US 20210314242A1

(19) United States

(12) Patent Application Publication (10) Pub. No.: US 2021/0314242 A1

Majumder et al. (43) Pub. Date: Oct. 7, 2021

(54) **CORRELATION SCORE BASED COMMONNESS INDICATION ASSOCIATED WITH A POINT ANOMALY PERTINENT TO DATA PATTERN CHANGES IN A CLOUD-BASED APPLICATION ACCELERATION AS A SERVICE ENVIRONMENT**

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(21) Appl. No.: **17/348,746**

(22) Filed: **Jun. 15, 2021**

Related U.S. Application Data

(63) Continuation-in-part of application No. 16/660,813, filed on Oct. 23, 2019, now Pat. No. 11,070,440.

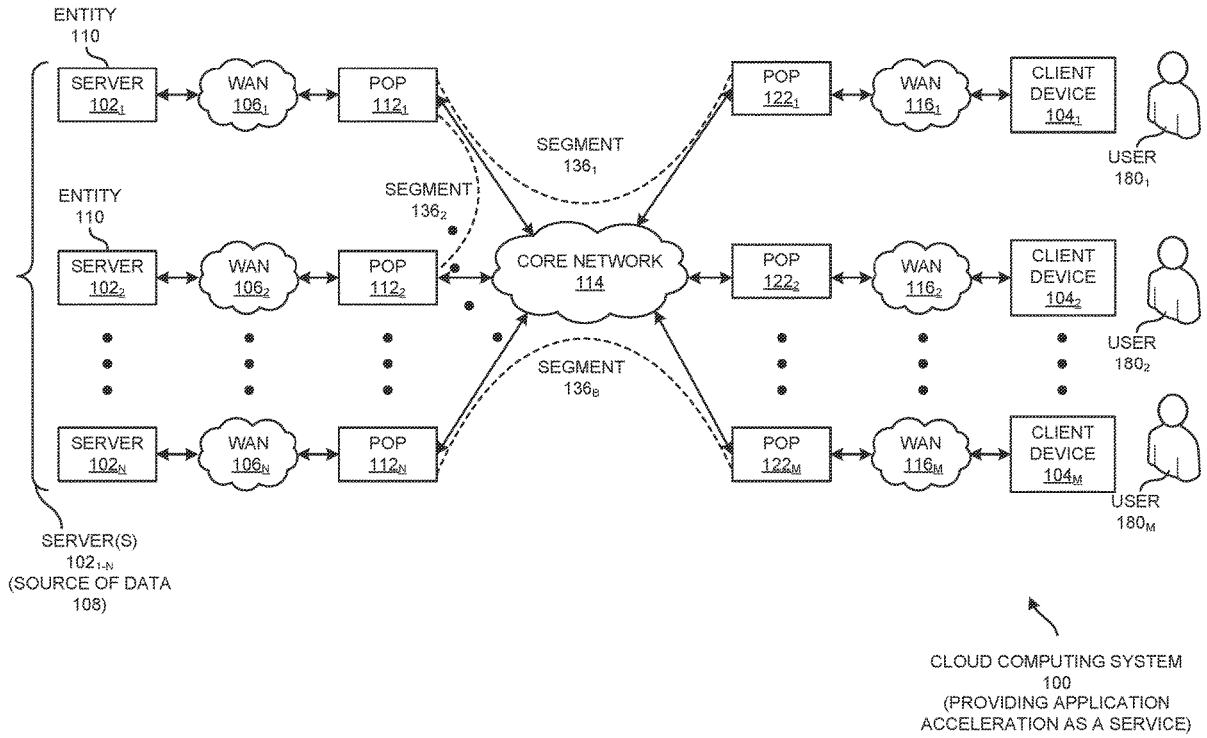
Publication Classification

(51) **Int. Cl.**
H04L 12/26 (2006.01)
H04L 29/08 (2006.01)

(52) **U.S. Cl.**
CPC ***H04L 43/04*** (2013.01); ***H04L 67/10*** (2013.01)

(57) **ABSTRACT**

A method implemented through a server of a cloud computing network including subscribers of application acceleration as a service provided therethrough includes detecting a point anomaly in real-time data associated with each network entity based on determining whether the real-time data falls outside a threshold expected value thereof, and representing the detected point anomaly in a full mesh Q node graph, with Q being a number of features applicable for the each network entity. The method also includes capturing a transition in the point anomaly associated with a newly detected anomaly or non-anomaly in the real-time data associated with one or more of the Q number of features via the representation of the full mesh Q node graph, and deriving a current data correlation score for the point anomaly across the captured transition via the representation of the full mesh Q node graph.



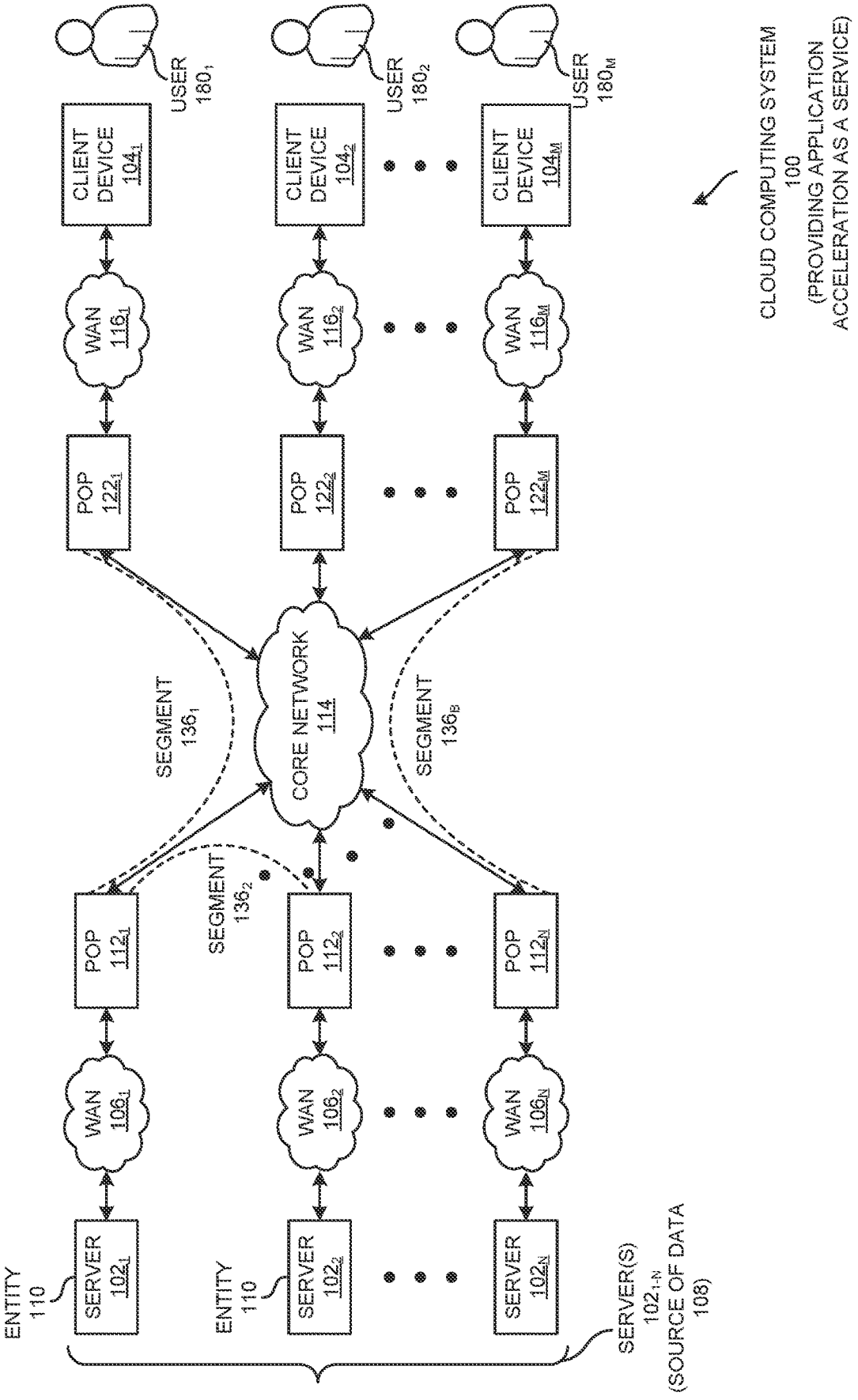

CLOUD COMPUTING SYSTEM
100
(PROVIDING APPLICATION
ACCELERATION AS A SERVICE)
USER
180$_1$
USER
180$_2$
USER
180$_M$
CLIENT
DEVICE
104$_1$
CLIENT
DEVICE
104$_2$
CLIENT
DEVICE
104$_M$
WAN
116$_1$
WAN
116$_2$
WAN
116$_M$
POP
122$_1$
POP
122$_2$
POP
122$_M$
CORE NETWORK
114
SEGMENT
136$_1$
SEGMENT
136$_2$
SEGMENT
136$_B$
POP
112$_1$
POP
112$_2$
POP
112$_N$
WAN
106$_1$
WAN
106$_2$
WAN
106$_N$
ENTITY
110
ENTITY
110
SERVER
102$_1$
SERVER
102$_2$
SERVER
102$_N$
SERVER(S)
102$_{1-N}$
(SOURCE OF DATA
108)

FIG. 1

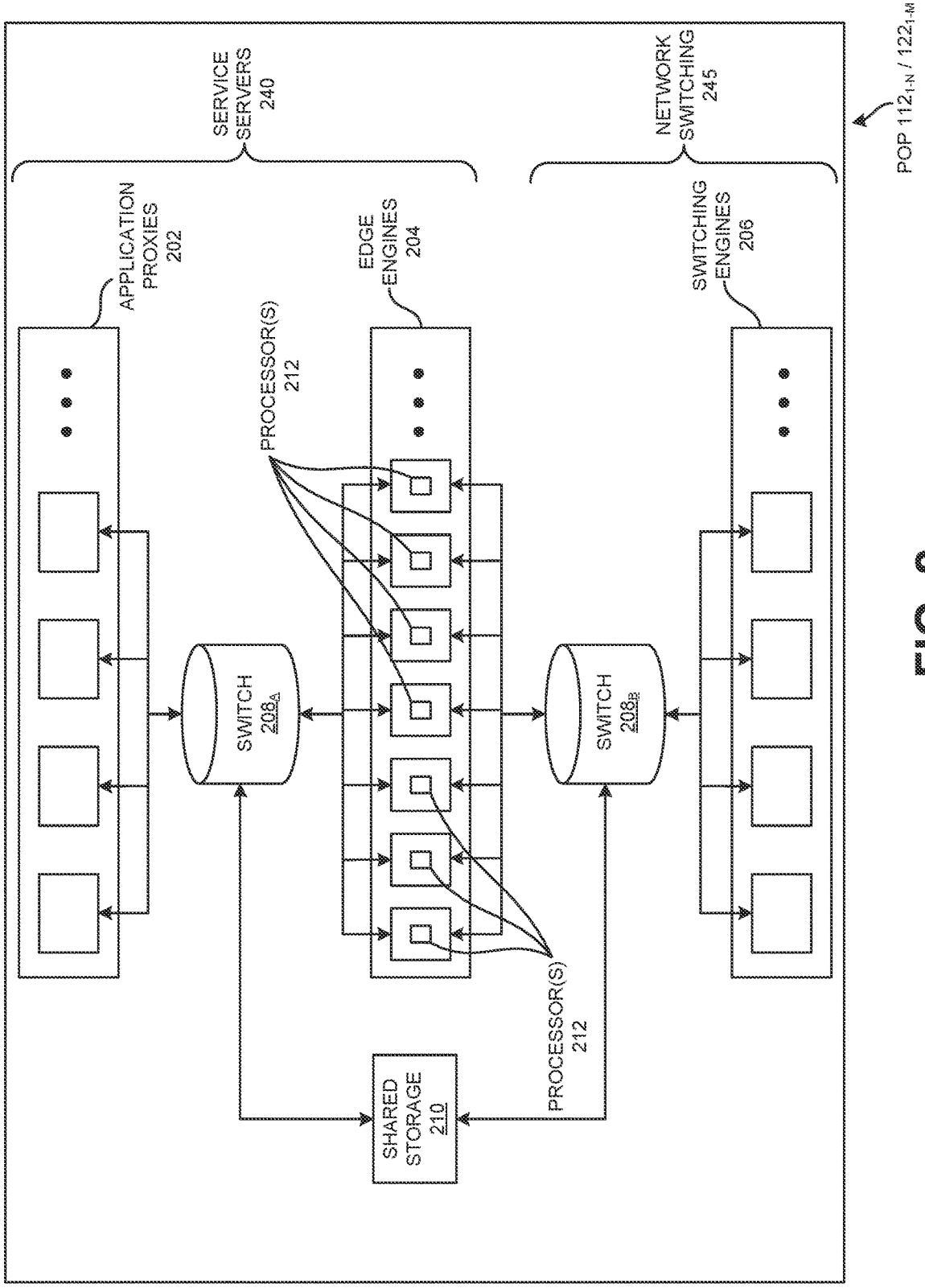

SERVICE SERVERS 240
NETWORK SWITCHING 245
POP 112$_{1-N}$ / 122$_{1-M}$
APPLICATION PROXIES 202
EDGE ENGINES 204
SWITCHING ENGINES 206
PROCESSOR(S) 212
SWITCH 208$_A$
SWITCH 208$_B$
PROCESSOR(S) 212
SHARED STORAGE 210

FIG. 2

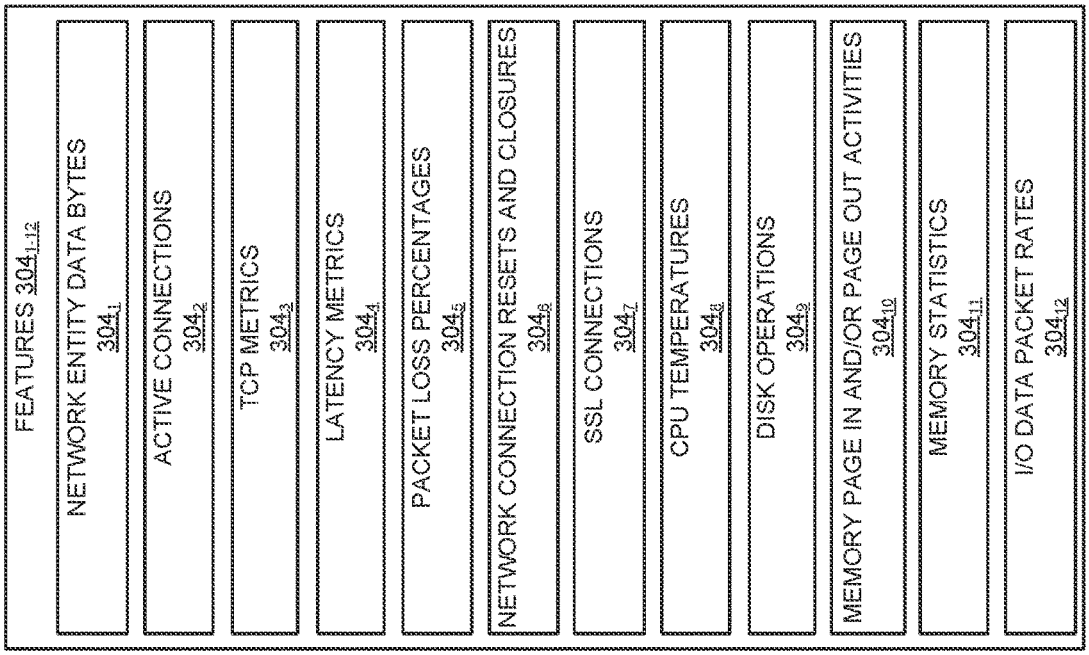

FEATURES 304$_{1-12}$
NETWORK ENTITY DATA BYTES 304$_1$
ACTIVE CONNECTIONS 304$_2$
TCP METRICS 304$_3$
LATENCY METRICS 304$_4$
PACKET LOSS PERCENTAGES 304$_5$
NETWORK CONNECTION RESETS AND CLOSURES 304$_6$
SSL CONNECTIONS 304$_7$
CPU TEMPERATURES 304$_8$
DISK OPERATIONS 304$_9$
MEMORY PAGE IN AND/OR PAGE OUT ACTIVITIES 304$_{10}$
MEMORY STATISTICS 304$_{11}$
I/O DATA PACKET RATES 304$_{12}$
NETWORK ENTITIES 302$_{1-4}$
ENTITIES DEPLOYED FOR SUBSCRIBERS 302$_1$
CORE NETWORK COMPONENTS 302$_2$
EDGE NETWORK COMPONENTS 302$_3$
POPs 302$_4$

