US012395398B2

(12) **United States Patent**
Titon et al.

(10) **Patent No.: US 12,395,398 B2**
(45) **Date of Patent: Aug. 19, 2025**

(54) **ASSIGNING A RELEVANCE SCORE TO A NEW METRIC USING NATURAL LANGUAGE PROCESSING**

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(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 81 days.

(21) Appl. No.: **18/524,683**

(22) Filed: **Nov. 30, 2023**

(65) **Prior Publication Data**

US 2025/0112816 A1 Apr. 3, 2025

Related U.S. Application Data

(60) Provisional application No. 63/586,626, filed on Sep. 29, 2023.

(51) **Int. Cl.**

H04L 41/0631	(2022.01)
G06F 40/20	(2020.01)
H04L 41/16	(2022.01)

(52) **U.S. Cl.**
CPC ***H04L 41/064*** (2013.01); ***G06F 40/20*** (2020.01); ***H04L 41/16*** (2013.01)

(58) **Field of Classification Search**
CPC G06F 40/20; H04L 41/064; H04L 41/16
See application file for complete search history.

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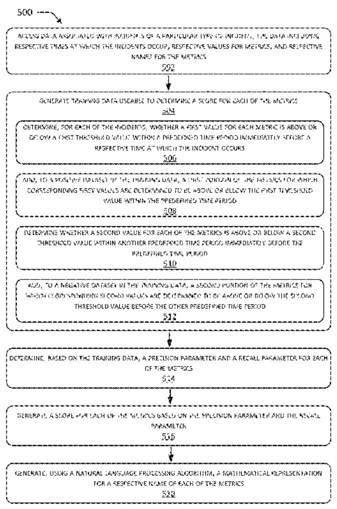
(57) **ABSTRACT**

Disclosed herein is a system for determining scores that are usable to filter a larger set of metrics (e.g., thousands of metrics) down to a smaller set of relevant metrics (e.g., hundreds of metrics) that can be more efficiently queried and ingested for root-cause analysis of an incident. During a training stage, the system analyzes known incidents and converts the names of the metrics, as described via customer-defined words, into mathematical representations (e.g., word embedding featurization vectors). When a new metric with a new name is received for a new incident, the system implements an incident inference stage during which the new name is converted into a new mathematical representation. The system compares the new mathematical representation to the mathematical representations to identify a similar mathematical representation. The system retrieves the score for the metric associated with the similar mathematical representation and assigns the retrieved score to the new metric.

20 Claims, 8 Drawing Sheets


500
ACCESS DATA ASSOCIATED WITH INCIDENTS OF A PARTICULAR TYPE OF INCIDENT, THE DATA INCLUDING RESPECTIVE TIMES AT WHICH THE INCIDENTS OCCUR, RESPECTIVE VALUES FOR METRICS, AND RESPECTIVE NAMES FOR THE METRICS
502
GENERATE TRAINING DATA USEABLE TO DETERMINE A SCORE FOR EACH OF THE METRICS
504
DETERMINE, FOR EACH OF THE INCIDENTS, WHETHER A FIRST VALUE FOR EACH METRIC IS ABOVE OR BELOW A FIRST THRESHOLD VALUE WITHIN A PREDEFINED TIME PERIOD IMMEDIATELY BEFORE A RESPECTIVE TIME AT WHICH THE INCIDENT OCCURS
506
ADD, TO A POSITIVE DATASET IN THE TRAINING DATA, A FIRST PORTION OF THE METRICS FOR WHICH CORRESPONDING FIRST VALUES ARE DETERMINED TO BE ABOVE OR BELOW THE FIRST THRESHOLD VALUE WITHIN THE PREDEFINED TIME PERIOD
508
DETERMINE WHETHER A SECOND VALUE FOR EACH OF THE METRICS IS ABOVE OR BELOW A SECOND THRESHOLD VALUE WITHIN ANOTHER PREDEFINED TIME PERIOD IMMEDIATELY BEFORE THE PREDEFINED TIME PERIOD
510
ADD, TO A NEGATIVE DATASET IN THE TRAINING DATA, A SECOND PORTION OF THE METRICS FOR WHICH CORRESPONDING SECOND VALUES ARE DETERMINED TO BE ABOVE OR BELOW THE SECOND THRESHOLD VALUE BEFORE THE OTHER PREDEFINED TIME PERIOD
512
DETERMINE, BASED ON THE TRAINING DATA, A PRECISION PARAMETER AND A RECALL PARAMETER FOR EACH OF THE METRICS
514
GENERATE A SCORE FOR EACH OF THE METRICS BASED ON THE PRECISION PARAMETER AND THE RECALL PARAMETER
516
GENERATE, USING A NATURAL LANGUAGE PROCESSING ALGORITHM, A MATHEMATICAL REPRESENTATION FOR A RESPECTIVE NAME OF EACH OF THE METRICS
518

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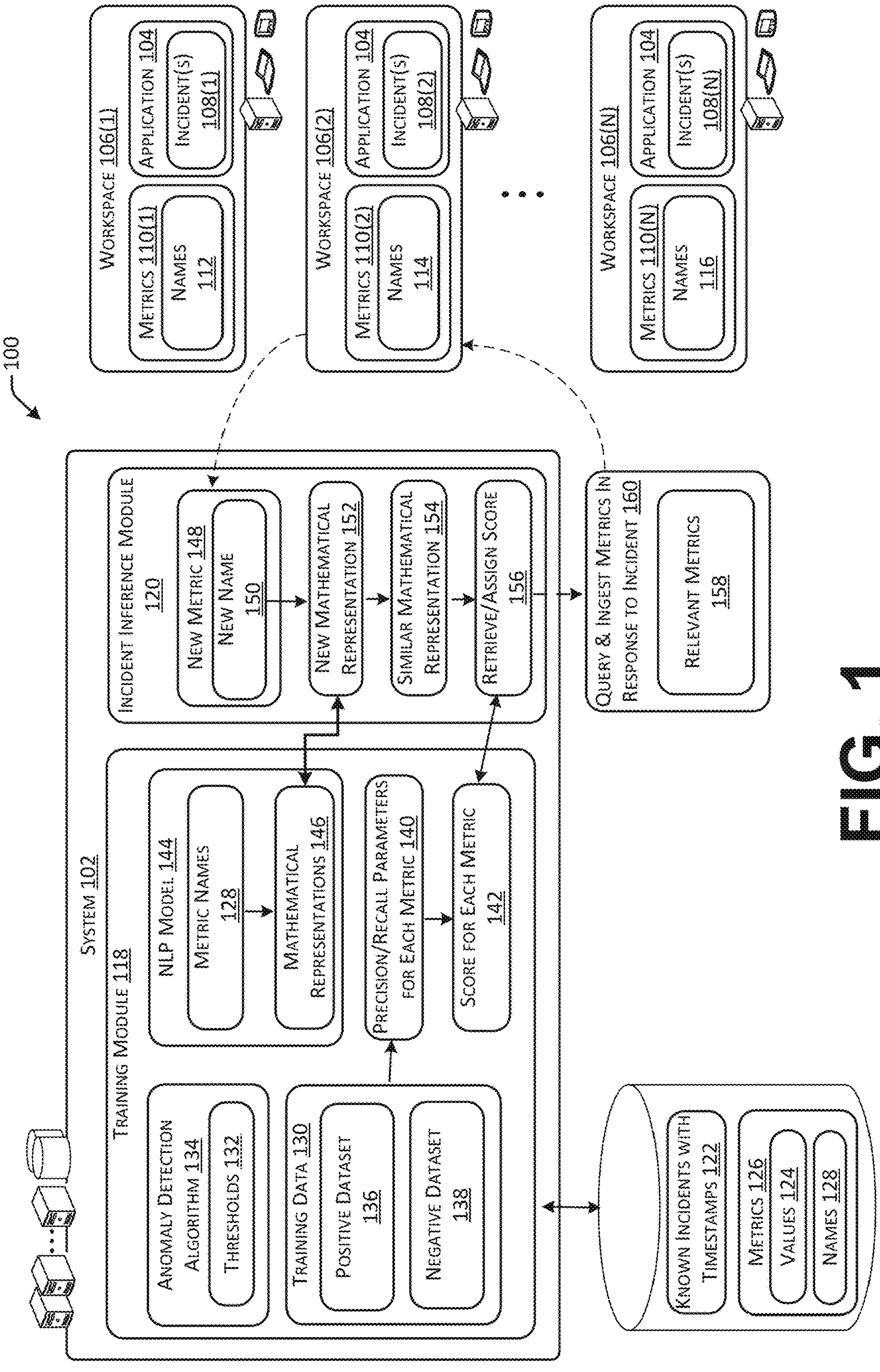
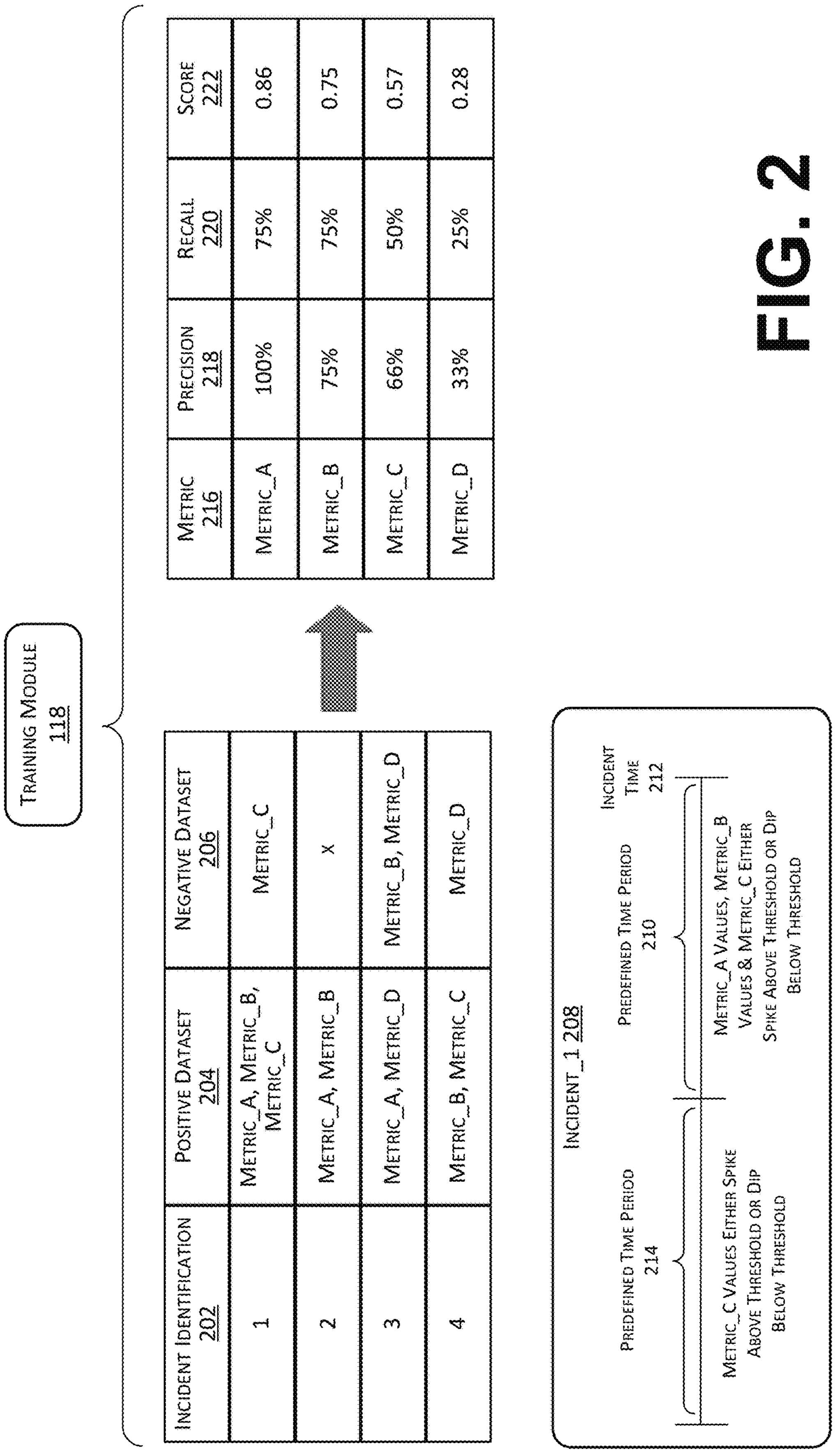

