US 20220027331A1

(19) **United States**

(12) **Patent Application Publication** (10) **Pub. No.: US 2022/0027331 A1**

Hwang et al. (43) **Pub. Date: Jan. 27, 2022**

(54) **CROSS-ENVIRONMENT EVENT CORRELATION USING DOMAIN-SPACE EXPLORATION AND MACHINE LEARNING TECHNIQUES**

(71) Applicant: **INTERNATIONAL BUSINESS MACHINES CORPORATION**, Armonk, NY (US)

(72) Inventors: **Jinho Hwang**, Ossining, NY (US); **Larisa Shwartz**, Greenwich, CT (US); **Srinivasan Parthasarathy**, White Plains, NY (US); **Qing Wang**, Chappaqua, NY (US); **Raghuram Srinivasan**, Aurora, IL (US); **Gene L. Brown**, Durham, CT (US); **Michael Elton Nidd**, Zurich (CH); **Frank Bagehorn**, Dottikon (CH); **Jakub Krchák**, Jindrichuv Hradec (CZ); **Ota Sandr**, Prague (CZ); **Tomáš Ondrej**, Prague (CZ); **Michal Mýlek**, Vrané nad Vltavou (CZ); **Altynbek Orumbayev**, Prague (CZ)

(21) Appl. No.: **16/937,425**

(22) Filed: **Jul. 23, 2020**

Publication Classification

(51) **Int. Cl.**

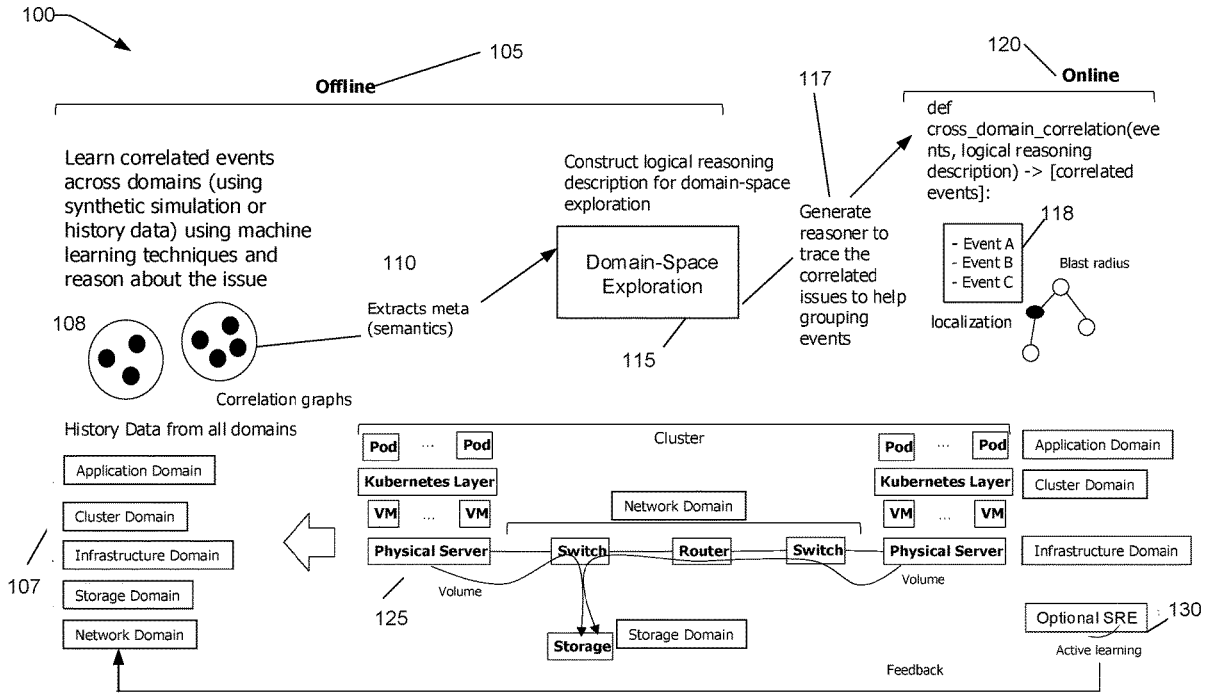
G06F 16/215	(2006.01)
G06N 5/02	(2006.01)
G06N 5/04	(2006.01)
G06N 20/00	(2006.01)

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

CPC ***G06F 16/215*** (2019.01); ***G06N 20/00*** (2019.01); ***G06N 5/04*** (2013.01); ***G06N 5/022*** (2013.01)

(57) **ABSTRACT**

A computer-implemented method of cross-environment event correlation includes determining one or more correlated events about an issue across a plurality of domains. A knowledge data is extracted from the issue determined from the one or more correlated events is performed. A correlation graph is generated from the extracted knowledge to trace the issue and group the correlated events into one or more event groups to represent their relationship with the issue. A logical reasoning description is constructed based on the generated correlation graph for a domain-space exploration related to how the issue in one domain affects another domain of the plurality of domains. The one or more event groups of correlated events is provided with an explanation about a cause of the issue based on the logical reasoning description.



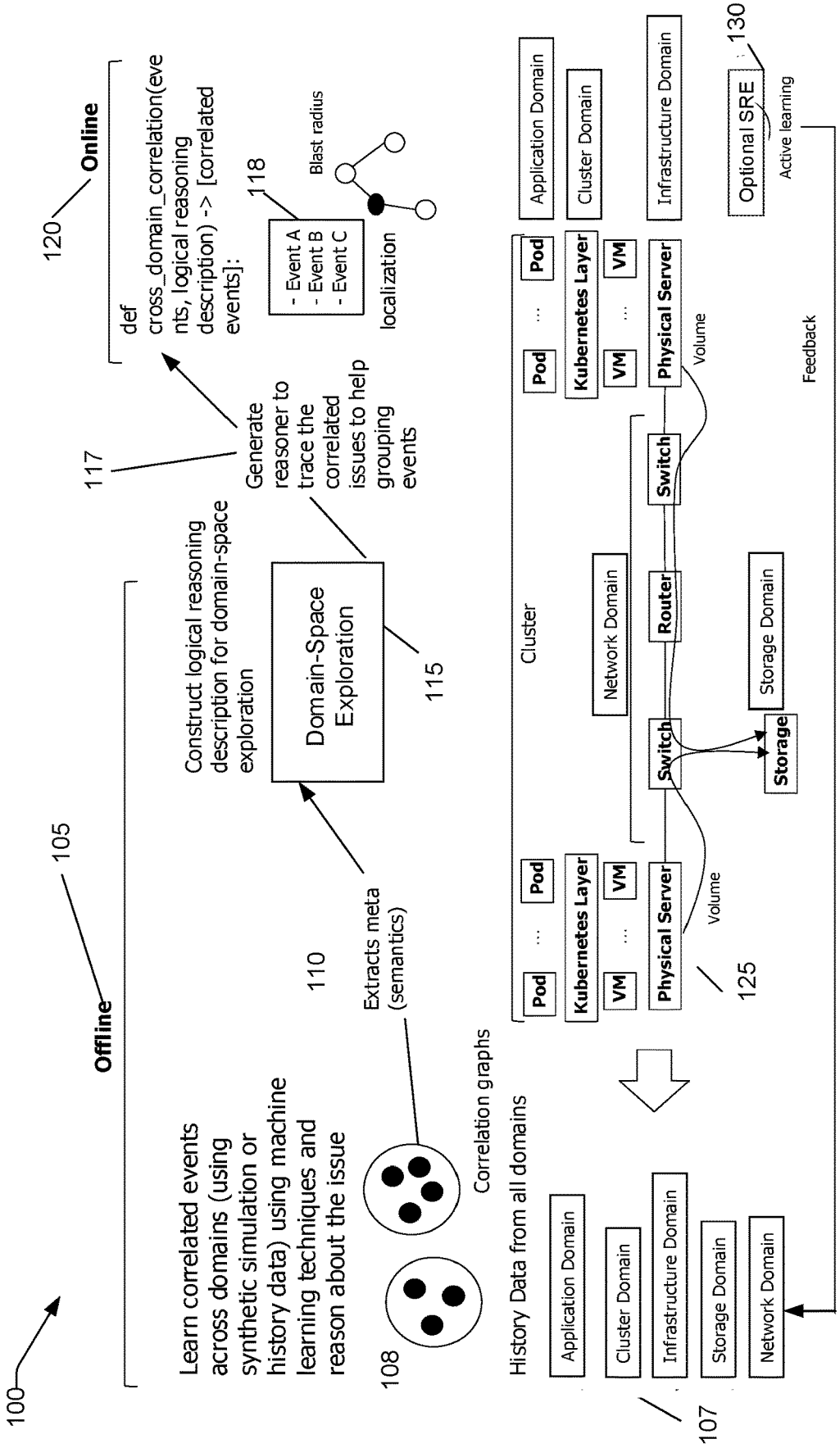

100
105
Offline
Learn correlated events across domains (using synthetic simulation or history data) using machine learning techniques and reason about the issue
108
Correlation graphs
110
Extracts meta (semantics)
Construct logical reasoning description for domain-space exploration
Domain-Space Exploration
115
Generate reasoner to trace the correlated issues to help grouping events
117
120
Online
def cross_domain_correlation(events, logical reasoning description) -> [correlated events]:
118
- Event A
- Event B
- Event C
localization
Blast radius
History Data from all domains
Application Domain
Cluster Domain
Infrastructure Domain
Storage Domain
Network Domain
107
Cluster
Pod
Kubernetes Layer
VM
Physical Server
Switch
Router
Storage
Network Domain
Storage Domain
Volume
125
Application Domain
Cluster Domain
Infrastructure Domain
Optional SRE
130
Active learning
Feedback

