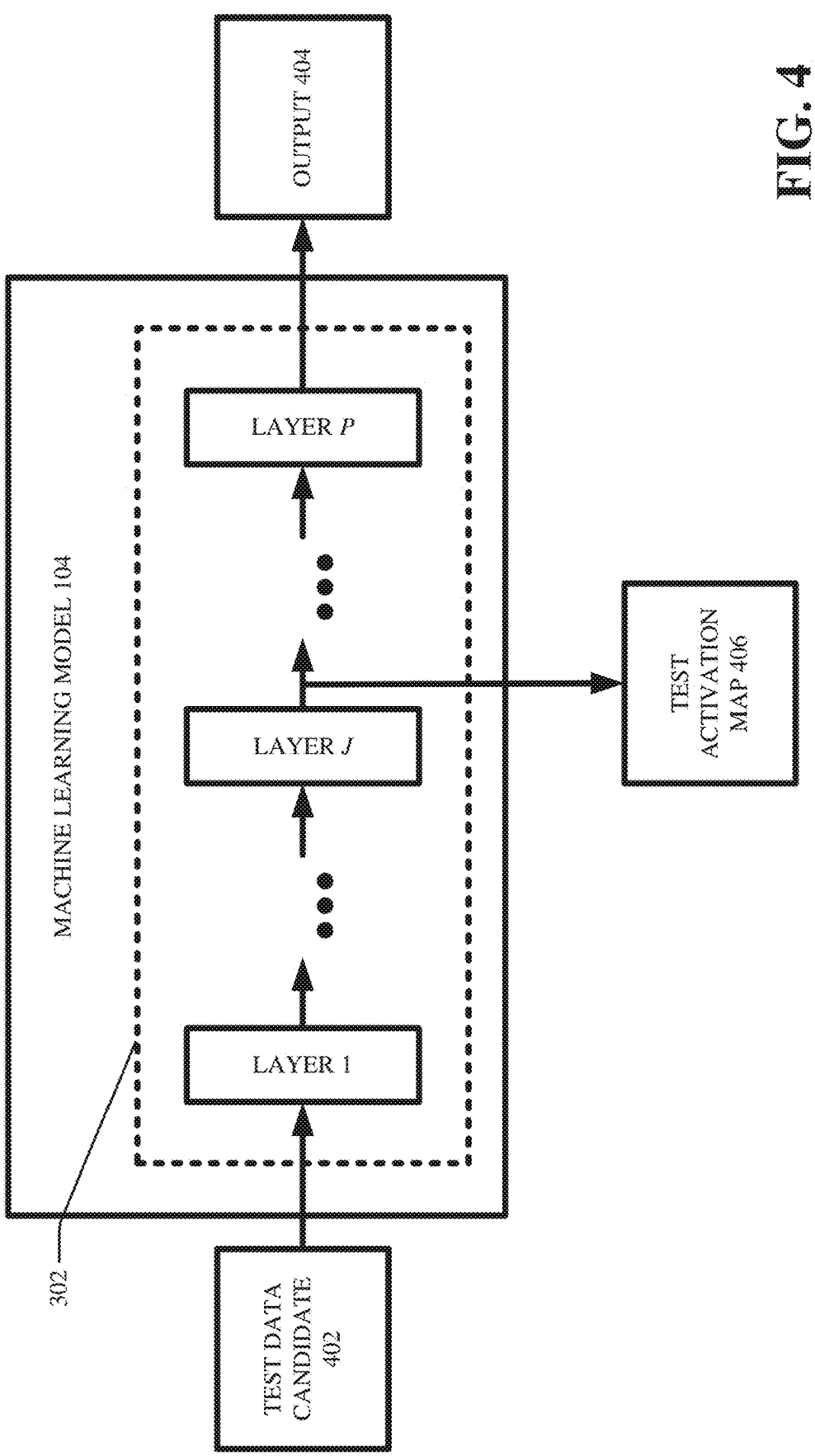

400
OUTPUT 404
MACHINE LEARNING MODEL 104
LAYER P
LAYER J
LAYER 1
TEST ACTIVATION MAP 406
302
TEST DATA CANDIDATE 402

FIG. 4

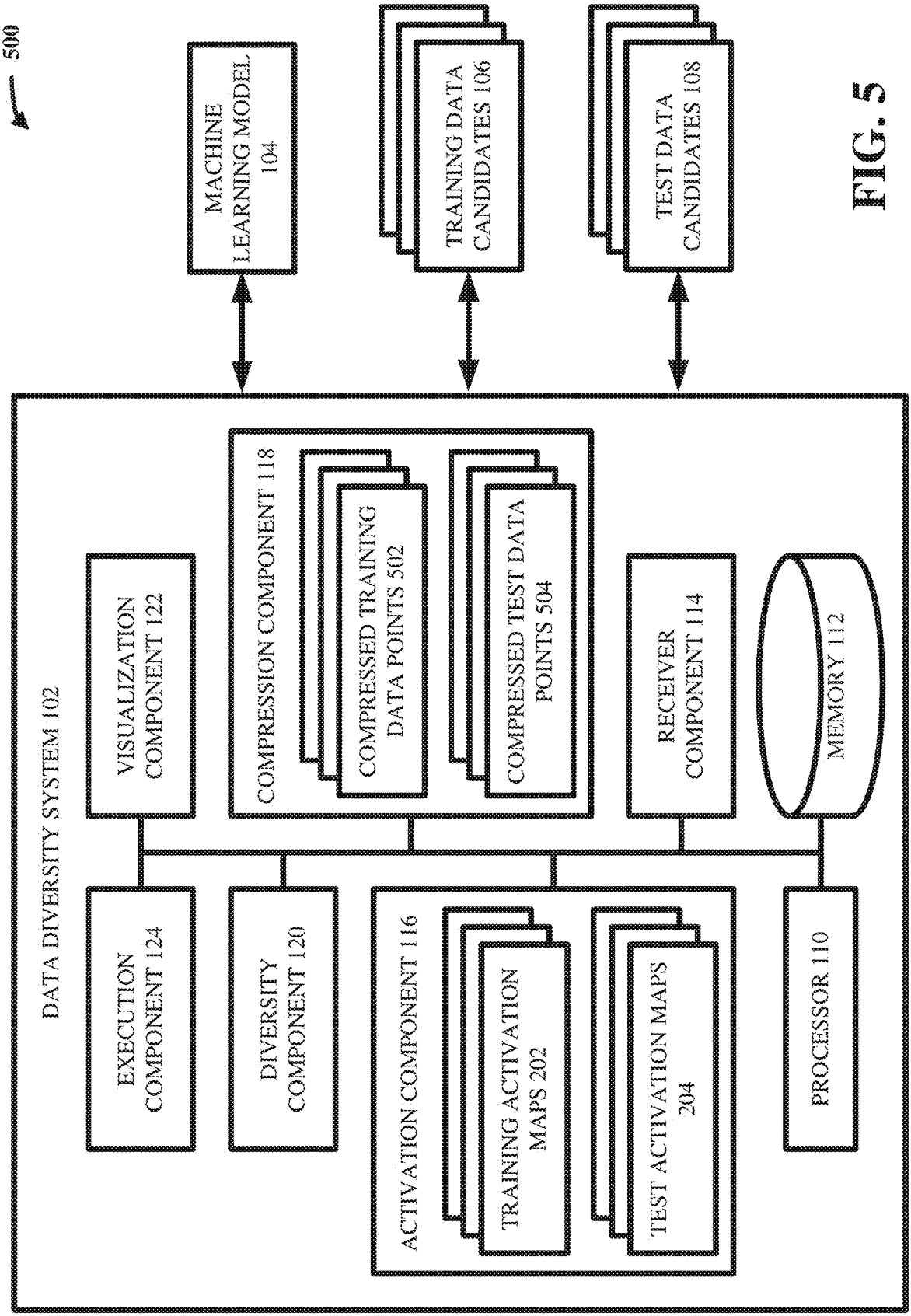

500
MACHINE LEARNING MODEL 104
TRAINING DATA CANDIDATES 106
TEST DATA CANDIDATES 108
DATA DIVERSITY SYSTEM 102
VISUALIZATION COMPONENT 122
COMPRESSION COMPONENT 118
COMPRESSED TRAINING DATA POINTS 502
COMPRESSED TEST DATA POINTS 504
RECEIVER COMPONENT 114
MEMORY 112
EXECUTION COMPONENT 124
DIVERSITY COMPONENT 120
ACTIVATION COMPONENT 116
TRAINING ACTIVATION MAPS 202
TEST ACTIVATION MAPS 204
PROCESSOR 110

FIG. 5

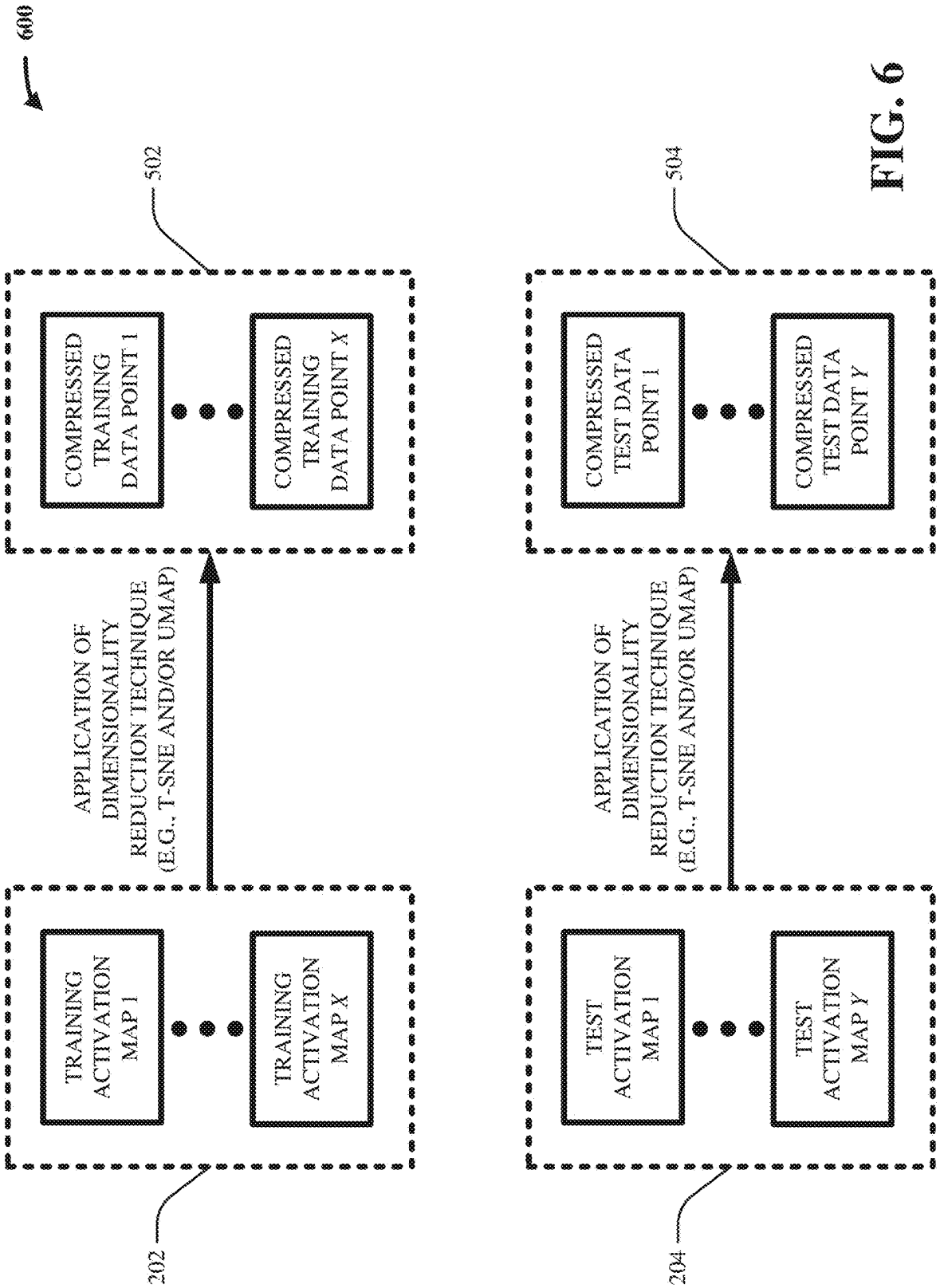

600
502
COMPRESSED TRAINING DATA POINT 1
COMPRESSED TRAINING DATA POINT X
APPLICATION OF DIMENSIONALITY REDUCTION TECHNIQUE (E.G., T-SNE AND/OR UMAP)
TRAINING ACTIVATION MAP 1
TRAINING ACTIVATION MAP X
202
504
COMPRESSED TEST DATA POINT 1
COMPRESSED TEST DATA POINT Y
APPLICATION OF DIMENSIONALITY REDUCTION TECHNIQUE (E.G., T-SNE AND/OR UMAP)
TEST ACTIVATION MAP 1
TEST ACTIVATION MAP Y
204

FIG. 6

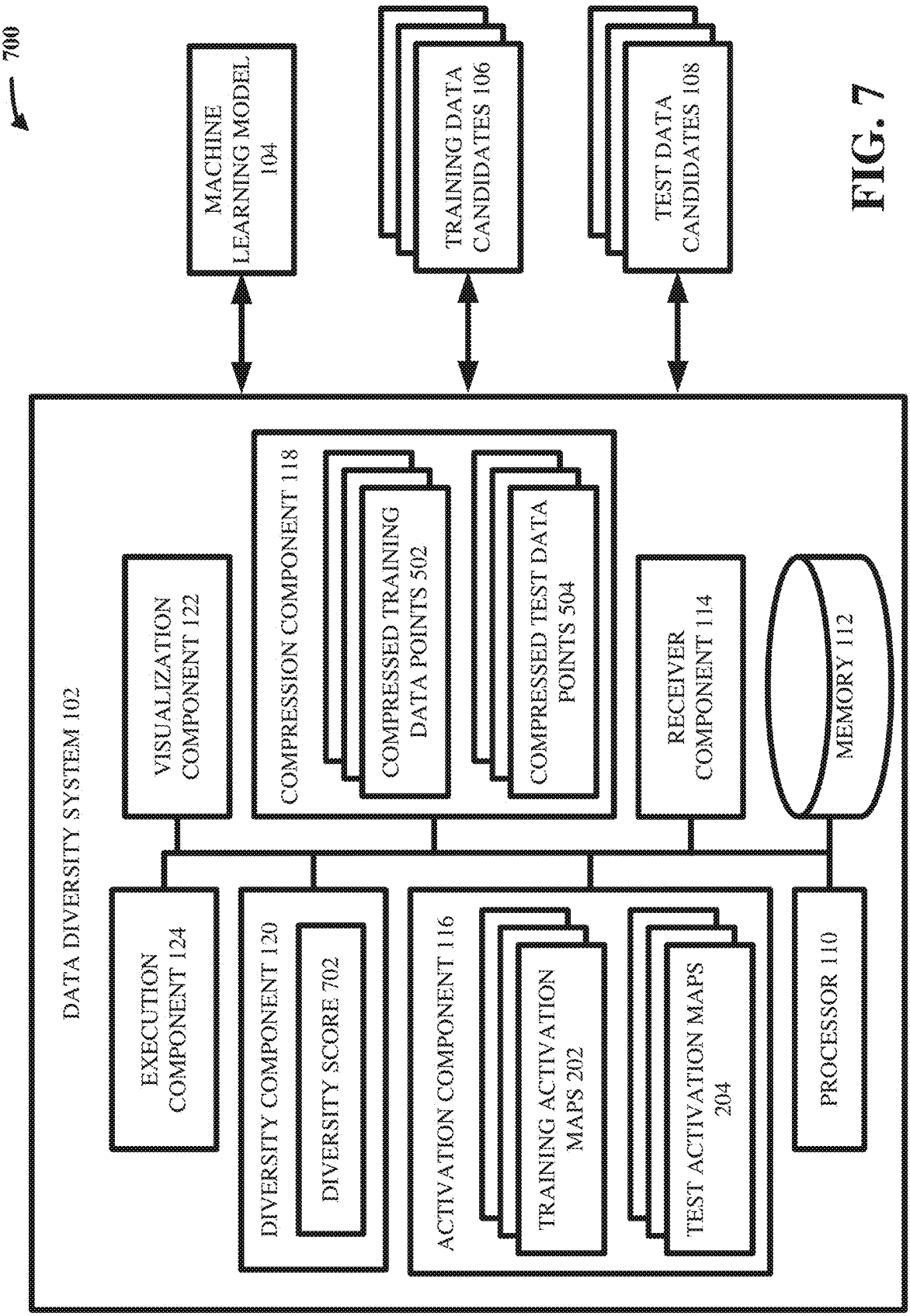

700
MACHINE LEARNING MODEL 104
TRAINING DATA CANDIDATES 106
TEST DATA CANDIDATES 108
DATA DIVERSITY SYSTEM 102
VISUALIZATION COMPONENT 122
COMPRESSION COMPONENT 118
COMPRESSED TRAINING DATA POINTS 502
COMPRESSED TEST DATA POINTS 504
RECEIVER COMPONENT 114
MEMORY 112
EXECUTION COMPONENT 124
DIVERSITY COMPONENT 120
DIVERSITY SCORE 702
ACTIVATION COMPONENT 116
TRAINING ACTIVATION MAPS 202
TEST ACTIVATION MAPS 204
PROCESSOR 110

FIG. 7

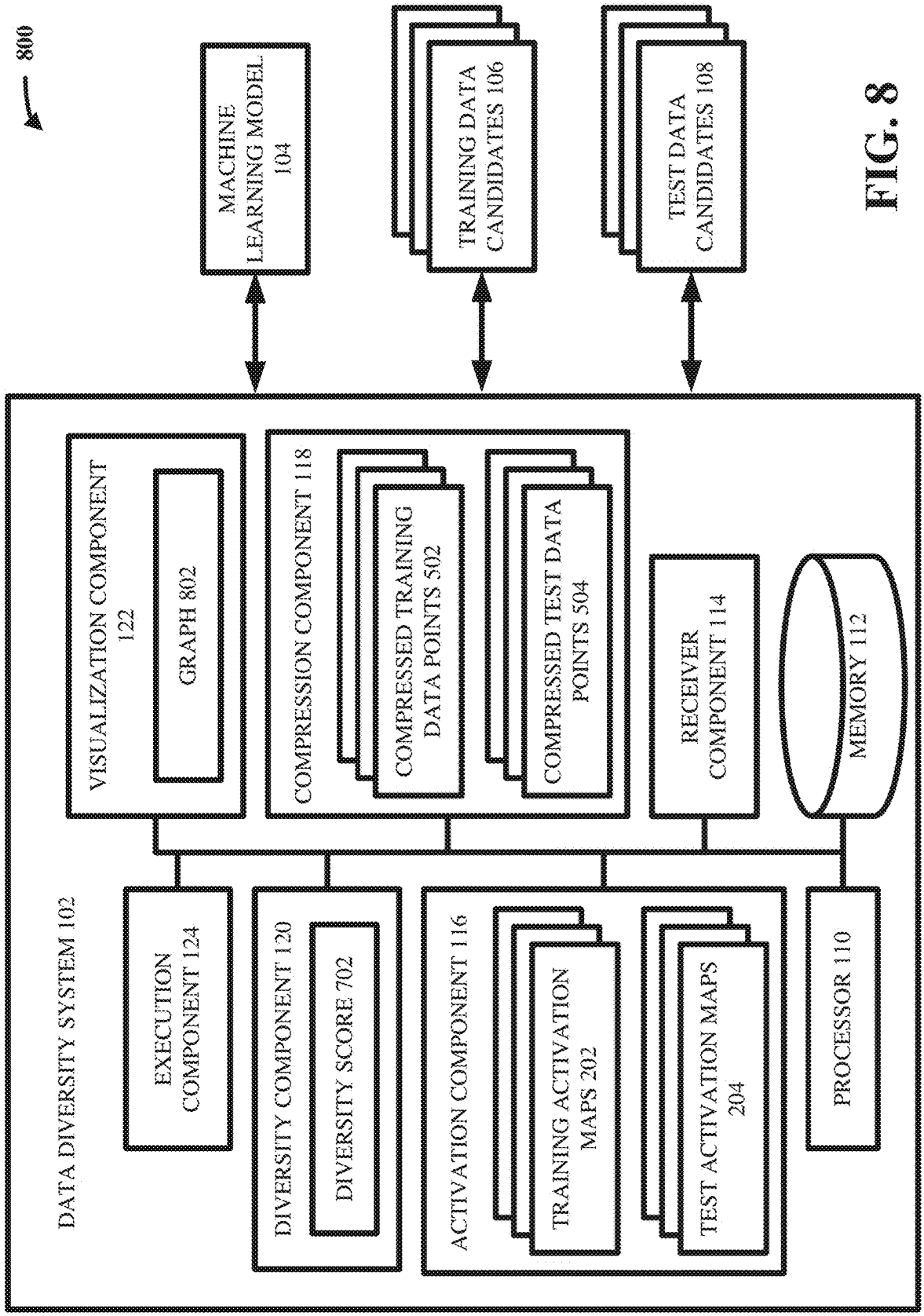

800
MACHINE LEARNING MODEL 104
TRAINING DATA CANDIDATES 106
TEST DATA CANDIDATES 108
DATA DIVERSITY SYSTEM 102
VISUALIZATION COMPONENT 122
GRAPH 802
COMPRESSION COMPONENT 118
COMPRESSED TRAINING DATA POINTS 502
COMPRESSED TEST DATA POINTS 504
RECEIVER COMPONENT 114
MEMORY 112
EXECUTION COMPONENT 124
DIVERSITY COMPONENT 120
DIVERSITY SCORE 702
ACTIVATION COMPONENT 116
TRAINING ACTIVATION MAPS 202
TEST ACTIVATION MAPS 204
PROCESSOR 110

FIG. 8

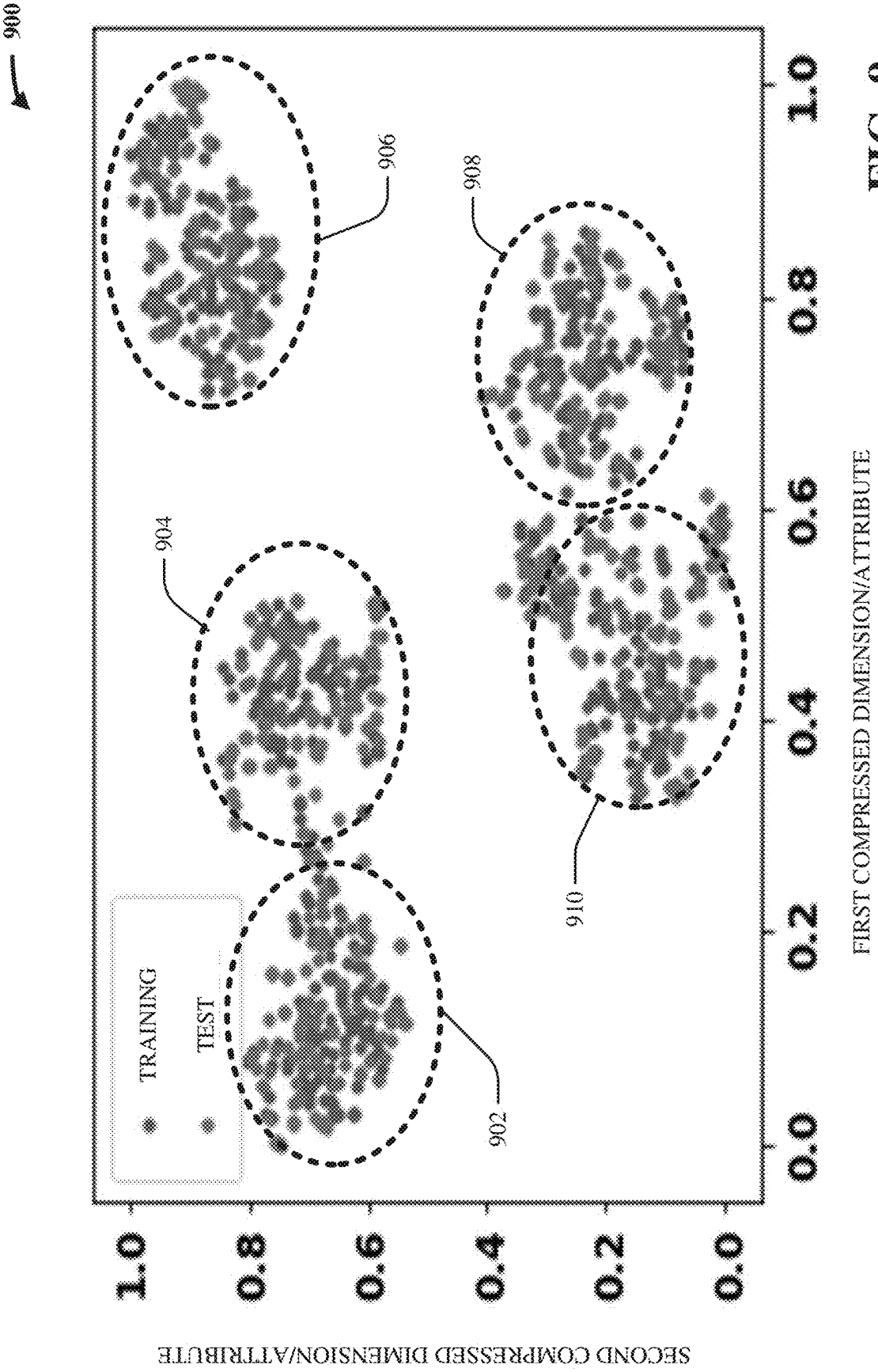

900
TRAINING
TEST
902
904
906
908
910
0.0
0.2
0.4
0.6
0.8
1.0
FIRST COMPRESSED DIMENSION/ATTRIBUTE
SECOND COMPRESSED DIMENSION/ATTRIBUTE