100
System 102
Training Module 118
Anomaly Detection Algorithm 134
Thresholds 132
Training Data 130
Positive Dataset 136
Negative Dataset 138
NLP Model 144
Metric Names 128
Mathematical Representations 146
Precision/Recall Parameters for Each Metric 140
Score for Each Metric 142
Incident Inference Module 120
New Metric 148
New Name 150
New Mathematical Representation 152
Similar Mathematical Representation 154
Retrieve/Assign Score 156
Query & Ingest Metrics in Response to Incident 160
Relevant Metrics 158
Known Incidents with Timestamps 122
Metrics 126
Values 124
Names 128
Workspace 106(1)
Metrics 110(1)
Names 112
Application 104
Incident(s) 108(1)
Workspace 106(2)
Metrics 110(2)
Names 114
Application 104
Incident(s) 108(2)
Workspace 106(N)
Metrics 110(N)
Names 116
Application 104
Incident(s) 108(N)

FIG. 1


Training Module 118
Incident_1 208
Predefined Time Period 214
Metric_C Values Either Spike Above Threshold or Dip Below Threshold
Predefined Time Period 210
Metric_A Values, Metric_B Values & Metric_C Either Spike Above Threshold or Dip Below Threshold
Incident Time 212

Incident Identification 202	Positive Dataset 204	Negative Dataset 206
1	Metric_A, Metric_B, Metric_C	Metric_C
2	Metric_A, Metric_B	x
3	Metric_A, Metric_D	Metric_B, Metric_D
4	Metric_B, Metric_C	Metric_D

Metric 216	Precision 218	Recall 220	Score 222
Metric_A	100%	75%	0.86
Metric_B	75%	75%	0.75
Metric_C	66%	50%	0.57
Metric_D	33%	25%	0.28

FIG. 2

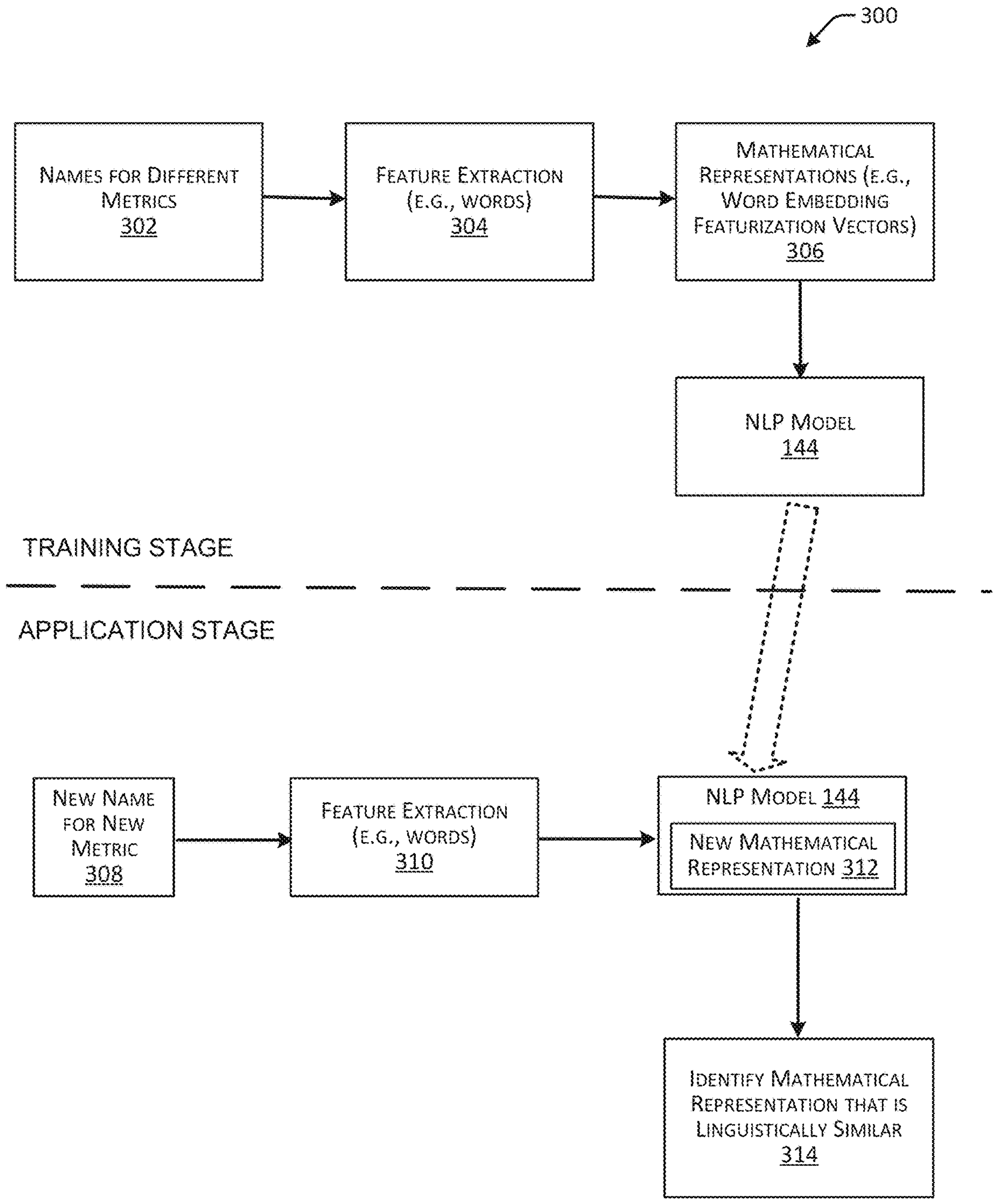
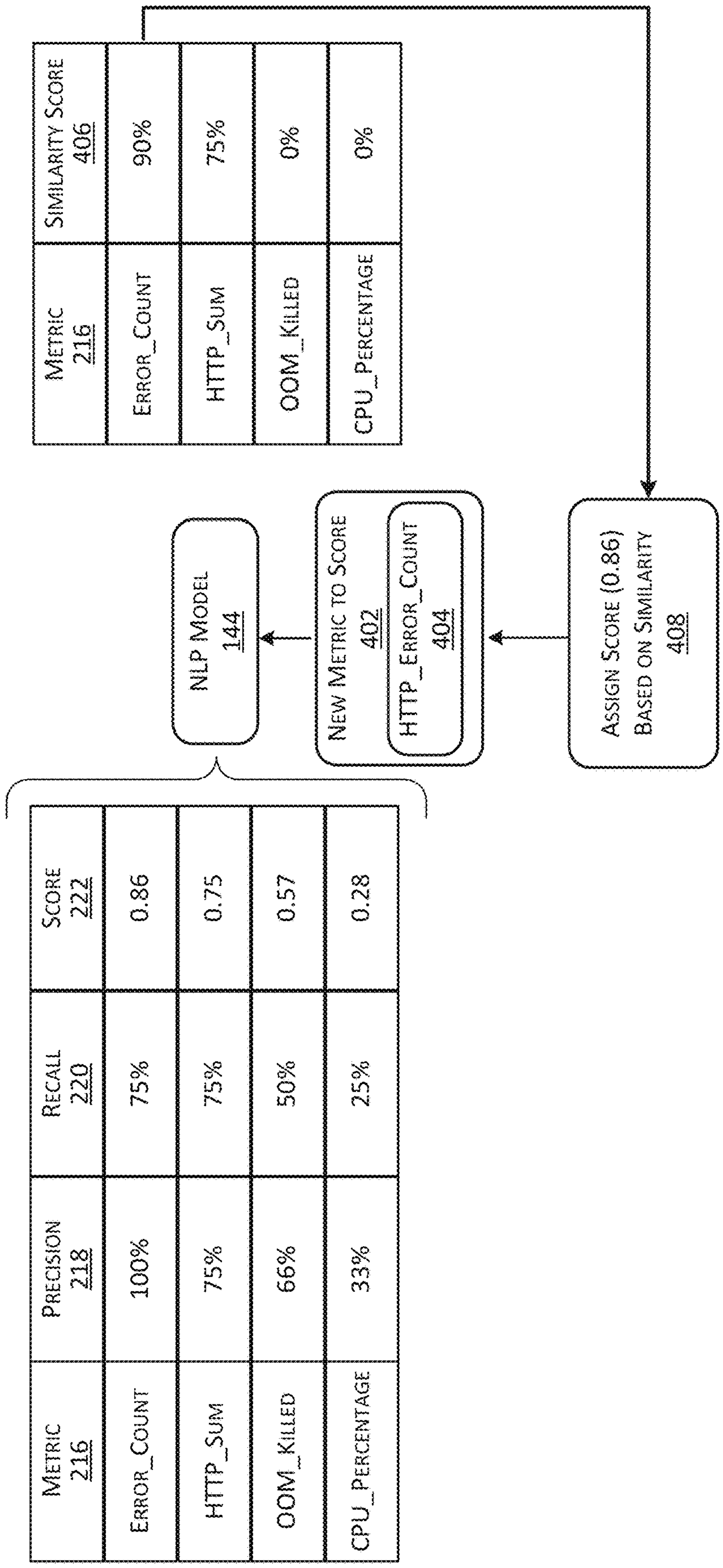

300
Names for Different Metrics 302
Feature Extraction (e.g., words) 304
Mathematical Representations (e.g., Word Embedding Featurization Vectors) 306
NLP Model 144
TRAINING STAGE
APPLICATION STAGE
New Name for New Metric 308
Feature Extraction (e.g., words) 310
NLP Model 144
New Mathematical Representation 312
Identify Mathematical Representation that is Linguistically Similar 314