FIG. 3

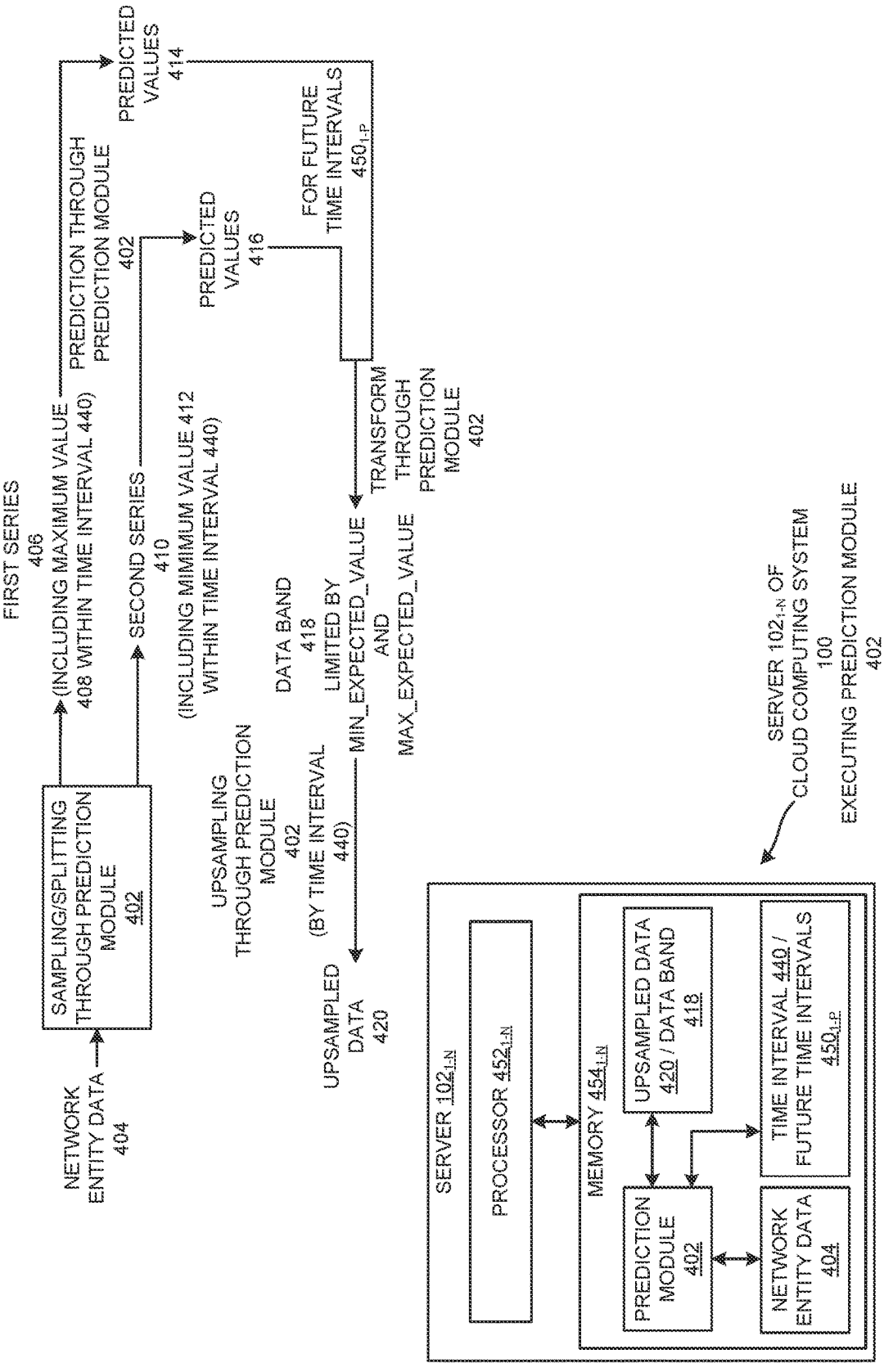

NETWORK ENTITY DATA 404
SAMPLING/SPLITTING THROUGH PREDICTION MODULE 402
FIRST SERIES 406
(INCLUDING MAXIMUM VALUE 408 WITHIN TIME INTERVAL 440)
SECOND SERIES 410
(INCLUDING MIMIMUM VALUE 412 WITHIN TIME INTERVAL 440)
PREDICTION THROUGH PREDICTION MODULE 402
PREDICTED VALUES 414
PREDICTED VALUES 416
FOR FUTURE TIME INTERVALS 450 1-P
UPSAMPLING THROUGH PREDICTION MODULE 402
UPSAMPLED DATA 420
(BY TIME INTERVAL 440)
DATA BAND 418
LIMITED BY MIN_EXPECTED_VALUE AND MAX_EXPECTED_VALUE
TRANSFORM THROUGH PREDICTION MODULE 402
SERVER 102 1-N OF CLOUD COMPUTING SYSTEM 100 EXECUTING PREDICTION MODULE 402
SERVER 102 1-N
PROCESSOR 452 1-N
MEMORY 454 1-N
PREDICTION MODULE 402
NETWORK ENTITY DATA 404
UPSAMPLED DATA 420 / DATA BAND 418
TIME INTERVAL 440 / FUTURE TIME INTERVALS 450 1-P

FIG. 4

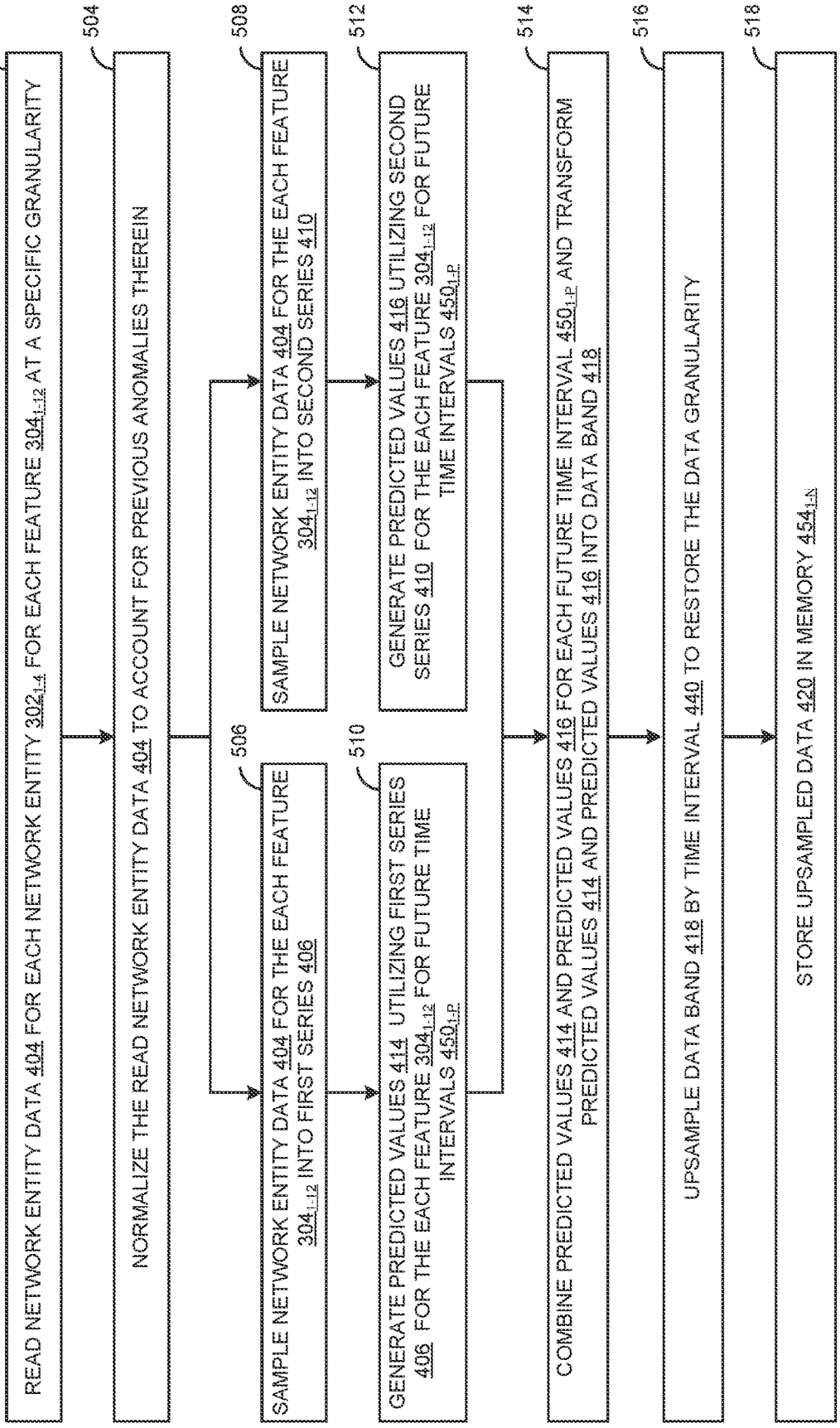

502
READ NETWORK ENTITY DATA 404 FOR EACH NETWORK ENTITY 302_{1-4} FOR EACH FEATURE 304_{1-12} AT A SPECIFIC GRANULARITY
504
NORMALIZE THE READ NETWORK ENTITY DATA 404 TO ACCOUNT FOR PREVIOUS ANOMALIES THEREIN
506
SAMPLE NETWORK ENTITY DATA 404 FOR THE EACH FEATURE 304_{1-12} INTO FIRST SERIES 406
508
SAMPLE NETWORK ENTITY DATA 404 FOR THE EACH FEATURE 304_{1-12} INTO SECOND SERIES 410
510
GENERATE PREDICTED VALUES 414 UTILIZING FIRST SERIES 406 FOR THE EACH FEATURE 304_{1-12} FOR FUTURE TIME INTERVALS 450_{1-P}
512
GENERATE PREDICTED VALUES 416 UTILIZING SECOND SERIES 410 FOR THE EACH FEATURE 304_{1-12} FOR FUTURE TIME INTERVALS 450_{1-P}
514
COMBINE PREDICTED VALUES 414 AND PREDICTED VALUES 416 FOR EACH FUTURE TIME INTERVAL 450_{1-P} AND TRANSFORM PREDICTED VALUES 414 AND PREDICTED VALUES 416 INTO DATA BAND 418
516
UPSAMPLE DATA BAND 418 BY TIME INTERVAL 440 TO RESTORE THE DATA GRANULARITY
518
STORE UPSAMPLED DATA 420 IN MEMORY 454_{1-N}