FIG. 1

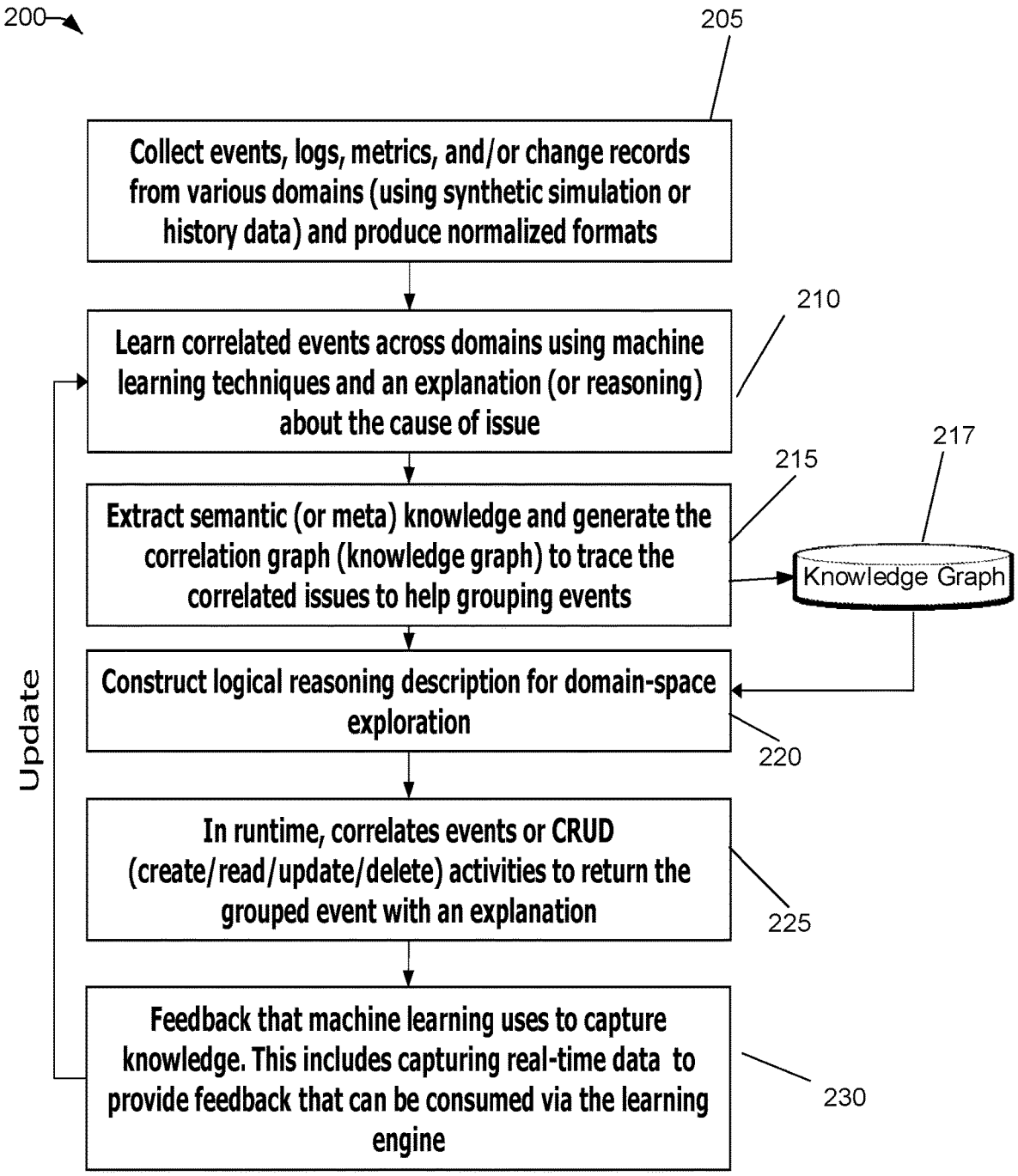

200
205
Collect events, logs, metrics, and/or change records from various domains (using synthetic simulation or history data) and produce normalized formats
210
Learn correlated events across domains using machine learning techniques and an explanation (or reasoning) about the cause of issue
215
217
Extract semantic (or meta) knowledge and generate the correlation graph (knowledge graph) to trace the correlated issues to help grouping events
Knowledge Graph
Construct logical reasoning description for domain-space exploration
220
In runtime, correlates events or CRUD (create/read/update/delete) activities to return the grouped event with an explanation
225
Feedback that machine learning uses to capture knowledge. This includes capturing real-time data to provide feedback that can be consumed via the learning engine
230
Update

FIG. 2

300 Real Scenario in cloud native environment

305
- **Today**: an application (172.1.1.1) running on VM (10.1.1.1.) hosted by physical server (9.1.1.1) can talk to an application (172.1.2.1) running on VM (10.1.2.1) hosted by physical server (9.1.2.1)

310
- **Tomorrow**: the router between 9.1.1.1 and 9.1.2.1 changes rule (allow 9.1.1.0/24 to 9.1.2.0/24) to (deny …). Current event management system does not know why application (172.1.1.1) can't talk to postgres (172.1.2.1)

315
- **Symptom**: the application (172.1.1.1) is not able to communicate with Postgres (172.1.2.1)

320
- **Cross-environment correlation**: Correlated information about the policy change in router and the **Symptom (above)** as a correlated group to diagnose the issue

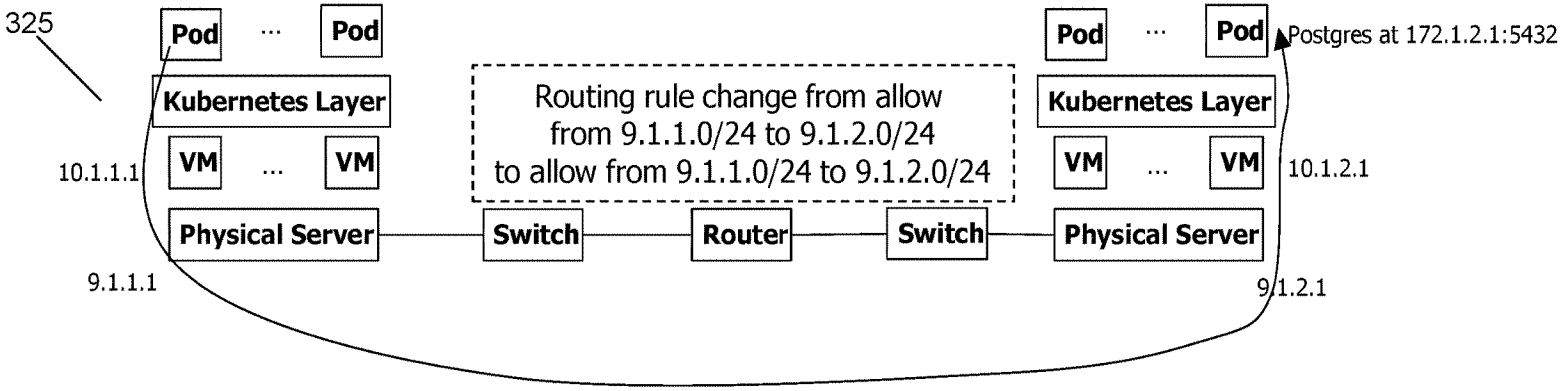


FIG. 3

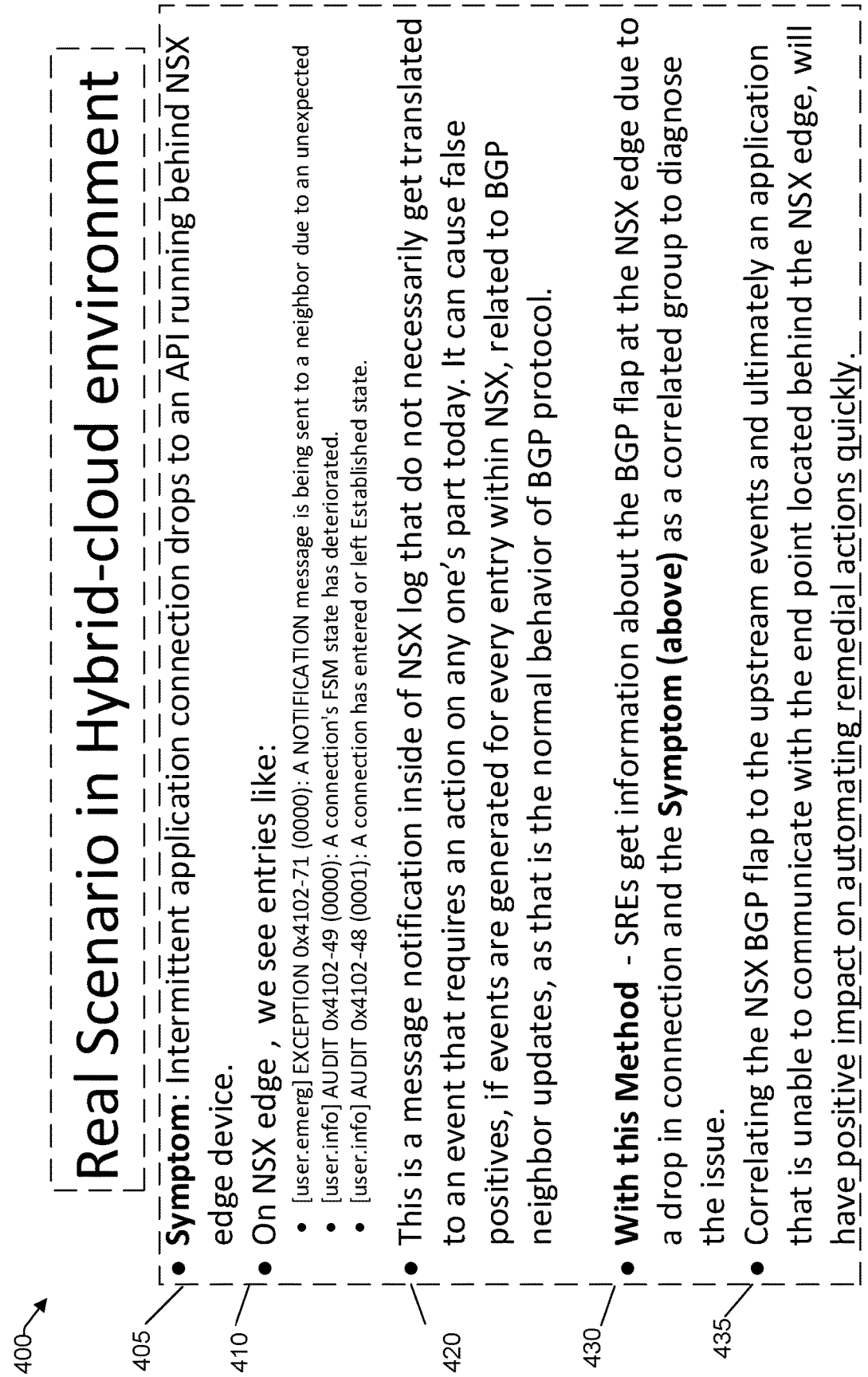

400
Real Scenario in Hybrid-cloud environment
405
• Symptom: Intermittent application connection drops to an API running behind NSX edge device.
410
• On NSX edge , we see entries like:
• [user.emerg] EXCEPTION 0x4102-71 (0000): A NOTIFICATION message is being sent to a neighbor due to an unexpected
• [user.info] AUDIT 0x4102-49 (0000): A connection's FSM state has deteriorated.
• [user.info] AUDIT 0x4102-48 (0001): A connection has entered or left Established state.
420
• This is a message notification inside of NSX log that do not necessarily get translated to an event that requires an action on any one's part today. It can cause false positives, if events are generated for every entry within NSX, related to BGP neighbor updates, as that is the normal behavior of BGP protocol.
430
• With this Method - SREs get information about the BGP flap at the NSX edge due to a drop in connection and the Symptom (above) as a correlated group to diagnose the issue.
435
• Correlating the NSX BGP flap to the upstream events and ultimately an application that is unable to communicate with the end point located behind the NSX edge, will have positive impact on automating remedial actions quickly.