FIG. 9

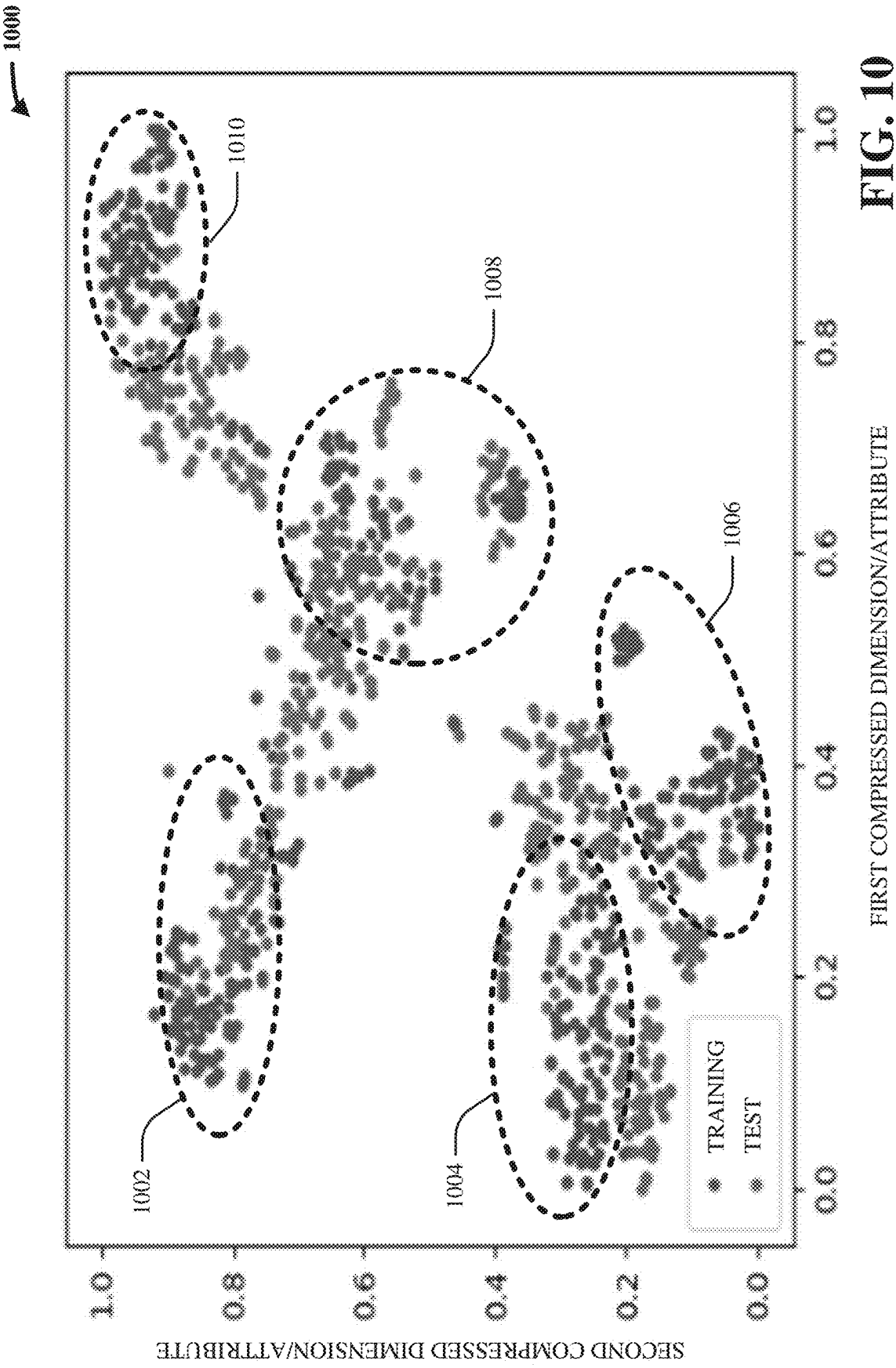

1000
1002
1004
1006
1008
1010
TRAINING
TEST
0.0
0.2
0.4
0.6
0.8
1.0
FIRST COMPRESSED DIMENSION/ATTRIBUTE
SECOND COMPRESSED DIMENSION/ATTRIBUTE

FIG. 10

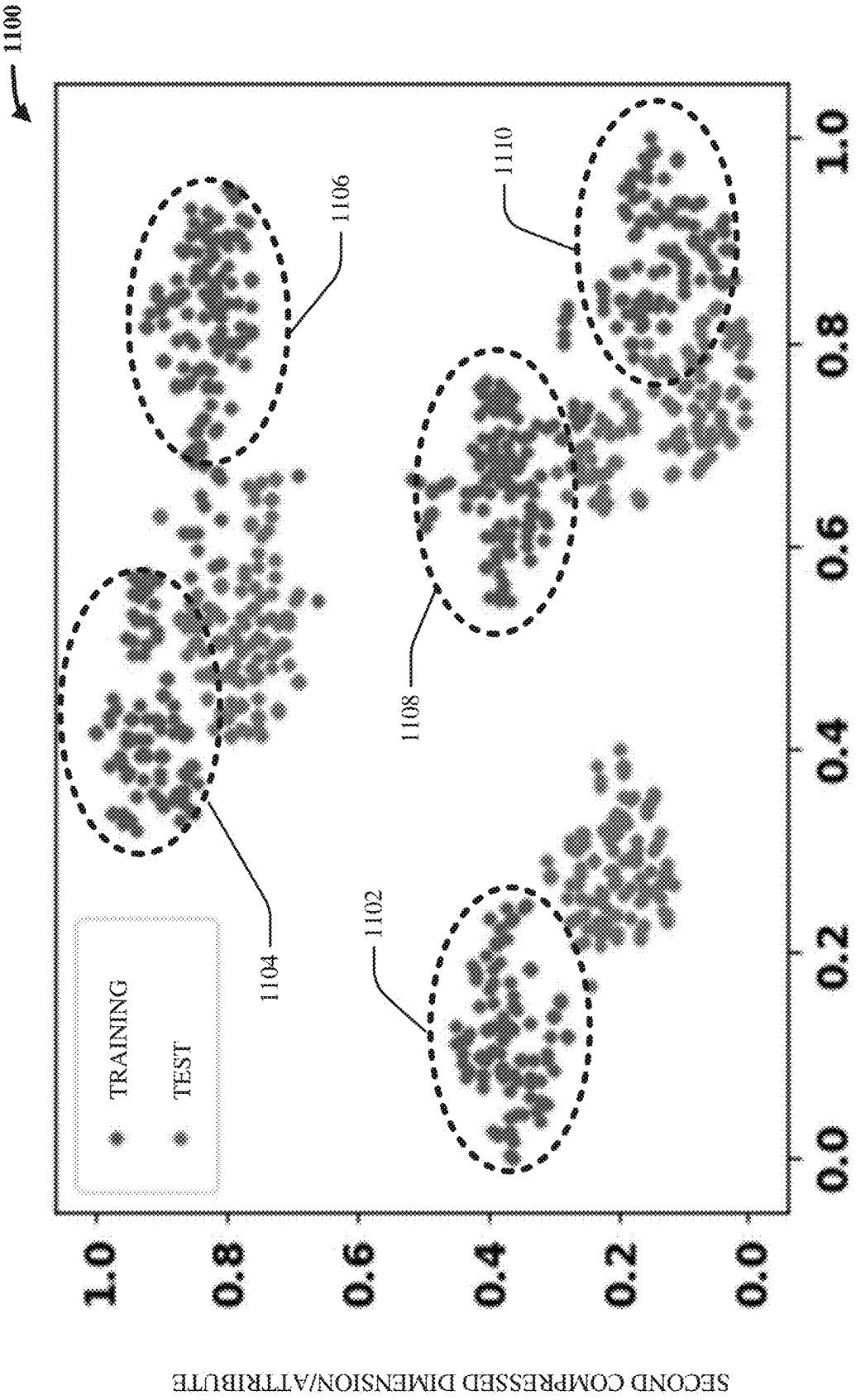

1100
TRAINING
TEST
1102
1104
1106
1108
1110
0.0
0.2
0.4
0.6
0.8
1.0
FIRST COMPRESSED DIMENSION/ATTRIBUTE
SECOND COMPRESSED DIMENSION/ATTRIBUTE

FIG. 11

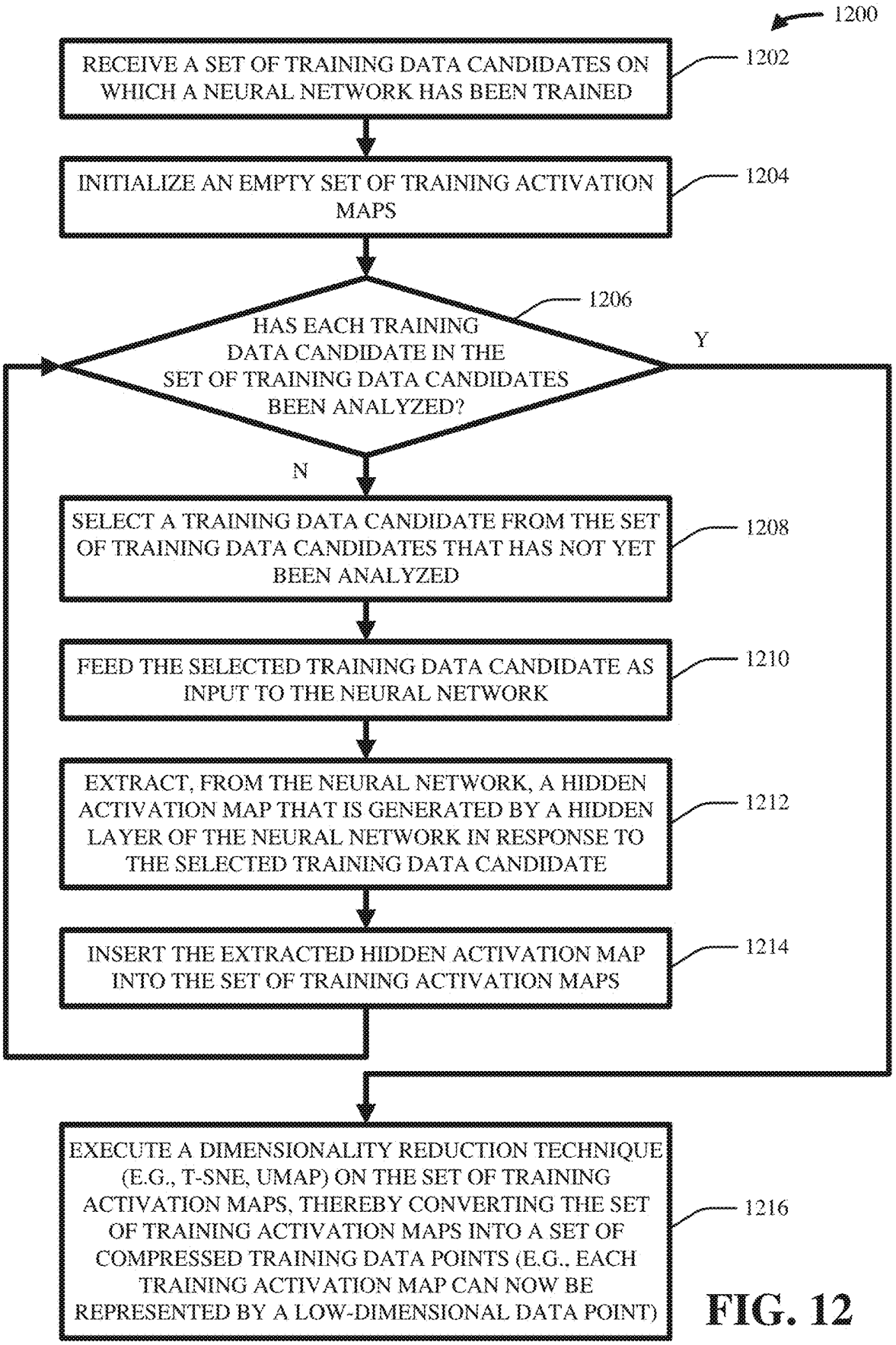

1200
RECEIVE A SET OF TRAINING DATA CANDIDATES ON WHICH A NEURAL NETWORK HAS BEEN TRAINED
1202
INITIALIZE AN EMPTY SET OF TRAINING ACTIVATION MAPS
1204
HAS EACH TRAINING DATA CANDIDATE IN THE SET OF TRAINING DATA CANDIDATES BEEN ANALYZED?
1206
Y
N
SELECT A TRAINING DATA CANDIDATE FROM THE SET OF TRAINING DATA CANDIDATES THAT HAS NOT YET BEEN ANALYZED
1208
FEED THE SELECTED TRAINING DATA CANDIDATE AS INPUT TO THE NEURAL NETWORK
1210
EXTRACT, FROM THE NEURAL NETWORK, A HIDDEN ACTIVATION MAP THAT IS GENERATED BY A HIDDEN LAYER OF THE NEURAL NETWORK IN RESPONSE TO THE SELECTED TRAINING DATA CANDIDATE
1212
INSERT THE EXTRACTED HIDDEN ACTIVATION MAP INTO THE SET OF TRAINING ACTIVATION MAPS
1214
EXECUTE A DIMENSIONALITY REDUCTION TECHNIQUE (E.G., T-SNE, UMAP) ON THE SET OF TRAINING ACTIVATION MAPS, THEREBY CONVERTING THE SET OF TRAINING ACTIVATION MAPS INTO A SET OF COMPRESSED TRAINING DATA POINTS (E.G., EACH TRAINING ACTIVATION MAP CAN NOW BE REPRESENTED BY A LOW-DIMENSIONAL DATA POINT)
1216

FIG. 12

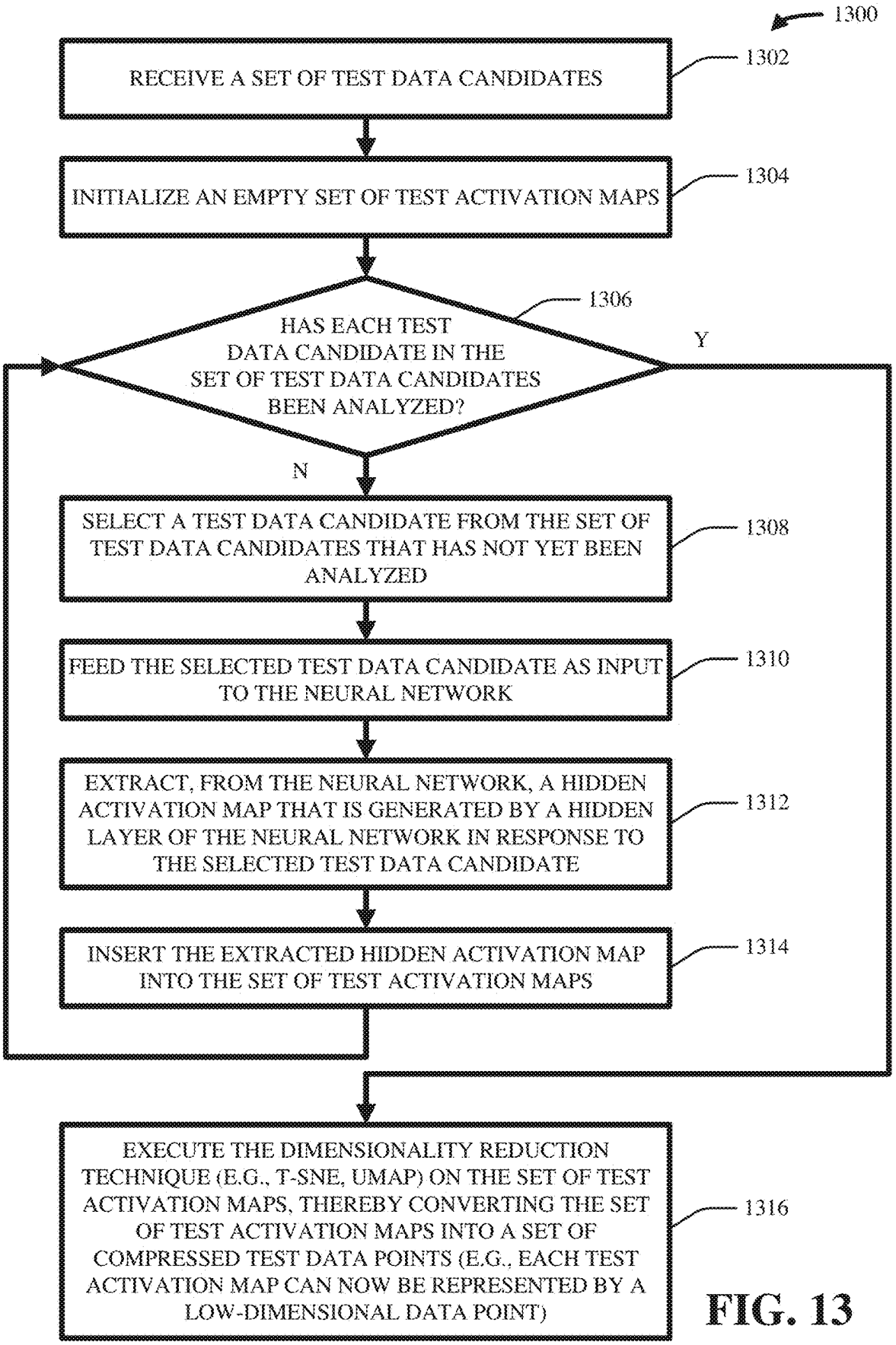

1300
RECEIVE A SET OF TEST DATA CANDIDATES
1302
INITIALIZE AN EMPTY SET OF TEST ACTIVATION MAPS
1304
HAS EACH TEST DATA CANDIDATE IN THE SET OF TEST DATA CANDIDATES BEEN ANALYZED?
1306
Y
N
SELECT A TEST DATA CANDIDATE FROM THE SET OF TEST DATA CANDIDATES THAT HAS NOT YET BEEN ANALYZED
1308
FEED THE SELECTED TEST DATA CANDIDATE AS INPUT TO THE NEURAL NETWORK
1310
EXTRACT, FROM THE NEURAL NETWORK, A HIDDEN ACTIVATION MAP THAT IS GENERATED BY A HIDDEN LAYER OF THE NEURAL NETWORK IN RESPONSE TO THE SELECTED TEST DATA CANDIDATE
1312
INSERT THE EXTRACTED HIDDEN ACTIVATION MAP INTO THE SET OF TEST ACTIVATION MAPS
1314
EXECUTE THE DIMENSIONALITY REDUCTION TECHNIQUE (E.G., T-SNE, UMAP) ON THE SET OF TEST ACTIVATION MAPS, THEREBY CONVERTING THE SET OF TEST ACTIVATION MAPS INTO A SET OF COMPRESSED TEST DATA POINTS (E.G., EACH TEST ACTIVATION MAP CAN NOW BE REPRESENTED BY A LOW-DIMENSIONAL DATA POINT)
1316

FIG. 13

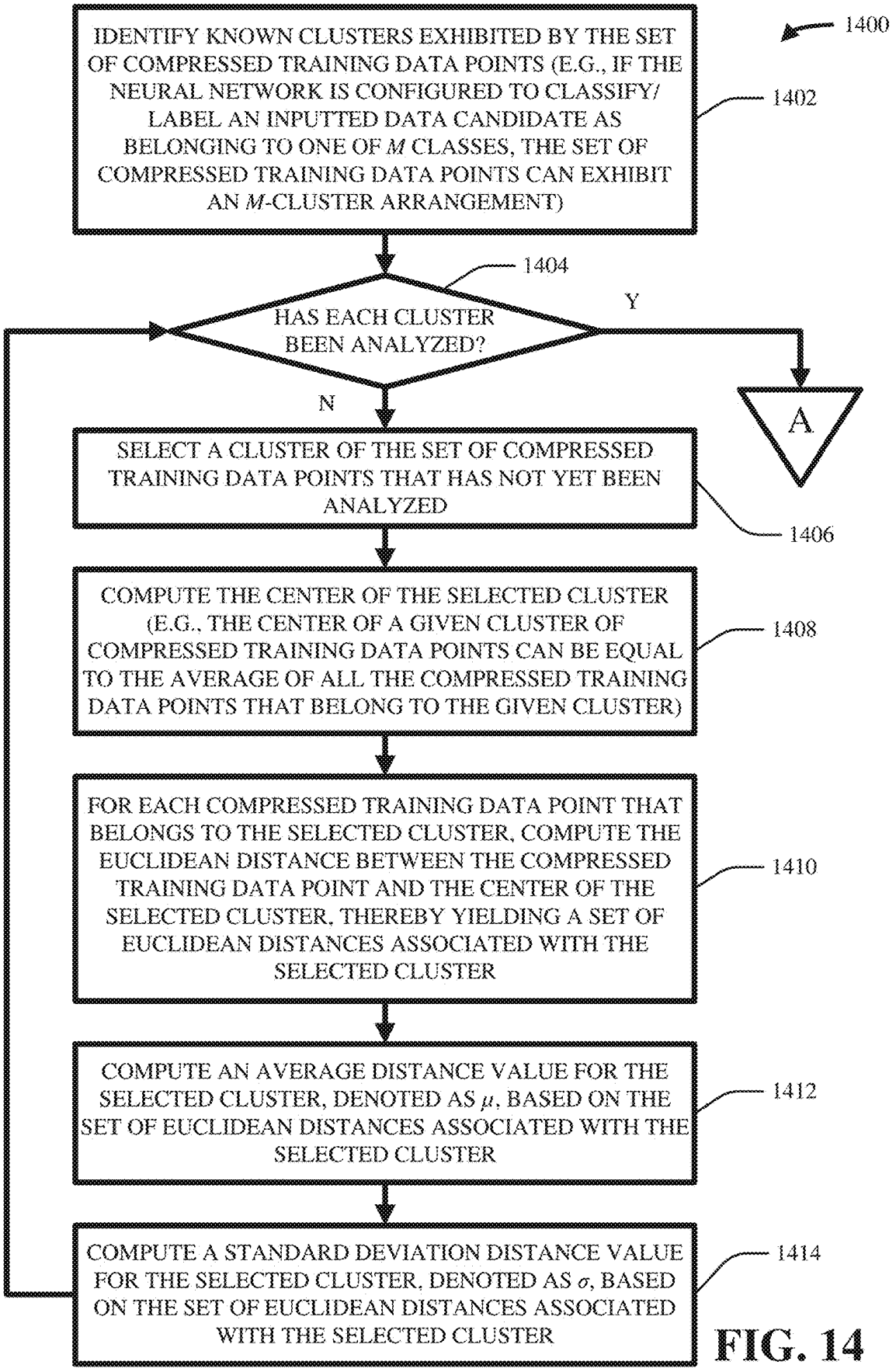

1400
IDENTIFY KNOWN CLUSTERS EXHIBITED BY THE SET OF COMPRESSED TRAINING DATA POINTS (E.G., IF THE NEURAL NETWORK IS CONFIGURED TO CLASSIFY/ LABEL AN INPUTTED DATA CANDIDATE AS BELONGING TO ONE OF M CLASSES, THE SET OF COMPRESSED TRAINING DATA POINTS CAN EXHIBIT AN M-CLUSTER ARRANGEMENT)
1402
1404
HAS EACH CLUSTER BEEN ANALYZED?
Y
N
A
SELECT A CLUSTER OF THE SET OF COMPRESSED TRAINING DATA POINTS THAT HAS NOT YET BEEN ANALYZED
1406
COMPUTE THE CENTER OF THE SELECTED CLUSTER (E.G., THE CENTER OF A GIVEN CLUSTER OF COMPRESSED TRAINING DATA POINTS CAN BE EQUAL TO THE AVERAGE OF ALL THE COMPRESSED TRAINING DATA POINTS THAT BELONG TO THE GIVEN CLUSTER)
1408
FOR EACH COMPRESSED TRAINING DATA POINT THAT BELONGS TO THE SELECTED CLUSTER, COMPUTE THE EUCLIDEAN DISTANCE BETWEEN THE COMPRESSED TRAINING DATA POINT AND THE CENTER OF THE SELECTED CLUSTER, THEREBY YIELDING A SET OF EUCLIDEAN DISTANCES ASSOCIATED WITH THE SELECTED CLUSTER
1410
COMPUTE AN AVERAGE DISTANCE VALUE FOR THE SELECTED CLUSTER, DENOTED AS μ, BASED ON THE SET OF EUCLIDEAN DISTANCES ASSOCIATED WITH THE SELECTED CLUSTER
1412
COMPUTE A STANDARD DEVIATION DISTANCE VALUE FOR THE SELECTED CLUSTER, DENOTED AS σ, BASED ON THE SET OF EUCLIDEAN DISTANCES ASSOCIATED WITH THE SELECTED CLUSTER
1414