FIG. 5

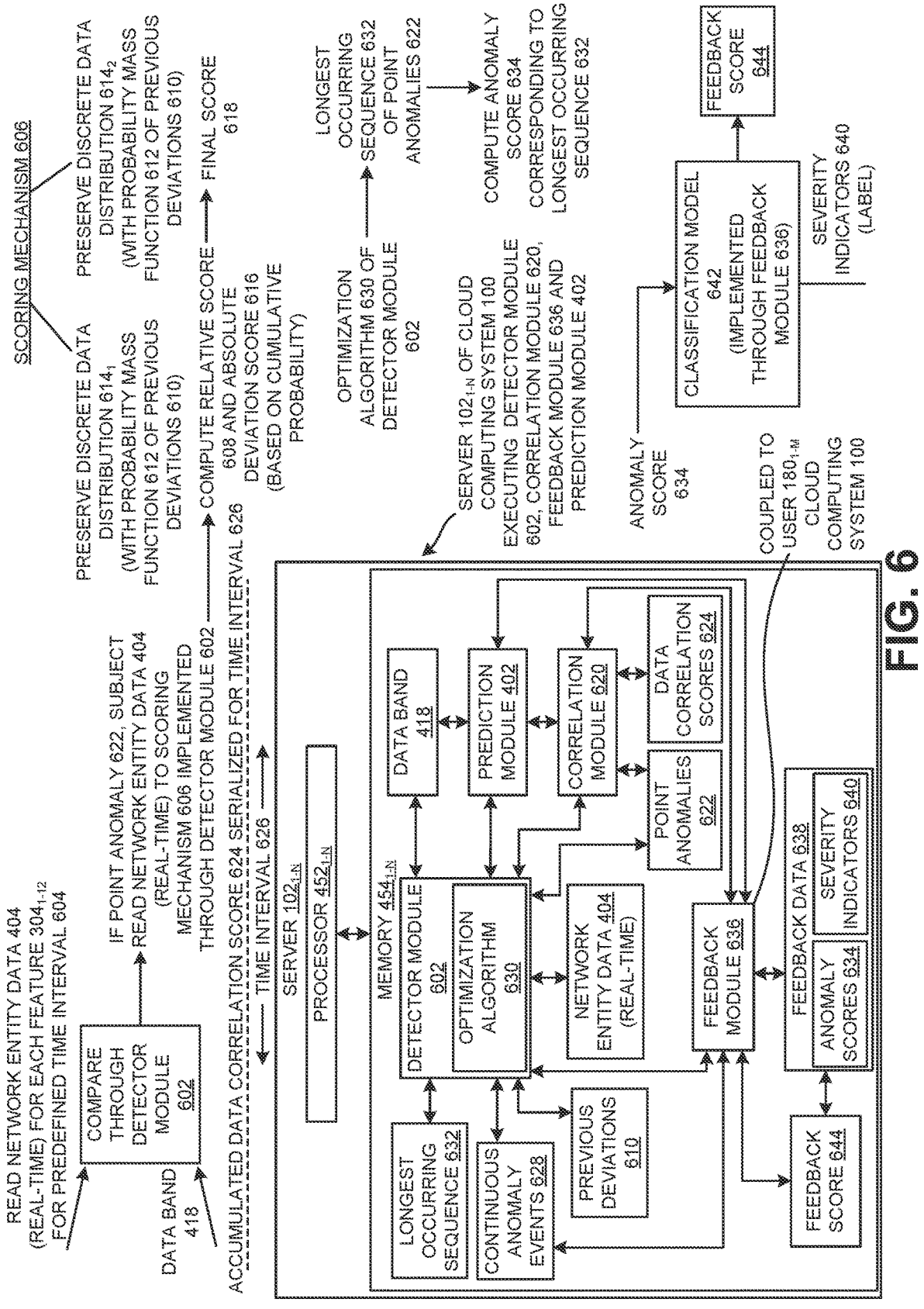

READ NETWORK ENTITY DATA 404 (REAL-TIME) FOR EACH FEATURE 304$_{1-12}$ FOR PREDEFINED TIME INTERVAL 604
COMPARE THROUGH DETECTOR MODULE 602
DATA BAND 418
IF POINT ANOMALY 622, SUBJECT READ NETWORK ENTITY DATA 404 (REAL-TIME) TO SCORING MECHANISM 606 IMPLEMENTED THROUGH DETECTOR MODULE 602
ACCUMULATED DATA CORRELATION SCORE 624 SERIALIZED FOR TIME INTERVAL 626
TIME INTERVAL 626
SERVER 102$_{1-N}$
PROCESSOR 452$_{1-N}$
MEMORY 454$_{1-N}$
DETECTOR MODULE 602
OPTIMIZATION ALGORITHM 630
LONGEST OCCURRING SEQUENCE 632
CONTINUOUS ANOMALY EVENTS 628
PREVIOUS DEVIATIONS 610
NETWORK ENTITY DATA 404 (REAL-TIME)
DATA BAND 418
PREDICTION MODULE 402
CORRELATION MODULE 620
POINT ANOMALIES 622
DATA CORRELATION SCORES 624
FEEDBACK MODULE 636
FEEDBACK SCORE 644
FEEDBACK DATA 638
ANOMALY SCORES 634
SEVERITY INDICATORS 640
SCORING MECHANISM 606
PRESERVE DISCRETE DATA DISTRIBUTION 614$_1$ (WITH PROBABILITY MASS FUNCTION 612 OF PREVIOUS DEVIATIONS 610)
PRESERVE DISCRETE DATA DISTRIBUTION 614$_2$ (WITH PROBABILITY MASS FUNCTION 612 OF PREVIOUS DEVIATIONS 610)
COMPUTE RELATIVE SCORE 608 AND ABSOLUTE DEVIATION SCORE 616 (BASED ON CUMULATIVE PROBABILITY)
FINAL SCORE 618
OPTIMIZATION ALGORITHM 630 OF DETECTOR MODULE 602
LONGEST OCCURRING SEQUENCE 632 OF POINT ANOMALIES 622
SERVER 102$_{1-N}$ OF CLOUD COMPUTING SYSTEM 100 EXECUTING DETECTOR MODULE 620, CORRELATION MODULE 636 AND FEEDBACK MODULE 636 AND PREDICTION MODULE 402
COMPUTE ANOMALY SCORE 634 CORRESPONDING TO LONGEST OCCURRING SEQUENCE 632
ANOMALY SCORE 634
CLASSIFICATION MODEL 642 (IMPLEMENTED THROUGH FEEDBACK MODULE 636)
SEVERITY INDICATORS 640 (LABEL)
FEEDBACK SCORE 644
COUPLED TO USER 180$_{1-M}$ CLOUD COMPUTING SYSTEM 100

FIG. 6

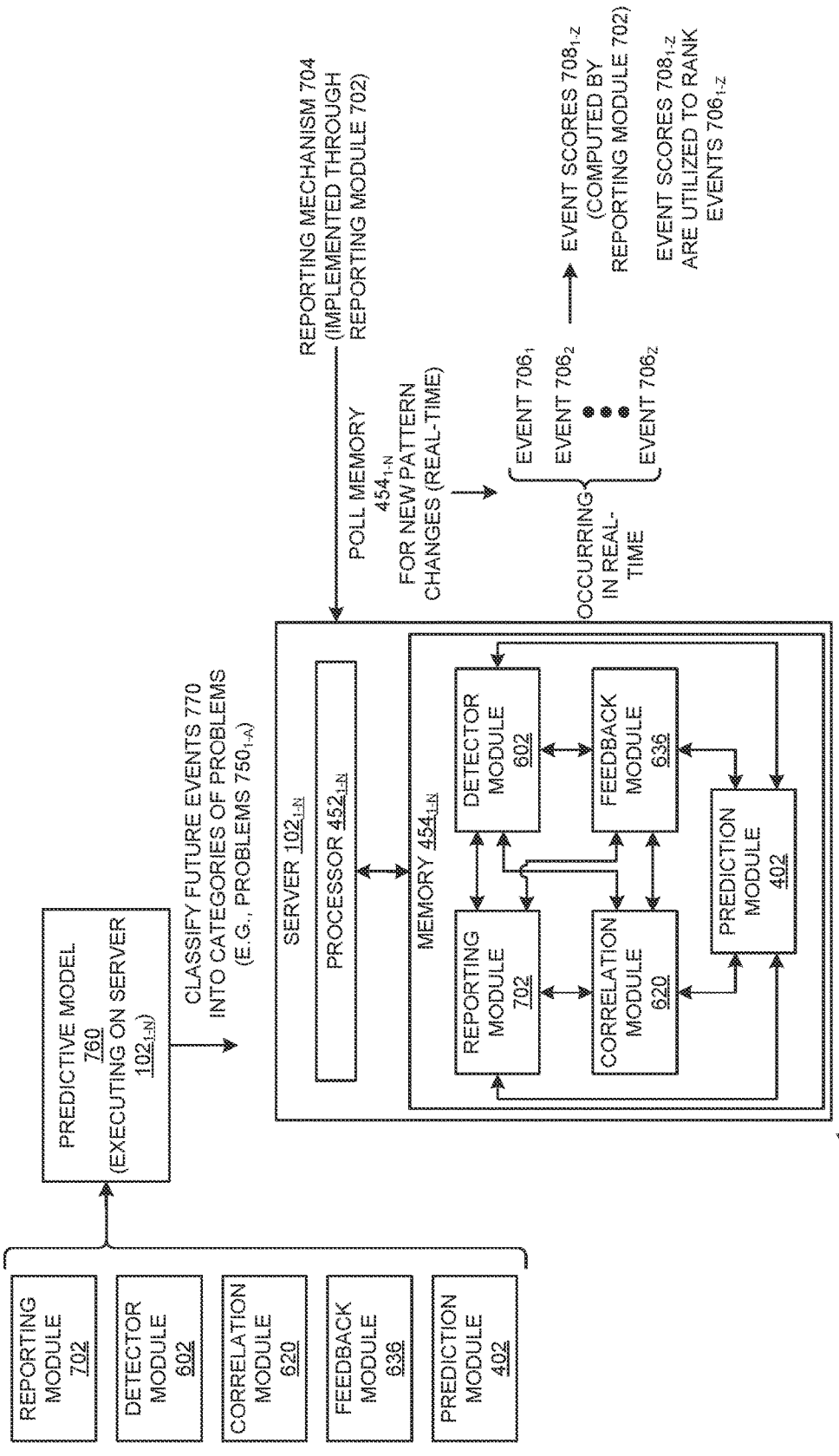

REPORTING MODULE 702
DETECTOR MODULE 602
CORRELATION MODULE 620
FEEDBACK MODULE 636
PREDICTION MODULE 402
PREDICTIVE MODEL 760 (EXECUTING ON SERVER 102$_{1-N}$)
CLASSIFY FUTURE EVENTS 770 INTO CATEGORIES OF PROBLEMS (E.G., PROBLEMS 750$_{1-A}$)
SERVER 102$_{1-N}$
PROCESSOR 452$_{1-N}$
MEMORY 454$_{1-N}$
REPORTING MODULE 702
DETECTOR MODULE 602
FEEDBACK MODULE 636
CORRELATION MODULE 620
PREDICTION MODULE 402
REPORTING MECHANISM 704 (IMPLEMENTED THROUGH REPORTING MODULE 702)
POLL MEMORY 454$_{1-N}$ FOR NEW PATTERN CHANGES (REAL-TIME)
OCCURRING IN REAL-TIME
EVENT 706$_1$
EVENT 706$_2$
EVENT 706$_Z$
EVENT SCORES 708$_{1-Z}$ (COMPUTED BY REPORTING MODULE 702)
EVENT SCORES 708$_{1-Z}$ ARE UTILIZED TO RANK EVENTS 706$_{1-Z}$
SERVER 102$_{1-N}$ OF CLOUD COMPUTING SYSTEM 100 EXECUTING REPORTING MODULE 702, DETECTOR MODULE 602, CORRELATION MODULE 620, FEEDBACK MODULE 636 AND PREDICTION MODULE 402

FIG. 7

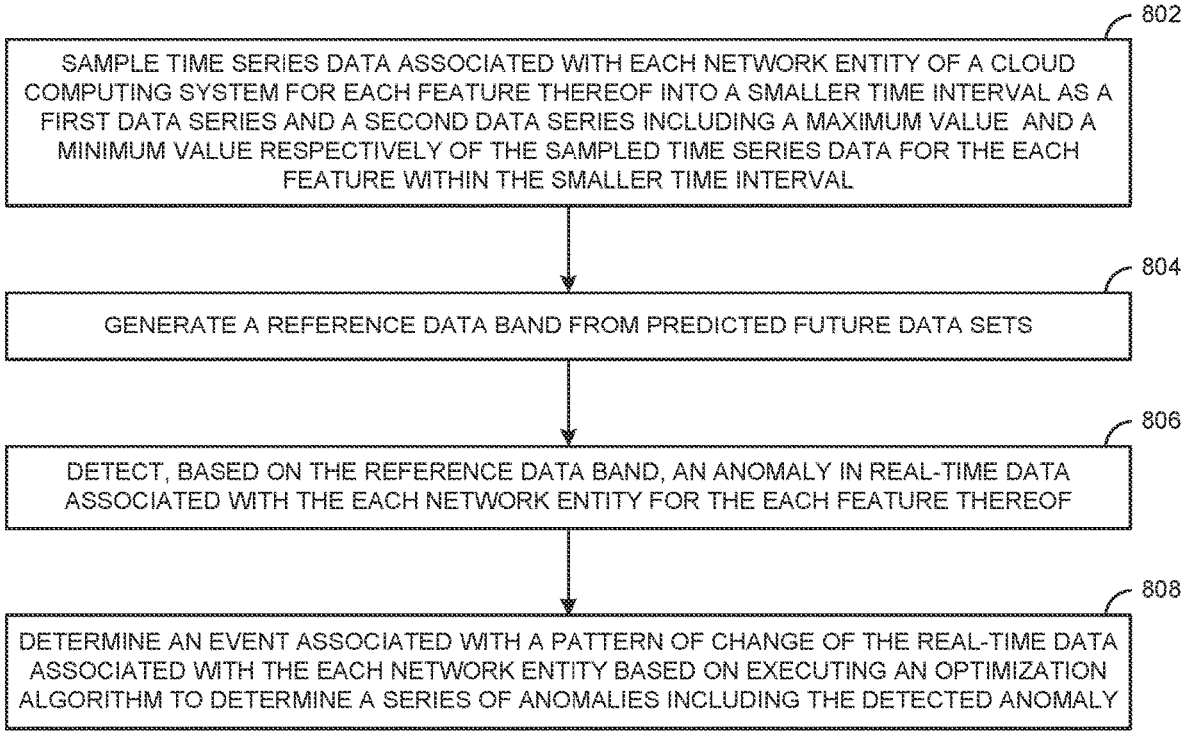

802
SAMPLE TIME SERIES DATA ASSOCIATED WITH EACH NETWORK ENTITY OF A CLOUD COMPUTING SYSTEM FOR EACH FEATURE THEREOF INTO A SMALLER TIME INTERVAL AS A FIRST DATA SERIES AND A SECOND DATA SERIES INCLUDING A MAXIMUM VALUE AND A MINIMUM VALUE RESPECTIVELY OF THE SAMPLED TIME SERIES DATA FOR THE EACH FEATURE WITHIN THE SMALLER TIME INTERVAL
804
GENERATE A REFERENCE DATA BAND FROM PREDICTED FUTURE DATA SETS
806
DETECT, BASED ON THE REFERENCE DATA BAND, AN ANOMALY IN REAL-TIME DATA ASSOCIATED WITH THE EACH NETWORK ENTITY FOR THE EACH FEATURE THEREOF
808
DETERMINE AN EVENT ASSOCIATED WITH A PATTERN OF CHANGE OF THE REAL-TIME DATA ASSOCIATED WITH THE EACH NETWORK ENTITY BASED ON EXECUTING AN OPTIMIZATION ALGORITHM TO DETERMINE A SERIES OF ANOMALIES INCLUDING THE DETECTED ANOMALY

FIG. 8

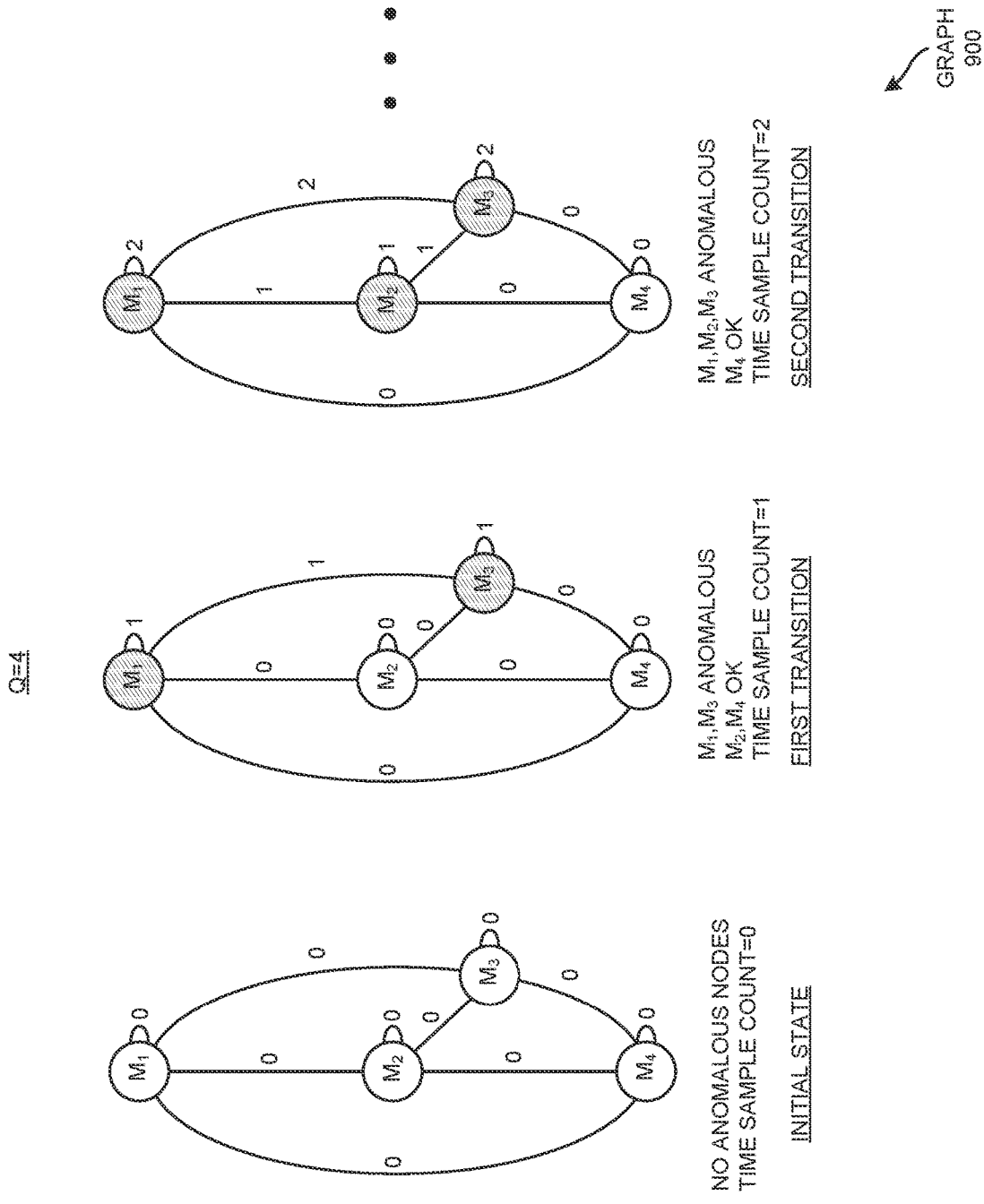

Q=4
M1
M2
M3
M4
NO ANOMALOUS NODES
TIME SAMPLE COUNT=0
INITIAL STATE
M1,M3 ANOMALOUS
M2,M4 OK
TIME SAMPLE COUNT=1
FIRST TRANSITION
M1,M2,M3 ANOMALOUS
M4 OK
TIME SAMPLE COUNT=2
SECOND TRANSITION
GRAPH
900