FIG. 4

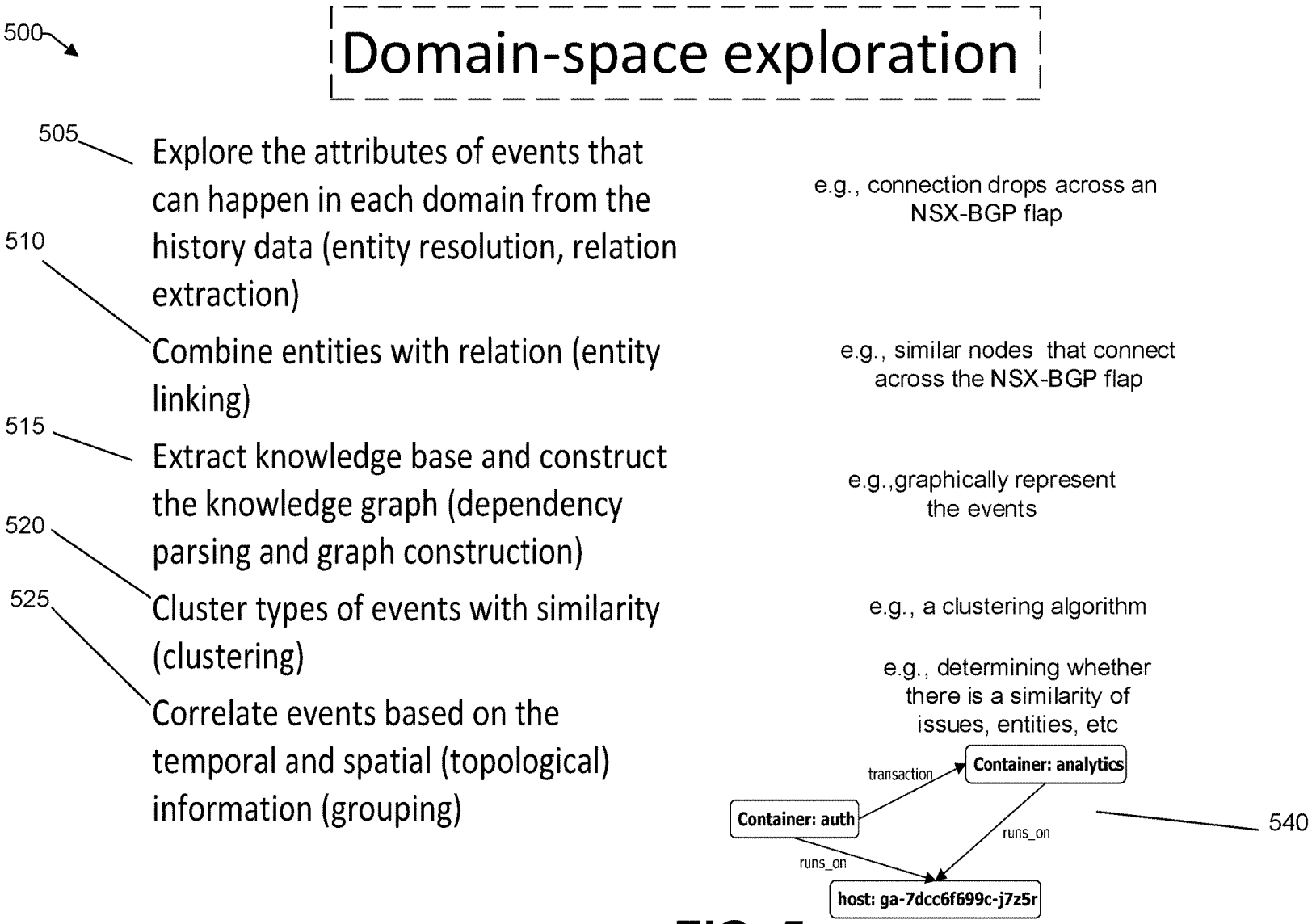

500
Domain-space exploration
505
Explore the attributes of events that can happen in each domain from the history data (entity resolution, relation extraction)
e.g., connection drops across an NSX-BGP flap
510
Combine entities with relation (entity linking)
e.g., similar nodes that connect across the NSX-BGP flap
515
Extract knowledge base and construct the knowledge graph (dependency parsing and graph construction)
e.g.,graphically represent the events
520
Cluster types of events with similarity (clustering)
e.g., a clustering algorithm
525
Correlate events based on the temporal and spatial (topological) information (grouping)
e.g., determining whether there is a similarity of issues, entities, etc
transaction
Container: analytics
Container: auth
runs_on
runs_on
host: ga-7dcc6f699c-j7z5r
540

FIG. 5

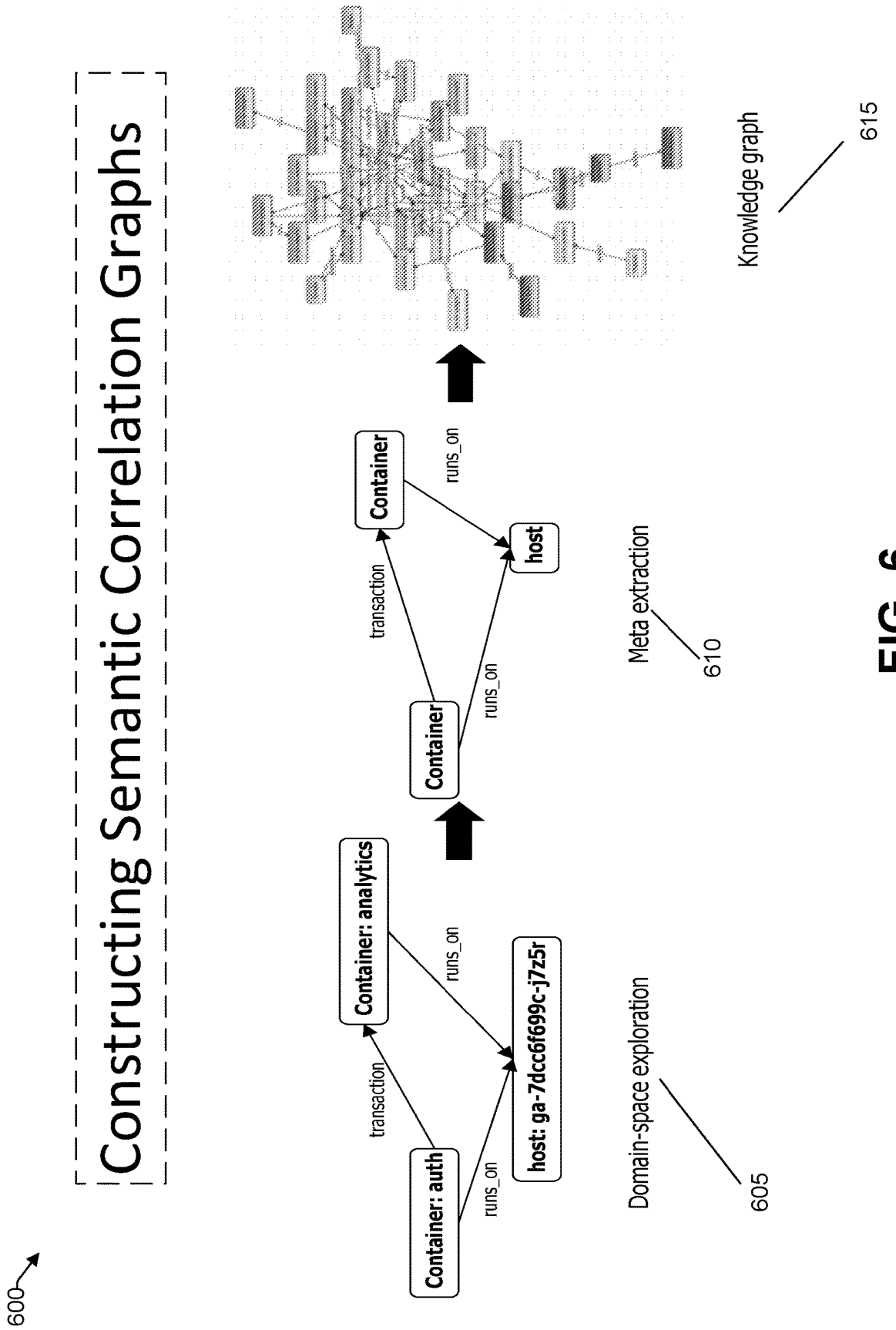

600
Constructing Semantic Correlation Graphs
Container: auth
transaction
Container: analytics
runs_on
host: ga-7dcc6f699c-j7z5r
runs_on
Container
transaction
Container
runs_on
host
runs_on
Domain-space exploration
605
Meta extraction
610
Knowledge graph
615

FIG. 6

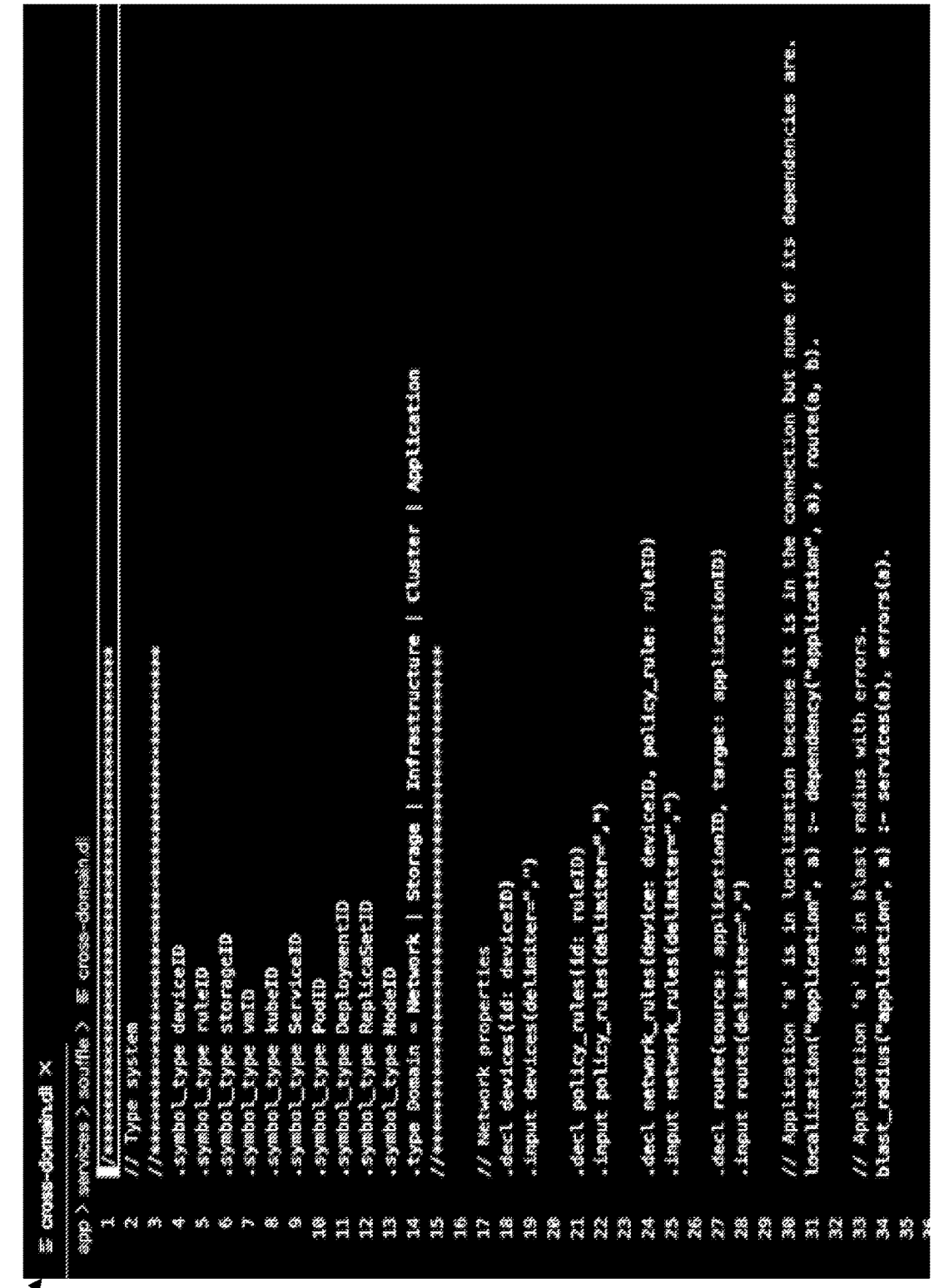

700
cross-domain.dl
app > services > souffle > cross-domain.dl
// Type system
.symbol_type deviceID
.symbol_type ruleID
.symbol_type storageID
.symbol_type vmID
.symbol_type kubeID
.symbol_type ServiceID
.symbol_type PodID
.symbol_type DeploymentID
.symbol_type ReplicaSetID
.symbol_type NodeID
.type Domain = Network | Storage | Infrastructure | Cluster | Application
// Network properties
.decl device(id: deviceID)
.input device(delimiter=",")
.decl policy_rules(id: ruleID)
.input policy_rules(delimiter=",")
.decl network_rules(device: deviceID, policy_rule: ruleID)
.input network_rules(delimiter=",")
.decl route(source: applicationID, target: applicationID)
.input route(delimiter=",")
// Application 'a' is in localization because it is in the connection but none of its dependencies are.
localization("application", a) :- dependency("application", a), route(a, b).
// Application 'a' is in blast radius with errors.
blast_radius("application", a) :- services(a), errors(a).