FIG. 14

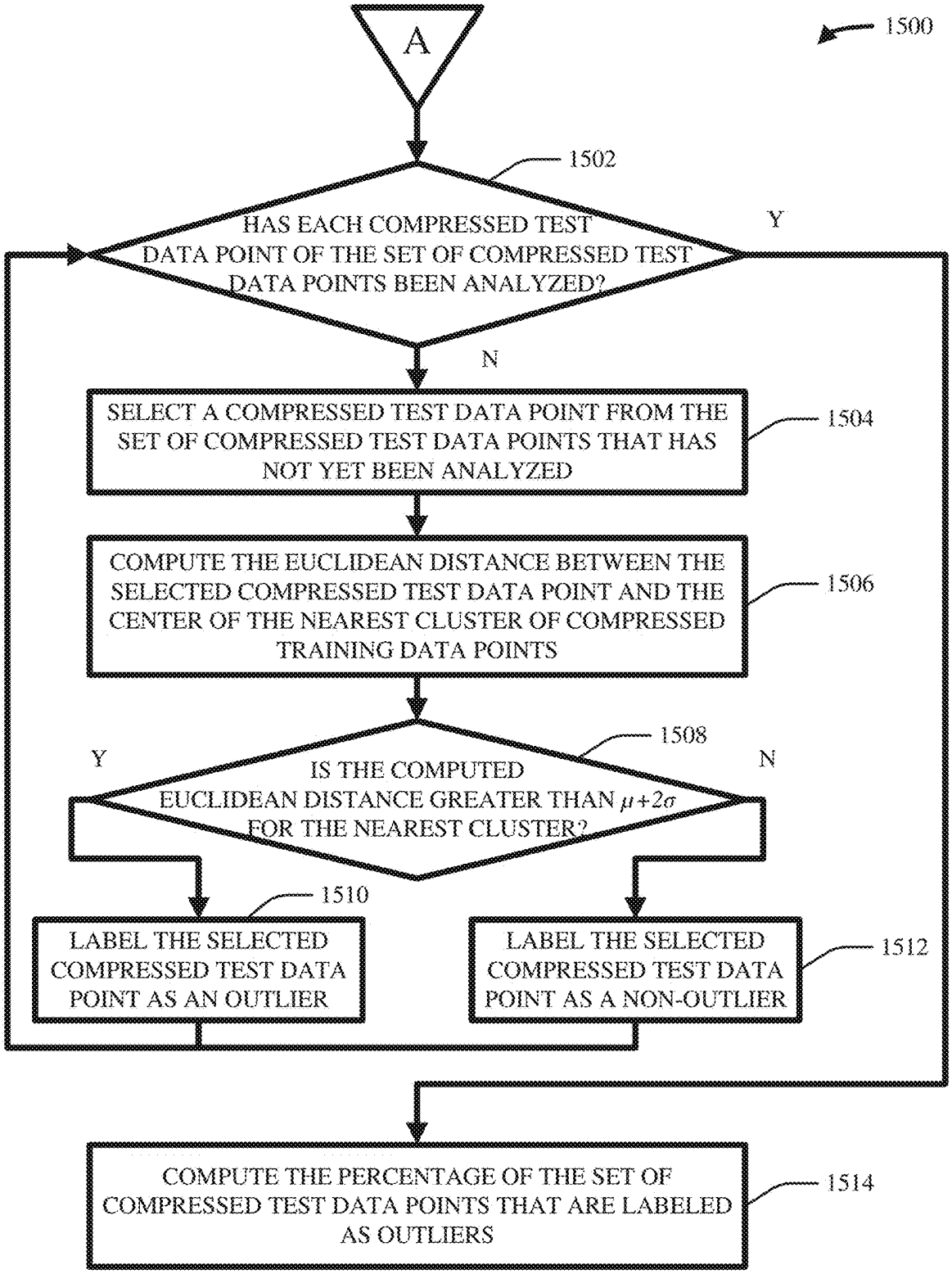

1500
A
1502
HAS EACH COMPRESSED TEST DATA POINT OF THE SET OF COMPRESSED TEST DATA POINTS BEEN ANALYZED?
Y
N
SELECT A COMPRESSED TEST DATA POINT FROM THE SET OF COMPRESSED TEST DATA POINTS THAT HAS NOT YET BEEN ANALYZED
1504
COMPUTE THE EUCLIDEAN DISTANCE BETWEEN THE SELECTED COMPRESSED TEST DATA POINT AND THE CENTER OF THE NEAREST CLUSTER OF COMPRESSED TRAINING DATA POINTS
1506
1508
IS THE COMPUTED EUCLIDEAN DISTANCE GREATER THAN $\mu+2\sigma$ FOR THE NEAREST CLUSTER?
Y
N
1510
LABEL THE SELECTED COMPRESSED TEST DATA POINT AS AN OUTLIER
LABEL THE SELECTED COMPRESSED TEST DATA POINT AS A NON-OUTLIER
1512
COMPUTE THE PERCENTAGE OF THE SET OF COMPRESSED TEST DATA POINTS THAT ARE LABELED AS OUTLIERS
1514

FIG. 15

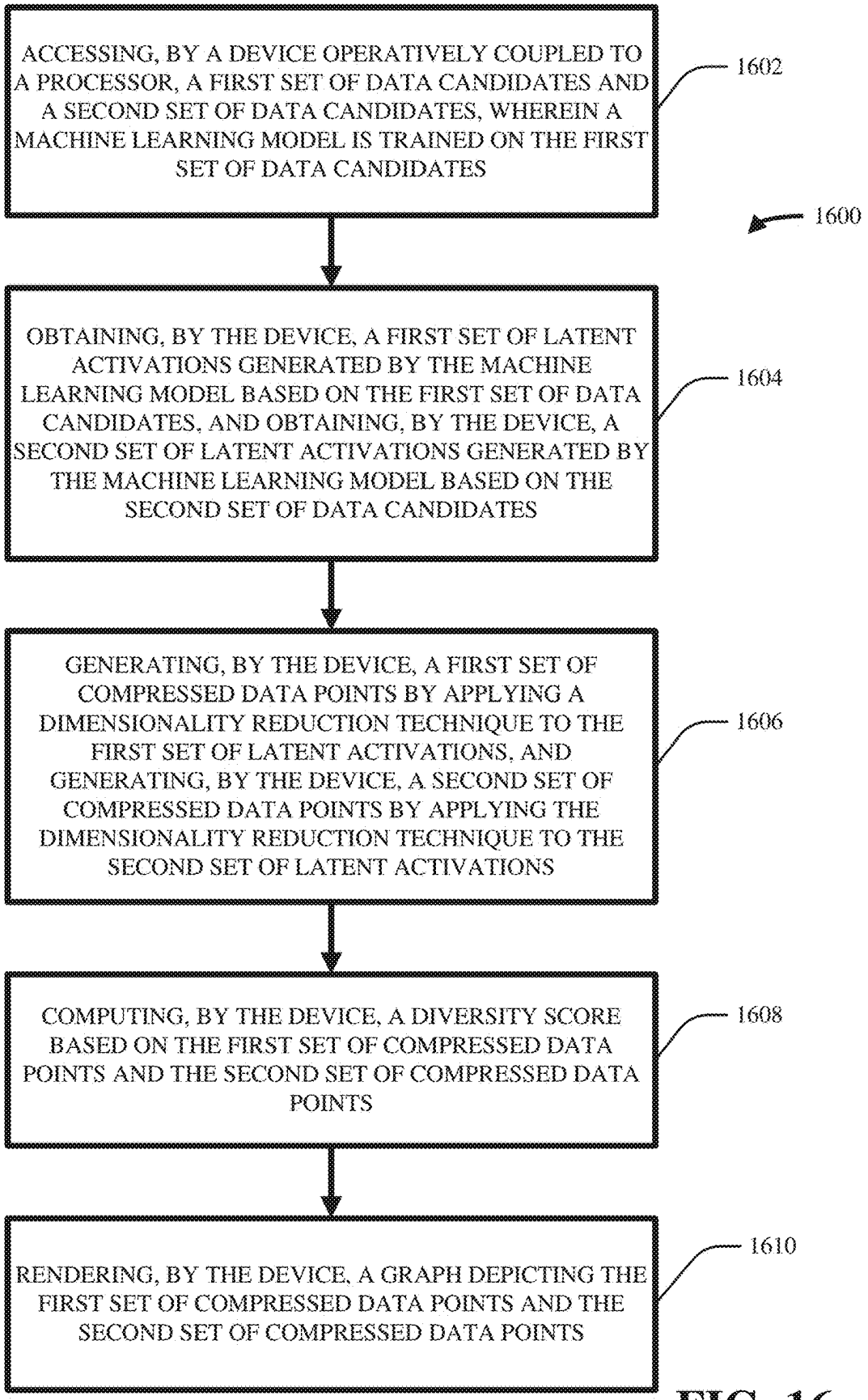

ACCESSING, BY A DEVICE OPERATIVELY COUPLED TO A PROCESSOR, A FIRST SET OF DATA CANDIDATES AND A SECOND SET OF DATA CANDIDATES, WHEREIN A MACHINE LEARNING MODEL IS TRAINED ON THE FIRST SET OF DATA CANDIDATES
1602
1600
OBTAINING, BY THE DEVICE, A FIRST SET OF LATENT ACTIVATIONS GENERATED BY THE MACHINE LEARNING MODEL BASED ON THE FIRST SET OF DATA CANDIDATES, AND OBTAINING, BY THE DEVICE, A SECOND SET OF LATENT ACTIVATIONS GENERATED BY THE MACHINE LEARNING MODEL BASED ON THE SECOND SET OF DATA CANDIDATES
1604
GENERATING, BY THE DEVICE, A FIRST SET OF COMPRESSED DATA POINTS BY APPLYING A DIMENSIONALITY REDUCTION TECHNIQUE TO THE FIRST SET OF LATENT ACTIVATIONS, AND GENERATING, BY THE DEVICE, A SECOND SET OF COMPRESSED DATA POINTS BY APPLYING THE DIMENSIONALITY REDUCTION TECHNIQUE TO THE SECOND SET OF LATENT ACTIVATIONS
1606
COMPUTING, BY THE DEVICE, A DIVERSITY SCORE BASED ON THE FIRST SET OF COMPRESSED DATA POINTS AND THE SECOND SET OF COMPRESSED DATA POINTS
1608
RENDERING, BY THE DEVICE, A GRAPH DEPICTING THE FIRST SET OF COMPRESSED DATA POINTS AND THE SECOND SET OF COMPRESSED DATA POINTS
1610

FIG. 16

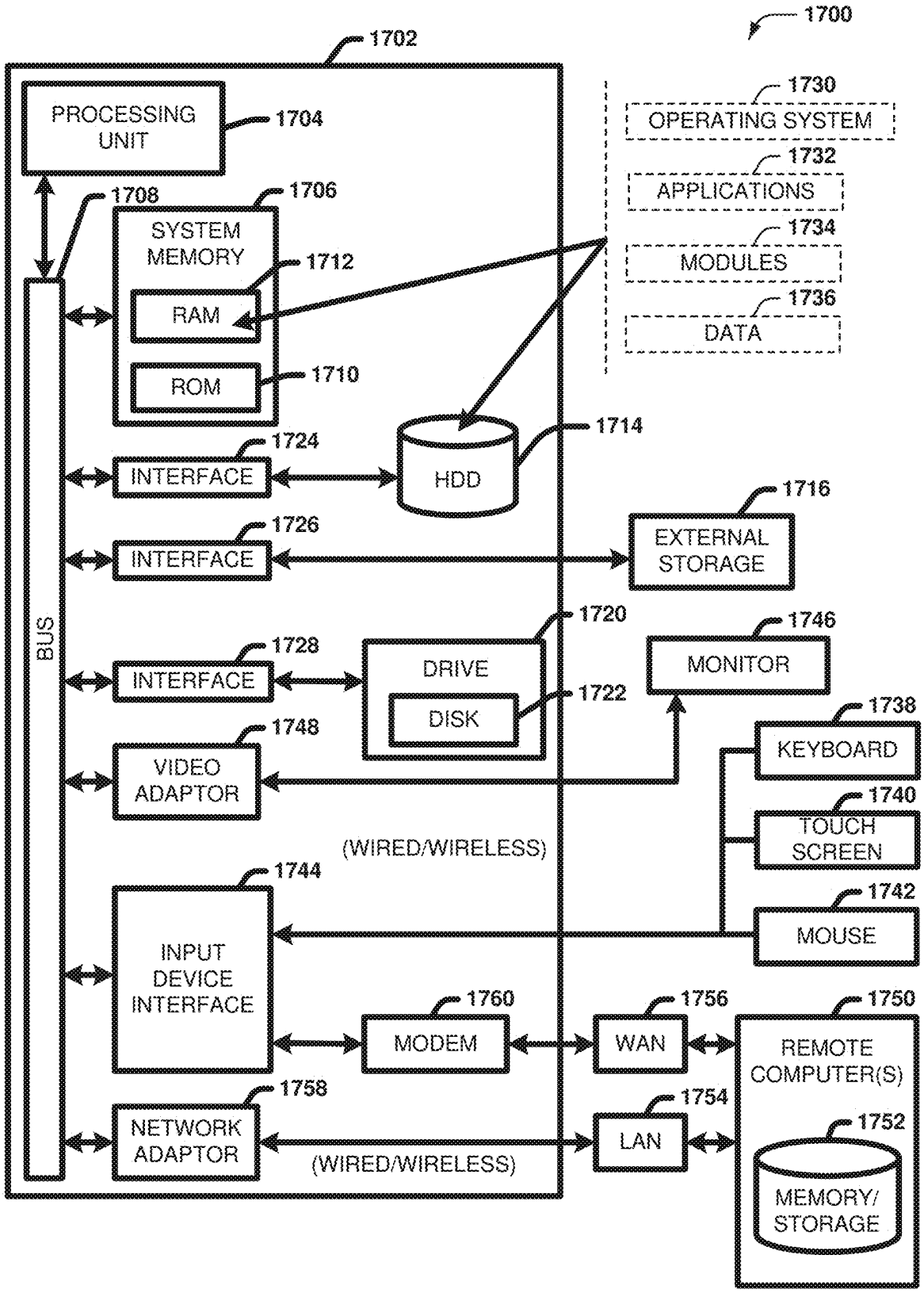

1700
1702
PROCESSING UNIT
1704
1730
OPERATING SYSTEM
1732
APPLICATIONS
1734
MODULES
1736
DATA
1708
1706
SYSTEM MEMORY
1712
RAM
ROM
1710
1714
HDD
1724
INTERFACE
1716
EXTERNAL STORAGE
1726
INTERFACE
BUS
1720
DRIVE
1746
MONITOR
1728
INTERFACE
DISK
1722
1738
KEYBOARD
1748
VIDEO ADAPTOR
1740
TOUCH SCREEN
(WIRED/WIRELESS)
1744
1742
MOUSE
INPUT DEVICE INTERFACE
1760
MODEM
1756
WAN
1750
REMOTE COMPUTER(S)
1758
NETWORK ADAPTOR
1754
LAN
1752
(WIRED/WIRELESS)
MEMORY/ STORAGE

FIG. 17

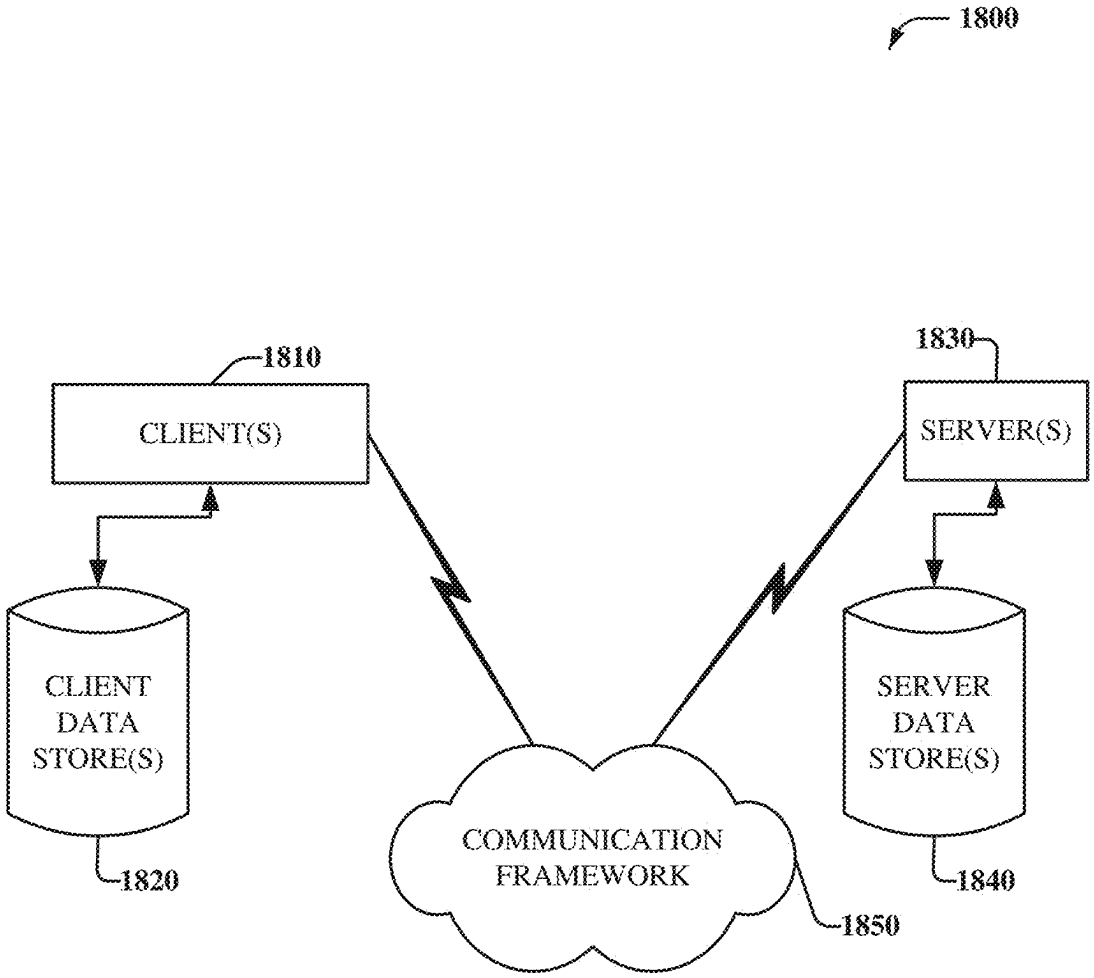

1800
1810
CLIENT(S)
1830
SERVER(S)
CLIENT DATA STORE(S)
1820
COMMUNICATION FRAMEWORK
1850
SERVER DATA STORE(S)
1840

FIG. 18

DATA DIVERSITY VISUALIZATION AND QUANTIFICATION FOR MACHINE LEARNING MODELS

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] The present matter claims priority to and is a continuation of U.S. patent application Ser. No. 17/243,046, filed Apr. 28, 2021 and titled "DATA DIVERSITY VISUALIZATION AND QUANTIFICATION FOR MACHINE LEARNING MODELS," the contents of which are incorporated by reference herein in their entirety.

TECHNICAL FIELD

[0002] The subject disclosure relates generally to machine learning models, and more specifically to techniques for visualizing and/or quantifying diversity in data analyzed by machine learning models.

BACKGROUND

[0003] The performance of a machine learning model depends upon the data on which the machine learning model is trained, the data on which the machine learning model is tested/validated, and/or the data which the machine learning model encounters when deployed in the field. For example, the performance of a trained machine learning model can be positively impacted if the machine learning model is further trained on data that significantly varies from the original training data. In contrast, the performance of the machine learning model can be negatively impacted if the machine learning model is further trained on data that does not significantly vary from the original training data. As another example, when deployed in the field, a trained machine learning model can accurately analyze data that is substantially similar to the original training data. In contrast, when deployed in the field, the machine learning model can inaccurately analyze data that is not substantially similar to the original training data. Therefore, being able to quickly and/or accurately determine whether two different machine learning datasets are similar to each other and/or vary from each other can be advantageous. Unfortunately, there are no conventional tools that facilitate rapid manual and/or automatic comparison of different machine learning datasets.

[0004] Accordingly, systems and/or techniques that can address this technical problem can be desirable.

SUMMARY

[0005] The following presents a summary to provide a basic understanding of one or more embodiments of the invention. This summary is not intended to identify key or critical elements, or delineate any scope of the particular embodiments or any scope of the claims. Its sole purpose is to present concepts in a simplified form as a prelude to the more detailed description that is presented later. In one or more embodiments described herein, devices, systems, computer-implemented methods, apparatus and/or computer program products that facilitate data diversity visualization and/or quantification for machine learning models are described.

[0006] According to one or more embodiments, a system is provided. The system can comprise a computer-readable memory that can store computer-executable components. The system can further comprise a processor that can be operably coupled to the computer-readable memory and that can execute the computer-executable components stored in the computer-readable memory. In various embodiments, the computer-executable components can comprise a receiver component. In various cases, the receiver component can access a first set of data candidates and a second set of data candidates, wherein a machine learning model is trained on the first set of data candidates. In various aspects, the computer-executable components can further comprise an activation component. In various cases, the activation component can obtain a first set of latent activations generated by the machine learning model based on the first set of data candidates, and can obtain a second set of latent activations generated by the machine learning model based on the second set of data candidates. In various instances, the computer-executable components can further comprise a compression component. In various cases, the compression component can generate a first set of compressed data points by applying a dimensionality reduction technique to the first set of latent activations, and can generate a second set of compressed data points by applying the dimensionality reduction technique to the second set of latent activations. In various aspects, the computer-executable components can further comprise a diversity component. In various cases, the diversity component can compute a diversity score based on the first set of compressed data points and the second set of compressed data points.

[0007] According to one or more embodiments, the above-described system can be implemented as a computer-implemented method and/or a computer program product.

DESCRIPTION OF THE DRAWINGS

[0008] The patent or application file contains at least one drawing executed in color. Copies of this patent or patent application publication with color drawing(s) will be provided by the Office upon request and payment of the necessary fec.

[0009] FIG. **1** illustrates a block diagram of an example, non-limiting system that facilitates visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein.

[0010] FIG. **2** illustrates a block diagram of an example, non-limiting system including activation maps that facilitates visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein.

[0011] FIGS. **3-4** illustrate example, non-limiting block diagrams showing how various activation maps can be obtained in accordance with one or more embodiments described herein.

[0012] FIG. **5** illustrates a block diagram of an example, non-limiting system including compressed data points that facilitates visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein.

[0013] FIG. **6** illustrates an example, non-limiting block diagram showing how various compressed data points can be obtained in accordance with one or more embodiments described herein.

[0014] FIG. **7** illustrates a block diagram of an example, non-limiting system including a diversity score that facilitates visualization and/or quantification of data diversity for

machine learning models in accordance with one or more embodiments described herein.

[0015] FIG. **8** illustrates a block diagram of an example, non-limiting system including a graph that facilitates visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein.

[0016] FIGS. **9-11** illustrate example, non-limiting graphs of compressed data points, in accordance with one or more embodiments described herein.

[0017] FIGS. **12-15** illustrate flow diagrams of example, non-limiting computer-implemented methods pertaining to quantification of data diversity for machine learning models in accordance with one or more embodiments described herein.

[0018] FIG. **16** illustrates a flow diagram of an example, non-limiting computer-implemented method that facilitates visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein.

[0019] FIG. **17** illustrates a block diagram of an example, non-limiting operating environment in which one or more embodiments described herein can be facilitated.