FIG. 9

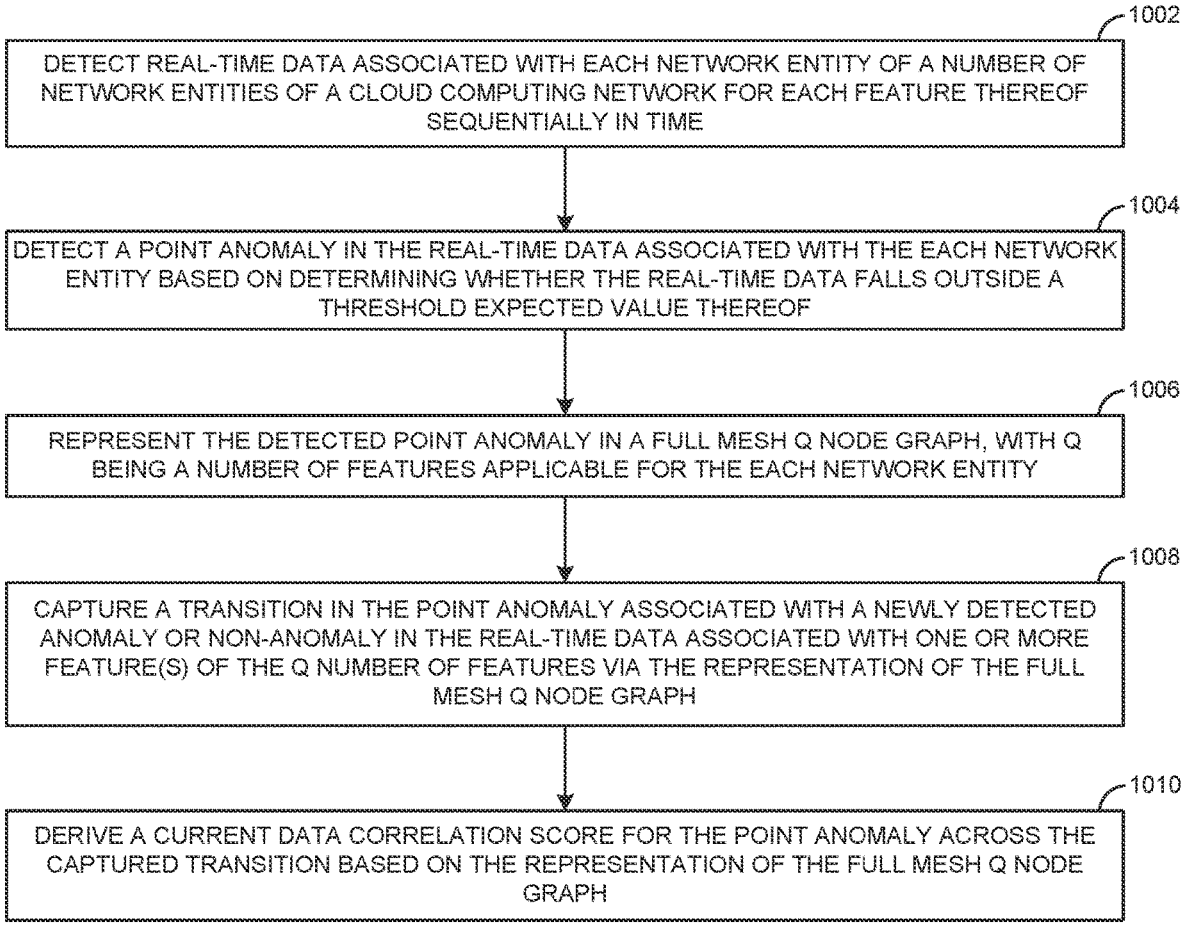

1002
DETECT REAL-TIME DATA ASSOCIATED WITH EACH NETWORK ENTITY OF A NUMBER OF NETWORK ENTITIES OF A CLOUD COMPUTING NETWORK FOR EACH FEATURE THEREOF SEQUENTIALLY IN TIME
1004
DETECT A POINT ANOMALY IN THE REAL-TIME DATA ASSOCIATED WITH THE EACH NETWORK ENTITY BASED ON DETERMINING WHETHER THE REAL-TIME DATA FALLS OUTSIDE A THRESHOLD EXPECTED VALUE THEREOF
1006
REPRESENT THE DETECTED POINT ANOMALY IN A FULL MESH Q NODE GRAPH, WITH Q BEING A NUMBER OF FEATURES APPLICABLE FOR THE EACH NETWORK ENTITY
1008
CAPTURE A TRANSITION IN THE POINT ANOMALY ASSOCIATED WITH A NEWLY DETECTED ANOMALY OR NON-ANOMALY IN THE REAL-TIME DATA ASSOCIATED WITH ONE OR MORE FEATURE(S) OF THE Q NUMBER OF FEATURES VIA THE REPRESENTATION OF THE FULL MESH Q NODE GRAPH
1010
DERIVE A CURRENT DATA CORRELATION SCORE FOR THE POINT ANOMALY ACROSS THE CAPTURED TRANSITION BASED ON THE REPRESENTATION OF THE FULL MESH Q NODE GRAPH

FIG. 10

CORRELATION SCORE BASED COMMONNESS INDICATION ASSOCIATED WITH A POINT ANOMALY PERTINENT TO DATA PATTERN CHANGES IN A CLOUD-BASED APPLICATION ACCELERATION AS A SERVICE ENVIRONMENT

CLAIM OF PRIORITY

[0001] This application is a Continuation-in-Part application of, and claims priority to, co-pending U.S. patent application Ser. No. 16/660,813 titled EFFICIENT DETECTION AND PREDICTION OF DATA PATTERN CHANGES IN A CLOUD-BASED APPLICATION ACCELERATION AS A SERVICE ENVIRONMENT filed on Oct. 23, 2019. The contents of the aforementioned Application are incorporated by reference herein in entirety thereof.

FIELD OF TECHNOLOGY

[0002] This disclosure relates generally to cloud computing networks and, particularly, to a method, a system and/or a device of correlation score based commonness indication associated with a point anomaly pertinent to data pattern changes in a cloud-based application acceleration as a service environment.

BACKGROUND

[0003] A cloud-based application acceleration as a service environment may include a number of network entities (e.g., Point of Presence (POP) locations, routers), sometimes even in the thousands and the tens of thousands. Each network entity may be associated with one or more feature(s) (e.g., latency metrics) that can be monitored. However, as the number of network entities in a typical cloud-based application acceleration as a service environment is large and each network entity is associated with one or more feature (s), detection of problematic data patterns associated with the number of network entities may be tedious and expensive, time-wise and storage-wise.

SUMMARY

[0004] Disclosed are a method, a system and/or a device of correlation score based commonness indication associated with a point anomaly pertinent to data pattern changes in a cloud-based application acceleration as a service environment.

[0005] In one aspect, a method includes detecting, through a server of a cloud computing network including a number of subscribers of application acceleration as a service provided by the cloud computing network at a corresponding number of client devices communicatively coupled to the server, real-time data associated with each network entity of a number of network entities of the cloud computing network for each feature thereof sequentially in time, and detecting, through the server, a point anomaly in the real-time data associated with the each network entity based on determining whether the real-time data falls outside a threshold expected value thereof.

[0006] The method also includes representing, through the server, the detected point anomaly in a full mesh Q node graph, with Q being a number of features applicable for the each network entity, capturing, through the server, a transition in the point anomaly associated with a newly detected anomaly or non-anomaly in the real-time data associated with one or more feature(s) of the Q number of features via the representation of the full mesh Q node graph, and deriving, through the server, a current data correlation score for the point anomaly across the captured transition as

$$CS = \sum_{i=1}^{APC} \frac{\left(1 - \frac{EWP_i}{TSAC}\right)}{APC}.$$

[0007] CS is the current data correlation score for the point anomaly across the captured transition, APC is a count of a total number of pairs of Y current anomalous features in the Q number of features and is given by ${}^{Y}C_2 + {}^{Y}C_1$, EWP_i is a weight of an edge of the i^{th} pair of the Y current anomalous features in the representation of the full mesh Q node graph, and TSAC is a total number of time samples of the point anomaly including the captured transition. The current data correlation score is indicative of a commonness of a combination of the Y current anomalous features contributing to the point anomaly with respect to an equivalent Y anomalous features contributing to another previously detected point anomaly associated with the each network entity.

[0008] In another aspect, a server of a cloud computing network including a number of subscribers of application acceleration as a service provided by the cloud computing network at a corresponding number of client devices communicatively coupled to the server, is disclosed. The server includes a memory and a processor communicatively coupled to the memory, and the processor executes instructions to detect real-time data associated with each network entity of a number of network entities of the cloud computing network for each feature thereof sequentially in time, and to detect a point anomaly in the real-time data associated with the each network entity based on determining whether the real-time data falls outside a threshold expected value thereof.

[0009] The processor also executes instructions to represent the detected point anomaly in a full mesh Q node graph, with Q being a number of features applicable for the each network entity, to capture a transition in the point anomaly associated with a newly detected anomaly or non-anomaly in the real-time data associated with one or more feature(s) of the Q number of features via the representation of the full mesh Q node graph, and to derive a current data correlation score for the point anomaly across the captured transition as CS=

$$CS = \sum_{i=1}^{APC} \frac{\left(1 - \frac{EWP_i}{TSAC}\right)}{APC}.$$

[0010] CS is the current data correlation score for the point anomaly across the captured transition, APC is a count of a total number of pairs of Y current anomalous features in the Q number of features and is given by ${}^{Y}C_2 + {}^{Y}C_1$, EWP_i is a weight of an edge of the i^{th} pair of the Y current anomalous features in the representation of the full mesh Q node graph, and TSAC is a total number of time samples of the point anomaly including the captured transition. The current data correlation score is indicative of a commonness of a com-

bination of the Y current anomalous features contributing to the point anomaly with respect to an equivalent Y anomalous features contributing to another previously detected point anomaly associated with the each network entity.

[0011] In yet another aspect, a cloud computing system includes a number of client devices associated with a number of subscribers of application acceleration as a service provided by the cloud computing system, a computer network, and a server communicatively coupled to the number of client devices through the computer network. The server executes instructions to detect real-time data associated with each network entity of a number of network entities of the cloud computing system for each feature thereof sequentially in time, and to detect a point anomaly in the real-time data associated with the each network entity based on determining whether the real-time data falls outside a threshold expected value thereof.

[0012] The server also executes instructions to represent the detected point anomaly in a full mesh Q node graph, with Q being a number of features applicable for the each network entity, to capture a transition in the point anomaly associated with a newly detected anomaly or non-anomaly in the real-time data associated with one or more feature(s) of the Q number of features via the representation of the full mesh Q node graph, and to derive a current data correlation score for the point anomaly across the captured transition as

$$CS = \sum_{i=1}^{APC} \frac{\left(1 - \frac{EWP_i}{TSAC}\right)}{APC}.$$

[0013] CS is the current data correlation score for the point anomaly across the captured transition, APC is a count of a total number of pairs of Y current anomalous features in the Q number of features and is given by ${}^{Y}C_2 + {}^{Y}C_1$, EWP_i is a weight of an edge of the i^{th} pair of the Y current anomalous features in the representation of the full mesh Q node graph, and TSAC is a total number of time samples of the point anomaly including the captured transition. The current data correlation score is indicative of a commonness of a combination of the Y current anomalous features contributing to the point anomaly with respect to an equivalent Y anomalous features contributing to another previously detected point anomaly associated with the each network entity.

[0014] The methods and systems disclosed herein may be implemented in any means for achieving various aspects, and may be executed in a form of a machine-readable medium embodying a set of instructions that, when executed by a machine, causes the machine to perform any of the operations disclosed herein. Other features will be apparent from the accompanying drawings and from the detailed description that follows.

BRIEF DESCRIPTION OF THE DRAWINGS

[0015] Example embodiments are illustrated by way of example and not limitation in the figures of accompanying drawings, in which like references indicate similar elements and in which:

[0016] FIG. **1** is a schematic view of a cloud computing system, according to one or more embodiments.

[0017] FIG. **2** is a schematic view of a Point of Presence (POP) device of FIG. **1**, according to one or more embodiments.

[0018] FIG. **3** is a list view of network entities in the cloud computing system of FIG. **1** and features associated therewith, according to one or more embodiments.

[0019] FIG. **4** is a schematic view of a prediction module configured to execute on a server of the cloud computing system of FIG. **1** and elements of data prediction thereof, according to one or more embodiments.

[0020] FIG. **5** is a process flow of the operations involved in the data prediction through the prediction module of FIG. **4**, according to one or more embodiments.

[0021] FIG. **6** is a schematic view of a detector module, a correlation module and a feedback module configured to execute on the server of the cloud computing system of FIGS. **1** and **4** and elements of functionalities thereof, according to one or more embodiments.

[0022] FIG. **7** is a schematic view of a reporting module configured to execute on the server of the cloud computing system of FIGS. **1**, **4** and **6** and elements of functionalities thereof, according to one or more embodiments.

[0023] FIG. **8** is a process flow diagram detailing the operations involved in efficient detection and prediction of data pattern changes in the cloud computing system of FIGS. **1**, **4**, **6** and **7**, according to one or more embodiments.

[0024] FIG. **9** is an illustrative view of a graph representation of a point anomaly associated with a network entity and transitions occurring therein when new anomalies are added thereto in an example implementation through the cloud computing system of FIGS. **1**, **4**, **6** and **7**.

[0025] FIG. **10** shows a process flow diagram detailing the operations involved in realizing correlation score based commonness indication associated with a point anomaly pertinent to data pattern changes in the cloud computing system of FIGS. **1**, **4**, **6** and **7**, according to one or more embodiments.

[0026] Other features of the present embodiments will be apparent from the accompanying drawings and from the detailed description that follows.

DETAILED DESCRIPTION

[0027] Example embodiments, as described below, may be used to realize correlation score based commonness indication associated with a point anomaly pertinent to data pattern changes in a cloud-based application acceleration as a service environment. It will be appreciated that the various embodiments discussed herein need not necessarily belong to the same group of exemplary embodiments, and may be grouped into various other embodiments not explicitly disclosed herein. In the following description, for purposes of explanation, numerous specific details are set forth in order to provide a thorough understanding of the various embodiments.