FIG. 7

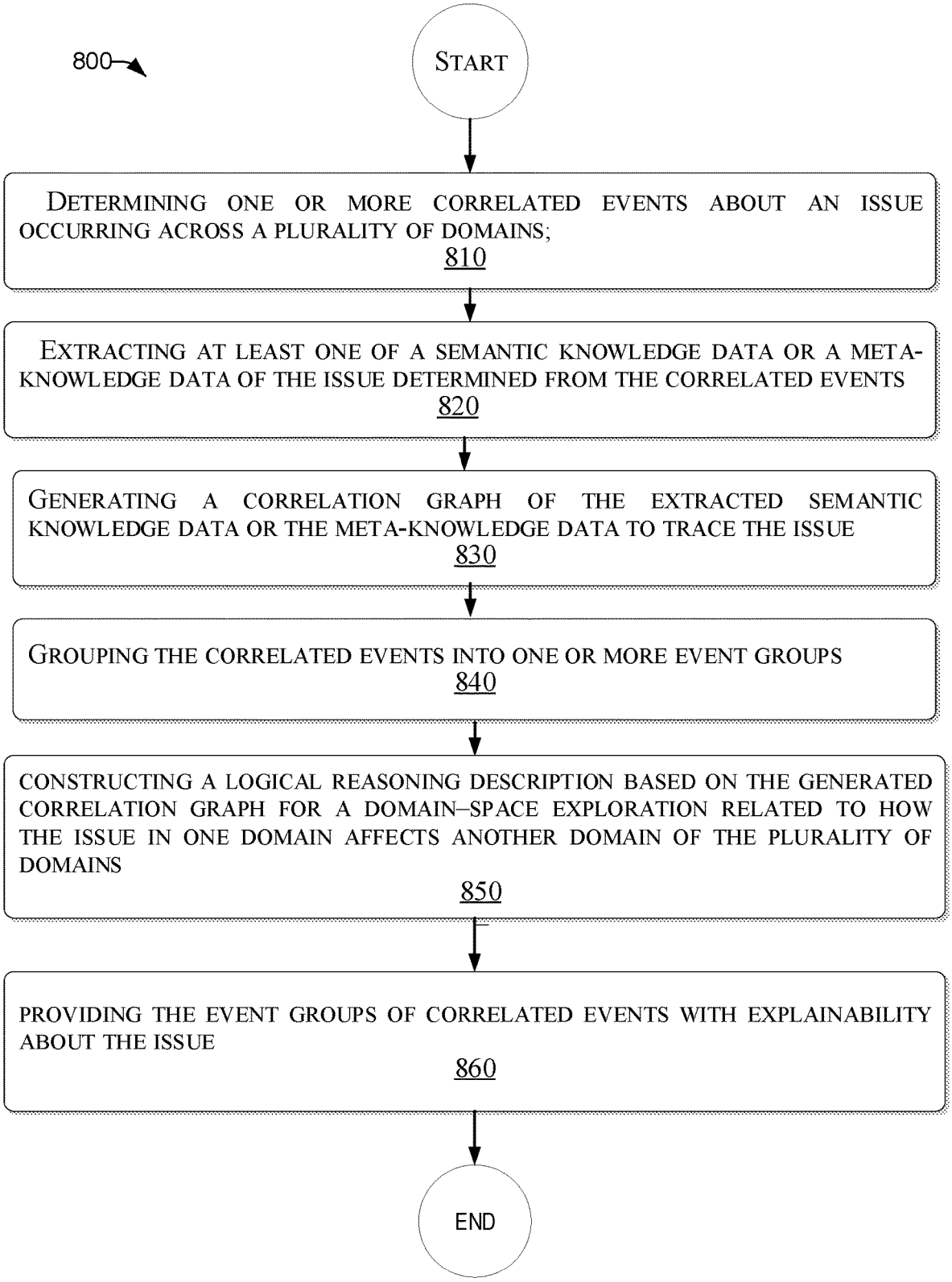

800
START
DETERMINING ONE OR MORE CORRELATED EVENTS ABOUT AN ISSUE OCCURRING ACROSS A PLURALITY OF DOMAINS;
810
EXTRACTING AT LEAST ONE OF A SEMANTIC KNOWLEDGE DATA OR A META-KNOWLEDGE DATA OF THE ISSUE DETERMINED FROM THE CORRELATED EVENTS
820
GENERATING A CORRELATION GRAPH OF THE EXTRACTED SEMANTIC KNOWLEDGE DATA OR THE META-KNOWLEDGE DATA TO TRACE THE ISSUE
830
GROUPING THE CORRELATED EVENTS INTO ONE OR MORE EVENT GROUPS
840
CONSTRUCTING A LOGICAL REASONING DESCRIPTION BASED ON THE GENERATED CORRELATION GRAPH FOR A DOMAIN–SPACE EXPLORATION RELATED TO HOW THE ISSUE IN ONE DOMAIN AFFECTS ANOTHER DOMAIN OF THE PLURALITY OF DOMAINS
850
PROVIDING THE EVENT GROUPS OF CORRELATED EVENTS WITH EXPLAINABILITY ABOUT THE ISSUE
860
END

FIG. 8

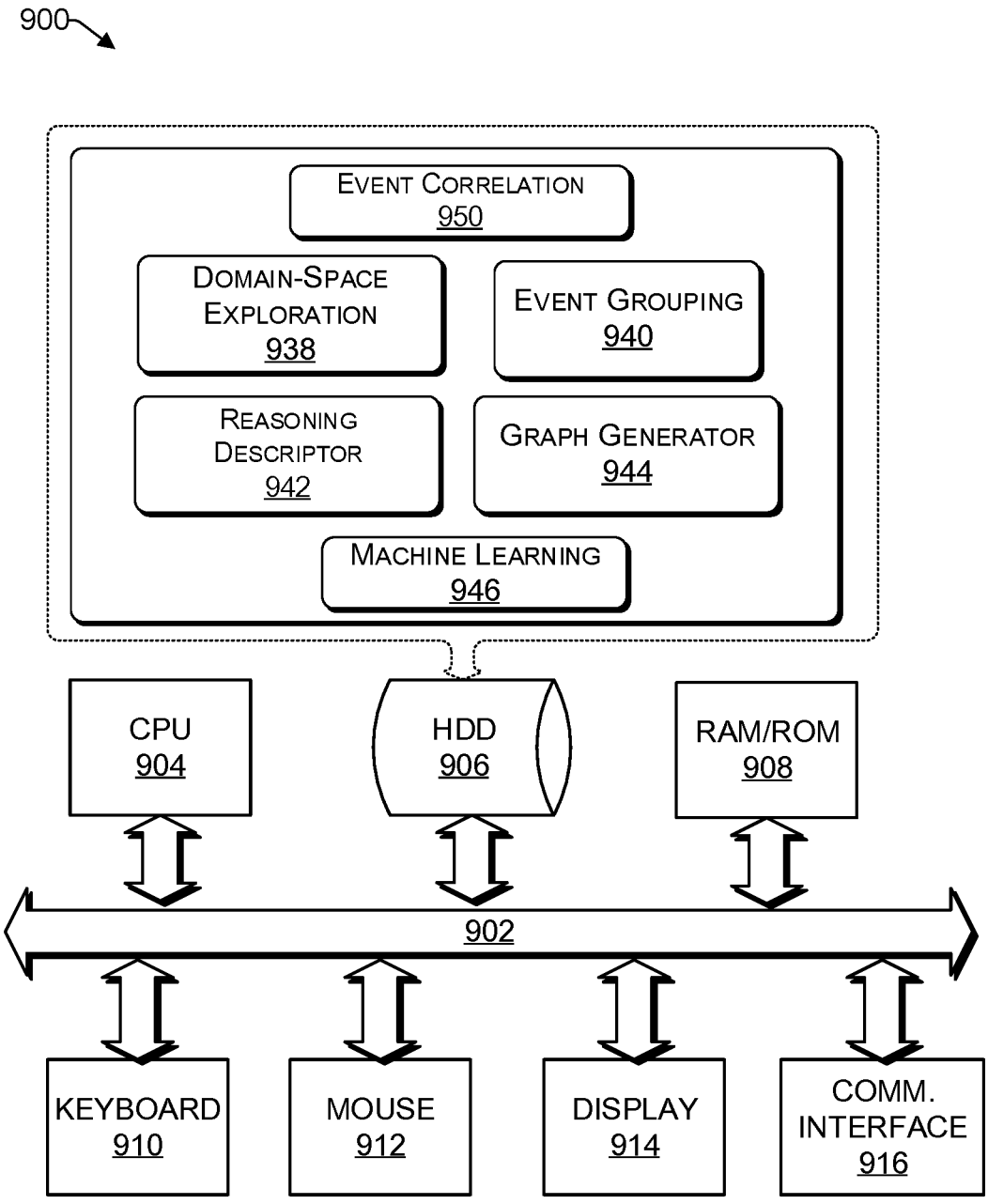

900
EVENT CORRELATION
950
DOMAIN-SPACE
EXPLORATION
938
EVENT GROUPING
940
REASONING
DESCRIPTOR
942
GRAPH GENERATOR
944
MACHINE LEARNING
946
CPU
904
HDD
906
RAM/ROM
908
902
KEYBOARD
910
MOUSE
912
DISPLAY
914
COMM.
INTERFACE
916