[0020] FIG. **18** illustrates an example networking environment operable to execute various implementations described herein.

DETAILED DESCRIPTION

[0021] The following detailed description is merely illustrative and is not intended to limit embodiments and/or application or uses of embodiments. Furthermore, there is no intention to be bound by any expressed or implied information presented in the preceding Background or Summary sections, or in the Detailed Description section.

[0022] One or more embodiments are now described with reference to the drawings, wherein like referenced numerals are used to refer to like elements throughout. In the following description, for purposes of explanation, numerous specific details are set forth in order to provide a more thorough understanding of the one or more embodiments. It is evident, however, in various cases, that the one or more embodiments can be practiced without these specific details.

[0023] As mentioned above, the performance (e.g., output accuracy, output precision) of a machine learning model (e.g., an artificial neural network) can depend upon the data on which the machine learning model is trained, the data on which the machine learning model is tested/validated, and/or the data which the machine learning model encounters when deployed in the field. For example, the performance of a trained machine learning model can be improved if the machine learning model is further trained on data that exhibits patterns/distributions that significantly vary from the patterns/distributions exhibited by the original training data. In contrast, the performance of the machine learning model can be negatively impacted if the machine learning model is further trained on data that exhibits patterns/distributions that do not significantly vary from the patterns/distributions exhibited by the original training data. In other words, additional training on redundant and/or duplicative data can cause overfitting, which can decrease the generalizability of the machine learning model. As another example, when deployed in the field, a trained machine learning model can accurately analyze data that exhibits patterns/distributions that are substantially similar to the patterns/distributions exhibited by the original training data. In contrast, when deployed in the field, the machine learning model can inaccurately analyze data that exhibits patterns/distributions that are not substantially similar to the patterns/distributions exhibited by the original training data. In other words, the machine learning model can perform poorly on data that is unlike the data on which the machine learning model was trained.

[0024] Therefore, being able to quickly compare the patterns/distributions exhibited by two different machine learning datasets (e.g., datasets which are analyzable by and/or otherwise receivable as input by a machine learning model) can allow for appropriate actions to be taken and/or decisions to be made by model developers. Unfortunately, conventional techniques do not facilitate rapid and/or objective comparisons between the patterns/distributions exhibited by two different machine learning datasets.

[0025] For example, suppose that a developer is deciding whether to further train an already-trained machine learning model on a particular dataset. As explained above, if the patterns/distributions exhibited by the particular dataset are sufficiently different from those exhibited by the dataset on which the machine learning model was already trained, further training on the particular dataset can be beneficial (e.g., overfitting can be avoided since the two datasets are not redundant and/or duplicative). However, if the patterns/distributions exhibited by the particular dataset are instead insufficiently different from those exhibited by the dataset on which the machine learning model was already trained, further training on the particular dataset can be detrimental (e.g., overfitting can occur since the two datasets are redundant and/or duplicative). Conventional techniques do not offer any tools which allow the developer to quickly and/or robustly determine whether the patterns/distributions of the particular dataset are sufficiently different from those of the training dataset. So, the developer has no rigorous and/or objective way of determining whether the machine learning model should be further trained on the particular dataset.

[0026] As another example, suppose that a developer is deciding whether a data augmentation strategy (e.g., modality-based augmentations, biology-based augmentations, mathematical transformation-based augmentations) is appropriate with respect to a machine learning model. In such case, the developer can create an augmented dataset by applying the augmentation strategy to an original dataset on which the machine learning model was trained. From a model development perspective, the augmentation strategy can be appropriate for the machine learning model if the augmented dataset "fills in the learning gaps" of the machine learning model. In other words, the augmentation strategy can be appropriate for the machine learning model if the patterns/distributions exhibited by the augmented dataset are sufficiently different from those exhibited by the original dataset, such that the machine learning model tends to inaccurately analyze the augmented dataset prior to any training on the augmented dataset. On the other hand, the augmentation strategy can be inappropriate for the machine learning model if the patterns/distributions exhibited by the augmented dataset are insufficiently different from the original dataset, such that the machine learning model tends to accurately analyze the augmented dataset prior to any training on the augmented dataset. Conventional techniques do not offer any tools which allow the developer to quickly and/or robustly compare the patterns/distributions of the

augmented dataset with those of the original dataset. So, the developer has no rigorous and/or objective way of determining whether the augmentation strategy is appropriate with respect to the machine learning model.

[0027] As yet another example, suppose that a developer is deciding whether to automatically annotate and/or curate a particular dataset via a machine learning model that was trained on an original dataset, or to instead manually annotate and/or curate the particular dataset. If the patterns/distributions exhibited by the particular dataset are sufficiently similar to those exhibited by the original dataset, automatic annotation/curation by the machine learning model can be appropriate. On the other hand, if the patterns/distributions exhibited by the particular dataset are not sufficiently similar to those exhibited by the original dataset, automatic annotation/curation by the machine learning model can be inappropriate, meaning that manual annotation/curation can be needed. Conventional techniques do not offer any tools which allow the developer to quickly and/or robustly determine whether the patterns/distributions of the particular dataset are sufficiently similar to those of the original dataset. So, the developer has no rigorous and/or objective way of determining whether automatic annotation/curation would be appropriate.

[0028] Various embodiments of the subject innovation can address one or more of these technical problems. One or more embodiments described herein include systems, computer-implemented methods, apparatus, and/or computer program products that can facilitate data diversity visualization and/or quantification for machine learning models. In various instances, embodiments of the subject innovation can be considered as a computerized tool (e.g., a combination of computer-executable hardware and/or computer-executable software) that can electronically access a first dataset and a second dataset, where a machine learning model has been trained on the first dataset, and can electronically quantify how different and/or diverse the second dataset is as compared to the first dataset, from the perspective of the machine learning model. In other words, the computerized tool can electronically compute a diversity score, which diversity score can indicate how differently the machine learning model tends to interpret the patterns/distributions exhibited by the second dataset as compared to how the machine learning model tends to interpret the patterns/distributions exhibited by the first dataset. Moreover, in various aspects, the computerized tool can electronically render visualizations (e.g., graphs, plots) that visually illustrate such differently-interpreted patterns/distributions. Accordingly, a model developer can take any suitable action and/or make any suitable decision with respect to the machine learning model, based on such quantification and/or visualization (e.g., can decide to initiate and/or forego additional training of the machine learning model on the second dataset based on the quantification and/or visualization; can decide to initiate automatic and/or manual annotation/curation of the second dataset based on the quantification and/or visualization). That is, in various embodiments, the computerized tool described herein can be considered as a computerized user interface which can be leveraged by the model developer, so as to allow the model developer to make more informed and/or objective design choices with respect to the machine learning model.

[0029] In various embodiments, such a computerized tool can comprise a receiver component, an activation component, a compression component, a diversity component, a visualization component, and/or an execution component.

[0030] In various embodiments, a machine learning model can comprise any suitable artificial neural network architecture. For instance, the machine learning model can include any suitable number of layers, can include any suitable numbers of neurons in various layers (e.g., different layers can have different numbers of neurons), can implement any suitable activation functions (e.g., softmax, hyperbolic tangent, sigmoid), and/or can implement any suitable interneuron connectivity patterns (e.g., forward connections, skip connections, recursive connections).

[0031] In various aspects, the machine learning model can be trained (e.g., via supervised training, unsupervised training, and/or reinforcement learning) to receive as input a data candidate and to produce some output based on the data candidate. In various cases, the data candidate can exhibit any suitable dimensionality and/or format (e.g., can be one or more scalars, one or more vectors, one or more matrices, one or more tensors, one or more strings, and/or any suitable combination thereof). Similarly, in various cases, the output can exhibit any suitable dimensionality and/or format (e.g., can be one or more scalars, one or more vectors, one or more matrices, one or more tensors, one or more strings, and/or any suitable combination thereof). As a non-limiting example, a data candidate can be a medical image of a patient (e.g., an X-ray image of a patient's knee, an MRI image of a patient's brain), and the output can be a label that classifies the medical image (e.g., that indicates the presence and/or absence of a particular anatomical structure in the medical image).

[0032] In various embodiments, there can be a first set of data candidates and a second set of data candidates. In various cases, the first set of data candidates can comprise any suitable number of data candidates. Likewise, the second set of data candidates can comprise any suitable number of data candidates (e.g., same number and/or different number as the first set of data candidates). In various instances, the machine learning model can have been trained (e.g., via supervised training, unsupervised training, and/or reinforcement learning) on the first set of data candidates. In some aspects, the second set of data candidates can represent data candidates obtained from a different source than the first set of data candidates, and a developer associated with the machine learning model can desire to determine whether the machine learning model can be expected to accurately analyze the data candidates from that different source and/or whether the machine learning model should be further trained (e.g., via backpropagation) on data candidates from that different source. In other aspects, the second set of data candidates can have been created by applying an augmentation strategy to the first set of data candidates, and the developer can desire to determine whether such augmentation strategy is appropriate to improve the generalizability of the machine learning model. In still other aspects, the second set of data candidates can be unannotated, and the developer can desire to determine whether automatic annotation techniques can be accurately applied to the second set of data candidates. As explained herein, the computerized tool can analyze the first set of data candidates and the second set of data candidates, and such analysis can be leveraged by the developer to objectively and/or rigorously make such determinations.

[0033] In various embodiments, the receiver component of the computerized tool can electronically receive and/or otherwise electronically access the machine learning model, the first set of data candidates, and/or the second set of data candidates. In various cases, the receiver component can electronically retrieve the machine learning model, the first set of data candidates, and/or the second set of data candidates from any suitable centralized and/or decentralized data structure (e.g., graph data structure, relational data structure, hybrid data structure), whether remote from and/or local to the receiver component. Accordingly, other components of the computerized tool described herein can electronically interact with the machine learning model, the first set of data candidates, and/or the second set of data candidates.

[0034] In various embodiments, the activation component of the computerized tool can electronically obtain a first set of latent activations and a second set of latent activations. In various aspects, the first set of latent activations can be generated by the machine learning model based on the first set of data candidates. Likewise, in various instances, the second set of latent activations can be generated by the machine learning model based on the second set of data candidates. For example, in various aspects, the activation component can electronically feed as input a particular data candidate from the first set of data candidates to the machine learning model. In various cases, a hidden layer of the machine learning model can generate a particular latent activation map based on the particular data candidate. Thus, a latent activation map can be obtained for each data candidate in the first set of data candidates, thereby resulting in the first set of latent activations. Similarly, in various aspects, the activation component can electronically feed as input a certain data candidate from the second set of data candidates to the machine learning model. In various cases, the hidden layer of the machine learning model can generate a certain latent activation map based on the certain data candidate. So, a latent activation map can be obtained for each data candidate in the second set of data candidates, thereby resulting in the second set of latent activations.

[0035] In various embodiments, the compression component of the computerized tool can electronically generate a first set of compressed data points based on the first set of latent activations. Likewise, in various cases, the compression component can electronically generate a second set of compressed data points based on the second set of latent activations. In various instances, the compression component can generate such sets of compressed data points via application of any suitable dimensionality reduction technique, such as t-distributed stochastic neighbor embedding (t-SNE) and/or uniform manifold approximation and projection (UMAP). For example, in various aspects, the compression component can electronically apply the dimensionality reduction technique to the first set of latent activations, thereby converting and/or transforming the first set of latent activations into the first set of compressed data points. A given latent activation map in the first set of latent activations can correspond to a given compressed data point in the first set of compressed data points, such that the given compressed data point that represents the given latent activation map but includes fewer dimensions (e.g., fewer numerical elements) than the given latent activation map. Similarly, in various aspects, the compression component can electronically apply the dimensionality reduction technique to the second set of latent activations, thereby converting and/or transforming the second set of latent activations into the second set of compressed data points. A given latent activation map in the second set of latent activations can correspond to a given compressed data point in the second set of compressed data points, such that the given compressed data point that represents the given latent activation map but includes fewer dimensions (e.g., fewer numerical elements) than the given latent activation map.

[0036] As mentioned above, a data candidate can, in various embodiments, have any suitable dimensionality (e.g., can be one or more scalars, one or more vectors, one or more matrices, one or more tensors, one or more strings, and/or any suitable combination thereof). Similarly, in various instances, a latent activation map can have any suitable dimensionality depending upon the configuration and/or structure of machine learning model. In various aspects, a compressed data point can have any suitable dimensionality that is lesser than the dimensionality of a latent activation map. As a non-limiting example, a latent activation map can be a matrix of hundreds and/or thousands of activation values outputted by a hidden layer of the machine learning model, and a compressed data point can be a two-element tuple (e.g., a two-element vector) that represents a corresponding latent activation map. As another non-limiting example, a latent activation map can be a matrix of hundreds and/or thousands of activation values outputted by a hidden layer of the machine learning model, and a compressed data point can be a fifty-element tuple (e.g., a fifty-element vector) that represents a corresponding latent activation map. More generally, a compressed data point can be an n-element tuple (e.g., an n-element vector), for any suitable positive integer n, where n is less than the number of elements in a latent activation map. Because a compressed data point can have a lower dimensionality than a latent activation map, it can be easier to perform computations on a compressed data point than on a latent activation map.

[0037] In various aspects, because the machine learning model can be trained on the first set of data candidates, the machine learning model can accurately analyze the patterns/distributions exhibited by the first set of data candidates. Such accurate analysis of the patterns/distributions exhibited by the first set of data candidates can ultimately cause the first set of compressed data points to be clustered according to the outputs which the machine learning model is configured/trained to produce. For example, suppose that the machine learning model is configured/trained to produce as output a binary label which indicates that an inputted data candidate is a member of one out of two classes. In such case, the first set of compressed data points can form two clusters: one cluster of compressed data points representing data candidates which the machine learning model infers belong to the first class, and another cluster of compressed data points representing data candidates which the machine learning model infers belong to the second class. More generally, if the machine learning model is configured/trained to classify a data candidate into one out of m classes, for any suitable positive integer m, the first set of compressed data points can be arranged into m clusters. In various cases, a cluster of compressed data points can be recognized as multiple compressed data points that have similar elements (e.g., that are separated by small and/or short Euclidean distances).

[0038] In various embodiments, the diversity component of the computerized tool can electronically compute a diver-

sity score based on the first set of compressed data points and/or based on the second set of compressed data points. In other words, the diversity component can implement any suitable statistical techniques and/or statistical calculations (e.g., mean, medium, mode, standard deviation, variance) in order to mathematically quantify statistical differences between the first set of compressed data points and the second set of compressed data points. In various cases, the diversity score can be a scalar (and/or, in other cases, a vector, a matrix, and/or a tensor) that indicates such statistical differences between the first set of compressed data points and the second set of compressed data points.

[0039] In various instances, the first set of latent activations can be considered as interpretations of the patterns/distributions of the first set of data candidates by the machine learning model, and the first set of compressed data points can be considered as dimensionally-reduced versions of the first set of latent activations. Thus, the first set of compressed data points can represent, in reduced and thus computation-amenable format, how the machine learning model interprets the patterns/distributions exhibited by the first set of data candidates. Likewise, in various cases, the second set of latent activations can be considered as interpretations of the patterns/distributions of the second set of data candidates by the machine learning model, and the second set of compressed data points can be considered as dimensionally-reduced versions of the second set of latent activations. So, the second set of compressed data points can represent, in reduced and thus computation-amenable format, how the machine learning model interprets the patterns/distributions exhibited by the second set of data candidates. Therefore, because the first set of compressed data points and the second set of compressed data points can be respectively derived from the first set of data candidates and the second set of data candidates, the diversity score can thus indicate statistical differences between the patterns/distributions exhibited by the first set of data candidates and the patterns/distributions exhibited by the second set of data candidates, from the perspective of the machine learning model.

[0040] In various aspects, the diversity score can indicate whether or not the second set of compressed data points fit into and/or otherwise conform to the clusters of the first set of compressed data points. If the second set of compressed data points fit into and/or conform to the clusters of the first set of compressed data points, the diversity score can be small in magnitude (e.g., can be below any suitable predetermined threshold). This can indicate that the machine learning model does not detect significant differences between the patterns/distributions exhibited by the first set of data candidates and those exhibited by the second set of data candidates (e.g., the machine learning model can be agnostic to the differences between the first set of data candidates and the second set of data candidates). On the other hand, if the second set of compressed data points do not fit into and/or conform to the clusters of the first set of compressed data points, the diversity score can be large in magnitude (e.g., can be above any suitable predetermined threshold). This can indicate that the machine learning model detects significant differences between the patterns/distributions exhibited by the first set of data candidates and those exhibited by the second set of data candidates (e.g., the machine learning model can be not agnostic to the differences between the first set of data candidates and the second set of data candidates).

[0041] In various aspects, the diversity component can compute and/or calculate the diversity score in any suitable fashion (e.g., via any suitable mathematical and/or statistical operations and/or functions). For example, the diversity component can, in various cases, compute a center for each cluster of the first set of compressed data points. That is, if each compressed data point is an n-element tuple, the diversity component can compute a central n-element tuple for each cluster of the first set of compressed data points. In various cases, the central n-element tuple of a given cluster can be equal to the average of all the n-element tuples that are in the first set of compressed data points and that belong to that cluster (e.g., it can be known to which cluster each of the first set of compressed data points belongs, since the first set of data candidates can be a training dataset with known ground-truth classifications and since the machine learning model can be trained on the first set of data candidates).

[0042] In various instances, for each cluster in the first set of compressed data points, the diversity component can then compute the Euclidean distance between the center of that cluster and every compressed data point that is in the first set of compressed data points and that belongs to that cluster. In various cases, for each cluster in the first set of compressed data points, the diversity component can thus compute the average and/or standard deviation of such computed Euclidean distances. The result can be an average Euclidean distance value, denoted for convenience as μ, and a standard deviation Euclidean distance value, denoted for convenience as σ, for each cluster in the first set of compressed data points. The μ and σ of a given cluster can be considered as statistically describing the density and/or distribution of that given cluster (e.g., μ_1 and σ_1 can describe the density and/or distribution of a cluster 1 of the first set of compressed data points; μ_2 and σ_2 can describe the density and/or distribution of a cluster 2 of the first set of compressed data points).

[0043] In various instances, the diversity component can assign each of the second set of compressed data points to a corresponding cluster of the first set of compressed data points. More specifically, the diversity component can, in various cases, assign a given compressed data point in the second set of compressed data points to a given cluster of the first set of compressed data points, if the given compressed data point is closer, in terms of Euclidean distance, to the center of the given cluster than to the center of any other cluster of the first set of compressed data points. In other words, the diversity component can assign each of the second set of compressed data points to the nearest cluster of the first set of compressed data points. Accordingly, for each cluster, the diversity component can compute the Euclidean distance between the center of that cluster and every compressed data point that is in the second set of compressed data points and that has been assigned to that cluster.

[0044] In various cases, for each cluster, the diversity component can compute the percentage and/or proportion of the second set of compressed data points that have been assigned to that cluster and that are within and/or outside of any suitable threshold Euclidean distance from the center of that cluster. As a non-limiting example, the threshold Euclidean distance for a given cluster can be equal to $\mu+2\sigma$ (e.g., $\mu_1+2\sigma_1$ can be the threshold Euclidean distance for cluster 1;

$\mu_2+2\sigma_2$ can be the threshold Euclidean distance for cluster 2). In various cases, if a compressed data point of the second set of compressed data points is within such threshold Euclidean distance of the center of its assigned cluster, that compressed data point can be considered as a non-outlier. On the other hand, if a compressed data point of the second set of compressed data points is farther than such threshold Euclidean distance from the center of its assigned cluster, that compressed data point can be considered as an outlier.

[0045] In various aspects, the diversity component can determine the total percentage and/or proportion of the second set of compressed data points that are considered as outliers. In various instances, the diversity score can be any suitable mathematical function of the such total percentage and/or proportion of the second set of compressed data points that are considered as outliers. In some cases, the diversity score can be equal to such total percentage and/or proportion of the second set of compressed data points that are considered as outliers. In any case, the diversity score can numerically represent how well and/or how poorly the second set of compressed data points fit into the clusters of the first set of compressed data points. Correspondingly, the diversity score can thus represent how differently the machine learning model interprets the patterns/distributions exhibited by the second set of data candidates as compared to how the machine learning model interprets the patterns/distributions exhibited by the first set of data candidates.

[0046] So, in various cases, a numerically high diversity score can indicate that a large proportion of the second set of compressed data points are considered as outliers (e.g., that a large proportion of the second set of compressed data points does not fit neatly into the clusters of the first set of compressed data points), which can mean that the machine learning model interprets the patterns/distributions of the second set of data candidates differently from those of the first set of data candidates. On the other hand, in various instances, a numerically low diversity score can indicate that a small proportion of the second set of compressed data points are considered as outliers (e.g., that only a small proportion of the second set of compressed data points does not fit neatly into the clusters of the first set of compressed data points), which can mean that the machine learning model interprets the patterns/distributions of the second set of data candidates similarly to those of the first set of data candidates.

[0047] Those having ordinary skill in the art will appreciate that any other suitable mathematical and/or statistical techniques can be implemented by the diversity component to compute the diversity score. Furthermore, although the herein disclosure mainly discusses a diversity score where numerically higher values indicate more diversity and numerically lower values indicate less diversity, those having ordinary skill in the art will appreciate that this is a mere non-limiting example. In various other embodiments, the diversity component can instead compute a similarity score, where higher numerical values indicate more similarity (e.g., less diversity) and where lower numerical values indicate less similarity (e.g., more diversity). In any case, the diversity component can quantify and/or measure how well and/or how poorly the second set of compressed data points fit int and/or conform to the clusters of the first set of compressed data points, which can correspondingly indicate how similar and/or how different the patterns/distributions exhibited by the second set of data candidates are as compared to the patterns/distributions exhibited by the first set of data candidates.

[0048] In various embodiments, if the compression component implements a dimensionality reduction technique that yields two-dimensional or three-dimensional compressed data points (e.g., n=2, and/or n=3), the visualization component of the computerized tool can electronically render and/or plot, on any suitable computer screen/monitor, a graph that depicts and/or shows the first set of compressed data points and/or the second set of compressed data points. In various cases, the clusters of the first set of compressed data points can be visually perceived in such graph. Furthermore, how well and/or how poorly the second set of compressed data points fit into and/or conform to the clusters of the first set of compressed data points can likewise be visually perceived in such graph. In some cases, the visualization component can further render, on and/or near the graph, the diversity score.

[0049] In various cases, the renditions of the visualization component can be viewed and/or viewable by the developer associated with the machine learning model (e.g., the graph and/or diversity score can be rendered on a computer screen/monitor that is viewable by the developer). Accordingly, the developer can be apprised/notified of the diversity score and/or can visually see the graph, so that the developer can understand how the second set of compressed data points differ from the first set of compressed data points, and thus can understand how the patterns/distributions exhibited by the second set of data candidates differ from those exhibited by the first set of data candidates. In various cases, the developer can reference the diversity score and/or the graph when making design choices/decisions regarding the machine learning model (e.g., when determining whether to further train the machine learning model on the second set of data candidates, when determining whether to automatically annotate the second set of data candidates).

[0050] In some cases, the graph can be interactable and/or clickable. That is, the developer can interact with the graph via any suitable human-computer interface device (e.g., a computer mouse, a touchscreen, voice command). In various cases, the developer can click on a compressed data point that is plotted on the graph, and the visualization component can, in response to such click, render a data candidate, from the first set of data candidates and/or the second set of data candidates, which corresponds to the compressed data point that is clicked. Accordingly, the developer can manually inspect any suitable data candidate as desired, by clicking on that data candidate's corresponding compressed data point.

[0051] In various embodiments, the execution component of the computerized tool can electronically take any suitable computerized action and/or can electronically make any suitable recommendation based on the diversity score. For example, if the developer desires to determine whether or not to further train the machine learning model on the second set of data candidates, the execution component can compare the diversity score to any suitable predetermined threshold. If the diversity score exceeds the predetermined threshold, the execution component can determine that the patterns/distributions of the second set of data candidates are sufficiently different from those of the first set of data candidates, such that overfitting can be avoided. Accordingly, the execution component can recommend that the machine learning model be further trained on the second set

of data candidates. On the other hand, if the diversity score does not exceed the predetermined threshold, the execution component can determine that the patterns/distributions of the second set of data candidates are insufficiently different from those of the first set of data candidates, such that overfitting can occur. Accordingly, the execution component can recommend that the machine learning model not be further trained on the second set of data candidates.

[0052] As another example, if the developer desires to determine whether or not to deploy the machine learning model in an environment associated with the second set of data candidates, the execution component can compare the diversity score to any suitable predetermined threshold. If the diversity score exceeds the predetermined threshold, the execution component can determine that the patterns/distributions of the second set of data candidates are insufficiently similar to those of the first set of data candidates, such that inaccurate performance is expected. Accordingly, the execution component can recommend that the machine learning model not be deployed in the environment associated with the second set of data candidates. On the other hand, if the diversity score does not exceed the predetermined threshold, the execution component can determine that the patterns/distributions of the second set of data candidates are sufficiently similar to those of the first set of data candidates, such that accurate performance can be expected. Accordingly, the execution component can recommend that the machine learning model be deployed in the environment associated the second set of data candidates.