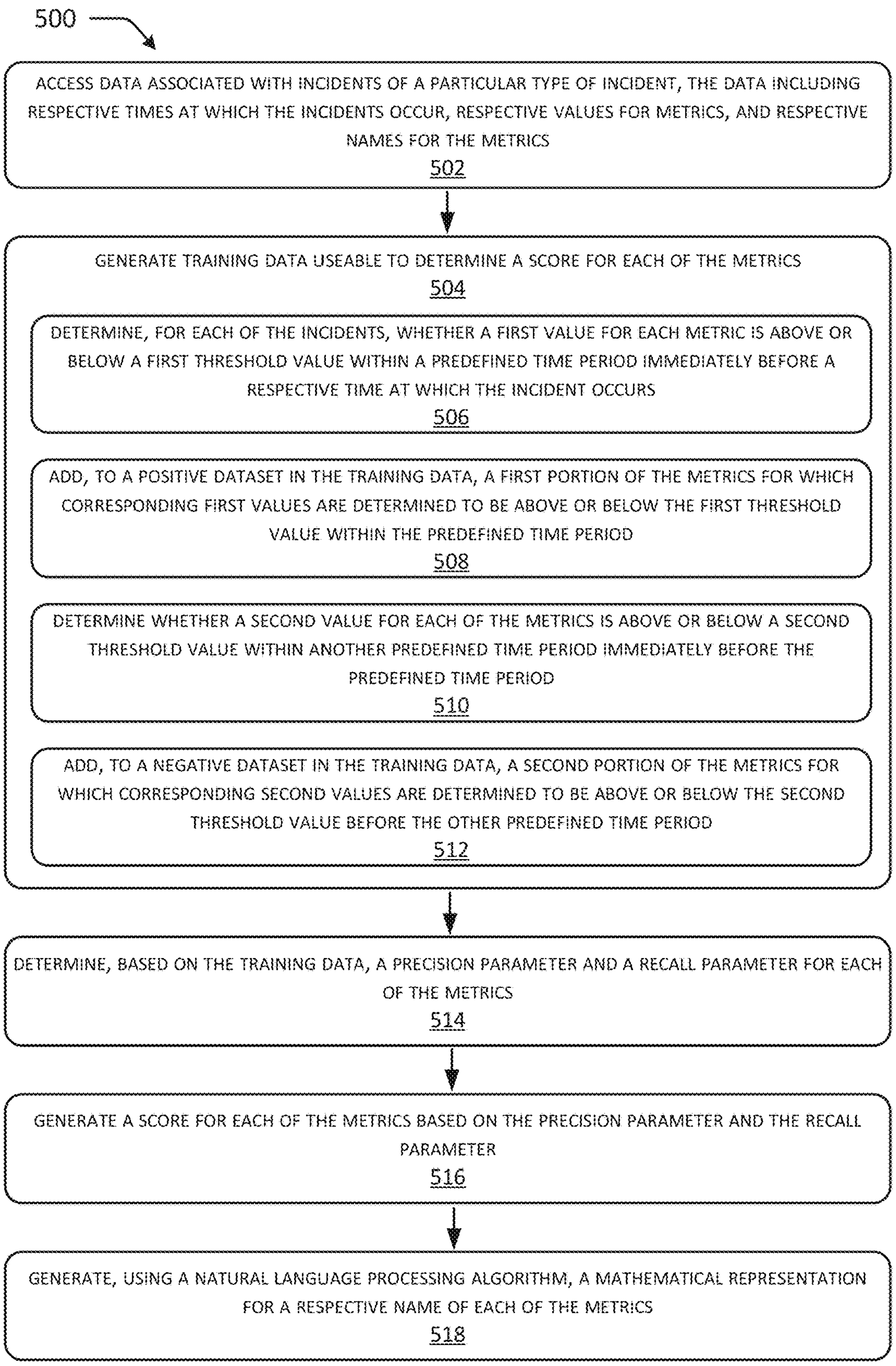
FIG. 3



Metric 216	Precision 218	Recall 220	Score 222
Error_Count	100%	75%	0.86
HTTP_Sum	75%	75%	0.75
OOM_Killed	66%	50%	0.57
CPU_Percentage	33%	25%	0.28

Metric 216	Similarity Score 406
Error_Count	90%
HTTP_Sum	75%
OOM_Killed	0%
CPU_Percentage	0%

FIG. 4


500
ACCESS DATA ASSOCIATED WITH INCIDENTS OF A PARTICULAR TYPE OF INCIDENT, THE DATA INCLUDING RESPECTIVE TIMES AT WHICH THE INCIDENTS OCCUR, RESPECTIVE VALUES FOR METRICS, AND RESPECTIVE NAMES FOR THE METRICS
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516
GENERATE, USING A NATURAL LANGUAGE PROCESSING ALGORITHM, A MATHEMATICAL REPRESENTATION FOR A RESPECTIVE NAME OF EACH OF THE METRICS
518

FIG. 5A

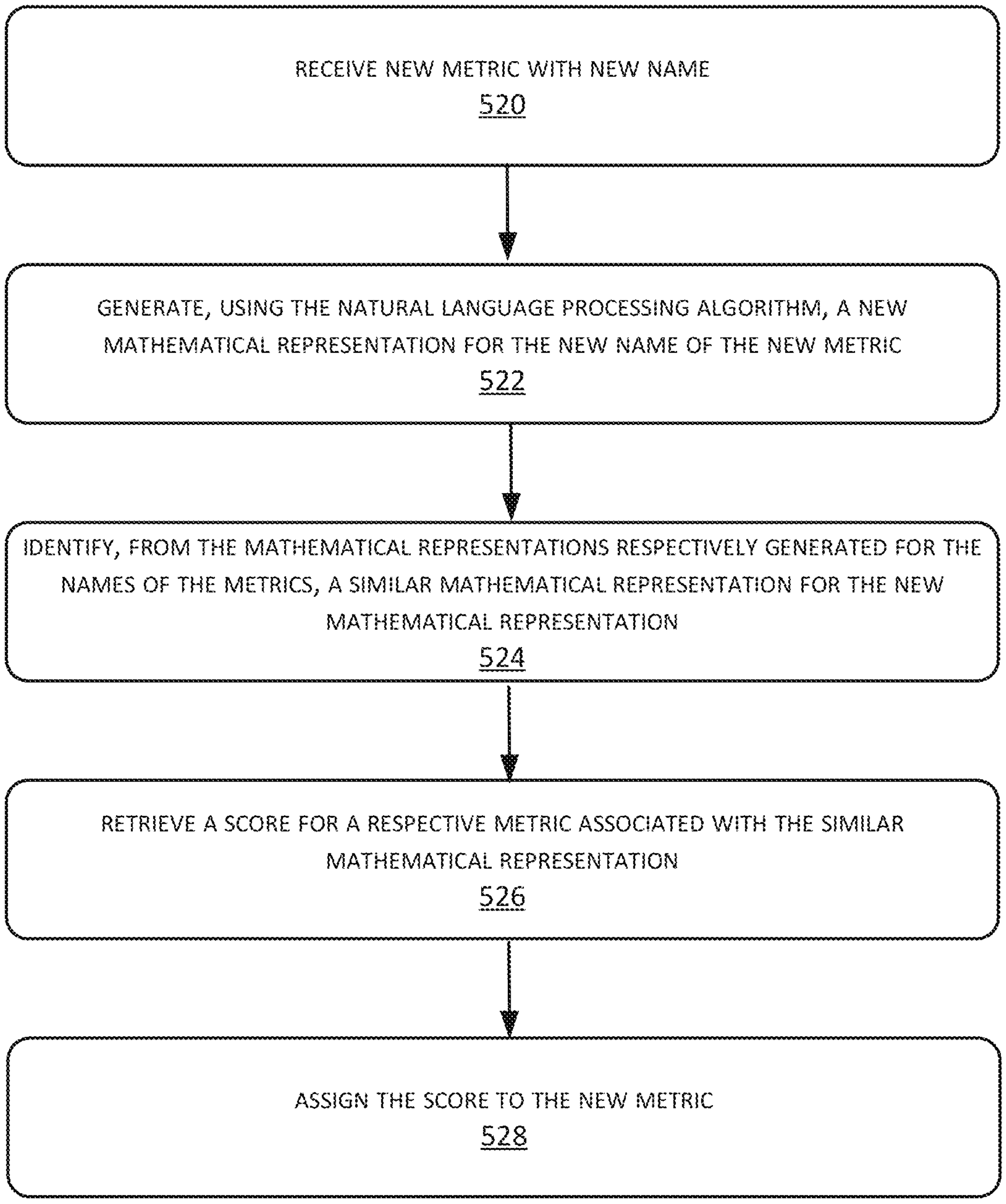
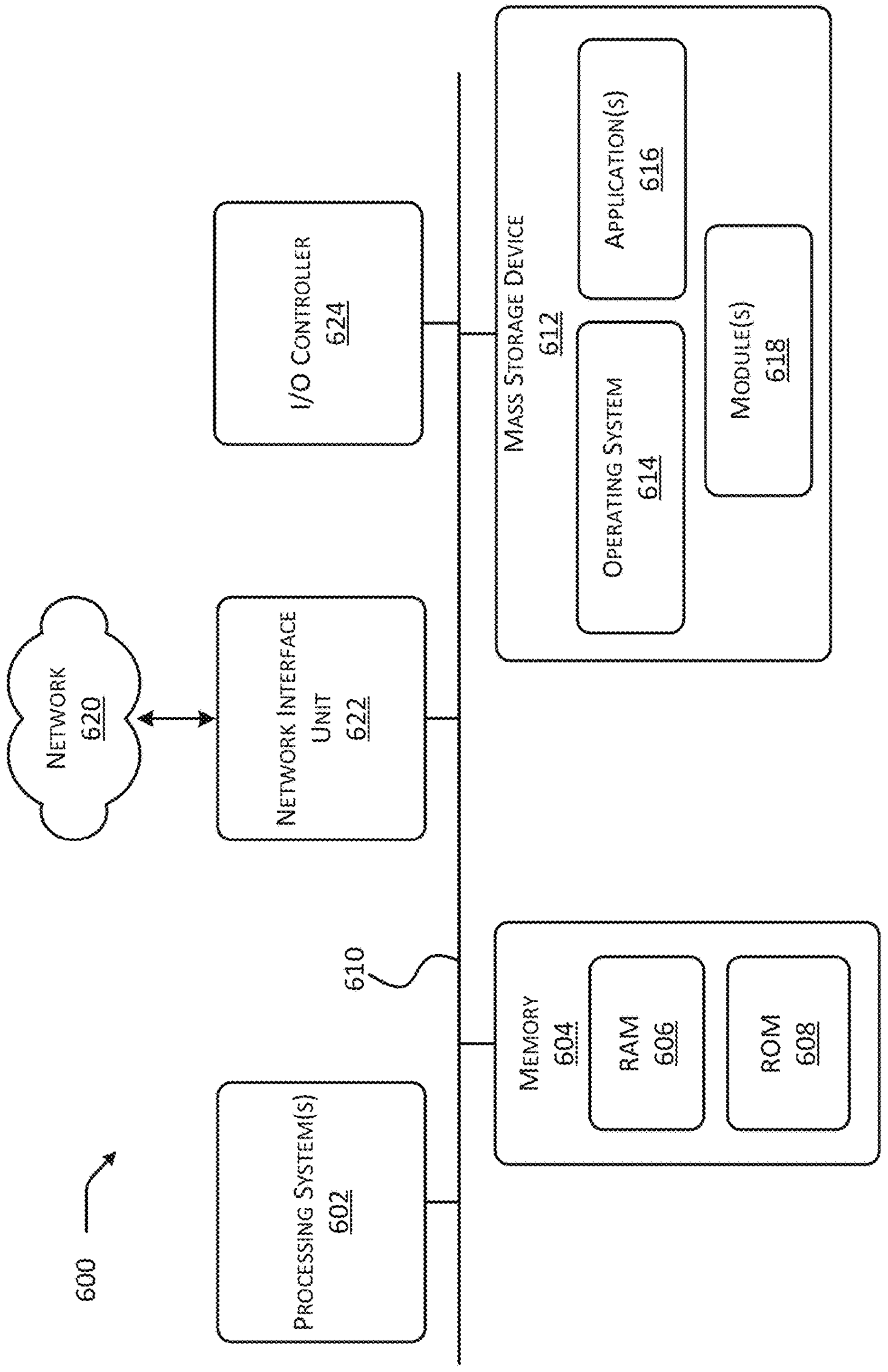