FIG. 9

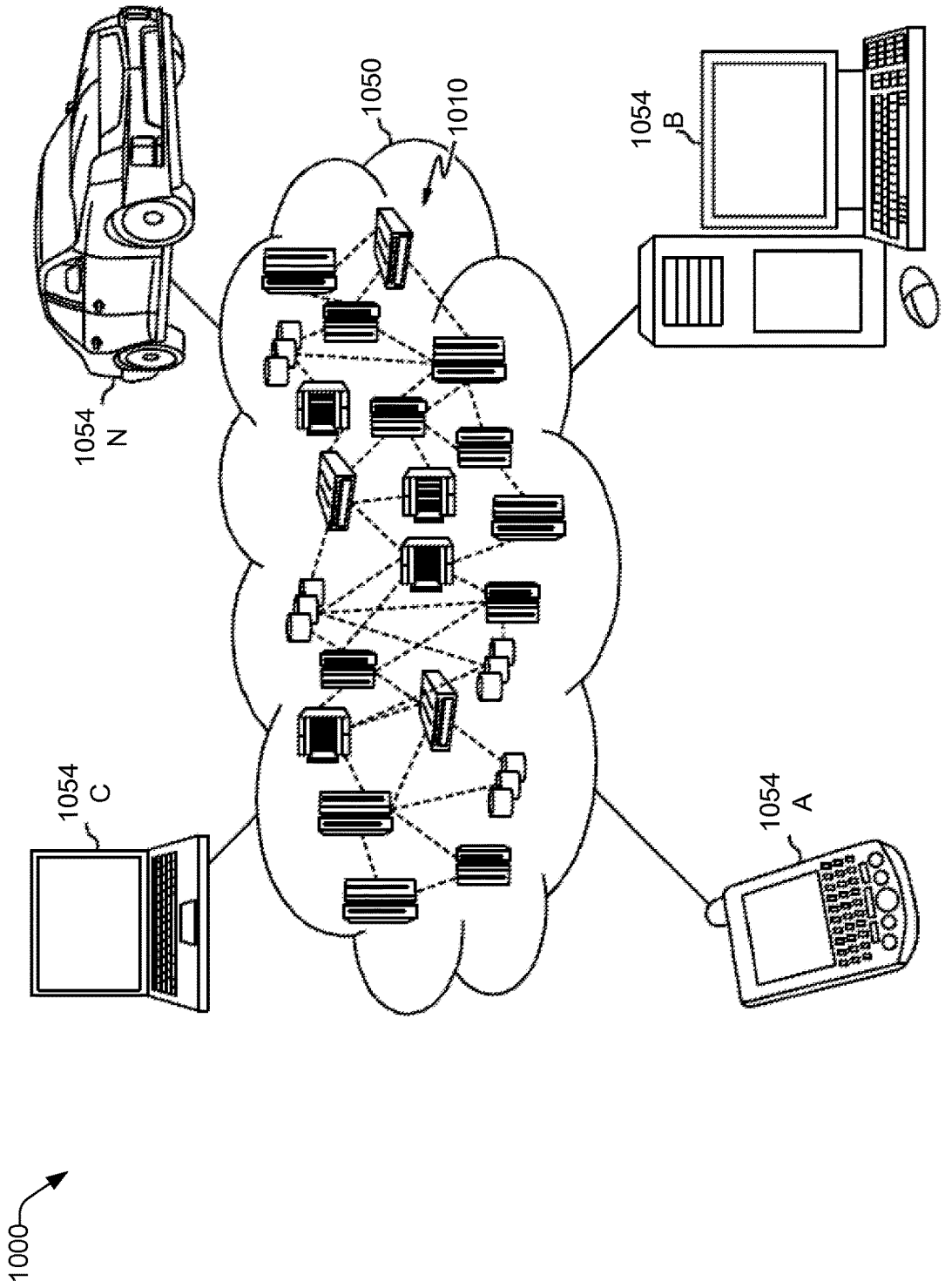


FIG. 10

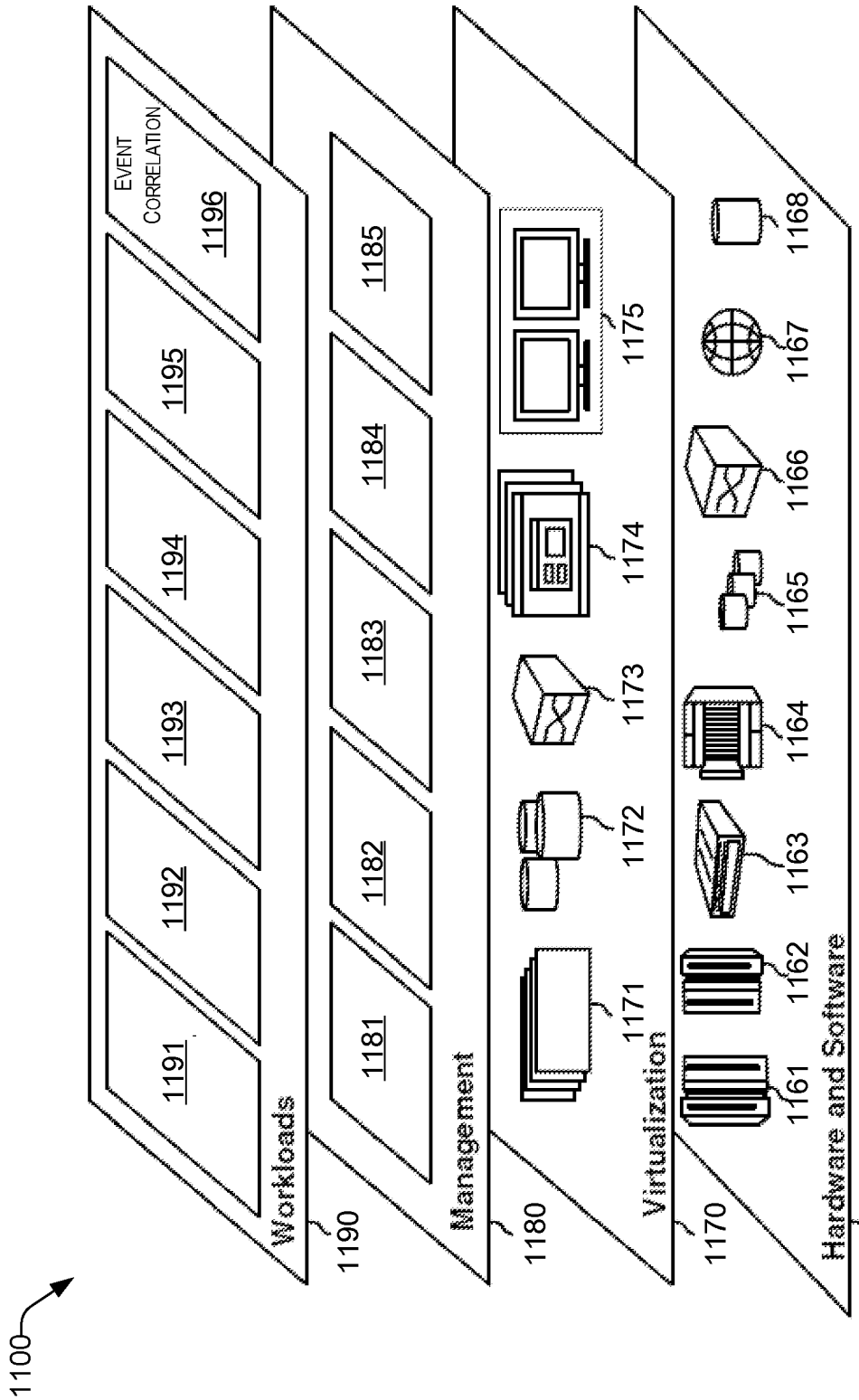

1100
Workloads
1190
1191
1192
1193
1194
1195
1196
EVENT CORRELATION
Management
1180
1181
1182
1183
1184
1185
Virtualization
1170
1171
1172
1173
1174
1175
Hardware and Software
1160
1161
1162
1163
1164
1165
1166
1167
1168

FIG. 11

CROSS-ENVIRONMENT EVENT CORRELATION USING DOMAIN-SPACE EXPLORATION AND MACHINE LEARNING TECHNIQUES

BACKGROUND

Technical Field

[0001] The present disclosure generally relates to event correlation in multiple domain operations, and more particularly, to systems and methods for cross-environment event correlation of multiple domain operations.

Description of the Related Art

[0002] As the information technology (IT) environment becomes more entangled, there is an increased interaction between different domains of a multiple domain computing environment. The result of such interaction is that a problem in one domain can affect the operations in other domains. Events or changes that originate in one of the respective domains are often made and reviewed independently, even though other domains may be affected by the events or changes.

[0003] For example, a rule or policy change made in one domain can cause an issue, a problem or an incident in the operation of a network device in another domain that is not easily discoverable. An issue in a storage server can adversely impact applications operating in another domain when a cross-domain communication is required. The debugging of an issue can be prolonged as events in different domains may not appear to be co-related. It is also challenging to understand the risks presented to other domains when a change or a problem occurs.

SUMMARY

[0004] According to one embodiment, a computer-implemented method of cross-environment event correlation includes the operations of determining one or more correlated events about an issue across a plurality of domains. A knowledge data of the issue determined is extracted from the one or more correlated events is performed. A correlation graph is issued of the extracted knowledge data to trace the issue and group the correlated events into one or more event groups to represent their relationship with the issue. A logical reasoning description is constructed based on the generated correlation graph for a domain-space exploration related to how the issue in one domain affects another domain of the plurality of domains. The one or more event groups of correlated events are provided with an explanation about a cause of the issue based on the logical reasoning description. The identification of the cause of an issue and the explanation facilitates diagnosis and corrective action to address an issue.

[0005] In one embodiment, the extracting of the knowledge data includes extracting one or more of a semantic knowledge data or a meta-knowledge data, and machine learning is utilized to determine the correlated events about the issue across a plurality of domains based on a history data or a synthetic data. The use of machine learning permits discovery of an event correlation that might otherwise be missed, and results in a time savings in diagnosis and an explanation of the cause of an issue, particularly across a plurality of domains.

[0006] In one embodiment, the use of machine learning includes training by an unsupervised learning technique using an association rule learning algorithm or a clustering algorithm. The unsupervised learning technique is particularly beneficial to discover correlations that otherwise may not have been detected.

[0007] In one embodiment, the use of machine learning includes training by a supervised learning technique using labeled data associated with data correlation. The use of a supervised learning technique can be used to direct the determining of correlated events to obtain more efficient results.

[0008] In one embodiment, the use of machine learning includes configuring by a supervised learning technique using a support vector machine (SVM), a convolutional neural network (CNN), or a long-short term memory (LSTM) based on a size of the correlation data. The use of SVM, CNN, and LSTM can provide for an increased correlation of events.

[0009] In one embodiment, the recommending of a most probable event group of correlated events of the one or more event groups to users with an explanation about a cause of the issue based on the logical reasoning description. There is an increased efficiency by the recommended probable event group.

[0010] In one embodiment, the recommending of the most probable event group of correlated events with an explanation of the cause of an issue is based on the logical reasoning description that includes performing in runtime a creating, reading, updating, and deleting (CRUD) of data. The use of CRUD brings a more dynamic recommending of the most probable event group than collecting data from logs.

[0011] In one embodiment, the use of machine learning includes a training operation based on feedback is received to train for the determining of the one or more correlated events.

[0012] In one embodiment, feedback is received to determine the one or more correlated events by an active learning methodology, which interactively queries a user or another information source to label new data points with the desired outputs. The feedback provides an advantage in the training operations in machine learning.

[0013] In one embodiment, one or more semantic relationships are constructed between the plurality of domains. There is a benefit in the determining of correlated events.