[0028] FIG. **1** shows a cloud computing system **100**, according to one or more embodiments. In one or more embodiments, cloud computing system **100** may include a number of servers $\mathbf{102}_{1\text{-}N}$ communicatively coupled to one another through a computer network (e.g., a Wide Area Network (WAN) $\mathbf{106}_{1\text{-}N}$, a Local Area Network (LAN) (not shown)) and a number of client devices $\mathbf{104}_{1\text{-}M}$ (example data processing devices such as desktops, laptops, and mobile devices; even servers may be examples of client devices $\mathbf{104}_{1\text{-}M}$) communicatively coupled to the number of

servers $\mathbf{102}_{1\text{-}N}$ through a corresponding WAN $\mathbf{116}_{1\text{-}M}$. In one or more embodiments, servers $\mathbf{102}_{1\text{-}N}$ may be a source of data **108** (e.g., multimedia data, text, video and/or audio data) to the aforesaid number of client devices $\mathbf{104}_{1\text{-}M}$.

[0029] In some embodiments, one or more server(s) $\mathbf{102}_{1\text{-}N}$ may be associated with a head office of a business entity (e.g., entity **110**) and one or more client device(s) $\mathbf{104}_{1\text{-}M}$ may be associated with branch offices of said business entity (e.g., entity **110**). In one or more embodiments, a number of Point of Presence (POP) locations, POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$, may be present in cloud computing system **100**. FIG. **1** shows a correspondence between the number of WANs, WANs $\mathbf{106}_{1\text{-}N}$ and WANs $\mathbf{116}_{1\text{-}M}$, and the number of POPs, POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$, merely for example purposes. The aforementioned correspondence should not be considered limiting.

[0030] Each POP location discussed above may be an access point to the Internet. For example, the each POP location may be a physical location that houses servers, routers, Asynchronous Transfer Mode (ATM) switches and/or digital/analog call aggregators. The each POP location may either be part of the facilities of a telecommunications provider that an Internet service provider (ISP) rents or a location separate from the telecommunications provider. The ISPs in cloud computing system **100** may have multiple POP locations, sometimes numbering in the thousands and the tens of thousands. The POPs, POP $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$, may also be located at Internet exchange points and co-location centers.

[0031] In one or more embodiments, servers $\mathbf{102}_{1\text{-}N}$ and client devices $\mathbf{104}_{1\text{-}M}$ may be spread across different geographies (e.g., regions, countries). In one or more embodiments, WANs $\mathbf{106}_{1\text{-}N}$ and WANs $\mathbf{116}_{1\text{-}M}$ may be enabled through a variety of networking protocols. In some embodiments, WANs $\mathbf{106}_{1\text{-}N}$ and WANs $\mathbf{116}_{1\text{-}M}$ may be leased lines or Internet (e.g., egress/ingress only). In one or more embodiments, cloud computing system **100** may include a core network **114** including a private network and/or a public network that utilizes WANs $\mathbf{116}_{1\text{-}M}$ to communicate with POPs $\mathbf{122}_{1\text{-}M}$. In one or more embodiments, core network **114** may also utilize WANs $\mathbf{116}_{1\text{-}M}$ to communicate with external services (e.g., associated with service providers) and/or Content Delivery Networks (CDNs).

[0032] In some embodiments, a server $\mathbf{102}_{1\text{-}N}$ and a client device $\mathbf{104}_{1\text{-}M}$ may securely share data **108** over a WAN $\mathbf{106}_{1\text{-}N}$ and a WAN $\mathbf{116}_{1\text{-}M}$ through a private network using any of public addresses of source and destination routers, pools of addresses represented by a firewall, using a Multiprotocol Label Switching (MPLS) label, and using a Virtual Local Area Network (VLAN) tag. In one such example embodiment, a client device $\mathbf{104}_{1\text{-}M}$ (e.g., a desktop, a laptop, a notebook) may be executing a client application such as Windows Explorer®, Microsoft® Word® and Internet Explorer® thereon and one or more open client connections to the number of servers $\mathbf{102}_{1\text{-}N}$. In one or more embodiments, communication of data **108** between the number of servers $\mathbf{102}_{1\text{-}N}$ and the number of client devices $\mathbf{104}_{1\text{-}M}$ may be accelerated using application acceleration services.

[0033] In one or more embodiments, POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$, and, for example, optional Customer Premise Equipment (CPE), may perform protocol dependent proxy functions (e.g., singly or split across POPs and/or optional CPEs) to resolve bandwidth limitation or to reduce communication times by simplifying the protocol or anticipating requests on behalf of users (e.g., users $\mathbf{180}_{1\text{-}M}$) of the number of client devices $\mathbf{104}_{1\text{-}M}$. A combination of protocol dependent and protocol independent functions to solve bandwidth reduction and/or communication time reduction may be defined as application acceleration. In one or more embodiments, cloud computing system **100** shown in FIG. **1** may provide application acceleration as a service.

[0034] It should be noted that, in one or more scenario(s), some data processing devices may also be communicatively coupled to one another through, for example, an internal LAN. In one or more embodiments, each of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may be a pool of servers providing WAN optimization and application acceleration (e.g., acceleration of data **108** as application data and/or an enterprise application associated with data **108**). In one or more embodiments, POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may be communicatively coupled to each other directly or indirectly through core network **114**. In one example embodiment, core network **114**, WANs $\mathbf{106}_{1\text{-}N}$ and WANs $\mathbf{116}_{1\text{-}M}$ may use leased lines and/or Internet.

[0035] In one or more embodiments, POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may route the transport streams and/or the packet streams that includes data **108** on behalf of a server $\mathbf{102}_{1\text{-}N}$ from a closest POP (e.g., POP $\mathbf{112}_{1\text{-}N}$) thereto to a closest POP $\mathbf{122}_{1\text{-}M}$ to a client device $\mathbf{104}_{1\text{-}M}$, and then onward to client device $\mathbf{104}_{1\text{-}M}$. In one or more embodiments, the optional CPEs (not shown) may be configured to perform secure transport of data **108** and communicate the secured data **108** from one or more server(s) $\mathbf{102}_{1\text{-}N}$ to client devices $\mathbf{104}_{1\text{-}M}$ (and even one or more other server(s) $\mathbf{102}_{1\text{-}N}$), with optional intervening firewalls, through an Internet Protocol Security (IPsec) tunnel, a Generic Routing Encapsulation (GRE) tunnel, VLANs, and MPLS labels using IP headers. In one or more embodiments, the use of the optional CPEs may enable resolving bandwidth limitation(s) in the first/last mile.

[0036] In one or more embodiments, the use of the optional CPEs may enable faster data communication between servers $\mathbf{102}_{1\text{-}N}$ and client devices $\mathbf{104}_{1\text{-}M}$ if the communication line has a low bandwidth. In one example embodiment, storage in the optional CPEs may be constituted by flash memory devices. In one or more alternate embodiments, the optional CPEs may be coupled to or internally include other types of non-volatile storage devices that include hard drives, flash drives, solid state devices, etc.

[0037] In one or more embodiments, the use of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may eliminate the requirement of having intelligent synchronized WAN optimization equipment for solving latency and bandwidth at the ends of servers $\mathbf{102}_{1\text{-}N}$ and client devices $\mathbf{104}_{1\text{-}M}$. In addition, in one or more embodiments, the use of MPLS may be eliminated at core network **114** as POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ speed up data communication with no loss in packets and/or delay. In one or more embodiments, acceleration of data **108** may be possible as POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ are intelligently designed to analyze the destination of packets of data **108** and to communicate said packets to client devices $\mathbf{104}_{1\text{-}M}$ without compromising and/or modifying client private networks.

[0038] FIG. **2** shows any of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ (device form), according to one or more embodiments. In one or more embodiments, every engine of each of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may be scalable with load balanc-

ers. Also, in one or more embodiments, the engines of the each of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may enable sharing of resources among different customers thereof, thereby enabling multi-tenancy (e.g., multiple customers accessing the same hardware and software resources in the each of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$).

[0039] In one or more embodiments, the each of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may include a pool of servers providing application acceleration. In one or more embodiments, the each of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may include application proxies **202** to implement and extend a number of protocols such as Common Internet File System (CIFS), Hypertext Transfer Protocol (HTTP), Messaging Application Programming Interface (MAPI), Simple Mail Transfer Protocol (SMTP), etc., edge engines **204** to perform WAN data redundancy removal, transparent object caching, IPsec/Secure Sockets Layer (SSL) security, POP stream shaping, POP-POP data encoding, etc., and switching engines **206** to perform POP-POP routing, Quality of Service (QoS), packet classification, stream shaping and load-balancing.

[0040] In one or more embodiments, the each of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may include switches $\mathbf{208}_{A\text{-}B}$ to enable communication between application proxies **202**, edge engines **204** and switching engines **206**. In one embodiment, application proxies **202**, edge engines **204** and switch $\mathbf{208}_{A}$ may function as service servers **240**. In one or more embodiments, the function as a service server **240** may execute on one machine, or as one process shared across customers or unique per customer. Service servers **240** may provide QoS as packets are delivered based on priority order using application proxies **202** and edge engines **204** based on the type of data **108**, application of data **108**, security of data **108**, etc.

[0041] Switch $\mathbf{208}_{B}$ and switching engines **206** may manage network switching **245**. In one or more embodiments, network switching **245** may be the function(s) performed by switching engine(s) **206** to forward packets of data **108** through the network (e.g., WANs $\mathbf{106}_{1\text{-}N}$ and WANs $\mathbf{116}_{1\text{-}M}$). In one or more embodiments, POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may also have an optional storage device (e.g., shared storage **210**) to aid data redundancy removal and transportation. In one or more embodiments, any of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may include a processor **212** to perform the functionalities described herein.

[0042] In one or more embodiments, data redundancy removal may include a class of techniques to remove duplicate information between senders and receivers by capturing histories of data streams and holding these histories beyond the lives of connections. In one or more embodiments, POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may be shared among different clients and different branches. In addition, in one embodiment, the engines of POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may be shared by different clients. In one or more embodiments, POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may be centrally controlled through a control station. Also, in one or more other embodiments, POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$ may be controlled from distributed locations.

[0043] In one or more embodiments, a segment (e.g., segments $\mathbf{136}_{1\text{-}B}$) may be a communication link between a POP and other POPs, as shown in FIG. **1**. In an event of a POP failure (e.g., due to a network congestion, a service unavailability, a segment policy, etc.), cloud computing system **100** may switch coupling to a different POP. In case of there being an intermediate POP failure, an alternate route may be determined based on which the data (e.g., data **108**) is re-routed.

[0044] In one or more embodiments, cloud computing system **100** may include a huge number of network entities whose current (or, historical) state may reflect the possibility (or, currency) of performance issues and/or failures for subscribers of the application acceleration as a service provided through cloud computing system **100**. In one or more embodiments, features relevant to said huge number of network entities of cloud computing system **100** may be analyzed therethrough to determine change in patterns of data associated therewith.

[0045] FIG. **3** lists network entities $\mathbf{302}_{1\text{-}4}$ in cloud computing system **100** and features $\mathbf{304}_{1\text{-}12}$ associated therewith, according to one or more embodiments. In one or more embodiments, network entities $\mathbf{302}_{1\text{-}4}$ may include entities deployed for subscribers (e.g., users $\mathbf{180}_{1\text{-}M}$ at client devices $\mathbf{104}_{1\text{-}M}$) of all services provided through cloud computing system **100** including the application acceleration as a service discussed above; the aforementioned is shown in FIG. **3** as entities deployed for subscribers $\mathbf{302}_{1}$.

[0046] In one or more embodiments, network entities $\mathbf{302}_{1\text{-}4}$ may also include components (e.g., software, hardware) associated with (e.g., inside) core network **114** such as network bus/buses, routers, hub(s) and/or Network Access Points as core network components $\mathbf{302}_{2}$, components (e.g., physical and virtual) placed at the peripheries (e.g., routers, the optional CPEs discussed above, Network Access Points, multiplexers, router switches) of core network **114**, WANs $\mathbf{106}_{1\text{-}N}$ and/or WANs $\mathbf{116}_{1\text{-}M}$ as edge network components $\mathbf{302}_{3}$, and POPs (e.g., POPs $\mathbf{112}_{1\text{-}N}$ and POPs $\mathbf{122}_{1\text{-}M}$) of nodes/machines in cloud computing system **100** as POPs $\mathbf{302}_{4}$. Other forms of network entities are within the scope of the exemplary embodiments discussed herein.

[0047] In one or more embodiments, features $\mathbf{304}_{1\text{-}12}$ relevant to network entities $\mathbf{302}_{1\text{-}4}$ utilized for analyses may include but are not limited to:

[0048] (a) bytes (e.g., optimized and/or unoptimized bytes; while optimized data bytes may refer to data through optimized network connections, unoptimized data bytes may refer to data through unoptimized network connections) of data transferred or received from a network entity $\mathbf{302}_{1\text{-}4}$; the aforementioned is shown in FIG. **3** as network entity data bytes $\mathbf{304}_{1}$,

[0049] (b) number of active connections (e.g., optimized and/or unoptimized network connections) from and/or to network entity $\mathbf{302}_{1\text{-}4}$; the aforementioned is shown in FIG. **3** as active connections $\mathbf{304}_{2}$,

[0050] (c) Transmission Control Protocol (TCP) metrics $\mathbf{304}_{3}$; in an example implementation of cloud computing system **100**, POP-POP architecture thereof may include TCP proxies (e.g., at layer 4) at each segment (e.g., segment $\mathbf{136}_{1\text{-}B}$),

[0051] (d) latency metrics $\mathbf{304}_{4}$, or, latency related to data communication (e.g., involving network entities $\mathbf{302}_{1\text{-}4}$) across cloud computing system **100**,

[0052] (e) packet loss percentages $\mathbf{304}_{5}$, or, percentage of packets related to data communication (e.g., involving network entities $\mathbf{302}_{1\text{-}4}$) across cloud computing system **100** not reaching destination(s) thereof,

[0053] (f) network connection resets and closures (e.g., through termination requests such as FINs) $\mathbf{304}_{6}$,

[0054] (g) SSL connections 304_7 from and/or to network entity 302_{1-4},

[0055] (h) Central Processing Unit (CPU) temperatures 304_8 specific to machines within cloud computing system **100**,

[0056] (i) disk operations 304_9 specific to machines within cloud computing system **100**,

[0057] (j) memory page in and/or page out activities 304_{10} specific to machines within cloud computing system **100**,

[0058] (k) memory statistics 304_{11} specific to machines within cloud computing system **100**, and

[0059] (l) Input/Output (I/O) data packet rate for each network entity 302_{1-4}, as I/O data packet rates 304_{12}.

[0060] In one or more embodiments, there may be tens of thousands of network entities (e.g., network entities 302_{1-4}) in cloud computing system **100**; thus, computational requirements involved in analyzing features 304_{1-12} in real-time may require large-scale processing through cloud computing system **100**. In one or more embodiments, analyses for problematic data patterns may have to be performed on different network entities 302_{1-4}, with each category of network entity 302_{1-4} (e.g., network entity 302_1, network entity 302_2, network entity 302_3 etc.) having own sets of features 304_{1-12} associated therewith on which said analyses have to be done.

[0061] Exemplary embodiments discussed herein provide for a self-adaptable, fault tolerant and linearly scalable process to analyze performance issues and/or failures for subscribers (e.g., user(s) 180_{1-M} associated with client device(s) 104_{1-M}) within cloud computing system **100** based on analyzing changes in patterns of data for each network entity 302_{1-4}. For example, one network entity 302_{1-4} may have several features 304_{1-12} to account for in order to completely describe a state thereof. In one or more embodiments, the aforementioned analyses may be performed on the one or more features 304_{1-12} across time steps to determine one or more changes in the patterns of data.