RECEIVE NEW METRIC WITH NEW NAME
520
GENERATE, USING THE NATURAL LANGUAGE PROCESSING ALGORITHM, A NEW MATHEMATICAL REPRESENTATION FOR THE NEW NAME OF THE NEW METRIC
522
IDENTIFY, FROM THE MATHEMATICAL REPRESENTATIONS RESPECTIVELY GENERATED FOR THE NAMES OF THE METRICS, A SIMILAR MATHEMATICAL REPRESENTATION FOR THE NEW MATHEMATICAL REPRESENTATION
524
RETRIEVE A SCORE FOR A RESPECTIVE METRIC ASSOCIATED WITH THE SIMILAR MATHEMATICAL REPRESENTATION
526
ASSIGN THE SCORE TO THE NEW METRIC
528

FIG. 5B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Processing System(s) 602
Memory 604
RAM 606
ROM 608
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Network 620
Network Interface Unit 622
I/O Controller 624
Mass Storage Device 612
Operating System 614
Application(s) 616
Module(s) 618

FIG. 6

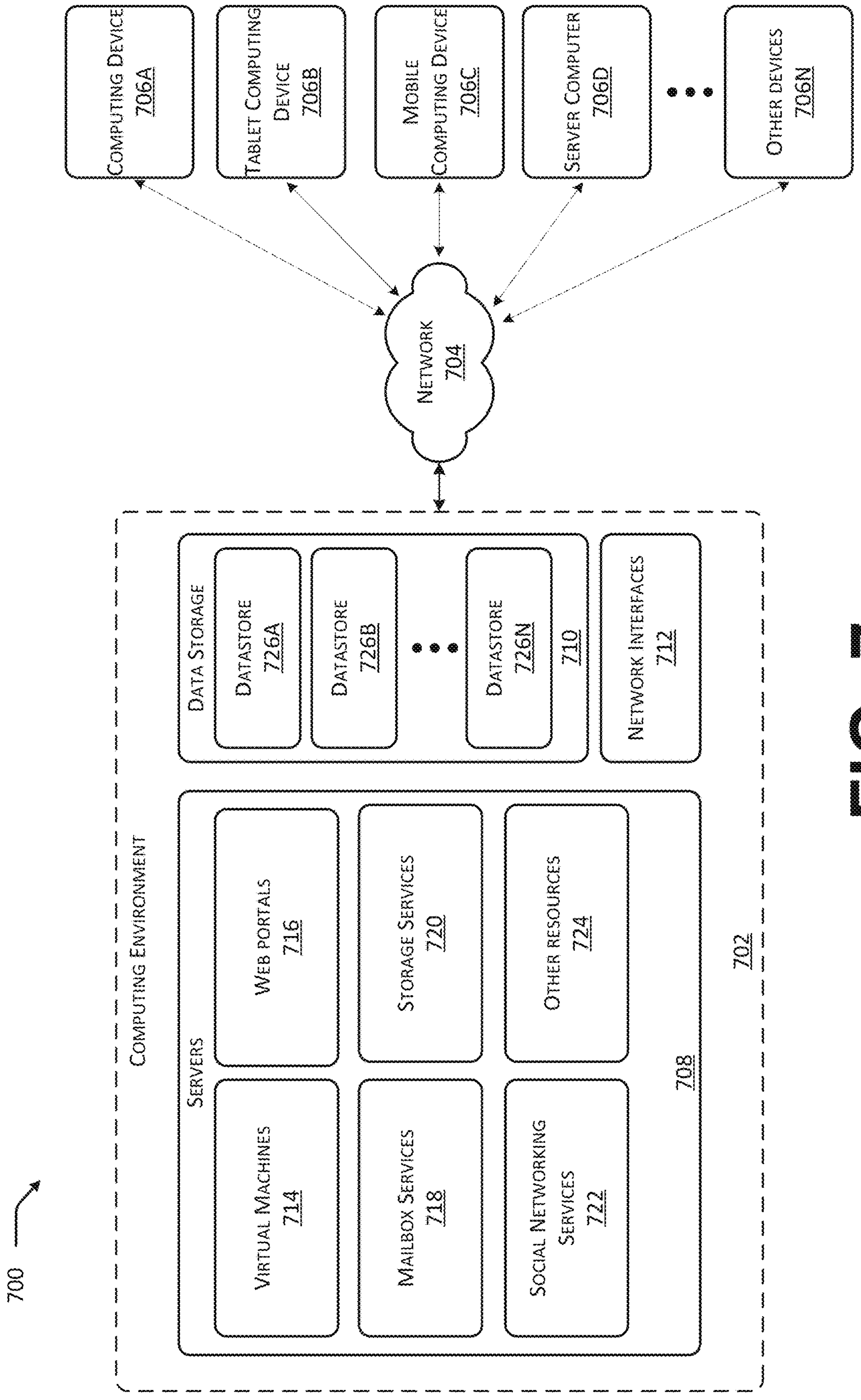
700
Computing Environment
Servers
Virtual Machines 714
Web portals 716
Mailbox Services 718
Storage Services 720
Social Networking Services 722
Other resources 724
708
702
Data Storage
Datastore 726A
Datastore 726B
Datastore 726N
710
Network Interfaces 712
Network 704
Computing Device 706A
Tablet Computing Device 706B
Mobile Computing Device 706C
Server Computer 706D
Other devices 706N

FIG. 7

ASSIGNING A RELEVANCE SCORE TO A NEW METRIC USING NATURAL LANGUAGE PROCESSING

PRIORITY APPLICATION

This application claims the benefit of and priority to U.S. Provisional Patent Application No. 63/586,626, filed Sep. 29, 2023, the entire contents of which are incorporated herein by reference.

BACKGROUND

As cloud computing rapidly gains popularity, more and more data and/or services are stored and/or provided via network connections. Providing an optimal and reliable customer experience is an important aspect for cloud providers that host services via cloud platforms (e.g., AMAZON WEB SERVICES, GOOGLE CLOUD PLATFORM, MICROSOFT AZURE). A cloud provider is the operator of a cloud platform. A tenant is a customer of the cloud provider that uses a cloud platform to provide a service to thousands or millions of end users geographically dispersed around a country, or even the world.

In various scenarios, the cloud provider can provision an application for use by different customers within separate workspaces. A workspace is a logical unit that belongs to the customer and that enables the customer to efficiently configure resources, manage applications, and execute services in a customized and secure manner. In one example, the cloud provider can provision the application to separate workspaces via a container-based orchestration process (e.g., KUBERNETES). Often, execution of the application in a workspace may be disrupted by an incident that negatively affects the performance of the application within the workspace and/or the security provided by the application within the workspace. When an incident occurs, the cloud provider is often required, e.g., in accordance with various service level agreements (SLAs), to investigate the incident and perform root-cause analysis.

In order to perform the root-cause analysis, an operator of the cloud platform implements a system configured to query and/or ingest metrics from resources within the workspace (e.g., KUBERNETES nodes and/or clusters) in which the incident occurs. The metrics reflect a state of the application and/or the infrastructure used to execute the application. Consequently, the metrics are analyzed by systems and/or users to perform the root-cause analysis.

Analyzing the metrics associated with an incident is a resource intensive, and thus, expensive task due to the large number of metrics that is available to be queried and ingested by the system. For instance, thousands of metrics are collected within the customer workspaces and are available for querying and ingestion. Consequently, it takes the cloud provider an unreasonable amount of time (e.g., over thirty minutes, an hour) to provide the results (e.g., the likely root cause of the incident) of the root-cause analysis if the all the available metrics are queried and ingested for analysis.

To shorten the amount of time it typically takes to provide the results of the root-cause analysis, the cloud provider attempts to identify a smaller set of more relevant metrics (e.g., hundreds of metrics rather than thousands of metrics) for querying, ingestion, and analysis purposes. However, identifying a smaller set of more relevant metrics has proven to be a difficult task for cloud provider. One reason the task is difficult is different customers use different names (e.g., descriptions using words or other string(s) of alphanumeric characters) to define the same or similar metrics for the application executing within their own workspace. For instance, a first customer may define a metric as "http_failed_requests_count" in their workspace while a second customer may define the same metric as "http_incomplete_requests_count".

Consequently, it is difficult for the cloud provider to learn which smaller set of metrics is relevant to an incident that occurs in a first workspace so that the same smaller set of relevant metrics can be queried and ingested in response to a similar incident of the same type that occurs in a second workspace. It is with respect to these and other considerations that the disclosure made herein is presented.

SUMMARY

The system disclosed herein addresses the challenges described above, among others, by determining scores that are usable to filter a larger set of metrics (e.g., thousands of metrics) down to a smaller set of relevant metrics (e.g., hundreds of metrics) that can be more efficiently queried and ingested when a particular type of incident occurs. To determine the scores, the system implements a training stage during which the system analyzes known incidents of the particular type. Moreover, the system converts the names of the metrics, as defined by customer-defined words or string(s) of alphanumeric characters that describe the metrics, into mathematical representations (e.g., word embedding featurization vectors).

When a new metric with a new name is received in association with a new incident of the particular type, the system implements an incident inference stage during which the new name is also converted into a new mathematical representation. The system then compares the new mathematical representation to the mathematical representations generated during the training stage to identify a similar mathematical representation. The system then retrieves the score for the metric associated with the similar mathematical representation and assigns the retrieved score to the new metric. The term "new" in this context reflects the fact that the information is not included in or part of the training stage.