[0053] As still another example, if the second set of data candidates are created via an augmentation strategy, and if the developer desires to determine whether or not the augmentation strategy is appropriate for the machine learning model, the execution component can compare the diversity score to any suitable predetermined threshold. If the diversity score exceeds the predetermined threshold, the execution component can determine that the machine learning model considers the patterns/distributions of the second set of data candidates to be sufficiently distinct from those of the first set of data candidates, such that the augmentation strategy is efficacious. Accordingly, the execution component can recommend that the augmentation strategy is appropriate for the machine learning model. On the other hand, if the diversity score does not exceed the predetermined threshold, the execution component can determine that the machine learning model considers the patterns/distributions exhibited by the second set of data candidates to be insufficiently distinct from those exhibited by the first set of data candidates, such that the augmentation strategy is not efficacious. Accordingly, the execution component can recommend that the augmentation strategy is inappropriate for the machine learning model.

[0054] As yet another example, if the second set of data candidates is unannotated, and if the developer desires to determine whether an automatic annotation technique would be appropriate for the second set of data candidates, the execution component can compare the diversity score to any suitable predetermined threshold. If the diversity score exceeds the predetermined threshold, the execution component can determine that the machine learning model considers the patterns/distributions of the second set of data candidates to be insufficiently similar to those of the first set of data candidates, such that automatic annotation would not yield accurate labels. Accordingly, the execution component can recommend that manual annotation be applied to the second set of data candidates. On the other hand, if the diversity score does not exceed the predetermined threshold, the execution component can determine that the machine learning model considers the patterns/distributions of the second set of data candidates to be sufficiently similar to those of the first set of data candidates, such that automatic annotation would yield accurate labels. Accordingly, the execution component can recommend that automatic annotation be applied to the second set of data candidates. In some embodiments, the execution component can recommend that only the data candidates corresponding to the outliers of the second set of compressed data points be manually annotated, and/or can recommend that only the data candidates corresponding to the non-outliers of the second set of compressed data points be automatically annotated.

[0055] Various embodiments of the subject innovation can be employed to use hardware and/or software to solve problems that are highly technical in nature (e.g., to facilitate data diversity visualization and/or quantification for machine learning models), that are not abstract and that cannot be performed as a set of mental acts by a human. Further, some of the processes performed can be performed by a specialized computer (e.g., trained machine learning model) for carrying out defined tasks related to data diversity visualization and/or quantification. For example, such defined tasks can include: accessing, by a device operatively coupled to a processor, a first set of data candidates and a second set of data candidates, wherein a machine learning model is trained on the first set of data candidates; obtaining, by the device, a first set of latent activations generated by the machine learning model based on the first set of data candidates, and obtaining, by the device, a second set of latent activations generated by the machine learning model based on the second set of data candidates; generating, by the device, a first set of compressed data points by applying a dimensionality reduction technique to the first set of latent activations, and generating, by the device, a second set of compressed data points by applying the dimensionality reduction technique to the second set of latent activations; computing, by the device, a diversity score based on the first set of compressed data points and the second set of compressed data points; and/or rendering, by the device, a graph depicting the first set of compressed data points and the second set of compressed data points. Such defined tasks are not conventionally performed manually by humans. Moreover, neither the human mind nor a human with pen and paper can electronically access a machine learning model, a first set of data candidates on which the machine learning model is trained, and a second set of data candidates; can electronically feed the first and second sets of data candidates to the machine learning model to obtain first and second sets of latent activations; can electronically apply dimensionality reduction to the first and second sets of latent activations, thereby yielding first and second sets of compressed data points; can electronically compute a diversity score that quantifies differences between the first and second sets of compressed data points; and/or can electronically render a graph that depicts the first and second sets of compressed data points. Instead, various embodiments of the subject innovation are inherently and inextricably tied to computer technology and cannot be implemented outside of a computing environment (e.g., embodiments of the subject

innovation constitute a computerized user interface that can automatically quantify and/or visualize differences between two different machine learning datasets; such a computerized tool cannot be practicably implemented in any sensible way without computers).

[0056] Moreover, various embodiments of the subject innovation can integrate into a practical application the disclosed teachings regarding data diversity visualization and/or quantification for machine learning models. As explained above, model developers do not have conventional tools that allow them to quickly and/or objectively make various design decisions when developing a machine learning model. For example, the model developer may want to determine ahead of time whether further training on a particular dataset would improve the generalizability of a particular machine learning model or would instead cause the particular machine learning model to become overfitted. If the model developer does not know such information ahead of time, there is a risk that training is performed and causes overfitting, which constitutes wasted time and/or resources. As another example, the model developer may want to determine ahead of time whether an augmentation strategy is appropriate for a particular machine learning model. If the model developer does not know such information ahead of time, there is a risk that the augmentation strategy is applied despite being inappropriate for the particular machine learning model, which constitutes wasted time and/or resources As yet another example, the model developer may want to determine ahead of time whether a particular unannotated dataset can be accurately labeled via automatic annotation techniques (e.g., transfer learning based on distance to known exemplars) or whether the particular dataset instead should be manually annotated. If the model developer does not know such information ahead of time, there is a risk that either manual annotation is needlessly performed or that automatic annotation is performed despite high levels of inaccuracy, both of which constitute wasted time and/or resources. Conventional tools do not aid the model developer in making these determinations, and so conventional tools cannot help the model developer to avoid such risks of wasting time and/or resources.

[0057] In stark contrast, the computerized tool described herein can assist the model developer in making such determinations and can thus help to avoid such risks of wasting time and/or resources. Specifically, the computerized tool described herein can electronically access a first dataset and a second data, where a machine learning model is trained on the first dataset. Moreover, the computerized tool can electronically obtain first and second sets of latent activation values, by respectively feeding the first and second datasets to the machine learning model and by respectively extracting the first and second sets of latent activation values from a hidden layer of the machine learning model. In various cases, the computerized tool can electronically compress, via any suitable dimensionality reduction technique (e.g., t-SNE and/or UMAP), the first and second sets of latent activation values into first and second sets of compressed data points. In various instances, the computerized tool can electronically compute a diversity score that quantifies and/or measures how closely the second set of compressed data points conform to clusters exhibited by the first set of compressed data points. A numerically high diversity score can indicate that the second set of compressed data points do not conform closely to the clusters of the first set of compressed data points, which can mean that the machine learning models is interpreting the second dataset differently from the first dataset. On the other hand, a numerically low diversity score can indicate that the second set of compressed data points conforms closely to the clusters of the first set of compressed data points, which can mean that the machine learning models is interpreting the second dataset similarly to the first dataset. In various cases, the computerized tool can visually render the diversity score and/or can visually render the first and second compressed data points on a graph that is visible to the model developer. Accordingly, the model developer can be notified of the diversity score and/or can manually view the graph. Thus, the model developer can determine whether the first and second datasets are sufficiently similar and/or sufficiently different, and the model developer can make design choices/decisions regarding the machine learning model accordingly (e.g., if the diversity score is sufficiently high, the machine learning model can be further trained on the second dataset without risk of overfitting; if the diversity score is sufficiently low, automatic annotation techniques can be applied to the second dataset). Such a computerized tool clearly constitutes a useful and practical application of computers.

[0058] Furthermore, various embodiments of the subject innovation can control real-world tangible devices based on the disclosed teachings. For example, various embodiments of the subject innovation can electronically access a machine learning model, which can be any suitable combination of tangible computing hardware and/or software. In various instances, embodiments of the subject innovation can electronically train and/or recommend training of the machine learning model on a given dataset. Moreover, in various aspects, embodiments of the subject innovation can electronically render, on any suitable computer screen, various visualizations and/or graphs.

[0059] It should be appreciated that the herein figures and description provide non-limiting examples of the subject innovation.

[0060] FIG. **1** illustrates a block diagram of an example, non-limiting system **100** that can facilitate visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein. As shown, a data diversity system **102** can be electronically integrated, via any suitable wired and/or wireless electronic connections, with a machine learning model **104**, a set of training data candidates **106**, and/or a set of test data candidates **108**.

[0061] In various cases, the machine learning model **104** can be an artificial neural network, which can exhibit any suitable artificial neural network architecture. For instance, the machine learning model **104** can include any suitable number of layers. In various instances, the machine learning model **104** can include any suitable numbers of neurons in various layers (e.g., different layers can have different numbers of neurons as each other, different layers can have the same number of neurons as each other). In various aspects, various neurons in the machine learning model **104** can implement any suitable activation functions (e.g., sigmoid, softmax, hyperbolic tangent, rectified linear unit). In various cases, the machine learning model **104** can implement any suitable connectivity patterns (e.g., forward connections between neurons, skip connections between neurons, recursive connections between neurons). Although the herein

disclosure mainly discusses embodiments in which the machine learning model **104** is an artificial neural network, this is merely a non-limiting example. In various embodiments, the machine learning model **104** can implement any other suitable machine learning architecture.

[0062] In various aspects, the machine learning model **104** can be configured in any suitable fashion, so as to be able to receive as input a data candidate and so as to be able to produce some output based on the data candidate. In various cases, the data candidate can have any suitable dimensionality (e.g., can be one or more scalars, one or more vectors, one or more matrices, one or more tensors, and/or one or more strings). In various instances, the output can have any suitable dimensionality (e.g., can be one or more scalars, one or more vectors, one or more matrices, one or more tensors, and/or one or more strings). For example, the machine learning model **104** can be configured to receive as input a medical image (e.g., an X-ray image, an MRI image, a CT image) and to produce as output a label that classifies the medical image into one of two or more different classes (e.g., a label that indicates an anatomical structure that is depicted in the medical image).

[0063] In various instances, the set of training data candidates **106** can comprise any suitable number of training data candidates. In various cases, a training data candidate can be a data candidate on which the machine learning model **104** is and/or has been trained. For example, internal parameters (e.g., weight matrices, bias values) of the machine learning model **104** can have been iteratively updated via backpropagation, based on the set of training data candidates **106** and/or based on ground-truth annotations that correspond to the set of training data candidates **106**. In some instances, the set of training data candidates **106** can be considered as a sample and/or a subset taken from an even larger collection of data candidates (not shown) on which the machine learning model **104** is and/or has been trained.

[0064] In various aspects, the set of test data candidates **108** can comprise any suitable number of test data candidates. In various cases, a test data candidate can be a data candidate on which the machine learning model **104** is not and/or has not yet been trained. In various instances, an operator (not shown) associated with the machine learning model **104** can desire to make a design choice and/or design decision regarding the set of test data candidates **108**. For example, in some cases, the set of test data candidates **108** can be sourced and/or sampled from a particular field and/or environment, and the operator can desire to determine whether the machine learning model **104** can be accurately deployed in the particular field and/or environment. As another example, the set of test data candidates **108** can be considered as potential training data; that is, the operator can desire to determine whether the machine learning model **104** can be trained on set of test data candidates **108** without experiencing overfitting. As yet another example, the set of test data candidates **108** can be created by applying a data augmentation strategy to the set of training data candidates **106**, and the operator can desire to determine whether the data augmentation strategy helps to generalize the machine learning model **104**. As still another example, the set of test data candidates **108** can be unannotated, and the operator can desire to determine whether the set of test data candidates **108** can be accurately automatically annotated. As explained herein, the data diversity system **102** can electronically generate results and/or visualizations based on the set of training data candidates **106** and/or the set of test data candidates **108**, and such results and/or visualizations can be leveraged by the operator to quickly and/or objectively make such determinations.

[0065] In various embodiments, the data diversity system **102** can comprise a processor **110** (e.g., computer processing unit, microprocessor) and a computer-readable memory **112** that is operably and/or operatively and/or communicatively connected/coupled to the processor **110**. The computer-readable memory **112** can store computer-executable instructions which, upon execution by the processor **110**, can cause the processor **110** and/or other components of the data diversity system **102** (e.g., receiver component **114**, activation component **116**, compression component **118**, diversity component **120**, visualization component **122**, and/or execution component **124**) to perform one or more acts. In various embodiments, the computer-readable memory **112** can store computer-executable components (e.g., receiver component **114**, activation component **116**, compression component **118**, diversity component **120**, visualization component **122**, and/or execution component **124**), and the processor **110** can execute the computer-executable components.

[0066] In various embodiments, the data diversity system **102** can comprise a receiver component **114**. In various aspects, the receiver component **114** can electronically retrieve and/or otherwise electronically access the machine learning model **104**, the set of training data candidates **106**, and/or the set of test data candidates **108**, from any suitable centralized and/or decentralized data structure (not shown), whether remote from and/or local to the receiver component **114**. Accordingly, in various instances, other components of the data diversity system **102** can manipulate and/or otherwise interact with the machine learning model **104**, the set of training data candidates **106**, and/or the set of test data candidates **108**.

[0067] In various embodiments, the data diversity system **102** can comprise an activation component **116**. In various aspects, the activation component **116** can electronically obtain a set of training activation maps based on the set of training data candidates **106**, and/or can electronically obtain a set of test activation maps based on the set of test data candidates **108**. More specifically, in various instances, the activation component **116** can electronically feed a training data candidate (e.g., one of the set of training data candidates **106**) to the machine learning model **104**, and the activation component **116** can electronically extract from the machine learning model **104** an activation map generated by a hidden layer of the machine learning model **104** based on the training data candidate (e.g., hence the name "training activation map"). The activation component **116** can repeat this for each (and/or fewer than each) training data candidate in the set of training data candidates **106**, thereby yielding the set of training activation maps. Likewise, in various instances, the activation component **116** can electronically feed a test data candidate (e.g., one of the set of test data candidates **108**) to the machine learning model **104**, and the activation component **116** can electronically extract from the machine learning model **104** an activation map generated by a hidden layer of the machine learning model **104** based on the test data candidate (e.g., hence the name "test activation map"). The activation component **116** can repeat this for each (and/or fewer than each) test data candidate in the set of test data candidates **108**, thereby yielding the set of test

activation maps. In various cases, the set of training activation maps can be considered as illustrating how the machine learning model **104** is internally interpreting the set of training data candidates **106**. Similarly, the set of test activation maps can be considered as illustrating how the machine learning model **104** is internally interpreting the set of test data candidates **108**.

[0068] In various embodiments, the data diversity system **102** can comprise a compression component **118**. In various aspects, the compression component **118** can electronically reduce the dimensionalities of the set of training activation maps and/or the set of test activation maps. More specifically, in various cases, the compression component **118** can electronically generate a set of compressed training data points by executing any suitable dimensionality reduction technique on the set of training activation maps. That is, the compression component **118** can convert a training activation map into a compressed training data point, where the compressed training data point can be a vector having a lower dimension (e.g., fewer elements) than the training activation map. The compression component **118** can repeat this for each (and/or fewer than each) training activation map in the set of training activation maps, thereby yielding the set of compressed training data points. Likewise, in various cases, the compression component **118** can electronically generate a set of compressed test data points by executing the dimensionality reduction technique on the set of test activation maps. That is, the compression component **118** can convert a test activation map into a compressed test data point, where the compressed test data point can be a vector having a lower dimension (e.g., fewer elements) than the test activation map. The compression component **118** can repeat this for each (and/or fewer than each) test activation map in the set of test activation maps, thereby yielding the set of compressed test data points.

[0069] In various cases, the set of compressed training data points can be considered as exhibiting and/or encapsulating, in a reduced feature space, how the machine learning model **104** interprets the patterns/distributions contained in the set of training data candidates **106**. Similarly, in various aspects, the set of compressed test data points can be considered as exhibiting and/or encapsulating, in the reduced feature space, how the machine learning model **104** interprets the patterns/distributions contained in the set of test data candidates **108**.

[0070] In various embodiments, the data diversity system **102** can comprise a diversity component **120**. In various aspects, the diversity component **120** can electronically compute a diversity score based on the set of compressed training data points and/or the set of compressed test data points. More specifically, the diversity component **120** can apply any suitable mathematical and/or statistical calculations so as to statistically compare the set of compressed training data points to the set of compressed test data points.

[0071] As mentioned above, because the machine learning model **104** can be trained on the set of training data candidates **106**, and because the set of compressed training data points can be derived from the set of training data candidates **106**, the set of compressed training data points can exhibit a clustered arrangement, which can correspond to the output that the machine learning model **104** is configured to produce. For example, if the machine learning model **104** is configured to produce a label that classifies an inputted data candidate into one of m different classes, for any suitable positive integer m, the set of compressed training data points can have m different clusters (e.g., m different subsets of similarly-valued compressed training data points).

[0072] In various instances, the diversity component **120** can compute statistical metrics (e.g., mean, median, mode, standard deviation) that define the clustered arrangement of the set of compressed training data points. In various aspects, the diversity component **120** can then determine whether the set of compressed test data points conform to the statistical metrics defining the clustered arrangement of the set of compressed training data points. If the set of compressed test data points do conform to such statistical metrics, the diversity component **120** can output a low diversity score, which can indicate a low level of diversity between the set of compressed training data points and the set of compressed test data points. Such low diversity score can correspondingly indicate a low level of difference between how the machine learning model **104** interprets the patterns/distributions exhibited by the set of training data candidates **106** and how the machine learning model **104** interprets the patterns/distributions exhibited by the set of test data candidates **108**. In contrast, if the set of compressed test data points do not conform to such statistical metrics, the diversity component **120** can output a high diversity score, which can indicate a high level of diversity between the set of compressed training data points and the set of compressed test data points. Such high diversity score can correspondingly indicate a high level of difference between how the machine learning model **104** interprets the patterns/distributions exhibited by the set of training data candidates **106** and how the machine learning model **104** interprets the patterns/distributions exhibited by the set of test data candidates **108**.

[0073] In various embodiments, the data diversity system **102** can comprise a visualization component **122**. In various aspects, if a compressed data point is a two-element vector and/or a three-element vector, the visualization component **122** can electronically render a graph depicting the set of compressed training data points and/or the set of compressed test data points on any suitable computer monitor/screen (not shown) that is viewable by the operator. In various cases, the visualization component **122** can also electronically render the diversity score on the computer monitor/screen. Accordingly, the operator can be visually notified of the diversity score and/or of the graph. In some cases, the graph can be interactable and/or clickable (e.g., via a computer mouse and/or any other suitable human-computer interface device). In various instances, when the operator clicks on a given compressed data point that is plotted in the graph, the visualization component can electronically render on the computer monitor/screen a data candidate that corresponds to the compressed data point that is clicked, thereby allowing the operator to quickly and manually inspect the data candidate as desired. In any case, the operator can thus leverage the diversity score and/or the graph when making various design decisions regarding the set of test data candidates **108** and/or the machine learning model **104**.

[0074] In various embodiments, the data diversity system **102** can comprise an execution component **124**. In various aspects, the execution component **124** can electronically transmit the diversity score and/or the graph to any other suitable computing device (not shown). In various instances,

the execution component **124** can make various electronic recommendations to the operator based on the diversity score. For example, if the operator desires to determine whether the machine learning model **104** can be trained on the set of test data candidates **108** without experiencing overfitting, the execution component **124** can compare the diversity score to any suitable threshold and can make a recommendation accordingly. As another example, if the operator desires to determine whether the machine learning model **104** can be accurately deployed in a field and/or environment associated with the set of test data candidates **108**, the execution component **124** can compare the diversity score to any suitable threshold and can make a recommendation accordingly. As yet another example, if the set of test data candidates **108** is created by modifying the set of training data candidates **106** via an augmentation strategy, and if the operator desires to determine whether such augmentation strategy helps to improve the generalizability of the machine learning model **104**, the execution component **124** can compare the diversity score to any suitable threshold and can make a recommendation accordingly. As still another example, if the set of test data candidates **108** is unannotated, and if the operator desires to determine whether automatic annotation can be accurately applied to the set of test data candidates **108**, the execution component **124** can compare the diversity score to any suitable threshold and can make a recommendation accordingly.

[0075] FIG. **2** illustrates a block diagram of an example, non-limiting system **200** including activation maps that can facilitate visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein. As shown, the system **200** can, in some cases, comprise the same components as the system **100**, and can further comprise a set of training activation maps **202** and/or a set of test activation maps **204**.

[0076] In various embodiments, the activation component **116** can electronically obtain the set of training activation maps **202** based on the set of training data candidates **106**, and/or can electronically obtain the set of test activation maps **204** based on the set of test data candidates **108**. More specifically, in various instances, the activation component **116** can electronically feed each of the set of training data candidates **106** to the machine learning model **104**, and can electronically extract activation values generated by a hidden layer of the machine learning model **104**, thereby yielding the set of training activation maps **202**. In similar fashion, the activation component **116** can, in various aspects, electronically feed each of the set of test data candidates **108** to the machine learning model **104**, and can electronically extract activation values generated by a hidden layer of the machine learning model **104**, thereby yielding the set of test activation maps **204**. This is explained in more detail with respect to FIGS. **3-4**.

[0077] FIGS. **3-4** illustrate example, non-limiting block diagrams showing how various activation maps can be obtained in accordance with one or more embodiments described herein.

[0078] As shown in FIG. **3**, the machine learning model **104** can, in various embodiments, comprise a set of layers **302**. In various instances, the set of layers **302** can include p layers, for any suitable positive integer p: that is, layer **1** to layer p. In various aspects, the layer **1** can be considered as an input layer, and the layer p can be considered as an output layer. In various cases, an intermediate and/or hidden layer in the set of layers **302** can be represented as the intermediate and/or hidden layer j, where j can be any suitable positive integer greater than 1 and less than p. Any layer other than the layer **1** and the layer p can be considered as a hidden layer of the machine learning model **104**. As mentioned above, each layer of the set of layers **302** can have any suitable number of neurons, can implement any suitable types of activation functions, and/or can be connected to other layers via any suitable connectivity pattern.

[0079] In various embodiments, the activation component **116** can feed a training data candidate **304** as input to the machine learning model **104**, where the training data candidate **304** can be one of the data candidates from the set of training data candidates **106**. Accordingly, the machine learning model **104** can analyze the training data candidate **304** and can generate an output **306** based on the training data candidate **304**. As explained above, the output **306** can be a label that classifies the training data candidate **304**.

[0080] In further detail, the layer I can receive the training data candidate **304** and can generate various latent activations (e.g., can generate one or more latent activation maps) based on the training data candidate **304**. In various cases, the latent activations generated by the layer **1** can be received by a next layer **2** (not shown). Based on the latent activations provided by the layer **1**, the layer **2** can generate its own latent activations, which can then be received by a next layer **3** (not shown). Similarly, the layer j can receive latent activations generated by a previous layer j−1, and can generate its own latent activations based on the latent activations provided by the previous layer j−1. As shown, the latent activations generated by the layer j can be referred to as the training activation map **308** (e.g., the term "training" can be used since the latent activations are based on the training data candidate **304**). Although FIG. **3** depicts the layer j as generating merely one activation map, this is a non-limiting example. In various cases, the layer j can generate any suitable number of activation maps. In various instances, a next layer j+1 (not shown) can then receive the training activation map **308** generated by the layer j, and can generate its own latent activations based on the training activation map **308**. Likewise, the layer p can receive latent activations produced by a previous layer p−1 (not shown) and can generate the output **306** based on the latent activations of the previous layer p−1.

[0081] In various aspects, after the activation component **116** feeds the training data candidate **304** to the layer **1**, the activation component **116** can electronically extract, capture, and/or otherwise record the training activation map **308** that is produced by the layer j. In various cases, the training activation map **308** can be considered as a latent activation map generated by a hidden layer (e.g., layer j) of the machine learning model **104** based on the training data candidate **304**. In various instances, the activation component **116** can repeat this procedure for every (and/or for fewer than every) data candidate in the set of training data candidates **106**. The ultimate result of such repetition can be the set of training activation maps **202**.

[0082] FIG. **4** is analogous to FIG. **3**. As shown in FIG. **4**, the activation component **116** can, in various embodiments, feed a test data candidate **402** as input to the machine learning model **104**, where the test data candidate **402** can be one of the data candidates from the set of test data candidates **108**. Accordingly, the machine learning model **104** can analyze the test data candidate **402** and can generate an

output **404** based on the test data candidate **402**. As explained above, the output **404** can be a label that classifies the test data candidate **402**.