[0062] FIG. **4** shows a prediction module **402** (e.g., including multiple sets of instructions) executing on servers 102_{1-N} of cloud computing system **100**, according to one or more embodiments. For illustrative purposes, FIG. **4** shows prediction module **402** executing on one server 102_{1-N}. As discussed above, in cloud computing system **100**, each network entity 302_{1-4} may generate data per unit of time (e.g., 1 minute), according to one or more embodiments. In one or more embodiments, said data may be collected at a central repository machine (e.g., server 102_{1-N} shown in FIG. **4**). FIG. **4** shows server 102_{1-N} as including a processor 452_{1-N} (e.g., a CPU, a Graphics Processing Unit (GPU) and/or a microprocessor, a cluster of processors) communicatively coupled to a memory 454_{1-N} (e.g., volatile and/or non-volatile memory/storage, a number of memories including memories of different types).

[0063] FIG. **4** also shows prediction module **402** stored in memory 454_{1-N} and configured to execute on processor 452_{1-N}; data associated with each network entity 302_{1-4} is shown as stored in memory 454_{1-N} as network entity data **404** and interfaced with prediction module **402**; said network entity data **404** may be available for a long duration of time (e.g., 1 month, 3 days). In one or more embodiments, prediction module **402** may be configured to read network entity data **404** as a time series for each network entity 302_{1-4} for each feature 304_{1-12}. In one or more embodiments, prediction module **402** may then sample network entity data **404** for the each feature 304_{1-12} into a smaller time interval (say, x minutes, compared to, say, 3 days; said smaller time interval may be predefined and/or preconfigured), and split network entity data **404** into two series of sampled data—a first series **406** including a maximum value **408** (or, one or more maximum values; first series **406** may include a set of maximum values of network entity data **404**) of network entity data **404** for the each feature 304_{1-12} within the smaller time interval and a second series **410** including a minimum value **412** (or, one or more minimum values; second series **410** may include a set of minimum values of network entity data **404**) of network entity data **404** for the each feature 304_{1-12} within the smaller time interval. It is quite easy to envision numbers (corresponding to maximum value **408** and minimum value **412**) of network entity data **404** within the smaller time interval.

[0064] In one or more embodiments, first series **406** and second series **410** may be utilized by prediction module **402** to create two separate data models to forecast (e.g., predicted values **414** associated with first series **406**, and predicted values **416** associated with second series **410**) network entity data **404** for the each feature 304_{1-12} for future time intervals 450_{1-P}. In one or more embodiments, prediction module **402** may combine predicted values **414** from first series **406** and predicted values **416** from second series **410** for each future time interval 450_{1-P} and transform said predicted values **414** and predicted values **416** into a data band **418**, where a minimum of predicted values **416** is regarded as a minimum boundary value (or, min_expected_value) of data band **418** and a maximum of predicted values **414** is regarded as a maximum boundary value (or, max_expected_value) of data band **418**.

[0065] In one or more embodiments, data band **418** may then be upsampled (or, extrapolated) by the smaller time interval (say, x minutes; FIG. **4** shows smaller time interval as time interval **440**) discussed above via prediction module **402** to restore data granularity. In one example implementation, the aforementioned upsampling may be done by copying x data samples in one minute. In one or more embodiments, the result of the upsampling, viz. upsampled data **420**, may be stored in memory 454_{1-N} (e.g., non-volatile storage).

[0066] FIG. **5** summarizes the operations involved in the abovementioned data prediction, according to one or more embodiments. In one or more embodiments, operation **502** may involve reading, through prediction module **402**, network entity data **404** as a time series for each network entity 302_{1-4} for each feature 304_{1-12} at a specific (e.g., predefined and/or preconfigured) granularity (e.g., 1 minute) from memory 454_{1-N}. In one or more embodiments, operation **504** may involve normalizing, through prediction module **402**, the read network entity data **404** to account for previous anomalies therein.

[0067] In one or more embodiments, the normalized read network entity data **404** may then be sampled by prediction module **402** for the each feature 304_{1-12} into a smaller time interval (say, x minutes; x, for example, can be 10 minutes); prediction module **402** may also split (the normalized read) network entity data **404** into two series of sampled data—first series **406** and second series **410**, both within time interval **440**, as discussed above. The aforementioned operations are detailed under two distinct chains: operation **506** involving sampling (the normalized read) network entity

data **404** for the each feature $\mathbf{304}_{1\text{-}12}$ into first series **406** and operation **508** involving sampling (the normalized read) network entity data **404** for the each feature $\mathbf{304}_{1\text{-}12}$ into second series **410** are shown as two distinct operations.

[0068] In one or more embodiments, operation **510** may involve prediction module **402** utilizing first series **406** to generate a first data model (e.g., predicted values **414**) to forecast network entity data **404** for the each feature $\mathbf{304}_{1\text{-}12}$ for future time intervals $\mathbf{450}_{1\text{-}P}$. For the aforementioned purpose, in one example implementation, prediction module **402** may implement one or more forecasting and/or predictive algorithms (e.g., exponential smoothing algorithm(s) such as algorithms based on triple exponential smoothing) on first series **406** to create predicted values **414**. Similarly, in one or more embodiments, operation **512** may involve prediction module **402** utilizing second series **410** to generate a second data model (e.g., predicted values **416**) to forecast network entity data **404** for the each feature $\mathbf{304}_{1\text{-}12}$ for future time intervals $\mathbf{450}_{1\text{-}P}$. Again, for the aforementioned purpose, prediction module **402** may utilize the one or more forecasting and/or predictive algorithms.

[0069] In one or more embodiments, operation **514** may involve prediction module **402** combining predicted values **414** from first series **406** and predicted values **416** from second series **410** for each future time interval $\mathbf{450}_{1\text{-}P}$ and transform said predicted values **414** and predicted values **416** into data band **418** discussed above. In one or more embodiments, as part of the combination of operation **514**, a minimum of predicted values **416** may be regarded as min_expected_value of data band **418** and a maximum of predicted values **414** may be regarded as max_expected_value of data band **418**.

[0070] In one or more embodiments, operation **516** may involve upsampling data band **418** by time interval **440** via prediction module **402** to restore the data granularity. In one or more embodiments, operation **518** may then involve storing upsampled data **420** in memory $\mathbf{454}_{1\text{-}N}$ (e.g., persistent/non-volatile storage). It can be understood that data band **418** or upsampled data **420** may be utilized in detection of anomalies in network entity data **404** collected in real-time.

[0071] FIG. **6** shows a detector module **602** executing on servers $\mathbf{102}_{1\text{-}N}$ of cloud computing system **100**, according to one or more embodiments. For illustrative purposes, FIG. **6** shows detector module **602** executing on the same one server $\mathbf{102}_{1\text{-}N}$ as prediction module **402** and communicatively coupled thereto. Again, in one or more embodiments, detector module **602** may be stored in memory $\mathbf{454}_{1\text{-}N}$ and configured to execute on processor $\mathbf{452}_{1\text{-}N}$. It should be noted that implementations where detector module **602** is executed on one or more server(s) $\mathbf{102}_{1\text{-}N}$ different from the one server $\mathbf{102}_{1\text{-}N}$ executing prediction module **402** and distributed implementations of detector module **602** and prediction module **402** across cloud computing system **100** are within the scope of the exemplary embodiments discussed herein.

[0072] In one or more embodiments, detector module **602** may be configured to read network entity data **404** in real-time. In one or more embodiments, for every unit of time (e.g., 1 minute; can be predefined and/or preconfigured), detector module **602** may read network entity data **404** for the each feature $\mathbf{304}_{1\text{-}12}$ for a predefined time interval **604** shown in FIG. **6**. In one or more embodiments, detector module **602** may then compare read network entity data **404** with data band **418** (or, upsampled data **420**). In one or more embodiments, if the value of network entity data **404** is determined to be outside data band **418**, detector module **602** may implement a sequence of operations to test whether said value is an anomaly. In one or more embodiments, once the aforementioned sequence of operations confirms that the value is a true anomaly (or, point anomaly), read network entity data **404** may be subjected to a scoring mechanism **606** (e.g., implemented through detector module **602**) that computes a score to describe anomalousness of said value.

[0073] In one or more embodiments, in accordance with scoring mechanism **606**, detector module **602** may compute a combination of a relative score **608** and a deviation score for the abovementioned value. In one or more embodiments, relative score **608** may be computed as:

$$\text{relative score} = \min\left(1, \frac{(\text{input} - \text{base})}{\text{base}}\right), \tag{1}$$

where min represents the minimum function that returns the smaller of two values, viz. 1 and

$$\frac{\text{input} - \text{base}}{\text{base}},$$

input represents the above value of real-time network entity data **404** to be compared with data band **418** (or, upsampled data **420**), base is min_expected_value of data band **418** discussed above if input is lower than min_expected_value, and base is max_expected_value of data band **418** discussed above if input is higher than max_expected_value.

[0074] In one or more embodiments, in accordance with scoring mechanism **606**, the deviation score for current network entity data **404** for each feature $\mathbf{304}_{1\text{-}12}$ may be computed based on previous deviations **610** thereof from data bands analogous to data band **418** (e.g., in effect, in a temporal future, data band **418** may form an element in a data set of a history of data bands). In one or more embodiments, previous deviations **610** from the data bands analogous to data band **418** may be preserved in memory $\mathbf{454}_{1\text{-}N}$ (e.g., in one or more rolling cache(s)). In one or more embodiments, scoring mechanism **606**, as implemented through detector module **602**, may preserve two discrete data distributions (e.g., discrete data distribution $\mathbf{614}_1$ and discrete data distribution $\mathbf{614}_2$) with a given probability mass function **612** of previous deviations **610** from the data bands analogous to data band **418**.

[0075] In one or more embodiments, the abovementioned two discrete data distributions may be preserved for each network entity $\mathbf{302}_{1\text{-}4}$ for each feature $\mathbf{304}_{1\text{-}12}$. In one or more embodiments, one discrete data distribution $\mathbf{614}_1$ may be preserved for point anomalies whose values are higher than max_expected_value discussed above and another discrete data distribution $\mathbf{614}_2$ may be preserved for point anomalies whose values are lower than min_expected_value. Here, in one or more embodiments, discrete data distribution $\mathbf{614}_1$ and discrete data distribution $\mathbf{614}_2$ may utilize previous deviations **610** that are absolute deviations from the data bands analogous to data band **418** for corresponding point anomalies.

[0076] In one or more embodiments, for a newly determined point anomaly based on network entity data **404** read, scoring mechanism **606** may chose discrete data distribution $\mathbf{614}_1$ or discrete data distribution $\mathbf{614}_2$ based on value of said network entity data **404** read and compute a cumulative probability utilizing a value of deviation of said point anomaly from data band **418**. In one or more embodiments, the aforementioned cumulative probability may be regarded as an absolute deviation score **616**.

[0077] In one or more embodiments, the final score (e.g., final score **618**) for the point anomaly may be expressed as:

$$\text{final score} = \text{sign} \times (\text{relative score} + \text{absolute deviation score}), \quad (2)$$

[0078] where sign=1, if input discussed above with regard to Equation (1) is higher than max_expected_value and sign=−1, if input discussed above with regard to Equation (1) is lower than min_expected_value.

[0079] FIG. **6** also shows a correlation module **620** communicatively coupled to detector module **602** (and, optionally, prediction module **402**), according to one or more embodiments. Again, in one or more embodiments, correlation module **620** may be stored in memory $\mathbf{454}_{1\text{-}N}$ and configured to execute on processor $\mathbf{452}_{1\text{-}N}$ to realize operations associated therewith; again, the aforementioned modules may be distributed across servers $\mathbf{102}_{1\text{-}N}$ of cloud computing system **100**, in some embodiments. In one or more embodiments, correlation module **620** may determine commonness of a pattern of continuous anomalies. In one or more embodiments, point anomalies (e.g., point anomalies **622**) discussed above may be fed into correlation module **620**, which organizes point anomalies **622** for each network entity $\mathbf{302}_{1\text{-}4}$ into a full mesh Q node graph, Q being the number of features (e.g., one or more of features $\mathbf{304}_{1\text{-}12}$) applicable to the each network entity $\mathbf{302}_{1\text{-}4}$; it is obvious that one network entity $\mathbf{302}_{1\text{-}4}$ may be associated with more features than another network entity $\mathbf{302}_{1\text{-}4}$. It is known to one skilled in the art that a full mesh graph may be a complete graph where every node is connected to every other node.

[0080] In one or more embodiments, a data correlation score **624** may be accumulated and updated by correlation module **620** for every determination of a point anomaly **622**. In one or more embodiments, correlation module **620** may enable accumulation of data correlation scores **624** for a sliding window of a large time interval **626** (e.g., L weeks); said data correlation scores **624** may also be serialized for time interval **626**. In one or more embodiments, correlation module **620** may keep track of a total number of point anomalies **622** determined for each network entity $\mathbf{302}_{1\text{-}4}$, and a count of point anomalies **622** determined for each feature $\mathbf{304}_{1\text{-}12}$ applicable thereto. In one or more embodiments, data correlation scores **624** may be stored in memory $\mathbf{454}_{1\text{-}N}$ (e.g., persistent storage).

[0081] In one or more embodiments, a separate asynchronous process executing periodically may be assigned (e.g., through detector module **602**) to crawl (or, scan) through all point anomalies **622** and determine a continuous anomaly event **628** that can be considered as signifying a data pattern change. In one or more embodiments, for each network entity $\mathbf{302}_{1\text{-}4}$, detector module **602** may implement an optimization algorithm **630** (e.g., stored in memory $\mathbf{454}_{1\text{-}N}$ and configured to execute through processor $\mathbf{452}_{1\text{-}N}$) utilizing one or more dynamic programming technique(s) (e.g., recursion) to find a longest occurring sequence **632** of point anomalies **622** among all features $\mathbf{304}_{1\text{-}12}$ of each network entity $\mathbf{302}_{1\text{-}4}$ that is capable of being interleaved for a duration up to R minutes.

[0082] In one or more embodiments, an optimal sub-solution for longest occurring sequence **632** may be stored in memory $\mathbf{454}_{1\text{-}N}$ (e.g., a cache), and every subsequent iteration starting from the first may utilize a previous optimal sub-solution for longest occurring sequence **632** to generate a new longest occurring sequence **632**. In one or more embodiments, in the process, detector module **602** may filter out sequences smaller than a predefined and/or pre-configured threshold by auto-ignoring short-lived (e.g., duration below another threshold) anomaly events. In one or more embodiments, detector module **602** may also compute an anomaly score **634** for each feature $\mathbf{304}_{1\text{-}12}$ corresponding to longest occurring sequence **632** based on summing up the number of point anomalies **622** of longest occurring sequence **632** for the each feature $\mathbf{304}_{1\text{-}12}$ and dividing said sum by a duration of longest occurring sequence **632**. In one or more embodiments, detector module **602** may determine that a point anomaly **622** is occurring currently (or, in real-time) and is part of the determined continuous anomaly event **628**; detector module **602** may then store the actively occurring continuous anomaly event **628** in memory $\mathbf{454}_{1\text{-}N}$ (e.g., into a separate table in a database).

[0083] FIG. **6** also shows a feedback module **636** configured to collect feedback (e.g., forming at least a part of feedback data **638**) from an end user (e.g., a user $\mathbf{180}_{1\text{-}M}$ on a client device $\mathbf{104}_{1\text{-}M}$) on one or more continuous anomaly events **628** reported thereto. Again, feedback module **636** is shown stored in memory $\mathbf{454}_{1\text{-}N}$; feedback module **636** is configured to execute on processor $\mathbf{452}_{1\text{-}N}$; in some embodiments, the modules may be distributed across cloud computing system **100**. FIG. **6** also shows feedback data **638** associated with feedback module **636**. In one or more embodiments, feedback data **638** for an event (e.g., continuous anomaly event **628**) may include anomaly score **634** thereof, along with a severity indicator **640** associated therewith; as seen above, at least a part of feedback data **638** may be constituted based on input(s) from the end user.