As described herein, the known incidents occur within a workspace of a customer. Moreover, the known incidents can be of a particular type of incident. For example, a first type of incident may be related to security. A second type of incident may be related to networking and the transmission of data. A third type of incident may be related to the processing of data and execution environments. A fourth type of incident may be related to the storage and maintenance of data. These example types of incidents are non-exhaustive, and the techniques described herein can be applied to other types of incidents. Further, an incident can be classified in more than one type (e.g., a storage incident can also be a security incident). The system is configured to access data associated with the known incidents to implement the training stage. The data includes respective times at which the incidents occur (e.g., captured by timestamps), respective values (e.g., time-series values) for the metrics, and respective names for the metrics as defined by the customer (e.g., an Information Technology (IT) representative of the customer).

Using the accessed data associated with the known incidents, the system generates training data useable to determine a score for each of the metrics. As described above, the score indicates the relevance of a metric to a particular type

of incident. More specifically, the system generates the training data by determining, for each known incident, whether a value for each metric is above or below a threshold value within a predefined time period immediately before a time at which the incident occurs. In one example, this predefined time period is from two to six hours. During this predefined time period there is an expectation that the values of a metric that is relevant to the incident would behave in an abnormal, or anomalous, manner. Stated alternatively, there is an expectation that the values of a metric that is relevant to the incident would spike above a higher threshold value established for the metric and/or dip below a lower threshold value established for the metric. If the values of the metric are determined to be above or below one of the threshold value(s) within the predefined time period, the system adds the metric to a positive dataset in the training data.

Similarly, the system generates the training data by determining, for each known incident, whether a value for each metric is above or below a threshold value during another predefined time period immediately before the predefined time period discussed in the preceding paragraph. In one example, this other predefined time period is from two to six hours. In another example, this other predefined time period can be from one to three days. During this other predefined time period, there is an expectation that the values of a metric that is relevant to the incident would behave in a normal, or non-anomalous, manner. Stated alternatively, there is an expectation that the values of a metric that is relevant to the incident would not spike above a higher threshold value established for the metric and/or would not dip below a lower threshold value established for the metric. If the values of the metric are determined to be above or below a threshold value within this other predefined time period, the system adds the metric to a negative dataset in the training data. The predefined time periods described above can be established based on the particular type of incident, and thus, can vary from one type of incident to the next. It is noted that a metric can be added to both the positive dataset and the negative dataset (e.g., if the metric spikes and/or dips in both predefined time periods discussed above).

The system can execute an anomaly detection algorithm to determine whether a value for a specific metric is above or below a threshold value. Accordingly, the thresholds and threshold values are established for individual metrics. In one example, the anomaly detection algorithm is a dynamic anomaly detection algorithm that implements time-based adjustments to a range of accepted or expected values for a metric over time by learning the aforementioned higher threshold value to define the top of the range and the aforementioned lower threshold value to define the bottom of the range. In another example, the anomaly detection algorithm can use static thresholds to define the top and the bottom of the range.

Now that the system has a positive dataset and a negative dataset in the training data, the system can analyze the training data to determine the relevance of individual metrics to a particular type of incident, which is captured by scores. In one example, the system determines a precision parameter and a recall parameter for each metric. The precision parameter is a fraction represented by a number of times a metric is seen in the positive dataset over a total number of times the metric is seen in both the positive dataset and negative dataset. The recall parameter is a fraction represented by a number of times a metric is seen in the positive dataset over a total number of known incidents

analyzed. The system then combines the precision parameter (Precision) and recall parameter (Recall) into a score for each metric. In one example, the score is an F-score that balances both precision and recall and is calculated as: F-score=2*(Precision*Recall)/(Precision+Recall).

As described above, in the context of different workspaces for different customers, names for the same or similar metrics that reflect the status of the same application may be vastly different as they are defined by different users. For instance, one workspace may broadly name a metric as "error_count" while another workspace may capture "error_count" based on type via more granular names as follows:

"afss_file_fetch_error_count",

"configmanager_activateconfigsetrevision_error_count_total", and

"configmanager_createconfigset_error_count_total".

Accordingly, the system uses a natural language processing model to represent the names of the metrics mathematically, e.g., via a word embedding featurization vector. The natural language processing model can use a natural language processing algorithm such as term frequency-inverse document frequency (TF-IDF), FastText, One Hot Encoding, Word2Vec, and so forth. Accordingly, the natural language processing model can be trained to map words and/or other strings of alphanumeric characters used to define a metric name to a linguistic context and to produce a vector space that includes the word embedding featurization vectors. The word embedding featurization vectors are positioned, in the vector space, so that names that are more likely to share common linguistic contexts are located in close proximity to one another. Consequently, the natural language processing model is configured to map different, but similar names to the same linguistic context.

When a new metric with a new name is received in association with a new incident of the particular type, the system implements an incident inference stage that calls on the natural language processing model to convert the new name into a new mathematical representation. The system then compares the new mathematical representation for the new name of the new metric to the mathematical representations of the metrics that have already been scored during the training stage. The comparison identifies a similar mathematical representation for the new mathematical representation. The system can then retrieve a score for the metric associated with the similar mathematical representation and assign the score to the new metric.

In various examples, new metrics with new names are received from a customer workspace that is different than a customer workspace from which the known incidents were received and analyzed. Consequently, the system described herein can efficiently assign scores to the new metrics with new names in a new customer workspace without having to implement the training stage described above. This enables the system to efficiently rank the new metrics based on relevance (e.g., the assigned scores) to the particular type of incident and to use the ranking to filter a larger set of metrics down to a smaller set of metrics that are relevant to the particular type of incident. For example, the system can use a threshold score (e.g., a score over 0.90, 0.80, 0.75, and so forth) and/or a threshold number N (e.g., the top N=100 scored metrics, the top N=200 scored metrics, the top N=300 scored metrics, and so forth) to determine the smaller set of relevant metrics. The system can then focus the querying and ingestion of metrics to this smaller set in order to improve the response time to return results of the root-cause analysis.

Consequently, the system described herein address the challenges presented when the names of the same or similar metrics vary from one customer workspace to another and/or when a number of customers for which there is data for the training stage is limited. Moreover, because the system is fully automated (e.g., does not require manual labelling for the training stage), the techniques described herein can be scaled to a large number (e.g., millions) of new customer workspaces.

This Summary is provided to introduce a selection of concepts in a simplified form that are further described below in the Detailed Description. This Summary is not intended to identify key or essential features of the claimed subject matter, nor is it intended to be used as an aid in determining the scope of the claimed subject matter. The term "techniques," for instance, may refer to system(s), method(s), computer-readable instructions, module(s), algorithms, hardware logic, and/or operation(s) as permitted by the context described above and throughout the document.

BRIEF DESCRIPTION OF THE DRAWINGS

The Detailed Description is described with reference to the accompanying figures. In the figures, the left-most digit(s) of a reference number identifies the figure in which the reference number first appears. The same reference numbers in different figures indicate similar or identical items. References made to individual items of a plurality of items can use a reference number with a letter of a sequence of letters to refer to each individual item. Generic references to the items may use the specific reference number without the sequence of letters.

FIG. **1** illustrates an example environment in which a system can determine scores that are usable to filter a larger set of metrics (e.g., thousands of metrics) down to a smaller set of relevant metrics (e.g., hundreds of metrics) that can be more efficiently queried and ingested for root-cause analysis purposes when a particular type of incident occurs.

FIG. **2** is a diagram illustrating the training stage that produces scores for an example set of metrics.

FIG. **3** is a block diagram illustrating a training stage and an application stage for the natural language processing model used to correlate different, but similar, names to the same metric.

FIG. **4** is a diagram illustrating the incident inference stage that assigns a score to a new metric.

FIGS. **5**A and **5**B include a flow diagram of an example method for determining scores that are usable to filter a larger set of metrics (e.g., thousands of metrics) down to a smaller set of relevant metrics (e.g., hundreds of metrics) that can be more efficiently queried and ingested for root-cause analysis purposes when a particular type of incident occurs.

FIG. **6** is a computer architecture diagram illustrating an illustrative computer hardware and software architecture for a computing system capable of implementing aspects of the techniques and technologies presented herein.

FIG. **7** is a diagram illustrating a distributed computing environment capable of implementing aspects of the techniques and technologies presented herein.

DETAILED DESCRIPTION

The following Detailed Description discloses techniques and technologies for determining scores that are usable to filter a larger set of metrics (e.g., thousands of metrics) down to a smaller set of relevant metrics (e.g., hundreds of metrics) that can be more efficiently queried and ingested for root-cause analysis purposes when a particular type of incident occurs. To determine the scores, the system implements a training stage during which the system analyzes known incidents of the particular type. Moreover, the system converts the names of the metrics, as defined by customer-defined words or string(s) of alphanumeric characters that describe the metrics, into mathematical representations (e.g., word embedding featurization vectors).

When a new metric with a new name is received in association with a new incident of the particular type, the system implements an incident inference stage during which the new name is also converted into a new mathematical representation. The system then compares the new mathematical representation to the mathematical representations generated during the training stage to identify a similar mathematical representation. The system then retrieves the score for the metric associated with the similar mathematical representation and assigns the retrieved score to the new metric. The term "new" in this context reflects the fact that the information is not included in or part of the training stage.

Various examples, scenarios, and aspects of the disclosed techniques are described below with reference to FIGS. **1**-**7**.

FIG. **1** is a diagram illustrating an example environment **100** in which a system **102** can determine scores that are usable to filter a larger set of metrics (e.g., thousands of metrics) down to a smaller set of relevant metrics (e.g., hundreds of metrics) that can be more efficiently queried and ingested (e.g., investigated) for root-cause analysis purposes when a particular type of incident occurs. As described above, a cloud provider can provision an application **104** for use by different customers within separate workspaces **106**(**1**-N). A workspace **106**(**1**-N) is a logical unit that belongs to the customer and that enables the customer to efficiently configure resources, manage applications, and execute services in a customized and secure manner. In one example, the cloud provider can provision the application to separate workspaces **106**(**1**-N) via a container-based orchestration process (e.g., KUBERNETES).

Often, execution of the application **104** in workspaces **106**(**1**-N) may be disrupted by incidents **108**(**1**-N) that negatively affect the performance of the application **104** within the workspaces **106**(**1**-N) and/or the security provided by the application within the workspaces **106**(**1**-N). When the incidents **108**(**1**-N) occur, the cloud provider is often required, e.g., in accordance with various service level agreements (SLAs), to investigate the incidents **108**(**1**-N) and perform root-cause analysis.