[0014] In one embodiment, the determining of one or more correlated events about an issue includes collecting one or more an event, a log, or a change record from at least some of the plurality of domains. One or more correlated events about the issue are determined by using machine learning techniques. Normalized formats are produced of the one or more collected events, logs or change records. Cross-domain event correlation is enhanced by the normalizing of formats.

[0015] In one embodiment, the collecting of events, logs, metrics, or change records is performed offline by using synthetic simulation.

[0016] In one embodiment, the collecting of events, logs, metrics, or change records is performed offline by using history data.

[0017] A non-transitory computer-readable storage medium tangibly embodying a computer-readable program code having computer-readable instructions that, when executed, causes a computer device to perform a method of

cross-environment event correlation, the method includes determining one or more correlated events about an issue across a plurality of domains. A knowledge data of the issue is extracted from the one or more correlated events. A correlation graph of the extracted knowledge data is generated to trace the issue and group the correlated events into one or more event groups. A logical reasoning description is constructed based on the generated correlation graph for a domain-space exploration related to how the issue in one domain affects another domain of the plurality of domains. The one or more event groups of correlated events are provided with an explanation about a cause of the issue based on the logical reasoning description. The identification of the cause of an issue and the explanation facilitates diagnosis and corrective action to address an issue.

[0018] In one embodiment, a computing device for cross-environment event correlation using space-exploration includes a processor, and a memory coupled to the processor. The memory storing instructions to cause the processor to perform acts including: determining one or more correlated events about an issue across a plurality of domains, extracting a knowledge data of the issue determined from the one or more correlated events; constructing a logical reasoning description for domain-space exploration related to how the issue in one domain affects another domain of the plurality of domains; generating correlation graphs based on the domain-space exploration to trace the issue and group the correlated events in one or more groups; constructing semantic relationships between different domains, and recommending the most probable event groups of correlated events with an explanation about a cause of the issue based on the logical reasoning description. The monitoring of events from different domains can be performed and an understanding of risks associated with changes or mutations in one domain and the impact on other domains can be provided.

[0019] In one embodiment, the extracting of the knowledge data includes extracting one or more of a semantic knowledge data or a meta-knowledge data, the processor is configured to perform machine learning of the cross-environment event correlation about the issue.

[0020] These and other features will become apparent from the following detailed description of illustrative embodiments thereof, which is to be read in connection with the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

[0021] The drawings are of illustrative embodiments. They do not illustrate all embodiments. Other embodiments may be used in addition to, or instead. Details that may be apparent or unnecessary may be omitted to save space or for more effective illustration. Some embodiments may be practiced with additional components or steps and/or without all the components or steps that are illustrated. When the same numeral appears in different drawings, it refers to the same or like components or steps.

[0022] FIG. **1** is an overview of an architecture of a system for cross-environment event correlation, consistent with an illustrative embodiment.

[0023] FIG. **2** is a system flow diagram for cross-environment event correlation using domain space exploration, consistent with an illustrative embodiment.

[0024] FIG. **3** illustrates a problem scenario in a cloud native environment that is addressed in the present disclosure.

[0025] FIG. **4** illustrates another problem scenario in a hybrid-cloud environment that is addressed in the present disclosure.

[0026] FIG. **5** illustrates a domain-space operation, consistent with an illustrative embodiment.

[0027] FIG. **6** illustrates the construction of correlation graphs, consistent with an illustrative embodiment.

[0028] FIG. **7** is a screenshot used in the building of a logical reason description, consistent with an illustrative embodiment.

[0029] FIG. **8** is a flowchart of a computer-implemented method for cross-environment event correlation, consistent with an illustrative embodiment.

[0030] FIG. **9** is a functional block diagram of a particularly configured computer hardware platform that can communicate with various networked components, consistent with an illustrative embodiment.

[0031] FIG. **10** depicts an illustrative cloud computing environment utilizing cloud computing.

[0032] FIG. **11** depicts a set of functional abstraction layers provided by a cloud computing environment.

DETAILED DESCRIPTION

Overview

[0033] In the following detailed description, numerous specific details are set forth by way of examples to provide a thorough understanding of the relevant teachings. However, it should be understood that the present teachings may be practiced without such details. In other instances, well-known methods, procedures, components, and/or circuitry have been described at a relatively high-level, without detail, to avoid unnecessarily obscuring aspects of the present teachings.

[0034] The present disclosure provides a computer-implemented method and system for cross-environment correlation. In multi-domain environments, events or changes that originate from different domains are typically reviewed independently without any correlation to upstream or downstream associations. As used herein, the term "issue" includes a problem or an incident in a multi-domain environment. Accordingly, an issue of a network device (e.g., a down or rule/policy change) in the path of communications between two applications can have a large impact on performance, and may even disable communications. Moreover, by way of an example, an issue with regard to a storage server (e.g., a scalability change, a bandwidth change, an authentication change, etc.,) that is attached as a Kubernetes persistence volume can significantly impact running an application and/or the scalability of the Kubernetes persistence volume of a cluster to grow while retaining its service-level objectives. The debugging of an issue based on an event in one domain can vary greatly both in time and complexity if the issue is affecting other domains, as the events may not be co-related, and/or expertise in other domains may not be at the level of the expertise in the domain where the event occurred. The computer-implemented method and system of the present disclosure can permit monitoring of events from different domains and provide an understanding of risks associated with changes or mutations in one domain and the impact on other domains.

[0035] The terms "semantic knowledge" and "meta-knowledge" are used herein. While there is some overlap between the two terms, semantic knowledge includes knowledge about words or phrases, and can include concepts, facts, and ideas. Meta-knowledge is a knowledge about a pre-selected knowledge or content, and includes, tagging, planning, modeling and learning modifications of a domain language.

[0036] In addition, the computer-implemented system and method according to the present disclosure provide for an improvement at least in the fields of the operation monitoring and risk assessment of multi-domain computing environments and the inter-related effects of the different domains on each other. In addition, the computer-implemented method and system of the present disclosure provide an improvement in the efficiency of computer operations, as the use of machine learning, for example, to monitor and assess the cross-environment correlation can increase reliability, and reduce or eliminate degraded operations in one or more domains due to an issue in another domain.

Example Architecture

[0037] FIG. **1** is an overview of an architecture **100** of a system for cross-environment event correlation, consistent with an illustrative embodiment. As shown in the bracket offline **105**, some of the operations may be performed with a system being offline, which can include data retrieval by collecting events, logs, metrics, or change records from various domains, using e.g., synthetic simulation or history data. A non-limiting example of domains **107** is shown, from which the history data may be obtained. Normalized formats may be generated from the retrieved data. There can be machine learning of correlated events **108** across domains and an explanation about a cause of the issue, for example, based on analyzing the issue.

[0038] With continued reference to FIG. **1**, semantic knowledge or meta-knowledge **110** can be extracted from the retrieved data, and a correlation graph (e.g., a knowledge graph) is generated to trace the correlated issues to help the grouping of events. There is a domain-space exploration **115** performed to construct a logical reasoning description for the domain space exploration. The correlated issues help to trace the correlated issues to help grouping events.

[0039] Under the bracket marked "online" **120** there are some runtime functions. For example, in runtime, there can be a cross-domain correlation of events or a create/read/update/delete (CRUD) operation to return a grouped event with an explanation about a cause of the issue. In one embodiment, there is a physical server **125** coupled to persistent storage (e.g., a Kubernetes layer) coupled with pods. Optionally, a system reliability engineer **230** can provide feedback in a training operation.

[0040] FIG. **2** is a system flow diagram **200** for cross-environment event correlation using domain space exploration, consistent with an illustrative embodiment. At operation **205**, the data from various domains are collect in the form of, for example, events, logs, metrics change records, etc. This data can be used to produce normalized formats.

[0041] At operation **210**, there is a learning of correlated events occurring across domains using machine learning techniques. As discussed herein, the machine learning may be based on supervised or unsupervised training. For example, the correlated events can be identified for grouping into one or more correlated groups with a confidence level. In unsupervised learning, there can be frequency-based approaches such as an association rule learning algorithm. In addition, similarity-based approaches, such as clustering algorithms, can be used with an association rule learning algorithm. In supervised learning techniques, there is a use of labeled data associated with a data correlation, or labels are created with a data correlation. In one example, a problem incident can be identified with tickets that include multiple events that are closed together. In addition, if the size of data is relatively small, traditional machine learning algorithms, such as a support vector machine (SVM), can be used for the classifications. In the case of big data, deep learning algorithms such as convolutional neural networks (CNN), long-short term memory (LSTM), etc., can be used.

[0042] At operation **215**, an extracting of the meta-knowledge (or semantic knowledge) is performed, and used to generate a correlation graph (e.g., knowledge graph **217**) to trace the correlated issues for the grouping of events. Meta-knowledge can be extracted number of ways, for example, by reading tags, extracting quantitative data sets, and using an information extraction (IE) system, or by an event-based information extraction software. At operation **220**, a constructing of a logical reasoning description from domain-space exploration is performed. For example, in domain-space exploration, there can be a number of operations performed, such as exploring of the attributes that have occurred in each domain from analyzing the history data, a combining of entities with relation (e.g., entity linking), extracting a knowledge base, and constructing a knowledge graph. A correlating of types of events with similar cluster types can be based on the temporal and spatial information.

[0043] At operation **225**, during runtime, there is a correlation of events performed to identify a group of events, and to return the grouped event with an explanation of a cause of an issue. The actions used to identify and return a grouped event with an explanation of the cause of an issue include performing actions such as create/read/update/delete (referred to in the art as "CRUD"). Then at operation **230**, feedback to capture knowledge of the correlated events may be provided to the machine learning of correlated events **210** based on capturing and analyzing real-time data. Feedback can be generated to determine the one or more correlated events by an active learning methodology, which interactively queries a user or another information source to label new data points with the desired outputs. Optionally, a site reliability engineer (SRE) or a subject matter experts (SMEs) can supplement the feedback.

[0044] FIG. **3** illustrates an example of a problem scenario **300** in a cloud native environment that is addressed in the present disclosure. FIG. **3** lists the state of the environment today **305**, tomorrow **310**, the symptom **315**, and the cross-environment correlation. A schematic **325** of the environment is also shown.

[0045] In the "today" 305 state, an application "172.1.1.1" running on VM 10.1.2.1, is hosted by a physical server 9.1.1.1. The application 172.1.1.1 can communicate with another application "postgres 172.1.2.1", which is hosted by another physical server 9.1.2.1. However, in the "tomorrow" 310 state, the router **327** between the two physical servers changes a rule to "deny", and now the application 172.1.1.1 cannot communicate with the postgres 172.1.2.1 application. The current event management system is not aware of the rule change in the router **327**, and it is not known why the application 172.1.1.1 cannot communicate with postgres

172.1.2.1 application. Through performing cross-environment correlation, the information about the policy change in the router, and the symptom are correlated as a group to diagnose the issue.