[0083] In further detail, the layer I can receive the test data candidate **402** and can generate various latent activations (e.g., can generate one or more latent activation maps) based on the test data candidate **402**. In various cases, the latent activations generated by the layer **1** can be received by a next layer **2** (not shown). Based on the latent activations provided by the layer **1**, the layer **2** can generate its own latent activations, which can then be received by a next layer **3** (not shown). Similarly, the layer j can receive latent activations generated by a previous layer j−1, and can generate its own latent activations based on the latent activations provided by the previous layer j−1. As shown, the latent activations generated by the layer j can be referred to as the test activation map **406** (e.g., the term "test" can be used since the latent activations are based on the test data candidate **402**). Although FIG. **4** depicts the layer j as generating merely one activation map, this is a non-limiting example. In various cases, the layer j can generate any suitable number of activation maps. In various instances, a next layer j+1 (not shown) can then receive the test activation map **406** generated by the layer j, and can generate its own latent activations based on the test activation map **406**. Likewise, the layer p can receive latent activations produced by a previous layer p−1 (not shown) and can generate the output **404** based on the latent activations of the previous layer p−1.

[0084] In various aspects, after the activation component **116** feeds the test data candidate **402** to the layer **1**, the activation component **116** can electronically extract, capture, and/or otherwise record the test activation map **406** that is produced by the layer j. In various cases, the test activation map **406** can be considered as a latent activation map generated by a hidden layer (e.g., layer j) of the machine learning model **104** based on the test data candidate **402**. In various instances, the activation component **116** can repeat this procedure for every (and/or for fewer than every) data candidate in the set of test data candidates **108**. The ultimate result of such repetition can be the set of test activation maps **204**.

[0085] As mentioned above, the training data candidate **304** and/or the test data candidate **402** can, in various embodiments, exhibit any suitable dimensionalities (e.g., can each be one or more scalars, one or more vectors, one or more matrices, one or more tensors, and/or any suitable combination thereof). Similarly, the output **306** and/or the output **404** can, in various instances, can exhibit any suitable dimensionalities. Moreover, in various aspects, the latent activations generated by the layers of the set of layers **302** can exhibit any suitable dimensionalities. Indeed, those having ordinary skill in the art will appreciate that the dimensionality of a latent activation map (e.g., **308** and/or **406**) can depend upon the number and/or arrangement of neurons in the layer that generates the latent activation map (e.g., different layers can have different numbers of neurons and thus can generate different latent activations having different dimensionalities).

[0086] Those having ordinary skill in the art will appreciate that the set of training activation maps **202** can represent and/or otherwise indicate how the machine learning model **104** is internally interpreting the set of training data candidates **106**. Likewise, the set of test activation maps **204** can be considered as representing and/or otherwise indicating how the machine learning model **104** is internally interpreting the set of test data candidates **108**. Accordingly, it can be desirable to compare the set of training activation maps **202** with the set of test activation maps **204**. However, because each activation map in the set of training activation maps **202** and/or in the set of test activation maps **204** can be a high-dimensional matrix and/or tensor (e.g., each activation map can include hundreds and/or thousands of elements), performing computations on the set of training activation maps **202** and/or on the set of test activation maps **204** can be difficult and/or suboptimal.

[0087] FIG. **5** illustrates a block diagram of an example, non-limiting system **500** including compressed data points that can facilitate visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein. As shown, the system **500** can, in some cases, comprise the same components as the system **200**, and can further comprise a set of compressed training data points **502** and/or a set of compressed test data points **504**.

[0088] In various embodiments, the compression component **118** can electronically generate the set of compressed training data points **502** based on the set of training activation maps **202**, and/or can electronically generate the set of compressed test data points **504** based on the set of test activation maps **204**. More specifically, in various instances, the compression component **118** can, via any suitable dimensionality reduction technique (e.g., t-SNE and/or UMAP), electronically reduce the dimensionality of each of the set of training activation maps **202**, thereby yielding the set of compressed training data points **502**. Similarly, in various cases, the compression component **118** can, via the dimensionality reduction technique, electronically reduce the dimensionality of each of the set of test activation maps **204**, thereby yielding the set of compressed test data points **504**. This is explained in more detail with respect to FIG. **6**.

[0089] FIG. **6** illustrates an example, non-limiting block diagram showing how various compressed data points can be obtained in accordance with one or more embodiments described herein.

[0090] As shown, in various cases, the set of training activation maps **202** can comprise any suitable number of training activation maps. That is, the set of training activation maps **202** can include a training activation map **1** to a training activation map x, for any suitable positive integer x. In various instances, the compression component **118** can electronically apply any suitable dimensionality reduction technique (e.g., t-SNE, UMAP) to the set of training activation maps **202**, thereby converting and/or transforming the set of training activation maps **202** into the set of compressed training data points **502**. As shown, the set of compressed training data points **502** can respectively correspond to the set of training activation maps **202**. In other words, because the set of training activation maps **202** can include x separate training activation maps, the set of compressed training data points **502** can include x separate compressed training data points (e.g., a compressed training data point **1** to a compressed training data point x). More specifically, the compressed training data point **1** can correspond to the training activation map **1**, meaning that the compressed training data point **1** can be considered as a compressed and/or dimensionally-reduced version of the training activation map **1**. For example, the training activa-

tion map **1** can be a matrix that has hundreds and/or thousands of elements, and the compressed training data point **1** can be an n-element vector that represents the training activation map **1**, for any suitable positive integer n (e.g., n=2, n=50). Similarly, the compressed training data point x can correspond to the training activation map x, meaning that the compressed training data point x can be considered as a compressed and/or dimensionally-reduced version of the training activation map x. For example, the training activation map x can be a matrix that has hundreds and/or thousands of elements, and the compressed training data point x can be an n-element vector that represents the training activation map x. Because the set of compressed training data points **502** can be derived from the set of training activation maps **202**, the set of compressed training data points **502** can exhibit the patterns/distributions of the set of training activation maps **202**. However, since the set of compressed training data points **502** can have a lower dimensionality than the set of training activation maps **202**, computations can be more easily performed on the set of compressed training data points **502** than on the set of training activation maps **202**.

[0091] As shown, in various cases, the set of test activation maps **204** can comprise any suitable number of training activation maps. That is, the set of test activation maps **204** can include a training activation map **1** to a training activation map y, for any suitable positive integer y (e.g., y can be equal to or not equal to x). In various instances, the compression component **118** can electronically apply any suitable dimensionality reduction technique (e.g., t-SNE, UMAP) to the set of test activation maps **204**, thereby converting and/or transforming the set of test activation maps **204** into the set of compressed test data points **504**. As shown, the set of compressed test data points **504** can respectively correspond to the set of test activation maps **204**. In other words, because the set of test activation maps **204** can include y separate test activation maps, the set of compressed test data points **504** can include y separate compressed test data points (e.g., a compressed test data point **1** to a compressed test data point y). More specifically, the compressed test data point **1** can correspond to the test activation map **1**, meaning that the compressed test data point **1** can be considered as a compressed and/or dimensionally-reduced version of the test activation map **1**. For example, the test activation map **1** can be a matrix that has hundreds and/or thousands of elements, and the compressed test data point **1** can be an n-element vector that represents the test activation map **1**, for any suitable positive integer n (e.g., n=2, n=50). Similarly, the compressed test data point y can correspond to the test activation map y, meaning that the compressed test data point y can be considered as a compressed and/or dimensionally-reduced version of the test activation map y. For example, the test activation map y can be a matrix that has hundreds and/or thousands of elements, and the compressed test data point y can be an n-element vector that represents the test activation map y. Because the set of compressed test data points **504** can be derived from the set of test activation maps **204**, the set of compressed test data points **504** can exhibit the patterns/distributions of the set of test activation maps **204**. However, since the set of compressed test data points **504** can have a lower dimensionality than the set of test activation maps **204**, computations can be more easily performed on the set of compressed test data points **504** than on the set of test activation maps **204**.

[0092] FIG. **7** illustrates a block diagram of an example, non-limiting system **700** including a diversity score that can facilitate visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein. As shown, the system **700** can, in some cases, comprise the same components as the system **500**, and can further comprise a diversity score **702**.

[0093] In various embodiments, the diversity component **120** can electronically compute the diversity score **702** based on the set of compressed training data points **502** and/or based on the set of compressed test data points **504**. More specifically, the diversity component **120** can statistically analyze the patterns/distributions exhibited by the set of compressed training data points **502**, and can compute a measure of how well and/or how poorly the set of compressed test data points **504** conform to those patterns/distributions.

[0094] In various embodiments, as explained above, because the set of compressed training data points **502** can be derived from the set of training data candidates **106**, and because the machine learning model **104** can be trained on the set of training data candidates **106**, the set of compressed training data points **502** can exhibit clusters that correspond to the output which the machine learning model **104** is configured to generate. For example, if the machine learning model **104** is configured to classify an inputted data candidate into one of m distinct classes, for any suitable positive integer m, the compressed training data points **502** can be arranged into m clusters. In various aspects, a cluster can be a collection and/or subset of compressed training data points that have similar elements as each other (e.g., if two training data candidates belong to the same class, the two compressed training data points that respectively correspond to those two training data candidates can have numerically similar elements and/or can otherwise be separated from each other by a relatively small Euclidean distance).

[0095] In various instances, for each cluster, the diversity component **120** can compute a center of that cluster. In various aspects, the center of a given cluster can be equal to the average of all the compressed training data points that belong to the given cluster. For example, if each compressed training data point is an n-element vector, then the center of a given cluster can be the average of all the n-element vectors that are in the set of compressed training data points **502** and that belong to the given cluster. So, if the set of compressed training data points **502** includes m clusters, the diversity component **120** can compute m centers (e.g., one center per cluster, and/or one average n-element vector per cluster).

[0096] In various aspects, for each cluster, the diversity component **120** can compute the Euclidean distance between the center of that cluster and every (and/or fewer than every) compressed training data point that belongs to that cluster. In various cases, the diversity component **120** can then compute the average of such Euclidean distances (denoted for convenience as μ) and/or the standard deviation of such Euclidean distances (denoted for convenience as σ) for each cluster. Accordingly, if the set of compressed training data points **502** includes m clusters, the diversity component **120** can compute m distinct μ values and/or m distinct o values (e.g., one (μ,σ) pair for each cluster, where the (μ,σ) pair for

a given cluster describes the density and/or spatial distribution of the compressed training data points in the given cluster).

[0097] In various instances, the diversity component **120** can assign each of the set of compressed test data points **504** to a corresponding cluster of the set of compressed training data points **502**. More specifically, for each compressed test data point, the diversity component **120** can compute the Euclidean distance between that compressed test data point and the center of each cluster of the set of compressed training data points **502**, and the diversity component **120** can assign that compressed test data point to the nearest and/or closest cluster. So, if the set of compressed training data points **502** includes m clusters, the diversity component **120** can determine which of those m clusters has a center that is nearest and/or closest (in terms of Euclidean distance) to a given compressed test data point, and the diversity component **120** can accordingly assign the given compressed test data point to that nearest and/or closest cluster.

[0098] In various instances, for each of the set of compressed test data points **504**, the diversity component **120** can determine whether that compressed test data point is an outlier or a non-outlier. In various cases, a given compressed test data point can be considered as an outlier if the Euclidean distance between the given compressed test data point and the center of the cluster to which the given compressed test data point is assigned is greater than a threshold Euclidean distance that corresponds to the cluster. Conversely, in various aspects, a given compressed test data point can be considered as a non-outlier if the Euclidean distance between the given compressed test data point and the center of the cluster to which the given compressed test data point is assigned is less than a threshold Euclidean distance that corresponds to the cluster. In various instances, the threshold Euclidean distance can vary by cluster. For example, the threshold Euclidean distance for a given cluster can be equal to $\mu+2\sigma$ (e.g., since μ and σ can vary by cluster, the threshold Euclidean distance can likewise vary by cluster). Thus, the diversity component **120** can label each of the set of compressed test data points **504** as either an outlier or a non-outlier.

[0099] In various aspects, the diversity component **120** can then compute the total proportion and/or percentage of the set of compressed test data points **504** that are considered as outliers. In various cases, such total proportion and/or percentage can be considered as equal to the diversity score **702**. In various other cases, the diversity score **702** can be any suitable mathematical function of such total proportion and/or percentage. In any case, the diversity score **702** can be configured such that a numerically higher magnitude of the diversity score **702** indicates that more of the set of compressed test data points **504** are outliers, which can indicate that the set of compressed test data points **504** does not conform neatly to the clusters of the set of compressed training data points **502**. This can mean that the machine learning model **104** is interpreting the patterns/distributions exhibited by the set of test data candidates **108** differently than how the machine learning model **104** is interpreting the patterns/distributions exhibited by the set of training data candidates **106**. Moreover, in any case, the diversity score **702** can be configured such that a numerically lower magnitude of the diversity score **702** indicates that more of the set of compressed test data points **504** are non-outliers, which can indicate that the set of compressed test data points **504** conforms more neatly to the clusters of the set of compressed training data points **502**. This can mean that the machine learning model **104** is interpreting the patterns/distributions exhibited by the set of test data candidates **108** similarly to how the machine learning model **104** is interpreting the patterns/distributions exhibited by the set of training data candidates **106**.

[0100] FIG. **8** illustrates a block diagram of an example, non-limiting system **800** including a graph that can facilitate visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein. As shown, the system **800** can, in some cases, comprise the same components as the system **700**, and can further comprise a graph **802**.

[0101] In various embodiments, the visualization component **122** can electronically render, on any suitable computer screen and/or monitor (not shown), the graph **802**, such that the graph **802** can be viewed by the operator of the machine learning model **104**. In various cases, the graph **802** can depict and/or illustrate the set of compressed training data points **502** and/or the set of compressed test data points **504**, if each of the set of compressed training data points **502** and/or each of the set of compressed test data points **504** is two-dimensional and/or three-dimensional (e.g., if n=2 and/or if n=3). In various aspects, how well and/or how poorly the set of compressed test data points **504** conforms to the clusters of the set of compressed training data points **502** can be easily visually perceived by viewing the graph **802**. In some cases, the graph **802** can further include the diversity score **702**. Accordingly, the operator of the machine learning model **104** can be visually apprised of the diversity score **702** and/or can visually see how well and/or how poorly the set of compressed test data points **504** conform to the clusters of the set of compressed training data points **502**. Therefore, the operator can leverage and/or rely on the diversity score **702** and/or on the graph **802** when making design decisions regarding the machine learning model **104** and/or the set of test data candidates **108**.

[0102] In various instances, the graph **802** can be interactable and/or clickable. For example, a compressed data point (e.g., either from **502** and/or **504**) that is plotted on the graph can be clickable, and the operator can leverage any suitable human-computer interface device (e.g., computer mouse, touchscreen, voice command) to click on the compressed data point. In various cases, the visualization component **122** can electronically render a data candidate (e.g., from either **106** and/or **108**) that corresponds to the compressed data point that is clicked, in response to the compressed data point being clicked. Thus, by selectively clicking different compressed data points that are plotted on the graph **802**, the operator of the machine learning model **104** can selectively manually inspect any data candidate as desired. Such functionality can further assist the operator in making design decisions regarding the machine learning model **104** and/or the set of test data candidates **108**.

[0103] In various embodiments, the execution component **124** can electronically transmit the diversity score **702** and/or the graph **802** to any suitable computing device (not shown). In various other embodiments, the execution component **124** can make recommendations to the operator based on the diversity score **702**. For example, if the operator desires to determine whether the machine learning model **104** can be trained on the set of test data candidates **108** without experiencing overfitting, the execution compo-

nent **124** can compare the diversity score **702** to any suitable threshold and can make a recommendation accordingly. If the diversity score **702** is above the threshold, the execution component **124** can determine that the machine learning model **104** is interpreting the set of test data candidates **108** sufficiently differently from the set of training data candidates **106**, such that the machine learning model **104** can be trained on the set of test data candidates **108** without risking overfitting. On the other hand, if the diversity score **702** is below the threshold, the execution component **124** can determine that the machine learning model **104** is interpreting the set of test data candidates **108** insufficiently differently from the set of training data candidates **106**, such that the machine learning model **104** cannot be trained on the set of test data candidates **108** without risking overfitting.

[0104] As another example, if the operator desires to determine whether the machine learning model **104** can be accurately deployed in a field and/or environment associated with the set of test data candidates **108**, the execution component **124** can compare the diversity score to any suitable threshold and can make a recommendation accordingly. If the diversity score **702** is below the threshold, the execution component **124** can determine that the machine learning model **104** is interpreting the set of test data candidates **108** sufficiently similarly to the set of training data candidates **106**, such that the machine learning model **104** can be deployed in the field and/or environment without risking frequently inaccurate performance. On the other hand, if the diversity score **702** is above the threshold, the execution component **124** can determine that the machine learning model **104** is interpreting the set of test data candidates **108** insufficiently similarly to the set of training data candidates **106**, such that the machine learning model **104** cannot be deployed in the field and/or environment without risking frequently inaccurate performance.

[0105] As yet another example, if the set of test data candidates **108** is created by modifying the set of training data candidates **106** via an augmentation strategy, and if the operator desires to determine whether such augmentation strategy helps to improve the generalizability of the machine learning model **104**, the execution component **124** can compare the diversity score to any suitable threshold and can make a recommendation accordingly. If the diversity score **702** is above the threshold, the execution component **124** can determine that the machine learning model **104** is interpreting the set of test data candidates **108** sufficiently differently from the set of training data candidates **106**, such that the augmentation strategy is filling in the learning gaps of the machine learning model **104**. On the other hand, if the diversity score **702** is below the threshold, the execution component **124** can determine that the machine learning model **104** is interpreting the set of test data candidates **108** insufficiently differently from the set of training data candidates **106**, such that the augmentation strategy is not filling in the learning gaps of the machine learning model **104**.

[0106] As still another example, if the set of test data candidates **108** is unannotated, and if the operator desires to determine whether automatic annotation can be accurately applied to the set of test data candidates **108**, the execution component **124** can compare the diversity score to any suitable threshold and can make a recommendation accordingly. If the diversity score **702** is below the threshold, the execution component **124** can determine that the machine learning model **104** is interpreting the set of test data candidates **108** sufficiently similarly to the set of training data candidates **106**, such that an automatic annotation technique can be accurately applied to the set of test data candidates **108**. On the other hand, if the diversity score **702** is above the threshold, the execution component **124** can determine that the machine learning model **104** is interpreting the set of test data candidates **108** insufficiently similarly to the set of training data candidates **106**, such that an automatic annotation technique cannot be accurately applied to the set of test data candidates **108**. On still another hand, because the diversity component **120** can have labeled each of the set of compressed test data points **504** as either an outlier or a non-outlier, the execution component **124** can recommend that an automatic annotation technique be applied to a compressed test data candidate that corresponds to a non-outlier, and/or can recommend that a manual annotation technique be applied to a compressed test data candidate that corresponds to an outlier.

[0107] FIGS. **9-11** illustrate example, non-limiting graphs **900-1100** of compressed data points, in accordance with one or more embodiments described herein. In other words, FIGS. **9-11** show example visualizations that can be rendered by the visualization component **122**.

[0108] In the non-limiting examples of FIGS. **9-11**, the machine learning model **104** was configured to classify an X-ray image of a patient's knee into one of five distinct classes: Tibia, Femoral, Sagittal Relevant, Coronal Relevant, or Irrelevant. Moreover, the set of training data candidates comprised 500 X-ray images in total: specifically, 100 X-ray images per class, where the machine learning model **104** had been trained on such images. Furthermore, the set of test data candidates **108** comprised 500 X-ray images that were randomly selected from a new data source (e.g., from a different hospital, from the same hospital but from a different X-ray scanner) as compared to the set of training data candidates **106**. The set of compressed training data points **502** and the set of compressed test data points **504** were then generated as described herein, using t-SNE as the dimensionality reduction technique, and where each compressed data point was a two-element vector. The graphs **900-1100** were then plotted.

[0109] The set of training data candidates **106** is the same across FIGS. **9-11**. However, the set of test data candidates **108** varies across FIGS. **9-11**, so that different levels of diversity can be seen. Because t-SNE is non-parametric, the absolute location of each compressed training data point is not fixed across FIGS. **9-11**, but the relative distances between the compressed training data points is maintained.

[0110] In FIG. **9**, the set of compressed training data points **502** is illustrated in red, and the set of compressed test data points **504** is illustrated in green. As shown, the set of compressed training data points **502** are grouped into five distinct clusters **902-910**, which correspond to the five distinct classes (e.g., Tibia, Femoral, Sagittal Relevant, Coronal Relevant, Irrelevant). As can be easily seen, the graph **900** shows a non-limiting example where the set of compressed test data points **504** nicely fit into and/or otherwise conform to the clusters of the set of compressed training data points **502**. In other words, the green dots in FIG. **9** are all located very close to the red dot clusters. Accordingly, the diversity score **702** that corresponds to the graph **900** can be small in magnitude. Based on the graph **900**, the operator can determine that the machine learning model **104** can be accurately deployed on the set of test data

candidates **108**, that the machine learning model **104** cannot be trained on the set of test data candidates **108** without overfitting, and/or that automatic annotation can be accurately applied to the set of test data candidates **108**.

[0111] In FIG. **10**, the set of compressed training data points **502** is illustrated in red, and the set of compressed test data points **504** is illustrated in green. As shown, the set of compressed training data points **502** are again grouped into five distinct clusters **1002-1010**, which correspond to the five distinct classes (e.g., Tibia, Femoral, Sagittal Relevant, Coronal Relevant, Irrelevant). As can be seen, the graph **1000** shows a non-limiting example where the set of compressed test data points **504** fit somewhat into and/or otherwise somewhat conform to the clusters of the set of compressed training data points **502**. In other words, some of the green dots in FIG. **10** are located close to the red dot clusters, while other of the green dots are not located close to the red dot clusters. Accordingly, the diversity score **702** that corresponds to the graph **1000** can be intermediate in magnitude.

[0112] In FIG. **11**, the set of compressed training data points **502** is illustrated in red, and the set of compressed test data points **504** is illustrated in green. As shown, the set of compressed training data points **502** are grouped into five distinct clusters **902-910**, which correspond to the five distinct classes (e.g., Tibia, Femoral, Sagittal Relevant, Coronal Relevant, Irrelevant). As can be easily seen, the graph **1100** shows a non-limiting example where the set of compressed test data points **504** do not nicely fit into and/or otherwise conform to the clusters of the set of compressed training data points **502**. In other words, the green dots in FIG. **11** are mostly located away from the red dot clusters. Accordingly, the diversity score **702** that corresponds to the graph **1100** can be large in magnitude. Based on the graph **1100**, the operator can determine that the machine learning model **104** likely cannot be accurately deployed on the set of test data candidates **108**, that the machine learning model **104** can be trained on the set of test data candidates **108** without overfitting, and/or that automatic annotation cannot be accurately applied to the set of test data candidates **108**.

[0113] FIGS. **12-15** illustrate flow diagrams of example, non-limiting computer-implemented methods **1200-1500** pertaining to quantification of data diversity for machine learning models in accordance with one or more embodiments described herein. In other words, FIGS. **12-15** collectively illustrate example and non-limiting operations/actions which the data diversity system **102** can facilitate in various embodiments.

[0114] First, consider the computer-implemented method **1200**, which illustrates how the data diversity system **102** can generate the set of compressed training data points **502** based on the set of training data candidates **106**.

[0115] In various embodiments, act **1202** can include receiving, by a device (e.g., **114**) operatively coupled to a processor, a set of training data candidates (e.g., **106**) on which a neural network (e.g., **104**) has been trained.

[0116] In various aspects, act **1204** can include initializing, by the device (e.g., **116**) an empty set of training activation maps (e.g., **202**).

[0117] In various instances, act **1206** can include determining, by the device (e.g., **116**), whether each training data candidate in the set of training data candidates has been analyzed by the device. If not, the computer-implemented method **1200** can proceed to act **1208**. If so, the computer-implemented method **1200** can proceed to act **1216**.

[0118] In various cases, act **1208** can include selecting, by the device (e.g., **116**), a training data candidate from the set of training data candidates that has not yet been analyzed.

[0119] In various aspects, act **1210** can include feeding, by the device (e.g., **116**), the selected training data candidate as input to the neural network.

[0120] In various instances, act **1212** can include extracting, by the device (e.g., **116**) and from the neural network, a hidden activation map that is generated by a hidden layer of the neural network based on and/or in response to the selected training data candidate.

[0121] In various cases, act **1214** can include inserting, by the device (e.g., **116**), the extracted hidden activation map into the set of training activation maps. In various aspects, the computer-implemented method **1200** can proceed back to act **1206**.

[0122] As shown, the computer-implemented method **1200** can iterate through acts **1206-1214** until every training data candidate has been analyzed (e.g., until a hidden activation map has been inserted into the set of training activation maps for each training data candidate). At this point, the computer-implemented method **1200** can proceed to act **1216**.

[0123] In various instances, act **1216** can include executing, by the device (e.g., **118**), a dimensionality reduction technique (e.g., t-SNE, UMAP) on the set of training activation maps, thereby converting the set of training activation maps into a set of compressed training data points (e.g., **502**). In other words, each training activation map can now be represented by a low-dimensional data point that is easier to visualize and/or mathematically manipulate.