In order to perform the root-cause analysis, a cloud provider operates the system **102**, which is configured to query and/or ingest metrics **110**(**1**-N) from the workspaces **106**(**1**-N). The metrics **110**(**1**-N) reflect a state of the application **104** and/or the infrastructure used to execute the application **104**. As described above, while the larger set of metrics **110**(**1**-N) available for querying and ingestion are essentially the same across the workspaces **106**(**1**-N), the names given to the metrics vary from one workspace to the next. Accordingly, FIG. **1** illustrates that the metrics **110**(**1**) reflecting the state of the application **104** in workspace **106**(**1**) have a first group of names **112**. Moreover, FIG. **1** illustrates that the metrics **110**(**2**) reflecting the state of the application **104** in workspace **106**(**2**) have a second group of names **114**. Finally, FIG. **1** illustrates that the metrics **110**(N) reflecting the state of the application **104** in workspace **106**(N) have an Nth group of names **116**.

To improve the way in which incidents can be queried and ingested, the system **102** includes a training module **118** to implement a training stage and an incident inference module **120** to implement an incident inference stage. The number of illustrated modules is just an example, and the number can vary higher or lower. That is, functionality described herein in association with the illustrated modules can be performed by a fewer number of modules or a larger number of modules on one device or spread across multiple devices.

The training module **118** is configured to access data associated with known incidents **122** (e.g., incidents **108(1)**) that occur within a workspace of a customer (e.g., workspace **106(1)**). The known incidents can be of a particular type of incident. For example, a first type of incident may be related to security. A second type of incident may be related to networking and the transmission of data. A third type of incident may be related to the processing of data and execution environments. A fourth type of incident may be related to the storage and maintenance of data. These example types of incidents are non-exhaustive, and the techniques described herein can be applied to other types of incidents. Further, an incident can be classified in more than one type (e.g., a storage incident can also be a security incident). The data includes respective times at which the known incidents **122** occur (e.g., captured by timestamps), respective values **124** (e.g., time-series values) for a large set of metrics **126** (e.g., metrics **110(1)**), and respective names **128** (e.g., names **112**) for the metrics **126** as defined by the customer (e.g., an Information Technology (IT) representative of the customer).

Using the accessed data associated with the known incidents **122**, the training module **118** is configured to generate training data **130**. As described herein, the training data **130** is useable to determine a score for each of the metrics **126**, and the score indicates the relevance of a metric **126** to a particular type of incident. The training module **118** generates the training data **130** by determining, for each known incident **122**, whether a value **124** for each metric **126** is above or below a threshold **132** (e.g., a threshold value) configured by an anomaly detection algorithm **134** within a predefined time period immediately before a time at which the incident **122** occurs, as determined via a timestamp. In one example, this predefined time period is from two to six hours. During this predefined time period there is an expectation that the values **124** of a metric **126** that is relevant to the incident would behave in an abnormal, or anomalous, manner. Stated alternatively, there is an expectation that the values **124** of a metric **126** that is relevant to the incident would spike above a higher threshold value established for the metric **126** and/or dip below a lower threshold value established for the metric **126**. If the values **124** of the metric **126** are determined to be above or below one of the threshold value(s) within the predefined time period, the training module **118** adds the metric **126** to a positive dataset **136** in the training data **130**.

Similarly, the training module **118** generates the training data **130** by determining, for each known incident **122**, whether a value **124** for each metric **126** is above or below a threshold **132** (e.g., threshold value) configured by the anomaly detection algorithm **134** during another predefined time period immediately before the predefined time period discussed in the preceding paragraph. In one example, this other predefined time period is from two to six hours. In another example, this other predefined time period can be from one to three days. During this other predefined time period, there is an expectation that the values **124** of a metric **126** that is relevant to the incident would behave in a normal, or non-anomalous, manner. Stated alternatively, there is an expectation that the values **124** of a metric **126** that is relevant to the incident would not spike above a higher threshold value established for the metric **126** and/or would not dip below a lower threshold value established for the metric **126**. If the values **124** of the metric **126** are determined to be above or below a threshold value within this other predefined time period, the training module **118** adds the metric **126** to a negative dataset **138** in the training data **130**.

The predefined time periods described above are non-overlapping and can be established based on the particular type of incident. Thus, the predefined time periods can vary from one type of incident to the next. It is noted that a metric **126** can be added to both the positive dataset **136** and the negative dataset **138** (e.g., if the metric spikes and/or dips in both predefined time periods).

The anomaly detection algorithm **134** establishes the thresholds **132** (e.g., threshold values) for individual metrics. In one example, the anomaly detection algorithm **134** is a dynamic anomaly detection algorithm that implements time-based adjustments to a range of accepted or expected values for a metric over time by learning a higher threshold value to define the top of the range and a lower threshold value to define the bottom of the range. In another example, the anomaly detection algorithm **134** can use static thresholds to define the higher threshold value and/or the lower threshold value.

The training module **118** is configured to analyze the training data **130** to determine the relevance of individual metrics **126** to a particular type of incident, as captured via scores. In one example, the training module **118** determines a precision parameter and a recall parameter for each metric **126**, as captured via reference **140**. The precision parameter is a fraction represented by a number of times a metric **126** is seen in the positive dataset **136** over a total number of times the metric **126** is seen in both the positive dataset **136** and negative dataset **138**. The recall parameter is a fraction represented by a number of times a metric **126** is seen in the positive dataset **136** over a total number of known incidents **122** analyzed. The training module **118** is configured to combine the precision parameter (Precision) and recall parameter (Recall) into a score for each metric, as captured via reference **142**. In one example, the score is an F-score that balances both precision and recall and is calculated as: F-score=2*(Precision*Recall)/(Precision+Recall).

As described above, in the context of different workspaces **106(1-N)** for different customers, names for the same or similar metrics **110(1-N)** that reflect the status of the same application **104** may be vastly different as they are defined by different users. For instance, one workspace **106(1)** may broadly name a metric as "error_count" while another workspace may capture "error_count" based on type via more granular names as follows:

"afss_file_fetch_error_count",

"configmanager_activateconfigsetrevision_error_count_total", and

"configmanager_createconfigset_error_count_total".

Accordingly, the training module **118** uses a natural language processing (NLP) model **144** to represent the names **128** of the metrics **126** mathematically, or as mathematical representations **146**. In one example, the mathematical representations **146** are word embedding featurization vectors. To this end, the natural language processing model **144** can use a natural language processing algorithm such as term frequency-inverse document frequency (TF-IDF), FastText, One Hot Encoding, Word2Vec, and so forth.

The natural language processing model **144** can be trained to map words and/or other strings of alphanumeric characters used to define a metric name **128** to a linguistic context and to produce a vector space that includes the word embedding featurization vectors. The word embedding featurization vectors are positioned, in the vector space, so that names that are more likely to share common linguistic contexts are located in close proximity to one another. Consequently, the natural language processing model **144** is configured to map different, but similar metric names **128** to the same linguistic context.

The incident inference module **120** implements the incident inference stage when a new metric **148** with a new name **150** is received in association with a new incident (e.g., incident **108**(**2**) of the particular type from a new workspace **106**(**2**)). The incident inference module **120** calls on the natural language processing model **144** to convert the new name **150** into a new mathematical representation **152**. The incident inference module **120** then compares the new mathematical representation **152** for the new name **150** of the new metric **148** to the mathematical representations **146** of the metrics **126** that have already been scored during the training stage. The comparison identifies a similar mathematical representation **154** for the new mathematical representation **152**. The incident inference module **120** can then retrieve a score for the metric **126** associated with the similar mathematical representation **154** and assign the retrieved score to the new metric **148**, as captured via reference **156**. The process implemented by the incident inference module can be reiterated for different new metrics **148** that are available to be queried and ingested.

In various examples, new metrics with new names are received from a customer workspace (e.g., workspace **106** (**2**)) that is different than a customer workspace (e.g., workspace **106**(**1**)) from which the known incidents **122** were received and analyzed. Consequently, the incident inference module **120** can efficiently assign scores to the new metrics with new names without having to implement the training stage described above. This enables the incident inference module **120** to efficiently rank the new metrics based on relevance (e.g., the assigned scores) to the particular type of incident and use the ranking to filter a larger set of metrics **110**(**2**) (e.g., thousands of metrics) down to a smaller set of metrics **158** (e.g., hundreds of metrics) that are relevant to the particular type of incident. For example, the incident inference module **120** can use a threshold score (e.g., a score over 0.90, 0.80, 0.75, and so forth) and/or a threshold number N (e.g., the top N=100 scored metrics, the top N=200 scored metrics, the top N=300 scored metrics, and so forth) to determine the smaller set of relevant metrics. The incident inference module **120** can then focus the querying and ingestion of metrics **160** to this smaller set of metrics **158** in order to improve the response time to return results of the root-cause analysis.

Consequently, the system **102** described herein address the challenges presented when the names of the same or similar metrics vary from one customer workspace to another and/or a number of customers for which there is data for the training stage is limited. Moreover, because the system is fully automated (e.g., does not require manual labelling for the training stage), the techniques described herein can be scaled to a large number (e.g., millions) of new customer workspaces.

FIG. **2** is a diagram illustrating the training stage, as implemented by the training module **118**, that produces scores for an example set of metrics. The table on the left side of FIG. **2** includes a column **202** that includes identifications for separate known incidents **122**, a column **204** that includes identifications (e.g., names) of metrics added to the positive dataset **136** on a per incident basis, and a column **206** that includes identifications (e.g., names) of metrics added to the negative dataset **138** on a per incident basis. The number of incidents and/or metrics used in this example is small (e.g., four incidents and four metrics) for ease of discussion. It is understood in the context of this disclosure that a larger number of known incidents can be analyzed during the training stage and/or a larger number of metrics (e.g., thousands) would be analyzed during the training stage.

As shown in FIG. **2**, "Metric_A", "Metric_B", and "Metric_C" have been added to the positive dataset **136**, while "Metric_C" has been added to the negative dataset **138** for incident "1". Additionally, "Metric_A" and "Metric_B" have been added to the positive dataset **136**, while no metric (as represented by the "x") has been added to the negative dataset **138** for incident "2". Further, "Metric_A" and "Metric_D" have been added to the positive dataset **136**, while "Metric_B" and "Metric_D" have been added to the negative dataset **138** for incident "3". Finally, "Metric_B" and "Metric_C" have been added to the positive dataset **136**, while "Metric_D" has been added to the negative dataset **138** for incident "4".

As shown in the example timing element **208** for incident "1" shown below the table, the anomaly detection algorithm **134** has determined that "Metric_A", "Metric_B", and "Metric_C" each have values determined to be above or below a threshold during a predefined time period **210** (e.g., two hours, three hours, four hours, five hours, six hours) immediately before a time **212** when the incident occurs (e.g., when the incident starts). During this predefined time period **210** leading up to the time **212** of the incident there is an expectation that the values of metrics that are relevant to the incident would behave in an abnormal, or anomalous, manner (e.g., signaling an issue).

Similarly, the anomaly detection algorithm **134** has determined that "Metric_C" has values determined to be above or below a threshold during a predefined time period **214** (e.g., two hours, three hours, four hours, five hours, six hours, a day, two days, three days) immediately before the predefined time period **210**. During this predefined time period **214**, which may be the same or longer than predefined time period **210** and which is removed from the time **212** of the incident (i.e., further away from the time **212** when compared to predefined time period **210**), there is an expectation that the values of metrics that are relevant to the incident would behave in a normal, or non-anomalous, manner.