[0084] In one or more embodiments, feedback module **636** may utilize feedback data **638** to generate a classification model **642** that takes anomaly scores **634** of features $\mathbf{304}_{1\text{-}12}$ for an event (e.g., continuous anomaly event **628**) as inputs thereto. In one or more embodiments, classification model **642** may consider a severity indicator **640** as a label of the event. In one example implementation, feedback module **636** may determine severity indicator **640** based on self-analyses and/or feedback from end users (e.g., users $\mathbf{180}_{1\text{-}M}$ on client device(s) $\mathbf{104}_{1\text{-}M}$) in accordance with some form of priority event(s) (e.g., potentially disruptive to one or more end user(s)) to be taken care of.

[0085] In the above implementation, severity indicators **640** may be grouped under four categories, for example, "Not a Problem," "Low," "Medium," and "High." Relevant values may be assigned to each these four categories. A typical range of values used to define severity indicators **640** may be 0-1. For example, "Not a Problem" may be mapped to a 0.25, "Low" to a 0.5, "Medium" to a 0.75 and "High" to a 1. Here, the choice of values used to define severity indicators **640** may depend on the process of handling high severity scenarios (e.g., by boosting anomaly scores **634**) and/or suppressing false positives. In one or more embodiments, boosting anomaly scores **634** may be a technique to

improve confidence level(s) of severity predictions as the collected data (e.g., based on network entity data **404** for all features $\mathbf{304}_{1\text{-}12}$) grows.

[0086] In one or more embodiments, classification model **642** may define different mappings of severity indicators **640** to applicable anomaly scores **634** for different sizes of data (e.g., based on network entity data **404**). In one or more embodiments, classification model **642** may generate a feedback score **644** based on the aforementioned mapping; said feedback score **644** is stored in memory $\mathbf{454}_{1\text{-}N}$ (e.g., a data store) along with the associated event (e.g., continuous anomaly event **628**).

[0087] In one or more embodiments, data pattern changes as reflected through continuous anomaly events **628**, for example, may be reported to a user (e.g., a network user such as a cloud administrator, a subscriber (e.g., a user $\mathbf{180}_{1\text{-}M}$) at a client device $\mathbf{104}_{1\text{-}M}$) of cloud computing system **100**. FIG. **7** shows a reporting module **702** executing on servers $\mathbf{102}_{1\text{-}N}$, according to one or more embodiments. In one or more embodiments, reporting module **702** may be communicatively coupled to each of feedback module **636**, correlation module **620**, detector module **602** and prediction module **402**. Again, in one or more embodiments, reporting module **702** may be stored in memory $\mathbf{454}_{1\text{-}N}$; instructions associated therewith may be configured to execute on processor $\mathbf{452}_{1\text{-}N}$; again, the aforementioned modules may be distributed across server(s) $\mathbf{102}_{1\text{-}N}$ of cloud computing system **100**.

[0088] In one or more embodiments, the abovementioned determined pattern changes may be reported to one or more user(s) (e.g., a network user such as a cloud administrator, subscriber(s) (e.g., user(s) $\mathbf{180}_{1\text{-}M}$) at client device(s) $\mathbf{104}_{1\text{-}M}$) of cloud computing system **100** in accordance with a reporting mechanism **704** implemented through reporting module **702**. In one or more embodiments, reporting mechanism **704** may poll memory $\mathbf{454}_{1\text{-}N}$ for new pattern changes occurring in real-time. In one or more embodiments, reporting mechanism **704** may filter out any event with a low (e.g., below a predefined and/or preconfigured threshold) data correlation score **624**, and apply a ranking on all events occurring in real-time. FIG. **7** shows events $\mathbf{706}_{1\text{-}Z}$ occurring in real-time. In one or more embodiments, an event score $\mathbf{708}_{1\text{-}Z}$ for an event $\mathbf{706}_{1\text{-}Z}$ may be computed by reporting module **702** by summing individual anomaly scores **634** for all features $\mathbf{304}_{1\text{-}12}$ and weighting the sum with respect to feedback score **644** stored in memory $\mathbf{454}_{1\text{-}N}$. In one or more embodiments, the abovementioned ranking may be based on an order (e.g., decreasing, increasing) of event scores $\mathbf{708}_{1\text{-}Z}$.

[0089] As discussed above, event score $\mathbf{708}_{1\text{-}Z}$ may be expressed as:

$$\text{event score}=\Sigma_{all\ features}\ \text{abs(anomaly score)}\times\text{feedback score}, \tag{3}$$

[0090] where abs is a function that returns the absolute value of the argument thereof; here, abs(anomaly score) may return the absolute value or magnitude of the corresponding anomaly score **634**.

[0091] In one or more embodiments, reporting module **702** may also capture feedback from the user, analogous to feedback module **636**. As discussed above, in one or more embodiments, the feedback may be used to further improve event scoring (e.g., computing event score $\mathbf{708}_{1\text{-}Z}$) by predicting severity thereof or a pattern change associated therewith. In one or more embodiments, the aforementioned feedback may also be utilized to classify events (e.g., events $\mathbf{706}_{1\text{-}Z}$) into categories and tag analyses of one or more events as valuable high level diagnoses of data pattern change(s) associated therewith. In one or more embodiments, in accordance therewith, reporting mechanism **704** may utilize anomaly scores **634** for each event $\mathbf{706}_{1\text{-}Z}$ as inputs to a classification model analogous to classification model **642** implemented therethrough, with each feature $\mathbf{304}_{1\text{-}12}$ becoming a dimension of the inputs.

[0092] In one or more embodiments, categories (e.g., through analogous severity indicators **640**) of the each event $\mathbf{706}_{1\text{-}Z}$ given as feedback may be used as the label thereof. In one or more embodiments, the models discussed above and implemented through prediction module **402**, detector module **602**, correlation module **620**, feedback module **636** and reporting module **702** may, thus, provide for a predictive model **760** to classify future events **770** analogous to events $\mathbf{706}_{1\text{-}Z}$ into categories of problems (e.g., problems $\mathbf{750}_{1\text{-}A}$ based on anomalous data patterns (and, feedback score **644**, event scores $\mathbf{708}_{1\text{-}Z}$) discussed above).

[0093] In one or more embodiments, the sampling of network entity data **404** for the each feature $\mathbf{304}_{1\text{-}12}$ discussed above into a smaller time interval and splitting of network entity data **404** into two series of sampled data enable detecting events $\mathbf{706}_{1\text{-}Z}$ through the modules implemented in one or more server(s) $\mathbf{102}_{1\text{-}N}$ much faster compared to a detection process involving no sampling and splitting. In one or more embodiments, this may provide for a faster and more efficient predictive model to classify future events. Additionally, in one or more embodiments, storage footprints associated with the new processes discussed above may be less compared to traditional detection of anomalies in network entity data **404**.

[0094] It should be noted that instructions associated with prediction module **402**, detector module **602**, correlation module **620**, feedback module **636** and reporting module **702** discussed above may be tangibly embodied on a non-transitory medium (e.g., a Compact Disc (CD), a Digital Video Disc (DVD), a hard disk/drive, a Blu-ray disc™) readable through a data processing device (e.g., a server $\mathbf{102}_{1\text{-}N}$). All reasonable variations are within the scope of the exemplary embodiments discussed herein.

[0095] FIG. **8** shows a process flow diagram detailing the operations involved in efficient detection and prediction of data pattern changes in a cloud-based application acceleration as a service environment (e.g., cloud computing system **100**), according to one or more embodiments. In one or more embodiments, operation **802** may involve sampling, through a server (e.g., one or more server(s) $\mathbf{102}_{1\text{-}N}$) of cloud computing system **100** including a number of subscribers (e.g., users $\mathbf{180}_{1\text{-}M}$) of the application acceleration as a service provided by cloud computing system **100** at a corresponding number of client devices (e.g., client devices $\mathbf{104}_{1\text{-}M}$) communicatively coupled to the server, time series data (e.g., network entity data **404**) associated with each network entity (e.g., network entity $\mathbf{302}_{1\text{-}4}$) of a number of network entities (e.g., network entities $\mathbf{302}_{1\text{-}4}$) of cloud computing system **100** for each feature (e.g., feature $\mathbf{304}_{1\text{-}12}$) thereof into a smaller time interval (e.g., time interval **440**) compared to that of the time series data as a first data series (e.g., first series **406**) including a maximum value (e.g., maximum value **408**) of the sampled time series data for the each feature within the smaller time interval and a second data series (e.g., second series **410**) including a minimum

value (e.g., minimum value **412**) of the sampled time series data for the each feature within the smaller time interval.

[0096] In one or more embodiments, operation **804** may involve generating, through the server, a reference data band (e.g., data band **418**) based on predicting a first future data set (e.g., predicted values **414**) of the each network entity for the each feature based on the first data series and a second future data set (e.g., predicted values **416**) of the each network entity for the each feature based on the second data series, combining the first future data set and the second future data set for each future time interval (e.g., time interval $\mathbf{450}_{1\text{-}P}$) thereof, and transforming the combined first future data set and the second future data set for the each future time interval into the reference data band.

[0097] In one or more embodiments, based on regarding a maximum of the first future data set as a maximum expected value (max_expected_value) of the reference data band and a minimum of the second future data set as a minimum expected value (min_expected_value) of the reference data band, operation **806** may involve detecting, through the server, one or more anomalies (e.g., point anomalies **622**) in real-time data (e.g., network entity data **404**) associated with the each network entity for the each feature thereof based on determining whether the real-time data falls outside the maximum expected value and the minimum expected value of the reference data band.

[0098] In one or more embodiments, operation **808** may then involve determining, through the server, an event (e.g., continuous anomaly event **628**, event $\mathbf{706}_{1\text{-}Z}$) associated with a pattern of change of the real-time data associated with the each network entity based on executing an optimization algorithm (e.g., optimization algorithm **630**) to determine, among all features of the each network entity, a series of anomalies including the detected one or more anomalies that constitutes a sequence of patterned anomalies in accordance with scanning detected anomalies associated with the real-time data associated with the each network entity including the detected one or more anomalies.

[0099] Referring back to FIG. **6** and the discussion associated therewith, correlation module **620** may help determine commonness of a pattern of continuous anomalies by providing intuition thereof. In one or more embodiments, the "pattern," as discussed herein, may refer to the combinations of features $\mathbf{304}_{1\text{-}12}$ that have led to an event (e.g., a continuous anomaly event **628**) or a continuous sequence of point anomalies **622**. In one or more embodiments, anomaly information (e.g., point anomaly **622**) for each network entity $\mathbf{302}_{1\text{-}4}$ for one or more features $\mathbf{304}_{1\text{-}12}$ associated therewith may be held (e.g., through correlation module **620**) in a full mesh Q node graph, where Q signifies the number of features (e.g., one or more of features $\mathbf{304}_{1\text{-}12}$) applicable to the each network entity $\mathbf{302}_{1\text{-}4}$. In one or more embodiments, data correlation score **624** corresponding thereto may be accumulated and updated for every report of new anomaly associated with the one or more features $\mathbf{304}_{1\text{-}12}$. It should be noted that, in one or more embodiments, data correlation score **624** may also be updated for every report of an anomaly in the one or more features $\mathbf{304}_{1\text{-}12}$ changing state thereof into a non-anomaly.

[0100] Thus, in one or more embodiments, detector module **602** may merely need to look up values of current data correlation scores **624** without the requirement of performing additional operations therefor. In one or more embodiments, the scoring mechanism may hold score information (e.g., data correlation scores **624** in memory $\mathbf{454}_{1\text{-}N}$) for a sliding window of a large time interval **626** (e.g., L weeks, 1 week), as discussed above. In one or more embodiments, correlation module **620** may also serialize graph snapshots into memory $\mathbf{454}_{1\text{-}N}$ (e.g., disk) in the form of a Q×Q matrix. In one or more embodiments, this may enable graph building on restart of the pattern commonness determination process. In one or more embodiments, the mechanism may keep track of a total number of point anomalies **622** reported for each network entity $\mathbf{302}_{1\text{-}4}$ and a count of point anomalies **622** associated with a feature $\mathbf{304}_{1\text{-}12}$.

[0101] FIG. **9** illustrates an example graph **900** representing a point anomaly **622** associated with a network entity $\mathbf{302}_{1\text{-}4}$ having features $\mathbf{304}_{1\text{-}Q}$ associated therewith and transitions occurring therein when new anomalies associated with features $\mathbf{304}_{1\text{-}Q}$ are added thereto. For example purposes, graph **900** may be constituted by 4 nodes (Q=4) M_1-M_4, where each of M_1-M_4 is a feature $\mathbf{304}_{1\text{-}4}$ (note that Q can be anything, so there may be more than 4 or even more than 12 features to account for). M_1-M_4 may be associated with metrics discussed above. Thus, each node M_1-M_4 of graph **900** may represent a feature $\mathbf{304}_{1\text{-}Q}$. An edge of graph **900** may represent a weight (e.g., a count). Point anomaly **622** may be monitored periodically (e.g., after every time interval T) through graph **900** and every time interval elapsing after an initial state may be counted as a time sample. The count of the number of time samples may also be monitored.

[0102] As shown in the initial state (time t=0), the time sample count may be 0. As part of a first transition (time t=T), M_1 and M_3 may be anomalous (e.g., associated with point anomaly **622**). This may cause the weight of each pair of features affected thereby (M_1-M_3) including self-pairs (M_1-M_1 and M_3-M_3) to be updated by 1, as shown in FIG. **9**. The total number of pairs of features $\mathbf{304}_{1\text{-}Q}$ affected may be ${}^2C_1+{}^2C_2=3$. Now, as this is the first sample, the time sample count may be updated to 1. Over time, as part of a second transition (time t=2T) from the first transition, M_2 may be newly anomalous. M_1 and M_3 may remain anomalous. The aforementioned transition may be tracked through graph **900** by the weight of each pair of features (M_1-M_2, M_2-M_3 and M_1-M_3) affected thereby including self-pairs (M_1-M_1, M_2-M_2 and M_3-M_3) being updated by 1, as shown in FIG. **9**.

[0103] The total number of pairs of features $\mathbf{304}_{1\text{-}Q}$ affected may be ${}^3C_1+{}^3C_2=3+3=6$. As this is the second transition, the time sample count may be updated to 2. It should be noted that if, for example, M_2 is non-anomalous in the third transition (not shown), the weight of each pair corresponding to M_2 may not be updated and may stay the same. M_2 may then be excluded from the nodes of graph **900** being accounted for in the calculation of a current data correlation score **624**. Thus, the transitions across a large number of samples may be averaged through correlation module **620** to obtain the current data correlation score **624** of point anomaly **622** as:

$$CS = \sum_{i=1}^{APC} \frac{\left(1 - \frac{EWP_i}{TSAC}\right)}{APC}. \tag{4}$$

[0104] where CS may be the current data correlation score **624**, APC may be the count of the total number of pairs of

Y current anomalous features out of the features $\mathbf{304}_{1\text{-}Q}$ (M_1-M_4 or $\mathbf{304}_{1\text{-}4}$), which may be given by ${}^{Y}C_2+{}^{Y}C_1$ for graph **900**, where Y (≤Q) is the number of features currently having anomalies associated therewith, EWP_i may be the edge weight of the i^{th} pair of the Y current anomalous features and TSAC may be the total number of time samples (or, count of the number of time samples). It should be noted that $EWP_i \leq TSAC$. In one or more embodiments, data correlation scores **624** may be employed in reporting mechanism **704** implemented through reporting module **702**, and factored into computation of event score(s) $\mathbf{708}_{1\text{-}Z}$ discussed above.