[0124] Next, consider the computer-implemented method **1300**, which illustrates how the data diversity system **102** can generate the set of compressed test data points **504** based on the set of test data candidates **108**.

[0125] In various embodiments, act **1302** can include receiving, by the device (e.g., **114**), a set of test data candidates (e.g., **108**).

[0126] In various aspects, act **1304** can include initializing, by the device (e.g., **116**) an empty set of test activation maps (e.g., **204**).

[0127] In various instances, act **1306** can include determining, by the device (e.g., **116**), whether each test data candidate in the set of test data candidates has been analyzed by the device. If not, the computer-implemented method **1300** can proceed to act **1308**. If so, the computer-implemented method **1300** can proceed to act **1316**.

[0128] In various cases, act **1308** can include selecting, by the device (e.g., **116**), a test data candidate from the set of test data candidates that has not yet been analyzed.

[0129] In various aspects, act **1310** can include feeding, by the device (e.g., **116**), the selected test data candidate as input to the neural network.

[0130] In various instances, act **1312** can include extracting, by the device (e.g., **116**) and from the neural network, a hidden activation map that is generated by a hidden layer of the neural network based on and/or in response to the selected test data candidate.

[0131] In various cases, act **1314** can include inserting, by the device (e.g., **116**), the extracted hidden activation map

into the set of test activation maps. In various aspects, the computer-implemented method **1300** can proceed back to act **1306**.

[0132] As shown, the computer-implemented method **1300** can iterate through acts **1306-1314** until every test data candidate has been analyzed (e.g., until a hidden activation map has been inserted into the set of test activation maps for each test data candidate). At this point, the computer-implemented method **1300** can proceed to act **1316**.

[0133] In various instances, act **1316** can include executing, by the device (e.g., **118**), the dimensionality reduction technique (e.g., t-SNE, UMAP) on the set of test activation maps, thereby converting the set of test activation maps into a set of compressed test data points (e.g., **504**). In other words, each test activation map can now be represented by a low-dimensional data point that is easier to visualize and/or mathematically manipulate.

[0134] Now, consider the computer-implemented method **1400**, which illustrates how the data diversity system **102** can analyze the set of compressed training data points **502**.

[0135] In various embodiments, act **1402** can include identifying, by the device (e.g., **120**), known clusters exhibited by the set of compressed training data points (e.g., **502**). In some cases, because the set of compressed training data points can be derived from the set of training data candidates, and because the neural network can be trained on the set of training data candidates, the set of compressed training data points can exhibit clusters that correspond to the output which the neural network is configured to generate. For example, if the neural network is configured to classify and/or label an inputted data candidate as belonging to one of m classes, for any suitable positive integer m, then the set of compressed training data points can exhibit an m-cluster arrangement (e.g., can have m clusters).

[0136] In various aspects, act **1404** can include determining, by the device (e.g., **120**), whether each cluster of the set of compressed training data points has been analyzed yet. If not, the computer-implemented method **1400** can proceed to act **1406**. If so, the computer-implemented method **1400** can proceed to act **1502** of the computer-implemented method **1500**.

[0137] In various instances, act **1406** can include selecting, by the device (e.g., **120**), a cluster of the set of compressed training data points that has not yet been analyzed.

[0138] In various cases, act **1408** can include computing, by the device (e.g., **120**), the center of the selected cluster. For example, the center of a given cluster of compressed training data points can be equal to the average of all the compressed training data points that belong to that given cluster.

[0139] In various aspects, act **1410** can include, for each compressed training data point that belongs to the selected cluster, computing, by the device (e.g., **120**), the Euclidean distance between the compressed training data point and the center of the selected cluster. When this is performed for each compressed training data point that belongs to the selected cluster, this is can result in a set of Euclidean distances that are associated with the selected cluster.

[0140] In various instances, act **1412** can include computing, by the device (e.g., **120**), an average distance value for the selected cluster, which average distance value can be denoted as u, based on the set of Euclidean distances associated with the selected cluster.

[0141] In various cases, act **1414** can include computing, by the device (e.g., **120**), a standard deviation distance value for the selected cluster, which standard deviation distance value can be denoted as o, based on the set of Euclidean distances associated with the selected cluster. In various aspects, the computer-implemented method **1400** can proceed back to act **1404**.

[0142] As shown, the computer-implemented method **1400** can iterate through acts **1404-1414**, until a μ and a σ are computed for each cluster of compressed training data points.

[0143] Finally, consider the computer-implemented method **1500**, which illustrates how the data diversity system **102** can analyze the set of compressed test data points **504**.

[0144] In various embodiments, act **1502** can include determining, by the device (e.g., **120**), whether each compress test data point in the set of compressed test data points (e.g., **504**) has been analyzed. If not, the computer-implemented method **1500** can proceed to act **1504**. If so, the computer-implemented method **1500** can proceed to act **1514**.

[0145] In various aspects, act **1504** can include selecting, by the device (e.g., **120**), a compressed test data point from the set of compressed test data points that has not yet been analyzed.

[0146] In various instances, act **1506** can include computing, by the device (e.g., **120**), the Euclidean distance between the selected compressed test data point and the nearest cluster of compressed training data points (e.g., the cluster whose center is closest and/or nearest in terms of Euclidean distance to the selected compressed test data point).

[0147] In various cases, act **1508** can include determining, by the device (e.g., **120**), whether the computed Euclidean distance is greater than a threshold of $\mu+2\sigma$ for the nearest cluster (e.g., where u and o correspond to the nearest cluster). In other words, the device can determine whether the selected compressed test data point is more than two standard deviations away from the center of the nearest cluster. If so, the computer-implemented method **1500** can proceed to act **1510**. If not, the computer-implemented method **1500** can proceed to act **1512**.

[0148] In various aspects, act **1510** can include labeling, by the device (e.g., **120**), the selected compressed test data point as an outlier. In various cases, the computer-implemented method **1500** can proceed back to act **1502**.

[0149] In various aspects, act **1512** can include labeling, by the device (e.g., **120**), the selected compressed test data point as a non-outlier. In various cases, the computer-implemented method **1500** can proceed back to act **1502**.

[0150] As shown, the computer-implemented method **1500** can iterate through acts **1502-1512** until each compressed test data point has been labeled as either an outlier or a non-outlier. At such time, the computer-implemented method **1500** can proceed to act **1514**.

[0151] In various instances, act **1514** can include computing, by the device (e.g., **120**), the percentage of the set of compressed test data points that are labeled as outliers. In various cases, this percentage can be considered as the diversity score **702**. In other cases, the diversity score **702** can be equal to any suitable mathematical function of this percentage. Although not explicitly shown in FIG. **15**, the percentage of the set of compressed test data points that are

considered as outliers can indicate how similar and/or how dissimilar the set of test data candidates are from the set of training data candidates. Accordingly, as mentioned above, the execution component **124** can take any suitable computing action based on the value of this percentage.

[0152] FIG. **16** illustrates a flow diagram of an example, non-limiting computer-implemented method **1600** that can facilitate visualization and/or quantification of data diversity for machine learning models in accordance with one or more embodiments described herein. In various cases, the computer-implemented method **1600** can be implemented by the data diversity system **102**.

[0153] In various embodiments, act **1602** can include accessing, by a device (e.g., **114**) operatively coupled to a processor, a first set of data candidates (e.g., **106**) and a second set of data candidates (e.g., **108**), wherein a machine learning model (e.g., **104**) is trained on the first set of data candidates.

[0154] In various instances, act **1604** can include obtaining, by the device (e.g., **116**), a first set of latent activations (e.g., **202**) generated by the machine learning model based on the first set of data candidates, and obtaining, by the device (e.g., **116**), a second set of latent activations (e.g., **204**) generated by the machine learning model based on the second set of data candidates.

[0155] In various aspects, act **1606** can include generating, by the device (e.g., **118**), a first set of compressed data points (e.g., **502**) by applying a dimensionality reduction technique to the first set of latent activations, and generating, by the device (e.g., **118**), a second set of compressed data points (e.g., **504**) by applying the dimensionality reduction technique to the second set of latent activations.

[0156] In various instances, act **1608** can include computing, by the device (e.g., **120**), a diversity score (e.g., **702**) based on the first set of compressed data points and the second set of compressed data points.

[0157] In various aspects, act **1610** can include rendering, by the device (e.g., **122**), a graph (e.g., **802**) depicting the first set of compressed data points and the second set of compressed data points.

[0158] Although not explicitly shown in FIG. **16**, a given compressed data point that is plotted in the graph can correspond to a given data candidate from the first set of data candidates or the second set of data candidates, the given compressed data point can be clickable as plotted on the graph, and/or the computer-implemented method **1600** can further comprise: rendering, by the device (e.g., **122**), the given data candidate in response to the given compressed data point being clicked.

[0159] Although not explicitly shown in FIG. **16**, the second set of data candidates can represent augmented versions of the first set of data candidates and/or can otherwise represent potential training data for the machine learning model, and the computer-implemented method **1600** can further comprise: recommending, by the device (e.g., **124**), that the machine learning model be trained on the second set of data candidates in response to a determination that the diversity score satisfies a predetermined threshold; and recommending, by the device (e.g., **124**), that the machine learning model not be trained on the second set of data candidates in response to a determination that the diversity score fails to satisfy the predetermined threshold.

[0160] Although not explicitly shown in FIG. **16**, the second set of data candidates can be unannotated, and the computer-implemented method **1600** can further comprise: identifying, by the device (e.g., **120**), one or more outlying compressed data points in the second set of compressed data points, by comparing the second set of compressed data points to the first set of compressed data points; and recommending, by the device (e.g., **124**), that one or more data candidates from the second set of data candidates which correspond to the one or more outlying compressed data points be manually annotated.

[0161] Although not explicitly shown in FIG. **16**, the second set of data candidates can be unannotated, and the computer-implemented method **1600** can further comprise: identifying, by the device (e.g., **120**), one or more non-outlying compressed data points in the second set of compressed data points, by comparing the second set of compressed data points to the first set of compressed data points; and recommending, by the device (e.g., **124**), that one or more data candidates from the second set of data candidates which correspond to the one or more non-outlying compressed data points be automatically annotated.

[0162] Various embodiments of the subject innovation pertain to a computerized tool that can automatically visualize and/or quantify diversity in input data for artificial intelligence applications. Such a computerized tool can be used for selecting new data candidates from a data lake, deciding on an augmentation strategy to implement, and/or determining which unannotated data candidates can be annotated/curated automatically. Indeed, choosing appropriate data candidates on which to train a machine learning model is important to help avoid overfitting and/or to help improve model generalizability. Moreover, choosing an appropriate data augmentation strategy can likewise be important to help avoid overfitting and/or to help improve model generalizability. Furthermore, because manual annotation is very cumbersome and time consuming, choosing appropriate data candidates for automatic annotation (e.g., semi-supervised annotation via an existing model, transfer learning) can be important to help save time and/or resources. Because the computerized tool described herein can assist a model developer in making these and/or other decisions regarding model design, the computerized tool described herein certainly constitutes a useful and practical application of computers.

[0163] In order to provide additional context for various embodiments described herein, FIG. **17** and the following discussion are intended to provide a brief, general description of a suitable computing environment **1700** in which the various embodiments of the embodiment described herein can be implemented. While the embodiments have been described above in the general context of computer-executable instructions that can run on one or more computers, those skilled in the art will recognize that the embodiments can be also implemented in combination with other program modules and/or as a combination of hardware and software.

[0164] Generally, program modules include routines, programs, components, data structures, etc., that perform particular tasks or implement particular abstract data types. Moreover, those skilled in the art will appreciate that the inventive methods can be practiced with other computer system configurations, including single-processor or multiprocessor computer systems, minicomputers, mainframe computers, Internet of Things (IoT) devices, distributed computing systems, as well as personal computers, handheld computing devices, microprocessor-based or program-

mable consumer electronics, and the like, each of which can be operatively coupled to one or more associated devices.

[0165] The illustrated embodiments of the embodiments herein can be also practiced in distributed computing environments where certain tasks are performed by remote processing devices that are linked through a communications network. In a distributed computing environment, program modules can be located in both local and remote memory storage devices.

[0166] Computing devices typically include a variety of media, which can include computer-readable storage media, machine-readable storage media, and/or communications media, which two terms are used herein differently from one another as follows. Computer-readable storage media or machine-readable storage media can be any available storage media that can be accessed by the computer and includes both volatile and nonvolatile media, removable and non-removable media. By way of example, and not limitation, computer-readable storage media or machine-readable storage media can be implemented in connection with any method or technology for storage of information such as computer-readable or machine-readable instructions, program modules, structured data or unstructured data.

[0167] Computer-readable storage media can include, but are not limited to, random access memory (RAM), read only memory (ROM), electrically erasable programmable read only memory (EEPROM), flash memory or other memory technology, compact disk read only memory (CD ROM), digital versatile disk (DVD), Blu-ray disc (BD) or other optical disk storage, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, solid state drives or other solid state storage devices, or other tangible and/or non-transitory media which can be used to store desired information. In this regard, the terms "tangible" or "non-transitory" herein as applied to storage, memory or computer-readable media, are to be understood to exclude only propagating transitory signals per se as modifiers and do not relinquish rights to all standard storage, memory or computer-readable media that are not only propagating transitory signals per se.

[0168] Computer-readable storage media can be accessed by one or more local or remote computing devices, e.g., via access requests, queries or other data retrieval protocols, for a variety of operations with respect to the information stored by the medium.

[0169] Communications media typically embody computer-readable instructions, data structures, program modules or other structured or unstructured data in a data signal such as a modulated data signal, e.g., a carrier wave or other transport mechanism, and includes any information delivery or transport media. The term "modulated data signal" or signals refers to a signal that has one or more of its characteristics set or changed in such a manner as to encode information in one or more signals. By way of example, and not limitation, communication media include wired media, such as a wired network or direct-wired connection, and wireless media such as acoustic, RF, infrared and other wireless media.

[0170] With reference again to FIG. **17**, the example environment **1700** for implementing various embodiments of the aspects described herein includes a computer **1702**, the computer **1702** including a processing unit **1704**, a system memory **1706** and a system bus **1708**. The system bus **1708** couples system components including, but not limited to, the system memory **1706** to the processing unit **1704**. The processing unit **1704** can be any of various commercially available processors. Dual microprocessors and other multi processor architectures can also be employed as the processing unit **1704**.

[0171] The system bus **1708** can be any of several types of bus structure that can further interconnect to a memory bus (with or without a memory controller), a peripheral bus, and a local bus using any of a variety of commercially available bus architectures. The system memory **1706** includes ROM **1710** and RAM **1712**. A basic input/output system (BIOS) can be stored in a non-volatile memory such as ROM, erasable programmable read only memory (EPROM), EEPROM, which BIOS contains the basic routines that help to transfer information between elements within the computer **1702**, such as during startup. The RAM **1712** can also include a high-speed RAM such as static RAM for caching data.

[0172] The computer **1702** further includes an internal hard disk drive (HDD) **1714** (e.g., EIDE, SATA), one or more external storage devices **1716** (e.g., a magnetic floppy disk drive (FDD) **1716**, a memory stick or flash drive reader, a memory card reader, etc.) and a drive **1720**, e.g., such as a solid state drive, an optical disk drive, which can read or write from a disk **1722**, such as a CD-ROM disc, a DVD, a BD, etc. Alternatively, where a solid state drive is involved, disk **1722** would not be included, unless separate. While the internal HDD **1714** is illustrated as located within the computer **1702**, the internal HDD **1714** can also be configured for external use in a suitable chassis (not shown). Additionally, while not shown in environment **1700**, a solid state drive (SSD) could be used in addition to, or in place of, an HDD **1714**. The HDD **1714**, external storage device(s) **1716** and drive **1720** can be connected to the system bus **1708** by an HDD interface **1724**, an external storage interface **1726** and a drive interface **1728**, respectively. The interface **1724** for external drive implementations can include at least one or both of Universal Serial Bus (USB) and Institute of Electrical and Electronics Engineers (IEEE) 1394 interface technologies. Other external drive connection technologies are within contemplation of the embodiments described herein.

[0173] The drives and their associated computer-readable storage media provide nonvolatile storage of data, data structures, computer-executable instructions, and so forth. For the computer **1702**, the drives and storage media accommodate the storage of any data in a suitable digital format. Although the description of computer-readable storage media above refers to respective types of storage devices, it should be appreciated by those skilled in the art that other types of storage media which are readable by a computer, whether presently existing or developed in the future, could also be used in the example operating environment, and further, that any such storage media can contain computer-executable instructions for performing the methods described herein.

[0174] A number of program modules can be stored in the drives and RAM **1712**, including an operating system **1730**, one or more application programs **1732**, other program modules **1734** and program data **1736**. All or portions of the operating system, applications, modules, and/or data can also be cached in the RAM **1712**. The systems and methods

described herein can be implemented utilizing various commercially available operating systems or combinations of operating systems.

[0175] Computer **1702** can optionally comprise emulation technologies. For example, a hypervisor (not shown) or other intermediary can emulate a hardware environment for operating system **1730**, and the emulated hardware can optionally be different from the hardware illustrated in FIG. **17**. In such an embodiment, operating system **1730** can comprise one virtual machine (VM) of multiple VMs hosted at computer **1702**. Furthermore, operating system **1730** can provide runtime environments, such as the Java runtime environment or the .NET framework, for applications **1732**. Runtime environments are consistent execution environments that allow applications **1732** to run on any operating system that includes the runtime environment. Similarly, operating system **1730** can support containers, and applications **1732** can be in the form of containers, which are lightweight, standalone, executable packages of software that include, e.g., code, runtime, system tools, system libraries and settings for an application.

[0176] Further, computer **1702** can be enable with a security module, such as a trusted processing module (TPM). For instance with a TPM, boot components hash next in time boot components, and wait for a match of results to secured values, before loading a next boot component. This process can take place at any layer in the code execution stack of computer **1702**, e.g., applied at the application execution level or at the operating system (OS) kernel level, thereby enabling security at any level of code execution.

[0177] A user can enter commands and information into the computer **1702** through one or more wired/wireless input devices, e.g., a keyboard **1738**, a touch screen **1740**, and a pointing device, such as a mouse **1742**. Other input devices (not shown) can include a microphone, an infrared (IR) remote control, a radio frequency (RF) remote control, or other remote control, a joystick, a virtual reality controller and/or virtual reality headset, a game pad, a stylus pen, an image input device, e.g., camera(s), a gesture sensor input device, a vision movement sensor input device, an emotion or facial detection device, a biometric input device, e.g., fingerprint or iris scanner, or the like. These and other input devices are often connected to the processing unit **1704** through an input device interface **1744** that can be coupled to the system bus **1708**, but can be connected by other interfaces, such as a parallel port, an IEEE 1394 serial port, a game port, a USB port, an IR interface, a BLUETOOTH® interface, etc.

[0178] A monitor **1746** or other type of display device can be also connected to the system bus **1708** via an interface, such as a video adapter **1748**. In addition to the monitor **1746**, a computer typically includes other peripheral output devices (not shown), such as speakers, printers, etc.

[0179] The computer **1702** can operate in a networked environment using logical connections via wired and/or wireless communications to one or more remote computers, such as a remote computer(s) **1750**. The remote computer(s) **1750** can be a workstation, a server computer, a router, a personal computer, portable computer, microprocessor-based entertainment appliance, a peer device or other common network node, and typically includes many or all of the elements described relative to the computer **1702**, although, for purposes of brevity, only a memory/storage device **1752** is illustrated. The logical connections depicted include wired/wireless connectivity to a local area network (LAN) **1754** and/or larger networks, e.g., a wide area network (WAN) **1756**. Such LAN and WAN networking environments are commonplace in offices and companies, and facilitate enterprise-wide computer networks, such as intranets, all of which can connect to a global communications network, e.g., the Internet.

[0180] When used in a LAN networking environment, the computer **1702** can be connected to the local network **1754** through a wired and/or wireless communication network interface or adapter **1758**. The adapter **1758** can facilitate wired or wireless communication to the LAN **1754**, which can also include a wireless access point (AP) disposed thereon for communicating with the adapter **1758** in a wireless mode.

[0181] When used in a WAN networking environment, the computer **1702** can include a modem **1760** or can be connected to a communications server on the WAN **1756** via other means for establishing communications over the WAN **1756**, such as by way of the Internet. The modem **1760**, which can be internal or external and a wired or wireless device, can be connected to the system bus **1708** via the input device interface **1744**. In a networked environment, program modules depicted relative to the computer **1702** or portions thereof, can be stored in the remote memory/storage device **1752**. It will be appreciated that the network connections shown are example and other means of establishing a communications link between the computers can be used.

[0182] When used in either a LAN or WAN networking environment, the computer **1702** can access cloud storage systems or other network-based storage systems in addition to, or in place of, external storage devices **1716** as described above, such as but not limited to a network virtual machine providing one or more aspects of storage or processing of information. Generally, a connection between the computer **1702** and a cloud storage system can be established over a LAN **1754** or WAN **1756** e.g., by the adapter **1758** or modem **1760**, respectively. Upon connecting the computer **1702** to an associated cloud storage system, the external storage interface **1726** can, with the aid of the adapter **1758** and/or modem **1760**, manage storage provided by the cloud storage system as it would other types of external storage. For instance, the external storage interface **1726** can be configured to provide access to cloud storage sources as if those sources were physically connected to the computer **1702**.

[0183] The computer **1702** can be operable to communicate with any wireless devices or entities operatively disposed in wireless communication, e.g., a printer, scanner, desktop and/or portable computer, portable data assistant, communications satellite, any piece of equipment or location associated with a wirelessly detectable tag (e.g., a kiosk, news stand, store shelf, etc.), and telephone. This can include Wireless Fidelity (Wi-Fi) and BLUETOOTH® wireless technologies. Thus, the communication can be a predefined structure as with a conventional network or simply an ad hoc communication between at least two devices.

[0184] FIG. **18** is a schematic block diagram of a sample computing environment **1800** with which the disclosed subject matter can interact. The sample computing environment **1800** includes one or more client(s) **1810**. The client(s) **1810** can be hardware and/or software (e.g., threads, processes, computing devices). The sample computing environ-

ment **1800** also includes one or more server(s) **1830**. The server(s) **1830** can also be hardware and/or software (e.g., threads, processes, computing devices). The servers **1830** can house threads to perform transformations by employing one or more embodiments as described herein, for example. One possible communication between a client **1810** and a server **1830** can be in the form of a data packet adapted to be transmitted between two or more computer processes. The sample computing environment **1800** includes a communication framework **1850** that can be employed to facilitate communications between the client(s) **1810** and the server(s) **1830**. The client(s) **1810** are operably connected to one or more client data store(s) **1820** that can be employed to store information local to the client(s) **1810**. Similarly, the server(s) **1830** are operably connected to one or more server data store(s) **1840** that can be employed to store information local to the servers **1830**.

[0185] The present invention may be a system, a method, an apparatus and/or a computer program product at any possible technical detail level of integration. The computer program product can include a computer readable storage medium (or media) having computer readable program instructions thereon for causing a processor to carry out aspects of the present invention. The computer readable storage medium can be a tangible device that can retain and store instructions for use by an instruction execution device. The computer readable storage medium can be, for example, but is not limited to, an electronic storage device, a magnetic storage device, an optical storage device, an electromagnetic storage device, a semiconductor storage device, or any suitable combination of the foregoing. A non-exhaustive list of more specific examples of the computer readable storage medium can also include the following: a portable computer diskette, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), a static random access memory (SRAM), a portable compact disc read-only memory (CD-ROM), a digital versatile disk (DVD), a memory stick, a floppy disk, a mechanically encoded device such as punch-cards or raised structures in a groove having instructions recorded thereon, and any suitable combination of the foregoing. A computer readable storage medium, as used herein, is not to be construed as being transitory signals per se, such as radio waves or other freely propagating electromagnetic waves, electromagnetic waves propagating through a waveguide or other transmission media (e.g., light pulses passing through a fiber-optic cable), or electrical signals transmitted through a wire.