[0046] FIG. **4** illustrates an example of a problem scenario **400** in a hybrid-cloud environment that is addressed in the present disclosure. In this illustration, the environment is a hybrid cloud, and the symptom **405** is that there is an intermittent application connection dropping to an application program interface (API) running behind a device operating NSX® software. The NSX® edge messages **410** state that a notification is being sent to a neighbor due to an unexpected condition, followed by a message that a connection's state has deteriorated, and that a connection has entered or left an established state. The messages, starting with an indication of an unexpected condition through the message regarding the connection has left an established state, are the sequence of the application dropping to the API. An explanation at **420** indicates that such message notifications normally do not get translated to an event as no action may be required, and that false positive messages can be generated, particularly if it related to Border Gateway Protocol (BGP), which is a standardized exterior gateway protocol that is designed to exchange information about routing and reachability among autonomous systems on the Internet. According to a method of the present disclosure, at **430** it is indicated that these types of messages and the symptom are correlated as a group to diagnose the issue and provided to an SRE or an automated remedial action file of similar messages that may be searchable. At **435**, it is indicated that by correlating the group events regarding the application connection drops (referred to as an "NSX BGP flap") to upstream events, and providing the information to an automated remedial action file of similar messages or an SRE will permit a faster ability to diagnose and undertake remedial actions with an application unable to communicate with an end point located behind the NSX edge.

[0047] FIG. **5** illustrates a domain-space exploration **500** operation, consistent with an illustrative embodiment. According to FIG. **5**, in a domain-space exploration, the attributes of events that can happen in each domain are explored from history data. One such example can be connection drops across an NSX-BGP flap as discussed above with regard to FIG. **4**. At operation **510** there is a combining of entities with a relation (e.g., entity linking). With regard to the scenario discussed in FIG. **4**, the combining of entities can include linking information regarding similar nodes that connect across the NSX-BGP flap.

[0048] At operation **515**, the knowledge base is extracted and a knowledge graph is constructed using, for example, by dependency parsing and graph construction. For example, the events can be graphically represented to make it easier to determine if there is a pattern or commonality to any problems.

[0049] At operation **520**, clustering is performed on types of events having similarities and events that are correlated based on the temporal and spatial (e.g., topological) information (e.g., grouping). A clustering algorithm can be used to correlate common issues and/or issues with entities sharing similar connections with certain applications. The domain-space exploration **540** is shown, with the relationship between container authorization, container analytics, and a host.

[0050] FIG. **6** illustrates the construction of correlation graphs **600**, consistent with an illustrative embodiment. The domain-space exploration **605**, a meta-extraction **610**, and a knowledge graph **615** are shown. The semantic correlation graph is constructed with learned information, and the meta-information is extracted from the domain-space exploration and converted to the knowledge graph. The domain-space exploration **605** depicts a relationship between container authorization, container analytics, and a host. The meta-extraction **610** can be extracted number of ways, for, example, by reading tags, extracting quantitative data sets, by using an information extraction (IE) system, or by an event-based information extraction software. The knowledge graph **615** is a programmatic way to model domain information, as it shows the links between various domains. There are various applications that can generate knowledge graphs, and their use can be applied to problem determination by providing links of events that may have occurred by various domains. FIG. **7** is a sample screenshot **700** used in the building of a logical reason description, consistent with an illustrative embodiment. The screenshot **700** is an example of space exploration logic used to find reasoning for localization and a blast radius. With the data from the domain-space exploration, deep design space explorations logic is updated with logic with iterative learning and optional SRE feedback (or an automated feedback). In runtime, the correlated events and reasoning can be found.

Example Process

[0051] With the foregoing overview of the example architecture, it may be helpful now to consider a high-level discussion of an example process. To that end, in conjunction with FIGS. **1** and **2**, FIG. **8** is a flowchart a computer-implemented method for cross-environment event correlation, consistent with an illustrative embodiment. Process **800** is illustrated as a collection of blocks, in a logical flowchart, which represents a sequence of operations that can be implemented in hardware, software, or a combination thereof. In the context of software, the blocks represent computer-executable instructions that, when executed by one or more processors, perform the recited operations. Generally, computer-executable instructions may include routines, programs, objects, components, data structures, and the like that perform functions or implement abstract data types. In each process, the order in which the operations are described is not intended to be construed as a limitation, and any number of the described blocks can be combined in any order and/or performed in parallel to implement the process. For discussion purposes, the process **800** is described with reference to the architecture of FIG. **1**.

[0052] At operation **810**, one or more correlated events are determined about an issue occurring across a plurality of domains. The issue can range, for example, from a hard failure to a degradation of service. The correlated events can have some type of commonality as a basis for grouping.

[0053] At operation **820**, at least one of a semantic knowledge data, or a meta-knowledge data of the issue determined from the correlated events are extracted. The meta-knowledge may be extracted, for example, from a domain-space exploration. The meta-knowledge can be extracted a number of ways, such as by reading tags, extracting quantitative data sets, and using an information extraction (IE) system, or by an event-based information extraction software.

[0054] At operation **830**, a correlation graph of the extracted semantic knowledge data or the meta-knowledge data is generated to trace the issue.

[0055] At operation **840**, the correlated events are grouped into one or more event groups. The events may be based on similar types of errors (e.g., network flapping such as discussed with regard to FIG. **4**), or errors occurring with a particular gateway, errors occurring at a similar period of time.

[0056] At operation **850**, a logical reasoning description is constructed based on the generated correlation graph. The correlation graph for a domain-space exploration is related to how the issue in one domain affects another domain of the plurality of domains.

[0057] At operation **860**, the event groups of correlated events are provided with an explanation about a cause of the issue. The explanation provides a better understanding about the issue.

[0058] The process in this illustrative embodiment ends after operation **860**.

Example Particularly Configured Computing Device

[0059] FIG. **9** provides a functional block diagram illustration of a computer hardware platform **900**. In particular, FIG. **9** illustrates a particularly configured network or host computer platform **900**, as may be used to implement the method as discussed herein above.

[0060] The computer platform **900** may include a central processing unit (CPU) **904**, a hard disk drive (HDD) **906**, random access memory (RAM) and/or read-only memory (ROM) **908**, a keyboard **910**, a mouse **912**, a display **914**, and a communication interface **916**, which are connected to a system bus **902**. The HDD **906** can include data stores.

[0061] In one embodiment, the HDD **906**, has capabilities that include storing a program that can execute various processes, such as for executing cross-environment event correlation **950**, in a manner described herein. The cross-environment event correlation module **950** includes a domain-space exploration module **938**, and an event grouping module **940**, A reasoning descriptor **942** generates a logical reasoning for domain-space exploration. A graph generator module **944** is configured to generate a correlation graph from extracted semantic or meta knowledge to trace the correlated issues to help group events. There can be various modules configured to perform different functions that can vary in quantity. For example, a machine learning module **946** may be configured to learn the cross-domain correlations and reason about the issue. Given data (history or synthetic), the correlated events are identified as a correlated group with a confidence level.

[0062] In one embodiment, a program, such as Apache™, can be stored for operating the system as a Web server. In one embodiment, the HDD **906** can store an executing application that includes one or more library software modules, such as those for the Java™ Runtime Environment program for realizing a JVM (Java™ virtual machine).

Example Cloud Platform

[0063] As discussed above, functions related to cross-environment event correlation according to the present disclosure may include a cloud. It is to be understood that although this disclosure includes a detailed description of cloud computing as discussed herein below, implementation of the teachings recited herein is not limited to a cloud computing environment. Rather, embodiments of the present disclosure are capable of being implemented in conjunction with any other type of computing environment now known or later developed.

[0064] Cloud computing is a model of service delivery for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, network bandwidth, servers, processing, memory, storage, applications, virtual machines, and services) that can be rapidly provisioned and released with minimal management effort or interaction with a provider of the service. This cloud model may include at least five characteristics, at least three service models, and at least four deployment models.

Characteristics are as follows:

[0065] On-demand self-service: a cloud consumer can unilaterally provision computing capabilities, such as server time and network storage, as needed automatically without requiring human interaction with the service's provider.

[0066] Broad network access: capabilities are available over a network and accessed through standard mechanisms that promote use by heterogeneous thin or thick client platforms (e.g., mobile phones, laptops, and PDAs).

[0067] Resource pooling: the provider's computing resources are pooled to serve multiple consumers using a multi-tenant model, with different physical and virtual resources dynamically assigned and reassigned according to demand. There is a sense of location independence in that the consumer generally has no control or knowledge over the exact location of the provided resources but may be able to specify location at a higher level of abstraction (e.g., country, state, or datacenter).

[0068] Rapid elasticity: capabilities can be rapidly and elastically provisioned, in some cases automatically, to quickly scale out and rapidly released to quickly scale in. To the consumer, the capabilities available for provisioning often appear to be unlimited and can be purchased in any quantity at any time.

[0069] Measured service: cloud systems automatically control and optimize resource use by leveraging a metering capability at some level of abstraction appropriate to the type of service (e.g., storage, processing, bandwidth, and active user accounts). Resource usage can be monitored, controlled, and reported, providing transparency for both the provider and consumer of the utilized service.

Service Models are as follows:

[0070] Software as a Service (SaaS): the capability provided to the consumer is to use the provider's applications running on a cloud infrastructure. The applications are accessible from various client devices through a thin client interface such as a web browser (e.g., web-based e-mail). The consumer does not manage or control the underlying cloud infrastructure including network, servers, operating systems, storage, or even individual application capabilities, with the possible exception of limited user-specific application configuration settings.

[0071] Platform as a Service (PaaS): the capability provided to the consumer is to deploy onto the cloud infrastructure consumer-created or acquired applications created using programming languages and tools supported by the provider. The consumer does not manage or control the underlying cloud infrastructure including networks, servers,

operating systems, or storage, but has control over the deployed applications and possibly application hosting environment configurations.

[0072] Infrastructure as a Service (IaaS): the capability provided to the consumer is to provision processing, storage, networks, and other fundamental computing resources where the consumer is able to deploy and run arbitrary software, which can include operating systems and applications. The consumer does not manage or control the underlying cloud infrastructure but has control over operating systems, storage, deployed applications, and possibly limited control of select networking components (e.g., host firewalls).

Deployment Models are as follows:

[0073] Private cloud: the cloud infrastructure is operated solely for an organization. It may be managed by the organization or a third party and may exist on-premises or off-premises.

[0074] Community cloud: the cloud infrastructure is shared by several organizations and supports a specific community that has shared concerns (e.g., mission, security requirements, policy, and compliance considerations). It may be managed by the organizations or a third party and may exist on-premises or off-premises.

[0075] Public cloud: the cloud infrastructure is made available to the general public or a large industry group and is owned by an organization selling cloud services.

[0076] Hybrid cloud: the cloud infrastructure is a composition of two or more clouds (private, community, or public) that remain unique entities but are bound together by standardized or proprietary technology that enables data and application portability (e.g., cloud bursting for load-balancing between clouds).

[0077] A cloud computing environment is service-oriented with a focus on statelessness, low coupling, modularity, and semantic interoperability. At the heart of cloud computing is an infrastructure that includes a network of interconnected nodes.

[0078] Referring now to FIG. **10**, an illustrative cloud computing environment **1000** utilizing cloud computing is depicted. As shown, cloud computing environment **1000** includes cloud **1050** having one or more cloud computing nodes **1010** with which local computing devices used by cloud consumers, such as, for example, personal digital assistant (PDA) or cellular telephone **1054**A, desktop computer **1054**B, laptop computer **1054**C, and/or automobile computer system **1054**N may communicate. Nodes **1010** may communicate with one another. They may be grouped (not shown) physically or virtually, in one or more networks, such as Private, Community, Public, or Hybrid clouds as described hereinabove, or a combination thereof. This allows cloud computing environment **1000** to offer infrastructure, platforms, and/or software as services for which a cloud consumer does not need to maintain resources on a local computing device. It is understood that the types of computing devices **1054**A-N shown in FIG. **10** are intended to be illustrative only and that computing nodes **1010** and cloud computing environment **1050** can communicate with any type of computerized device over any type of network and/or network addressable connection (e.g., using a web browser).