The table on the right side of FIG. **2** includes a column **216** for the different metrics, a column **218** for the precision parameter, a column **220** for the recall parameter, and a column **222** for the score.

The precision parameter is a fraction represented by a number of times a metric is seen in the positive dataset **136** over a total number of times the metric is seen in both the positive dataset **136** and negative dataset **138**. Consequently, the training module **118** calculates a precision parameter of 100% for "Metric_A" based on the table on the left side of FIG. **2**. That is, "Metric_A" is seen three times in the positive dataset **136** and "Metric_A" is seen a total number of three times in both the positive dataset **136** and negative dataset **138**. The training module **118** calculates a precision parameter of 75% for "Metric_B" based on the table on the left side of FIG. **2**. That is, "Metric_B" is seen three times in the positive dataset **136** and "Metric_B" is seen a total number of four times in both the positive dataset **136** and negative dataset **138**. The training module **118** calculates a precision parameter of 66% for "Metric_C" based on the table on the left side of FIG. **2**. That is, "Metric_C" is seen two times in the positive dataset **136** and "Metric_C" is seen a total number of three times in both the positive dataset **136** and negative dataset **138**. Finally, the training module **118** calculates a precision parameter of 33% for "Metric_D" based on the table on the left side of FIG. **2**. That is, "Metric_D" is seen one time in the positive dataset **136** and "Metric_D" is seen a total number of three times in both the positive dataset **136** and negative dataset **138**.

As mentioned above, the recall parameter is a fraction represented by a number of times a metric is seen in the positive dataset **136** over a total number of known incidents **122** analyzed. Consequently, the training module **118** calculates a recall parameter of 75% for "Metric_A" based on the table on the left side of FIG. **2**. That is, "Metric_A" is seen three times in the positive dataset **136** and there is a total number of four incidents analyzed. The training module **118** calculates a recall parameter of 75% for "Metric_B" based on the table on the left side of FIG. **2**. That is, "Metric_B" is seen three times in the positive dataset **136** and there is a total number of four incidents analyzed. The training module **118** calculates a recall parameter of 50% for "Metric_C" based on the table on the left side of FIG. **2**. That is, "Metric_C" is seen two times in the positive dataset **136** and there is a total number of four incidents analyzed. Finally, the training module **118** calculates a recall parameter of 25% for "Metric_D" based on the table on the left side of FIG. **2**. That is, "Metric_D" is seen one time in the positive dataset **136** and there is a total number of four incidents analyzed.

The training module **118** is configured to combine the precision parameter (Precision) and recall parameter (Recall) into a score for each metric. In one example, the score is an F-score that balances both precision and recall and is calculated as: F-score=2*(Precision*Recall)/(Precision+Recall). Accordingly, as shown in FIG. **2** via the score column **222**, the training module **118** calculates an F-score of "0.86" for "Metric_A", an F-score of "0.75" for "Metric_B", an F-score of "0.57" for "Metric_C", and an F-score of "0.28" for "Metric_D".

FIG. **3** is a block diagram illustrating a training stage and an application stage for the natural language processing model **144** used to correlate different, but similar, names to the same metric. During the training stage, the natural language processing model **144** can be learned by using, as a training data set, names for different metrics **302** associated with known incidents **122**. The training module **118** performs feature extraction **304** on the names of the metrics **302** and uses the extracted features **304** to generate mathematical representations **306** (e.g., word embedding featurization vectors) useable to train the natural language processing model **144**.

Consequently, the natural language processing model **144** is trained to map words and/or other strings of alphanumeric characters used in a name to a linguistic context. The natural language processing model **144** may use neural networks to produce word embedding featurization vectors and to construct the linguistic contexts of the words and/or other strings of alphanumeric characters used in the names. The natural language processing model **144** can produce a vector space that includes the word embedding featurization vectors and that positions the word embedding featurization vectors so that names that are more likely to share common linguistic contexts are located in close proximity to one another. Consequently, the natural language processing model **144** is configured to map different names to the same or similar linguistic context and to determine metrics that are similar based on the names.

After the training stage is complete, the natural language processing model **144** is called on in the application stage to perform the inference task. That is, provided a new name for a new metric **308**, the training module **118** implements feature extraction **310** on the name of the new metric **308** and applies the natural language processing model **144** in order to generate a new mathematical representation **312** and to compare the new mathematical representation to the mathematical representations **306**. Accordingly, the natural language processing model **144** can identify a mathematical representation **306** that is linguistically similar **314** to the new mathematical representation **312**. For instance, the natural language processing model **144** can compute a cosine distance between a new word embedding featurization vector and each word embedding featurization vector generated during the training stage. The lowest cosine distance computed yields the word embedding featurization vector that is most similar to the new word embedding featurization vector.

FIG. **4** is a diagram illustrating the incident inference stage that assigns a score to a new metric. The table on the left side of FIG. **4** is similar to the table on the right side of FIG. **2**, except the following metrics names-"Error_Count", "HTTP_Sum", "OOM_Killed", "CPU_Percentage"—have respectively replaced the use of "Metric_A", "Metric_B", "Metric_C", and "Metric_D". In accordance with the discussion above, the natural language processing model **144** is configured to generate mathematical representations for each of "Error_Count", "HTTP_Sum", "OOM_Killed", and "CPU_Percentage" as part of the training stage. As shown in FIG. **4**, the incident inference module **120** receives a new metric to score **402** with a name "HTTP Error_Count" **404**. The natural language processing model **144** generates a new mathematical representation for the name "HTTP Error_Count" **404** and compares the new mathematical representation to the mathematical representations generated during the training stage. The comparison yields similarity scores **406** (e.g., established based on a cosine distance between two vectors) as shown in the table on the right side of FIG. **4**.

The metric that has the mathematical representation with the highest similarity score (e.g., "Error_Count") is then identified and its score (e.g., "0.86") is retrieved and assigned **408** to the new metric that is to be scored **402**. In various examples where a single metric includes multiple different scores which have been established in the training stage for multiple different workspaces, the assigned score can be an average of the multiple different scores. Alternatively, the assigned score can be the highest score in the multiple different scores.

Proceeding to FIGS. **5**A and **5**B, aspects of a method **500** for determining scores that are usable to filter a larger set of metrics (e.g., thousands of metrics) down to a smaller set of relevant metrics (e.g., hundreds of metrics) that can be more efficiently queried and ingested for root-cause analysis purposes when a particular type of incident occurs are shown and described. With respect to FIG. **5**A, the process **500** begins at operation **502** where a system initiates the training stage by accessing data associated with incidents of a particular type of incident. As described above, the data includes respective times at which the incidents occur, respective values for metrics, and respective names for the metrics.

At operation **504**, the system generates training data useable to determine a score for each of the metrics. As described above, the score indicates relevance of the metric to the particular type of incident. Moreover, as shown in FIG. **5**A, generating the training data includes operations **506**, **508**, **510**, and **512**.

At operation **506**, the system determines, for each incident of the incidents, whether a first value for each of the metrics is above or below a first threshold value within a predefined time period immediately before a respective time at which the incident occurs.

At operation **508**, the system adds, to a positive dataset in the training data, a first portion of the metrics for which corresponding first values are determined to be above or below the first threshold value within the predefined time period.

At operation **510**, the system determines whether a second value for each metric of the metrics is above or below a second threshold value within another predefined time period immediately before the predefined time period.

At operation **512**, the system adds, to a negative dataset in the training data, a second portion of the metrics for which corresponding second values are determined to be above or below the second threshold value before the other predefined time period.

At operation **514**, the system determines, based on the training data, a precision parameter and a recall parameter for each of the metrics.

At operation **516**, the system generates a score for each of the metrics based on the precision parameter and the recall parameter.

At operation **518**, the system generates, using a natural language processing algorithm, a mathematical representation for a respective name of each of the metrics.

In FIG. **5**B, the system initiates the incident inference stage at operation **520**, where in association with a new incident, a new metric with a new name is received.

At operation **522**, the system generates, using the natural language processing algorithm, a new mathematical representation for the new name of the new metric.

At operation **524**, the system identifies, from the mathematical representations respectively generated for the names of the metrics, a similar mathematical representation for the new mathematical representation.

At operation **526**, the system retrieves a score for a respective metric associated with the similar mathematical representation.

At operation **528**, the system assigns the score to the new metric.

For ease of understanding, the process discussed in this disclosure is delineated as separate operations represented as independent blocks. However, these separately delineated operations should not be construed as necessarily order dependent in their performance. The order in which the process is described is not intended to be construed as a limitation, and any number of the described process blocks may be combined in any order to implement the process or an alternate process. Moreover, it is also possible that one or more of the provided operations is modified or omitted.

The particular implementation of the technologies disclosed herein is a matter of choice dependent on the performance and other requirements of a computing device. Accordingly, the logical operations described herein are referred to variously as states, operations, structural devices, acts, or modules. These states, operations, structural devices, acts, and modules can be implemented in hardware, software, firmware, in special-purpose digital logic, and any combination thereof. It should be appreciated that more or fewer operations can be performed than shown in the figures and described herein. These operations can also be performed in a different order than those described herein.

It also should be understood that the illustrated methods can end at any time and need not be performed in their entireties. Some or all operations of the methods, and/or substantially equivalent operations, can be performed by execution of computer-readable instructions included on a computer-storage media, as defined below. The term “computer-readable instructions,” and variants thereof, as used in the description and claims, is used expansively herein to include routines, applications, application modules, program modules, programs, components, data structures, algorithms, and the like. Computer-readable instructions can be implemented on various system configurations, including single-processor or multiprocessor systems, minicomputers, mainframe computers, personal computers, hand-held computing devices, microprocessor-based, programmable consumer electronics, combinations thereof, and the like.

Thus, it should be appreciated that the logical operations described herein are implemented (1) as a sequence of computer implemented acts or program modules running on a computing system and/or (2) as interconnected machine logic circuits or circuit modules within the computing system. The implementation is a matter of choice dependent on the performance and other requirements of the computing system. Accordingly, the logical operations described herein are referred to variously as states, operations, structural devices, acts, or modules. These operations, structural devices, acts, and modules may be implemented in software, in firmware, in special purpose digital logic, and any combination thereof.

For example, the operations of the process **500** can be implemented, at least in part, by modules running the features disclosed herein can be a dynamically linked library (DLL), a statically linked library, functionality produced by an application programing interface (API), a compiled program, an interpreted program, a script, or any other executable set of instructions. Data can be stored in a data structure in one or more memory components. Data can be retrieved from the data structure by addressing links or references to the data structure.

Although the illustration may refer to the components of the figures, it should be appreciated that the operations of the process **500** may also be implemented in other ways. In addition, one or more of the operations of the process **500** may alternatively or additionally be implemented, at least in part, by a chipset working alone or in conjunction with other software modules. In the example described below, one or more modules of a computing system can receive and/or process the data disclosed herein. Any service, circuit, or application suitable for providing the techniques disclosed herein can be used in operations described herein.