[0186] Computer readable program instructions described herein can be downloaded to respective computing/processing devices from a computer readable storage medium or to an external computer or external storage device via a network, for example, the Internet, a local area network, a wide area network and/or a wireless network. The network can comprise copper transmission cables, optical transmission fibers, wireless transmission, routers, firewalls, switches, gateway computers and/or edge servers. A network adapter card or network interface in each computing/processing device receives computer readable program instructions from the network and forwards the computer readable program instructions for storage in a computer readable storage medium within the respective computing/processing device. Computer readable program instructions for carrying out operations of the present invention can be assembler instructions, instruction-set-architecture (ISA) instructions, machine instructions, machine dependent instructions, microcode, firmware instructions, state-setting data, configuration data for integrated circuitry, or either source code or object code written in any combination of one or more programming languages, including an object oriented programming language such as Smalltalk, C++, or the like, and procedural programming languages, such as the "C" programming language or similar programming languages. The computer readable program instructions can execute entirely on the user's computer, partly on the user's computer, as a stand-alone software package, partly on the user's computer and partly on a remote computer or entirely on the remote computer or server. In the latter scenario, the remote computer can be connected to the user's computer through any type of network, including a local area network (LAN) or a wide area network (WAN), or the connection can be made to an external computer (for example, through the Internet using an Internet Service Provider). In some embodiments, electronic circuitry including, for example, programmable logic circuitry, field-programmable gate arrays (FPGA), or programmable logic arrays (PLA) can execute the computer readable program instructions by utilizing state information of the computer readable program instructions to personalize the electronic circuitry, in order to perform aspects of the present invention.

[0187] Aspects of the present invention are described herein with reference to flowchart illustrations and/or block diagrams of methods, apparatus (systems), and computer program products according to embodiments of the invention. It will be understood that each block of the flowchart illustrations and/or block diagrams, and combinations of blocks in the flowchart illustrations and/or block diagrams, can be implemented by computer readable program instructions. These computer readable program instructions can be provided to a processor of a general purpose computer, special purpose computer, or other programmable data processing apparatus to produce a machine, such that the instructions, which execute via the processor of the computer or other programmable data processing apparatus, create means for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks. These computer readable program instructions can also be stored in a computer readable storage medium that can direct a computer, a programmable data processing apparatus, and/or other devices to function in a particular manner, such that the computer readable storage medium having instructions stored therein comprises an article of manufacture including instructions which implement aspects of the function/act specified in the flowchart and/or block diagram block or blocks. The computer readable program instructions can also be loaded onto a computer, other programmable data processing apparatus, or other device to cause a series of operational acts to be performed on the computer, other programmable apparatus or other device to produce a computer implemented process, such that the instructions which execute on the computer, other programmable apparatus, or other device implement the functions/acts specified in the flowchart and/or block diagram block or blocks.

[0188] The flowcharts and block diagrams in the Figures illustrate the architecture, functionality, and operation of possible implementations of systems, methods, and computer program products according to various embodiments of the present invention. In this regard, each block in the

flowchart or block diagrams can represent a module, segment, or portion of instructions, which comprises one or more executable instructions for implementing the specified logical function(s). In some alternative implementations, the functions noted in the blocks can occur out of the order noted in the Figures. For example, two blocks shown in succession can, in fact, be executed substantially concurrently, or the blocks can sometimes be executed in the reverse order, depending upon the functionality involved. It will also be noted that each block of the block diagrams and/or flowchart illustration, and combinations of blocks in the block diagrams and/or flowchart illustration, can be implemented by special purpose hardware-based systems that perform the specified functions or acts or carry out combinations of special purpose hardware and computer instructions.

[0189] While the subject matter has been described above in the general context of computer-executable instructions of a computer program product that runs on a computer and/or computers, those skilled in the art will recognize that this disclosure also can or can be implemented in combination with other program modules. Generally, program modules include routines, programs, components, data structures, etc. that perform particular tasks and/or implement particular abstract data types. Moreover, those skilled in the art will appreciate that the inventive computer-implemented methods can be practiced with other computer system configurations, including single-processor or multiprocessor computer systems, mini-computing devices, mainframe computers, as well as computers, hand-held computing devices (e.g., PDA, phone), microprocessor-based or programmable consumer or industrial electronics, and the like. The illustrated aspects can also be practiced in distributed computing environments in which tasks are performed by remote processing devices that are linked through a communications network. However, some, if not all aspects of this disclosure can be practiced on stand-alone computers. In a distributed computing environment, program modules can be located in both local and remote memory storage devices.

[0190] As used in this application, the terms "component," "system," "platform," "interface," and the like, can refer to and/or can include a computer-related entity or an entity related to an operational machine with one or more specific functionalities. The entities disclosed herein can be either hardware, a combination of hardware and software, software, or software in execution. For example, a component can be, but is not limited to being, a process running on a processor, a processor, an object, an executable, a thread of execution, a program, and/or a computer. By way of illustration, both an application running on a server and the server can be a component. One or more components can reside within a process and/or thread of execution and a component can be localized on one computer and/or distributed between two or more computers. In another example, respective components can execute from various computer readable media having various data structures stored thereon. The components can communicate via local and/or remote processes such as in accordance with a signal having one or more data packets (e.g., data from one component interacting with another component in a local system, distributed system, and/or across a network such as the Internet with other systems via the signal). As another example, a component can be an apparatus with specific functionality provided by mechanical parts operated by electric or electronic circuitry, which is operated by a software or firmware application executed by a processor. In such a case, the processor can be internal or external to the apparatus and can execute at least a part of the software or firmware application. As yet another example, a component can be an apparatus that provides specific functionality through electronic components without mechanical parts, wherein the electronic components can include a processor or other means to execute software or firmware that confers at least in part the functionality of the electronic components. In an aspect, a component can emulate an electronic component via a virtual machine, e.g., within a cloud computing system.

[0191] In addition, the term "or" is intended to mean an inclusive "or" rather than an exclusive "or." That is, unless specified otherwise, or clear from context, "X employs A or B" is intended to mean any of the natural inclusive permutations. That is, if X employs A; X employs B; or X employs both A and B, then "X employs A or B" is satisfied under any of the foregoing instances. Moreover, articles "a" and "an" as used in the subject specification and annexed drawings should generally be construed to mean "one or more" unless specified otherwise or clear from context to be directed to a singular form. As used herein, the terms "example" and/or "exemplary" are utilized to mean serving as an example, instance, or illustration. For the avoidance of doubt, the subject matter disclosed herein is not limited by such examples. In addition, any aspect or design described herein as an "example" and/or "exemplary" is not necessarily to be construed as preferred or advantageous over other aspects or designs, nor is it meant to preclude equivalent exemplary structures and techniques known to those of ordinary skill in the art.

[0192] As it is employed in the subject specification, the term "processor" can refer to substantially any computing processing unit or device comprising, but not limited to, single-core processors; single-processors with software multithread execution capability; multi-core processors; multi-core processors with software multithread execution capability; multi-core processors with hardware multithread technology; parallel platforms; and parallel platforms with distributed shared memory. Additionally, a processor can refer to an integrated circuit, an application specific integrated circuit (ASIC), a digital signal processor (DSP), a field programmable gate array (FPGA), a programmable logic controller (PLC), a complex programmable logic device (CPLD), a discrete gate or transistor logic, discrete hardware components, or any combination thereof designed to perform the functions described herein. Further, processors can exploit nano-scale architectures such as, but not limited to, molecular and quantum-dot based transistors, switches and gates, in order to optimize space usage or enhance performance of user equipment. A processor can also be implemented as a combination of computing processing units. In this disclosure, terms such as "store," "storage," "data store," data storage," "database," and substantially any other information storage component relevant to operation and functionality of a component are utilized to refer to "memory components," entities embodied in a "memory," or components comprising a memory. It is to be appreciated that memory and/or memory components described herein can be either volatile memory or nonvolatile memory, or can include both volatile and nonvolatile memory. By way of illustration, and not limitation, nonvola-

tile memory can include read only memory (ROM), programmable ROM (PROM), electrically programmable ROM (EPROM), electrically erasable ROM (EEPROM), flash memory, or nonvolatile random access memory (RAM) (e.g., ferroelectric RAM (FeRAM). Volatile memory can include RAM, which can act as external cache memory, for example. By way of illustration and not limitation, RAM is available in many forms such as synchronous RAM (SRAM), dynamic RAM (DRAM), synchronous DRAM (SDRAM), double data rate SDRAM (DDR SDRAM), enhanced SDRAM (ESDRAM), Synchlink DRAM (SLDRAM), direct Rambus RAM (DRRAM), direct Rambus dynamic RAM (DRDRAM), and Rambus dynamic RAM (RDRAM). Additionally, the disclosed memory components of systems or computer-implemented methods herein are intended to include, without being limited to including, these and any other suitable types of memory.

[0193] What has been described above include mere examples of systems and computer-implemented methods. It is, of course, not possible to describe every conceivable combination of components or computer-implemented methods for purposes of describing this disclosure, but one of ordinary skill in the art can recognize that many further combinations and permutations of this disclosure are possible. Furthermore, to the extent that the terms "includes," "has," "possesses," and the like are used in the detailed description, claims, appendices and drawings such terms are intended to be inclusive in a manner similar to the term "comprising" as "comprising" is interpreted when employed as a transitional word in a claim.

[0194] The descriptions of the various embodiments have been presented for purposes of illustration, but are not intended to be exhaustive or limited to the embodiments disclosed. Many modifications and variations will be apparent to those of ordinary skill in the art without departing from the scope and spirit of the described embodiments. The terminology used herein was chosen to best explain the principles of the embodiments, the practical application or technical improvement over technologies found in the marketplace, or to enable others of ordinary skill in the art to understand the embodiments disclosed herein.

[0195] Further aspects of various embodiments of the subject claimed innovation are provided in the subject matter that follows:

[0196] 1. A system, comprising: a processor that executes computer-executable components stored in a computer-readable memory, the computer-executable components comprising: a receiver component that accesses a first set of data candidates and a second set of data candidates, wherein a machine learning model is trained on the first set of data candidates; an activation component that obtains a first set of latent activations generated by the machine learning model based on the first set of data candidates, and that obtains a second set of latent activations generated by the machine learning model based on the second set of data candidates; a compression component that generates a first set of compressed data points by applying a dimensionality reduction technique to the first set of latent activations, and that generates a second set of compressed data points by applying the dimensionality reduction technique to the second set of latent activations; and a diversity component that computes a diversity score based on the first set of compressed data points and the second set of compressed data points.

[0197] 2. The system of any preceding clause, wherein the computer-executable components further comprise: a visualization component that renders a graph depicting the first set of compressed data points and the second set of compressed data points.

[0198] 3. The system of any preceding clause, wherein a given compressed data point that is plotted on the graph corresponds to a given data candidate from the first set of data candidates or the second set of data candidates, wherein the given compressed data point is clickable as plotted on the graph, and wherein the visualization component renders the given data candidate in response to the given compressed data point being clicked.

[0199] 4. The system of any preceding clause, wherein the second set of data candidates represents augmented versions of the first set of data candidates or otherwise represents potential training data for the machine learning model, and wherein the computer-executable components further comprise: an execution component that recommends training the machine learning model on the second set of data candidates in response to a determination that the diversity score satisfies a predetermined threshold, and that recommends not training the machine learning model on the second set of data candidates in response to a determination that the diversity score fails to satisfy the predetermined threshold.

[0200] 5. The system of any preceding clause, wherein the second set of data candidates is unannotated, and wherein the computer-executable components further comprise: an execution component that identifies one or more outlying compressed data points in the second set of compressed data points, by comparing the second set of compressed data points to the first set of compressed data points, and that recommends that one or more data candidates from the second set of data candidates which correspond to the one or more outlying compressed data points be manually annotated.

[0201] 6. The system of any preceding clause, wherein the second set of data candidates is unannotated, and wherein the computer-executable components further comprise: an execution component that identifies one or more non-outlying compressed data points in the second set of compressed data points, by comparing the second set of compressed data points to the first set of compressed data points, and that recommends that one or more data candidates from the second set of data candidates which correspond to the one or more non-outlying compressed data points be automatically annotated.

[0202] 7. The system of any preceding clause, wherein the dimensionality reduction technique is a t-distributed stochastic neighbor embedding (tSNE) technique or a uniform manifold approximation and projection (UMAP) technique.

[0203] 8. A computer-implemented method, comprising: accessing, by a device operatively coupled to a processor, a first set of data candidates and a second set of data candidates, wherein a machine learning model is trained on the first set of data candidates; obtaining, by the device, a first set of latent activations generated

by the machine learning model based on the first set of data candidates, and obtaining, by the device, a second set of latent activations generated by the machine learning model based on the second set of data candidates; generating, by the device, a first set of compressed data points by applying a dimensionality reduction technique to the first set of latent activations, and generating, by the device, a second set of compressed data points by applying the dimensionality reduction technique to the second set of latent activations; and computing, by the device, a diversity score based on the first set of compressed data points and the second set of compressed data points.

[0204] 9. The computer-implemented method of any preceding clause, further comprising: rendering, by the device, a graph depicting the first set of compressed data points and the second set of compressed data points.

[0205] 10. The computer-implemented method of any preceding clause, wherein a given compressed data point that is plotted on the graph corresponds to a given data candidate from the first set of data candidates or the second set of data candidates, wherein the given compressed data point is clickable as plotted on the graph, and further comprising: rendering, by the device, the given data candidate in response to the given compressed data point being clicked.

[0206] 11. The computer-implemented method of any preceding clause, wherein the second set of data candidates represents augmented versions of the first set of data candidates or otherwise represents potential training data for the machine learning model, and further comprising: recommending, by the device, that the machine learning model be trained on the second set of data candidates in response to a determination that the diversity score satisfies a predetermined threshold; and recommending, by the device, that the machine learning model not be trained on the second set of data candidates in response to a determination that the diversity score fails to satisfy the predetermined threshold.

[0207] 12. The computer-implemented method of any preceding clause, wherein the second set of data candidates is unannotated, and further comprising: identifying, by the device, one or more outlying compressed data points in the second set of compressed data points, by comparing the second set of compressed data points to the first set of compressed data points; and recommending, by the device, that one or more data candidates from the second set of data candidates which correspond to the one or more outlying compressed data points be manually annotated.

[0208] 13. The computer-implemented method of any preceding clause, wherein the second set of data candidates is unannotated, and further comprising: identifying, by the device, one or more non-outlying compressed data points in the second set of compressed data points, by comparing the second set of compressed data points to the first set of compressed data points; and recommending, by the device, that one or more data candidates from the second set of data candidates which correspond to the one or more non-outlying compressed data points be automatically annotated.

[0209] 14. The computer-implemented method of any preceding clause, wherein the dimensionality reduction technique is a t-distributed stochastic neighbor embedding (tSNE) technique or a uniform manifold approximation and projection (UMAP) technique.

[0210] 15. A computer program product for facilitating data diversity visualization and quantification for machine learning models, the computer program product comprising a computer-readable memory having program instructions embodied therewith, the program instructions executable by a processor to cause the processor to: access a first set of data candidates and a second set of data candidates, wherein a machine learning model is trained on the first set of data candidates; obtain a first set of latent activations generated by the machine learning model based on the first set of data candidates, and obtain a second set of latent activations generated by the machine learning model based on the second set of data candidates; generate a first set of compressed data points by applying a dimensionality reduction technique to the first set of latent activations, and generate a second set of compressed data points by applying the dimensionality reduction technique to the second set of latent activations; and compute a diversity score based on the first set of compressed data points and the second set of compressed data points.

[0211] 16. The computer program product of any preceding clause, wherein the program instructions are further executable to cause the processor to: render a graph depicting the first set of compressed data points and the second set of compressed data points.

[0212] 17. The computer program product of any preceding clause, wherein a given compressed data point that is plotted on the graph corresponds to a given data candidate from the first set of data candidates or the second set of data candidates, wherein the given compressed data point is clickable as plotted on the graph, and wherein the processor renders the given data candidate in response to the given compressed data point being clicked.

[0213] 18. The computer program product of any preceding clause, wherein the second set of data candidates represents augmented versions of the first set of data candidates or otherwise represents potential training data for the machine learning model, and wherein the program instructions are further executable to cause the processor to: recommend training the machine learning model on the second set of data candidates in response to a determination that the diversity score satisfies a predetermined threshold; and recommend not training the machine learning model on the second set of data candidates in response to a determination that the diversity score fails to satisfy the predetermined threshold.

[0214] 19. The computer program product of any preceding clause, wherein the second set of data candidates is unannotated, and wherein the program instructions are further executable to cause the processor to: identify one or more outlying compressed data points in the second set of compressed data points, by comparing the second set of compressed data points to the first set of compressed data points; and recommend that one or more data candidates from the second set of data

candidates which correspond to the one or more outlying compressed data points be manually annotated.

[0215] 20. The computer program product of any preceding clause, wherein the second set of data candidates is unannotated, and wherein the program instructions are further executable to cause the processor to: identify one or more non-outlying compressed data points in the second set of compressed data points, by comparing the second set of compressed data points to the first set of compressed data points; and recommend that one or more data candidates from the second set of data candidates which correspond to the one or more non-outlying compressed data points be automatically annotated.

What is claimed is:

1. A system, comprising:

a memory that stores computer-executable components; and

a processor that executes at least one of the computer-executable components that:

accesses a first set of data candidates and a second set of data candidates, wherein a machine learning model is trained on the first set of data candidates or the second set of data candidates;

obtains a first set of latent activations generated by the machine learning model based on the first set of data candidates;

obtains a second set of latent activations generated by the machine learning model based on the second set of data candidates;

generates a diversity score based on the first set of latent activations and the second set of latent activations, wherein the diversity score represents a degree of diversity of the second set of latent activations from the first set of latent activations from a perspective of the machine learning model, and wherein generating the diversity score comprises:

grouping latent activations of the first set of latent activations into clusters,

for each cluster, determining a respective threshold distance in the defined space from a center of the cluster based on a density of latent activations in the cluster and a distribution of latent activations in the cluster,

assigning latent activations of the second set of latent activations into the clusters based on a defined criterion, and

determining the diversity score based on an amount of respective latent activations of the second set of latent activations in the defined space that are outside of the respective threshold distances from the respective centers of the clusters assigned to the respective latent activations of the second set of latent activations;

recommends training the machine learning model on the second set of data candidates in response to determining that the diversity score satisfies a predetermined threshold; and

recommends not training the machine learning model on the second set of data candidates in response to determining that the diversity score fails to satisfy the predetermined threshold.

2. The system of claim **1**, wherein the at least one of the computer-executable components further comprises:

generating a first set of compressed data points in a defined space by applying a dimensionality reduction technique to the first set of latent activations; and

generating a second set of compressed data points in the defined space by applying the dimensionality reduction technique to the second set of latent activations.

3. The system of claim **2**, wherein the at least one of the computer-executable components further:

renders a graph depicting the first set of compressed data points and the second set of compressed data points.

4. The system of claim **3**, wherein a given compressed data point that is plotted on the graph corresponds to a given data candidate from the first set of data candidates or the second set of data candidates, wherein the given compressed data point is clickable as plotted on the graph, and wherein the at least one of the computer-executable components further:

renders the given data candidate in response to the given compressed data point being clicked.

5. The system of claim **1**, wherein the second set of data candidates is unannotated, and wherein the at least one of the computer-executable components further:

recommends that one or more data candidates from the second set of data candidates which correspond to one or more of the respective latent activations of the second set of latent activations that are outside of the respective threshold distances be manually annotated.

6. The system of claim **1**, wherein the second set of data candidates is unannotated, and wherein the at least one of the computer-executable components further:

recommends that one or more data candidates from the second set of data candidates which do not correspond to any of the respective latent activations of the second set of latent activations that are outside of the respective threshold distances be automatically annotated.

7. The system of claim **2**, wherein the dimensionality reduction technique is a t-distributed stochastic neighbor embedding (tSNE) technique or a uniform manifold approximation and projection (UMAP) technique.

8. The system of claim **1**, wherein the at least one of the computer-executable components further:

in response to recommending training the machine learning model on the second set of data candidates, retraining the machine learning model using the second set of data candidates, wherein the second set of data candidates represents at least one of augmented versions of the first set of data candidates or potential training data for the machine learning model.

9. A computer-implemented method, comprising:

accessing, by a device operatively coupled to a processor, a first set of data candidates and a second set of data candidates, wherein a machine learning model is trained on the first set of data candidates or the second set of data candidates, wherein the second set of data candidates represents at least one of augmented versions of the first set of data candidates or potential training data for the machine learning model;

obtaining, by the device, a first set of latent activations generated by the machine learning model based on the first set of data candidates;

obtaining, by the device, a second set of latent activations generated by the machine learning model based on the second set of data candidates;

generating a diversity score based on the first set of latent activations and the second set of latent activations, wherein the diversity score represents a degree of diversity of the second set of latent activations from the first set of latent activations from a perspective of the machine learning model, and wherein generating the diversity score comprises:

grouping latent activations of the first set of latent activations into clusters,

for each cluster, determining a respective threshold distance in the defined space from a center of the cluster based on a density of latent activations in the cluster and a distribution of latent activations in the cluster,

assigning latent activations of the second set of latent activations into the clusters based on a defined criterion, and

determining the diversity score based on an amount of respective latent activations of the second set of latent activations in the defined space that are outside of the respective threshold distances from the respective centers of the clusters assigned to the respective latent activations of the second set of latent activations;

recommends training the machine learning model on the second set of data candidates in response to determining that the diversity score satisfies a predetermined threshold; and

recommends not training the machine learning model on the second set of data candidates in response to determining that the diversity score fails to satisfy the predetermined threshold.

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

generating a first set of compressed data points in a defined space by applying a dimensionality reduction technique to the first set of latent activations; and

generating a second set of compressed data points in the defined space by applying the dimensionality reduction technique to the second set of latent activations.

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

rendering, by the device, a graph depicting the first set of compressed data points and the second set of compressed data points.

12. The computer-implemented method of claim **11**, wherein a given compressed data point that is plotted on the graph corresponds to a given data candidate from the first set of data candidates or the second set of data candidates, wherein the given compressed data point is clickable as plotted on the graph, and further comprising:

rendering, by the device, the given data candidate in response to the given compressed data point being clicked.

13. The computer-implemented method of claim **10**, wherein the second set of data candidates is unannotated, and further comprising:

recommending, by the device, that one or more data candidates from the second set of data candidates which correspond to one or more of the respective compressed data points of the second set of compressed data points that are outside of the respective threshold distances be manually annotated.

14. The computer-implemented method of claim **10**, wherein the second set of data candidates is unannotated, and further comprising:

recommending, by the device, that one or more data candidates from the second set of data candidates which do not correspond to any of the respective compressed data points of the second set of compressed data points that are outside of the respective threshold distances be automatically annotated.

15. The computer-implemented method of claim **10**, wherein the dimensionality reduction technique is a t-distributed stochastic neighbor embedding (tSNE) technique or a uniform manifold approximation and projection (UMAP) technique.

16. The computer-implemented method of claim **10**, wherein the second set of data candidates is unannotated, and further comprising:

in response to recommending training the machine learning model on the second set of data candidates, retraining, by the device, the machine learning model using the second set of data candidates.

17. A computer program product for facilitating data diversity visualization and quantification for machine learning models, the computer program product comprising a non-transitory computer-readable medium having program instructions embodied therewith, the program instructions executable by a processor to cause the processor to:

access a first set of data candidates and a second set of data candidates, wherein a machine learning model is trained on the first set of data candidates or the second set of data candidates, wherein the second set of data candidates represents at least one of augmented versions of the first set of data candidates or potential training data for the machine learning model;

obtain a first set of latent activations generated by the machine learning model based on the first set of data candidates;

obtain a second set of latent activations generated by the machine learning model based on the second set of data candidates;

generate a diversity score based on the first set of latent activations and the second set of latent activations, wherein the diversity score represents a degree of diversity of the second set of latent activations from the first set of latent activations from a perspective of the machine learning model, and wherein generating the diversity score comprises:

grouping latent activations of the first set of latent activations into clusters,

for each cluster, determining a respective threshold distance in the defined space from a center of the cluster based on a density of latent activations in the cluster and a distribution of latent activations in the cluster,

assigning latent activations of the second set of latent activations into the clusters based on a defined criterion, and

determining the diversity score based on an amount of respective latent activations of the second set of latent activations in the defined space that are outside of the respective threshold distances from the respective centers of the clusters assigned to the respective latent activations of the second set of latent activations;

recommends training the machine learning model on the second set of data candidates in response to determining that the diversity score satisfies a predetermined threshold; and

recommends not training the machine learning model on the second set of data candidates in response to determining that the diversity score fails to satisfy the predetermined threshold.

18. The computer program product of claim **17**, wherein the program instructions are further executable to cause the processor to:

generate a first set of compressed data points in a defined space by applying a dimensionality reduction technique to the first set of latent activations; and

generate a second set of compressed data points in the defined space by applying the dimensionality reduction technique to the second set of latent activations.

19. The computer program product of claim **18**, wherein the program instructions are further executable to cause the processor to:

render a graph depicting the first set of compressed data points and the second set of compressed data points.

20. The computer program product of claim **19**, wherein a given compressed data point that is plotted on the graph corresponds to a given data candidate from the first set of data candidates or the second set of data candidates, wherein the given compressed data point is clickable as plotted on the graph, and wherein the processor renders the given data candidate in response to the given compressed data point being clicked.

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