[0079] Referring now to FIG. **11**, a set of functional abstraction layers **1100** provided by cloud computing environment **1000** (FIG. **10**) is shown. It should be understood in advance that the components, layers, and functions shown in FIG. **11** are intended to be illustrative only and embodiments of the disclosure are not limited thereto. As depicted, the following layers and corresponding functions are provided:

[0080] Hardware and software layer **1160** include hardware and software components. Examples of hardware components include: mainframes **1161**; RISC (Reduced Instruction Set Computer) architecture based servers **1162**; servers **1163**; blade servers **1164**; storage devices **1165**; and networks and networking components **1166**. In some embodiments, software components include network application server software **1167** and database software **1168**.

[0081] Virtualization layer **1170** provides an abstraction layer from which the following examples of virtual entities may be provided: virtual servers **1171**; virtual storage **1172**; virtual networks **1173**, including virtual private networks; virtual applications and operating systems **1174**; and virtual clients **1175**.

[0082] In one example, management layer **1180** may provide the functions described below. Resource provisioning **1181** provides dynamic procurement of computing resources and other resources that are utilized to perform tasks within the cloud computing environment. Metering and Pricing **1182** provide cost tracking as resources are utilized within the cloud computing environment, and billing or invoicing for consumption of these resources. In one example, these resources may include application software licenses. Security provides identity verification for cloud consumers and tasks, as well as protection for data and other resources. User portal **1183** provides access to the cloud computing environment for consumers and system administrators. Service level management **1184** provides cloud computing resource allocation and management such that required service levels are met. Service Level Agreement (SLA) planning and fulfillment **1185** provide pre-arrangement for, and procurement of, cloud computing resources for which a future requirement is anticipated in accordance with an SLA.

[0083] Workloads layer **1190** provides examples of functionality for which the cloud computing environment may be utilized. Examples of workloads and functions which may be provided from this layer include: mapping and navigation **1191**; software development and lifecycle management **1192**; virtual classroom education delivery **1193**; data analytics processing **1194**; transaction processing **1195**; and an event correlation module **1196**, as discussed herein.

CONCLUSION

[0084] The descriptions of the various embodiments of the present teachings have been presented for purposes of illustration, but are not intended to be exhaustive or limited to the embodiments disclosed. Many modifications and variations will be apparent to those of ordinary skill in the art without departing from the scope and spirit of the described embodiments. The terminology used herein was chosen to best explain the principles of the embodiments, the practical application or technical improvement over technologies found in the marketplace, or to enable others of ordinary skill in the art to understand the embodiments disclosed herein.

[0085] While the foregoing has described what are considered to be the best state and/or other examples, it is understood that various modifications may be made therein and that the subject matter disclosed herein may be imple-

mented in various forms and examples, and that the teachings may be applied in numerous applications, only some of which have been described herein. It is intended by the following claims to claim any and all applications, modifications and variations that fall within the true scope of the present teachings.

[0086] The components, steps, features, objects, benefits, and advantages that have been discussed herein are merely illustrative. None of them, nor the discussions relating to them, are intended to limit the scope of protection. While various advantages have been discussed herein, it will be understood that not all embodiments necessarily include all advantages. Unless otherwise stated, all measurements, values, ratings, positions, magnitudes, sizes, and other specifications that are set forth in this specification, including in the claims that follow, are approximate, not exact. They are intended to have a reasonable range that is consistent with the functions to which they relate and with what is customary in the art to which they pertain.

[0087] Numerous other embodiments are also contemplated. These include embodiments that have fewer, additional, and/or different components, steps, features, objects, benefits and advantages. These also include embodiments in which the components and/or steps are arranged and/or ordered differently.

[0088] The flowchart, and diagrams in the figures herein illustrate the architecture, functionality, and operation of possible implementations according to various embodiments of the present disclosure.

[0089] While the foregoing has been described in conjunction with exemplary embodiments, it is understood that the term "exemplary" is merely meant as an example, rather than the best or optimal. Except as stated immediately above, nothing that has been stated or illustrated is intended or should be interpreted to cause a dedication of any component, step, feature, object, benefit, advantage, or equivalent to the public, regardless of whether it is or is not recited in the claims.

[0090] It will be understood that the terms and expressions used herein have the ordinary meaning as is accorded to such terms and expressions with respect to their corresponding respective areas of inquiry and study except where specific meanings have otherwise been set forth herein. Relational terms such as first and second and the like may be used solely to distinguish one entity or action from another without necessarily requiring or implying any such actual relationship or order between such entities or actions. The terms "comprises," "comprising," or any other variation thereof, are intended to cover a non-exclusive inclusion, such that a process, method, article, or apparatus that comprises a list of elements does not include only those elements but may include other elements not expressly listed or inherent to such process, method, article, or apparatus. An element proceeded by "a" or "an" does not, without further constraints, preclude the existence of additional identical elements in the process, method, article, or apparatus that comprises the element.

[0091] The Abstract of the Disclosure is provided to allow the reader to quickly ascertain the nature of the technical disclosure. It is submitted with the understanding that it will not be used to interpret or limit the scope or meaning of the claims. In addition, in the foregoing Detailed Description, it can be seen that various features are grouped together in various embodiments for the purpose of streamlining the disclosure. This method of disclosure is not to be interpreted as reflecting an intention that the claimed embodiments have more features than are expressly recited in each claim. Rather, as the following claims reflect, the inventive subject matter lies in less than all features of a single disclosed embodiment. Thus, the following claims are hereby incorporated into the Detailed Description, with each claim standing on its own as a separately claimed subject matter.

What is claimed is:

1. A computer-implemented method for cross-environment event correlation, the method comprising:

determining one or more correlated events about an issue occurring across a plurality of domains;

extracting a knowledge data of the issue determined from the one or more correlated events;

generating a correlation graph of the extracted knowledge data to trace the issue;

grouping the correlated events into one or more event groups to represent a relationship with the issue;

constructing a logical reasoning description based on the generated correlation graph for a domain-space exploration related to how the issue in one domain affects another domain of the plurality of domains; and

providing the one or more event groups of correlated events with an explanation about a cause of the issue for the one or more correlated events based on the logical reasoning description.

2. The computer-implemented method of claim **1**, further comprising using machine learning for the determining of the correlated events about the issue occurring across a plurality of domains based on a history data or a synthetic data, wherein the extracting of the knowledge data includes extracting one or more of a semantic knowledge data or a meta-knowledge data.

3. The computer-implemented method of claim **2**, wherein using the machine learning includes training by an unsupervised learning technique using an association rule learning algorithm or a clustering algorithm.

4. The computer-implemented method of claim **2**, wherein using the machine learning includes training by a supervised learning technique using labeled data associated with a data correlation.

5. The computer-implemented method of claim **2**, further comprising configuring the machine learning by a supervised learning technique using a support vector machine (SVM), a convolutional neural network (CNN), or a long-short term memory (LSTM) based on a size of the correlation data.

6. The computer-implemented method of claim **2**, further comprising:

recommending a most probable event group of correlated events of the one or more event groups to users with an explanation about the cause of the issue.

7. The computer-implemented method of claim **6**, wherein the recommending of the most probable event group of correlated events with the explanation of the cause of the issue is based on performing in a runtime a creating, reading, updating, and deleting (CRUD) of data.

8. The computer-implemented method of claim **6**, wherein using the machine learning includes a training operation based on receiving feedback to train for the determining of the one or more correlated events.

9. The computer-implemented method of claim **6**, further comprising receiving feedback for the determining of the

one or more correlated events by an active learning methodology which interactively queries a user or an information source to label new data points with desired outputs.

10. The computer-implemented method of claim **1**, further comprising constructing one or more semantic relationships between the plurality of domains.

11. The computer-implemented method of claim **1**, wherein the determining of one or more correlated events about an issue comprises:

collecting one or more of an event, a log, or a change record from at least some of the plurality of domains;

determining one or more correlated events about the issue by using one or more machine learning techniques; and

producing normalized formats of the one or more collected events, logs, or change records.

12. The computer-implemented method of claim **11**, wherein at least the collecting of the event, the log, the metric, or the change record is performed offline using a synthetic simulation.

13. The computer-implemented method of claim **11**, wherein at least the collecting of the event, the log, the metric, or the change record is performed offline using history data.

14. A non-transitory computer-readable storage medium tangibly embodying a computer-readable program code having computer-readable instructions that, when executed, causes a computer device to perform a method of cross-environment event correlation, the method comprising:

determining one or more correlated events about an issue across a plurality of domains;

extracting a knowledge data of the issue determined from the one or more correlated events;

generating a correlation graph of the extracted knowledge data to trace the issue;

grouping the correlated events into one or more event groups to represent a relationship with the issue;

constructing a logical reasoning description based on the generated correlation graph for a domain-space exploration related to how the issue in one domain affects another domain of the plurality of domains; and

providing the one or more event groups of correlated events with an explanation about a cause of the issue for the one or more correlated events based on the logical reasoning description.

15. The computer-readable storage medium according to claim **14**, wherein:

the extracting of the knowledge data includes extracting one or more of a semantic knowledge data or a meta-knowledge data, and

the determining of the one or more correlated events is performed by machine learning; and

the method further comprises recommending a most probable event group of correlated events of the one or more event groups to users with explainability about the issue.

16. The computer-readable storage medium according to claim **14**, wherein the recommending of the most probable event group of correlated events with explainability is based on performing in a runtime a creating, reading, updating and deleting (CRUD) of data.

17. The computer-readable storage medium according to claim **14**, the method further comprising constructing one or more semantic relationships between the plurality of domains, and wherein the determining one or more correlated events about an issue comprises:

collecting one or more of events, one or more logs, one or more metrics, or one or more change records from at least some of the plurality of domains;

determining one or more correlated events about the issue by using machine learning techniques; and

producing normalized formats of the one or more collected events, one or more logs, or one or more change records.

18. The computer-readable storage medium according to claim **17**, wherein the collecting of events, logs, metrics, or change records is performed offline using a synthetic simulation or a history data.

19. A computing device for cross-environment event correlation using space-exploration, comprising:

a processor;

a memory coupled to the processor, the memory storing instructions to cause the processor to perform acts comprising:

determining one or more correlated events about an issue across a plurality of domains;

extracting a knowledge data of the issue determined from the one or more correlated events;

constructing a logical reasoning description for domain-space exploration related to how the issue in one domain affects another domain of the plurality of domains;

generating one or more correlation graphs based on the domain-space exploration to trace the issue;

grouping the correlated events in one or more groups;

constructing semantic relationships between different domains, and

recommending the most probable event groups of correlated events with an explanation about a cause of the issue for the one or more correlated events based on the logical reasoning description.

20. The computing device according to claim **19**, wherein:

the extracting of the knowledge data includes extracting one or more of a semantic knowledge data or a meta-knowledge data, and

the processor is configured to perform machine learning of the cross-environment event correlation about the issue.

* * * * *