[0105] In one or more embodiments, data correlation score **624** for every point anomaly **622** may be updated over time as seen in the equation (4) above. In one or more embodiments, by assigning a (current) data correlation score **624** to a point anomaly **622**, a commonness of a combination of the anomalous features (e.g., Y features) contributing to point anomaly **622** associated with the each network entity $\mathbf{302}_{1\text{-}4}$ with respect to an equivalent combination of the anomalous features contributing to another previously detected point anomaly **622** associated with the each network entity $\mathbf{302}_{1\text{-}4}$ may be indicated by way of the current data correlation score **624**. It should be noted that several graphs **900** pertaining to point anomalies **622** may be represented and analyzed through correlation module **620**.

[0106] It should be noted that transitions associated with both new anomalies and changes of existing anomalies into non-anomalies may be captured through graph **900**. In one or more embodiments, when a continuous anomaly event **628** occurs, detector module **602** may check for scores (e.g., anomaly scores **634**, data correlation scores **624**) for the combination of features $\mathbf{304}_{1\text{-}12}$ (or $\mathbf{304}_{1\text{-}4}$) leading to continuous anomaly event **628**. In one or more embodiments, scoring mechanism **606** implemented through detector module **602** may also compute a probability for each possible combination of features $\mathbf{304}_{1\text{-}12}$ (or, $\mathbf{304}_{1\text{-}4}$) leading to continuous anomaly event **628**. In one or more embodiments, the reversal of the probability may provide an intuition as to how uncommon the sequence of point anomalies **622** is. In one or more embodiments, the probabilities of all combinations of features $\mathbf{304}_{1\text{-}12}$ (or $\mathbf{304}_{1\text{-}4}$) leading to continuous anomaly event **628** may be averaged to obtain a score value that may be stored (e.g., in persistent memory $\mathbf{454}_{1\text{-}N}$) against the corresponding continuous anomaly event **628**.

[0107] FIG. **10** is a process flow diagram detailing the operations involved in realizing correlation score (e.g., data correlation score **624**) based commonness indication associated with a point anomaly (e.g., point anomaly **622**) pertinent to data pattern changes in cloud computing system **100** of FIGS. **1**, **4**, **6** and **7**, according to one or more embodiments. In one or more embodiments, operation **1002** may involve detecting, through a server (e.g., one or more server(s) $\mathbf{102}_{1\text{-}N}$) of a cloud computing network (e.g., cloud computing system **100**) including a number of subscribers (e.g., users $\mathbf{180}_{1\text{-}M}$) of application acceleration as a service provided by the cloud computing network at a corresponding number of client devices (e.g., client devices $\mathbf{104}_{1\text{-}M}$) communicatively coupled to the server, real-time data (e.g., network entity data **404**) associated with each network entity of a number of network entities (e.g., network entities $\mathbf{302}_{1\text{-}4}$) of the cloud computing network for each feature thereof (e.g., feature $\mathbf{304}_{1\text{-}12}$) sequentially in time.

[0108] In one or more embodiments, operation **1004** may involve detecting, through the server, a point anomaly (e.g., point anomaly **622**) in the real-time data associated with the each network entity based on determining whether the real-time data falls outside a threshold expected value (e.g., max_expected_value, min_expected value) thereof. In one or more embodiments, operation **1006** may involve representing, through the server, the detected point anomaly in a full mesh Q node graph (e.g., graph **900**), with Q being a number of features applicable for the each network entity. In one or more embodiments, operation **1008** may involve capturing, through the server, a transition in the point anomaly associated with a newly detected anomaly or non-anomaly in the real-time data associated with one or more feature(s) of the Q number of features via the representation of the full mesh Q node graph. In one or more embodiments, operation **1010** may then involve deriving, through the server, a current data correlation score (e.g., data correlation score **624**) for the point anomaly across the captured transition as

$$CS = \sum_{i=1}^{APC} \frac{\left(1 - \frac{EWP_i}{TSAC}\right)}{APC}.$$

[0109] In one or more embodiments, CS may be the current data correlation score for the point anomaly across the captured transition, APC may be a count of a total number of pairs of Y current anomalous features in the Q number of features and may be given by ${}^{Y}C_2+{}^{Y}C_1$, EWP_i may be a weight of an edge of the i^{th} pair of the Y current anomalous features in the representation of the full mesh Q node graph, and TSAC may be a total number of time samples of the point anomaly including the captured transition. In one or more embodiments, the current data correlation score may be indicative of a commonness of a combination of the Y current anomalous features contributing to the point anomaly with respect to an equivalent Y anomalous features contributing to another previously detected point anomaly associated with the each network entity.

[0110] Although the present embodiments have been described with reference to specific example embodiments, it will be evident that various modifications and changes may be made to these embodiments without departing from the broader spirit and scope of the various embodiments. For example, the various devices and modules described herein may be enabled and operated using hardware circuitry (e.g., CMOS based logic circuitry), firmware, software or any combination of hardware, firmware, and software (e.g., embodied in a machine readable medium). For example, the various electrical structures and methods may be embodied using transistors, logic gates, and electrical circuits (e.g., application specific integrated (ASIC) circuitry and/or in Digital Signal Processor (DSP) circuitry).

[0111] In addition, it will be appreciated that the various operations, processes, and methods disclosed herein may be embodied in a machine-readable medium and/or a machine accessible medium compatible with a data processing system (e.g., one or more server(s) $\mathbf{102}_{1\text{-}N}$), and may be performed in any order (e.g., including using means for achieving the various operations). Accordingly, the specifi-

cation and drawings are to be regarded in an illustrative rather than a restrictive sense.

What is claimed is:

1. A method comprising:

detecting, through a server of a cloud computing network comprising a plurality of subscribers of application acceleration as a service provided by the cloud computing network at a corresponding plurality of client devices communicatively coupled to the server, real-time data associated with each network entity of a plurality of network entities of the cloud computing network for each feature thereof sequentially in time;

detecting, through the server, a point anomaly in the real-time data associated with the each network entity based on determining whether the real-time data falls outside a threshold expected value thereof;

representing, through the server, the detected point anomaly in a full mesh Q node graph, wherein Q is a number of features applicable for the each network entity;

capturing, through the server, a transition in the point anomaly associated with a newly detected one of: anomaly and non-anomaly in the real-time data associated with at least one feature of the Q number of features via the representation of the full mesh Q node graph; and

deriving, through the server, a current data correlation score for the point anomaly across the captured transition as:

$$CS = \sum_{i=1}^{APC} \frac{\left(1 - \frac{EWP_i}{TSAC}\right)}{APC},$$

wherein CS is the current data correlation score for the point anomaly across the captured transition, APC is a count of a total number of pairs of Y current anomalous features in the Q number of features and is given by ${}^{Y}C_2 + {}^{Y}C_1$, EWP_i is a weight of an edge of the i^{th} pair of the Y current anomalous features in the representation of the full mesh Q node graph, and TSAC is a total number of time samples of the point anomaly comprising the captured transition, and

wherein the current data correlation score is indicative of a commonness of a combination of the Y current anomalous features contributing to the point anomaly with respect to an equivalent Y anomalous features contributing to another previously detected point anomaly associated with the each network entity.

2. The method of claim **1**, comprising the threshold expected value being one of: a maximum expected value and a minimum expected value.

3. The method of claim **1**, further comprising detecting, through the server, at least one anomaly in the real-time data associated with the each network entity for the each feature thereof including the point anomaly in accordance with computing a score for the at least one anomaly indicative of anomalousness thereof, the computation of the score involving both relative scoring and absolute deviation scoring, and the absolute deviation scoring being based on previous data deviations from reference data bands.

4. The method of claim **3**, further comprising determining, through the server, an event associated with a pattern of change of the real-time data associated with the each network entity based on executing an optimization algorithm to determine, among all features of the each network entity, a series of anomalies comprising the detected at least one anomaly that constitutes a sequence of patterned anomalies in accordance with scanning detected anomalies associated with the real-time data associated with the each network entity including the detected at least one anomaly.

5. The method of claim **4**, wherein determining, through the server, the event based on executing the optimization algorithm further comprises finding, based on at least one dynamic programming technique, a longest occurring sequence of anomalies as the series of anomalies among all the features of the each network entity that is capable of being interleaved for a specific duration.

6. The method of claim **4**, further comprising enabling, through the server, predictive classification of a future event associated with the each network entity into a category of determined problems based on the determined event associated with the pattern of change of the real-time data associated with the each network entity.

7. The method of claim **4**, further comprising at least one of:

collecting, through the server, feedback from a subscriber of the plurality of subscribers at a corresponding client device communicatively coupled to the server;

determining, through the server, a severity indicator for the determined event based on the feedback from the subscriber;

generating, through the server utilizing the determined severity indicator, an event score for the determined event into which the current data correlation score is factored; and

ranking, through the server, the determined event with respect to a plurality of events based on the generated event score.

8. A server of a cloud computing network comprising a plurality of subscribers of application acceleration as a service provided by the cloud computing network at a corresponding plurality of client devices communicatively coupled to the server, comprising:

a memory; and

a processor communicatively coupled to the memory, the processor executing instructions to:

detect real-time data associated with each network entity of a plurality of network entities of the cloud computing network for each feature thereof sequentially in time,

detect a point anomaly in the real-time data associated with the each network entity based on determining whether the real-time data falls outside a threshold expected value thereof,

represent the detected point anomaly in a full mesh Q node graph, wherein Q is a number of features applicable for the each network entity,

capture a transition in the point anomaly associated with a newly detected one of: anomaly and non-anomaly in the real-time data associated with at least one feature of the Q number of features via the representation of the full mesh Q node graph, and

derive a current data correlation score for the point anomaly across the captured transition as:

$$CS = \sum_{i=1}^{APC} \frac{\left(1 - \frac{EWP_i}{TSAC}\right)}{APC},$$

wherein CS is the current data correlation score for the point anomaly across the captured transition, APC is a count of a total number of pairs of Y current anomalous features in the Q number of features and is given by ${}^{Y}C_2 + {}^{Y}C_1$, EWP_i is a weight of an edge of the i^{th} pair of the Y current anomalous features in the representation of the full mesh Q node graph, and TSAC is a total number of time samples of the point anomaly comprising the captured transition, and

wherein the current data correlation score is indicative of a commonness of a combination of the Y current anomalous features contributing to the point anomaly with respect to an equivalent Y anomalous features contributing to another previously detected point anomaly associated with the each network entity.

9. The server of claim **8**, wherein the threshold expected value is one of: a maximum expected value and a minimum expected value.

10. The server of claim **8**, wherein the processor further executes instructions to detect at least one anomaly in the real-time data associated with the each network entity for the each feature thereof including the point anomaly in accordance with computing a score for the at least one anomaly indicative of anomalousness thereof, the computation of the score involving both relative scoring and absolute deviation scoring, and the absolute deviation scoring being based on previous data deviations from reference data bands.

11. The server of claim **10**, wherein the processor further executes instructions to determine an event associated with a pattern of change of the real-time data associated with the each network entity based on executing an optimization algorithm to determine, among all features of the each network entity, a series of anomalies comprising the detected at least one anomaly that constitutes a sequence of patterned anomalies in accordance with scanning detected anomalies associated with the real-time data associated with the each network entity including the detected at least one anomaly.

12. The server of claim **11**, wherein the processor executes instructions to determine the event based on executing the optimization algorithm in accordance with finding, based on at least one dynamic programming technique, a longest occurring sequence of anomalies as the series of anomalies among all the features of the each network entity that is capable of being interleaved for a specific duration.

13. The server of claim **11**, wherein the processor further executes instructions to enable predictive classification of a future event associated with the each network entity into a category of determined problems based on the determined event associated with the pattern of change of the real-time data associated with the each network entity.

14. The server of claim **11**, wherein the processor further executes instructions to at least one of:

collect feedback from a subscriber of the plurality of subscribers at a corresponding client device communicatively coupled to the server,

determine a severity indicator for the determined event based on the feedback from the subscriber,

generate, utilizing the determined severity indicator, an event score for the determined event into which the current data correlation score is factored, and

rank the determined event with respect to a plurality of events based on the generated event score.

15. A cloud computing system comprising:

a plurality of client devices associated with a plurality of subscribers of application acceleration as a service provided by the cloud computing system;

a computer network; and

a server communicatively coupled to the plurality of client devices through the computer network, wherein the server executes instructions to:

detect real-time data associated with each network entity of a plurality of network entities of the cloud computing system for each feature thereof sequentially in time,

detect a point anomaly in the real-time data associated with the each network entity based on determining whether the real-time data falls outside a threshold expected value thereof,

represent the detected point anomaly in a full mesh Q node graph, wherein Q is a number of features applicable for the each network entity,

capture a transition in the point anomaly associated with a newly detected one of: anomaly and non-anomaly in the real-time data associated with at least one feature of the Q number of features via the representation of the full mesh Q node graph, and

derive a current data correlation score for the point anomaly across the captured transition as:

$$CS = \sum_{i=1}^{APC} \frac{\left(1 - \frac{EWP_i}{TSAC}\right)}{APC},$$

wherein CS is the current data correlation score for the point anomaly across the captured transition, APC is a count of a total number of pairs of Y current anomalous features in the Q number of features and is given by ${}^{Y}C_2 + {}^{Y}C_1$, EWP_i is a weight of an edge of the i^{th} pair of the Y current anomalous features in the representation of the full mesh Q node graph, and TSAC is a total number of time samples of the point anomaly comprising the captured transition, and

wherein the current data correlation score is indicative of a commonness of a combination of the Y current anomalous features contributing to the point anomaly with respect to an equivalent Y anomalous features contributing to another previously detected point anomaly associated with the each network entity.

16. The cloud computing system of claim **15**, wherein the threshold expected value is one of: a maximum expected value and a minimum expected value.

17. The cloud computing system of claim **15**, wherein the server further executes instructions to detect at least one anomaly in the real-time data associated with the each network entity for the each feature thereof including the point anomaly in accordance with computing a score for the at least one anomaly indicative of anomalousness thereof,

the computation of the score involving both relative scoring and absolute deviation scoring, and the absolute deviation scoring being based on previous data deviations from reference data bands.

18. The cloud computing system of claim **17**, wherein the server further executes instructions to determine an event associated with a pattern of change of the real-time data associated with the each network entity based on executing an optimization algorithm to determine, among all features of the each network entity, a series of anomalies comprising the detected at least one anomaly that constitutes a sequence of patterned anomalies in accordance with scanning detected anomalies associated with the real-time data associated with the each network entity including the detected at least one anomaly.

19. The cloud computing system of claim **18**, wherein the server executes instructions to determine the event based on executing the optimization algorithm in accordance with finding, based on at least one dynamic programming technique, a longest occurring sequence of anomalies as the series of anomalies among all the features of the each network entity that is capable of being interleaved for a specific duration.

20. The cloud computing system of claim **18**, wherein the server further executes instructions to at least one of:

collect feedback from a subscriber of the plurality of subscribers at a corresponding client device communicatively coupled to the server,

determine a severity indicator for the determined event based on the feedback from the subscriber,

generate, utilizing the determined severity indicator, an event score for the determined event into which the current data correlation score is factored, and

rank the determined event with respect to a plurality of events based on the generated event score.

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