FIG. **6** shows additional details of an example computer architecture **600** for a device, such as a computer or a server configured as part of the system **102**, capable of executing computer instructions (e.g., a module or a program component described herein). The computer architecture **600** illustrated in FIG. **6** includes processing system **602**, a system memory **604**, including a random-access memory **606** (RAM) and a read-only memory (ROM) **608**, and a system bus **610** that couples the memory **604** to the processing system **602**. The processing system **602** comprises processing unit(s). In various examples, the processing unit(s) of the processing system **602** are distributed. Stated another way, one processing unit of the processing system **602** may be located in a first location (e.g., a rack within a datacenter) while another processing unit of the processing system **602** is located in a second location separate from the first location. Moreover, the systems discussed herein can be provided as a distributed computing system such as a cloud service.

Processing unit(s), such as processing unit(s) of processing system **602**, can represent, for example, a CPU-type processing unit, a GPU-type processing unit, a field-programmable gate array (FPGA), another class of digital signal processor (DSP), or other hardware logic components that may, in some instances, be driven by a CPU. For example, illustrative types of hardware logic components that can be used include Application-Specific Integrated Circuits (ASICs), Application-Specific Standard Products (ASSPs), System-on-a-Chip Systems (SOCs), Complex Programmable Logic Devices (CPLDs), and the like.

A basic input/output system containing the basic routines that help to transfer information between elements within the computer architecture **600**, such as during startup, is stored in the ROM **608**. The computer architecture **600** further includes a mass storage device **612** for storing an operating system **614**, application(s) **616**, modules **618**, and other data described herein.

The mass storage device **612** is connected to processing system **602** through a mass storage controller connected to the bus **610**. The mass storage device **612** and its associated computer-readable media provide non-volatile storage for the computer architecture **600**. Although the description of computer-readable media contained herein refers to a mass storage device, the computer-readable media can be any available computer-readable storage media or communication media that can be accessed by the computer architecture **600**.

Computer-readable media includes computer-readable storage media and/or communication media. Computer-readable storage media includes one or more of volatile memory, nonvolatile memory, and/or other persistent and/or auxiliary computer storage media, removable and non-removable computer storage media implemented in any method or technology for storage of information such as computer-readable instructions, data structures, program modules, or other data. Thus, computer storage media includes tangible and/or physical forms of media included in a device and/or hardware component that is part of a device or external to a device, including RAM, static RAM (SRAM), dynamic RAM (DRAM), phase change memory (PCM), ROM, erasable programmable ROM (EPROM), electrically EPROM (EEPROM), flash memory, compact disc read-only memory (CD-ROM), digital versatile disks (DVDs), optical cards or other optical storage media, magnetic cassettes, magnetic tape, magnetic disk storage, magnetic cards or other magnetic storage devices or media, solid-state memory devices, storage arrays, network attached storage, storage area networks, hosted computer storage or any other storage memory, storage device, and/or storage medium that can be used to store and maintain information for access by a computing device.

In contrast to computer-readable storage media, communication media can embody computer-readable instructions, data structures, program modules, or other data in a modulated data signal, such as a carrier wave, or other transmission mechanism. As defined herein, computer storage media does not include communication media. That is, computer-readable storage media does not include communications media consisting solely of a modulated data signal, a carrier wave, or a propagated signal, per se.

According to various configurations, the computer architecture **600** may operate in a networked environment using logical connections to remote computers through the network **620**. The computer architecture **600** may connect to the network **620** through a network interface unit **622** connected to the bus **610**. The computer architecture **600** also may include an input/output controller **624** for receiving and processing input from a number of other devices, including a keyboard, mouse, touch, or electronic stylus or pen. Similarly, the input/output controller **624** may provide output to a display screen, a printer, or other type of output device.

The software components described herein may, when loaded into the processing system **602** and executed, transform the processing system **602** and the overall computer architecture **600** from a general-purpose computing system into a special-purpose computing system customized to facilitate the functionality presented herein. The processing system **602** may be constructed from any number of transistors or other discrete circuit elements, which may individually or collectively assume any number of states. More specifically, the processing system **602** may operate as a finite-state machine, in response to executable instructions contained within the software modules disclosed herein. These computer-executable instructions may transform the processing system **602** by specifying how the processing system **602** transition between states, thereby transforming the transistors or other discrete hardware elements constituting the processing system **602**.

FIG. **7** depicts an illustrative distributed computing environment **700** capable of executing the software components described herein. Thus, the distributed computing environment **700** illustrated in FIG. **7** can be utilized to execute any aspects of the software components presented herein.

Accordingly, the distributed computing environment **700** can include a computing environment **702** operating on, in communication with, or as part of the network **704**. The network **704** can include various access networks. One or more client devices **706**A-**706**N (hereinafter referred to collectively and/or generically as "computing devices **706**") can communicate with the computing environment **702** via the network **704**. In one illustrated configuration, the computing devices **706** include a computing device **706**A such as a laptop computer, a desktop computer, or other computing device; a slate or tablet computing device ("tablet computing device") **706**B; a mobile computing device **706**C such as a mobile telephone, a smart phone, or other mobile computing device; a server computer **706**D; and/or other devices **706**N. It should be understood that any number of computing devices **706** can communicate with the computing environment **702**.

In various examples, the computing environment **702** includes servers **708**, data storage **710**, and one or more network interfaces **712**. The servers **708** can host various services, virtual machines, portals, and/or other resources. In the illustrated configuration, the servers **708** host virtual machines **714**, Web portals **716**, mailbox services **718**, storage services **720**, and/or social networking services **722**. As shown in FIG. **7** the servers **708** also can host other services, applications, portals, and/or other resources ("other resources") **724**.

As mentioned above, the computing environment **702** can include the data storage **710**. According to various implementations, the functionality of the data storage **710** is provided by one or more databases operating on, or in communication with, the network **704**. The functionality of the data storage **710** also can be provided by one or more servers configured to host data for the computing environment **700**. The data storage **710** can include, host, or provide one or more real or virtual datastores **726**A-**726**N (hereinafter referred to collectively and/or generically as "datastores **726**"). The datastores **726** are configured to host data used or created by the servers **808** and/or other data. That is, the datastores **726** also can host or store web page documents, word documents, presentation documents, data structures, algorithms for execution by a recommendation engine, and/or other data utilized by any application program. Aspects of the datastores **726** may be associated with a service for storing files.

The computing environment **702** can communicate with, or be accessed by, the network interfaces **712**. The network interfaces **712** can include various types of network hardware and software for supporting communications between two or more computing devices including the computing devices and the servers. It should be appreciated that the network interfaces **712** also may be utilized to connect to other types of networks and/or computer systems.

It should be understood that the distributed computing environment **700** described herein can provide any aspects of the software elements described herein with any number of virtual computing resources and/or other distributed computing functionality that can be configured to execute any aspects of the software components disclosed herein. According to various implementations of the concepts and technologies disclosed herein, the distributed computing environment **700** provides the software functionality described herein as a service to the computing devices. It should be understood that the computing devices can include real or virtual machines including server computers, web servers, personal computers, mobile computing devices, smart phones, and/or other devices. As such, various configurations of the concepts and technologies disclosed herein enable any device configured to access the distributed computing environment **700** to utilize the functionality described herein for providing the techniques disclosed herein, among other aspects.

Conditional language such as, among others, "can," "could," "might" or "may," unless specifically stated otherwise, are understood within the context to present that certain examples include, while other examples do not include, certain features, elements and/or steps. Thus, such conditional language is not generally intended to imply that certain features, elements and/or steps are in any way required for one or more examples or that one or more examples necessarily include logic for deciding, with or without user input or prompting, whether certain features, elements and/or steps are included or are to be performed in any particular example. Conjunctive language such as the phrase "at least one of X, Y or Z," unless specifically stated otherwise, is to be understood to present that an item, term, etc. may be either X, Y, or Z, or a combination thereof.

The terms "a," "an," "the" and similar referents used in the context of describing the invention (especially in the context of the following claims) are to be construed to cover both the singular and the plural unless otherwise indicated herein or clearly contradicted by context. The terms "based on," "based upon," and similar referents are to be construed as meaning "based at least in part" which includes being "based in part" and "based in whole" unless otherwise indicated or clearly contradicted by context.

In addition, any reference to "first," "second," etc. elements within the Summary and/or Detailed Description is not intended to and should not be construed to necessarily correspond to any reference of "first," "second," etc. elements of the claims. Rather, any use of "first" and "second" within the Summary, Detailed Description, and/or claims may be used to distinguish between two different instances of the same element (e.g., two different workspaces).

In closing, although the various configurations have been described in language specific to structural features and/or methodological acts, it is to be understood that the subject matter defined in the appended representations is not necessarily limited to the specific features or acts described. Rather, the specific features and acts are disclosed as example forms of implementing the claimed subject matter.

What is claimed is:

1. A method comprising:
- accessing data associated with incidents of a particular type of incident, wherein the data includes:
  - respective times at which the incidents occur;
  - respective values for metrics; and
  - respective names for the metrics;
- generating training data useable to determine a score for each metric of the metrics, wherein:
  - the score indicates relevance of the metric to the particular type of incident; and
  - generating the training data includes, for each incident of the incidents:
    - determining whether a first value for each metric of the metrics is above or below a first threshold value within a predefined time period immediately before a respective time at which the incident occurs;
    - adding, to a positive dataset in the training data, a first portion of the metrics for which corresponding first values are determined to be above or below the first threshold value within the predefined time period;
    - determining whether a second value for each metric of the metrics is above or below a second threshold value within another predefined time period immediately before the predefined time period; and
    - adding, to a negative dataset in the training data, a second portion of the metrics for which corresponding second values are determined to be above or below the second threshold value before the other predefined time period;
- determining, based on the training data, a precision parameter and a recall parameter for each metric of the metrics;
- generating a score for each metric of the metrics based on the precision parameter and the recall parameter;
- generating, using a natural language processing algorithm, a mathematical representation for a respective name of each of the metrics;
- in association with a new incident:
  - receiving a new metric with a new name;
  - generating, using the natural language processing algorithm, a new mathematical representation for the new name of the new metric;
  - identifying, from the mathematical representations respectively generated for the names of the metrics, a similar mathematical representation for the new mathematical representation;
  - retrieving a score for a respective metric associated with the similar mathematical representation; and
  - assigning the score to the new metric.

2. The method of claim **1**, wherein the assigned score is useable to reduce a number of metrics to be queried as part of a root-cause analysis of the new incident.

3. The method of claim 1, wherein:
the incidents occur in a first workspace of a first customer;
the respective names for the metrics are defined by the first customer;
the new incident occurs in a second workspace of a second customer; and
the new name for the new metric is defined by the second customer.

4. The method of claim 1, wherein:
the natural language processing algorithm comprises term frequency-inverse document frequency (TF-IDF);
the mathematical representations generated for the respective names of the metrics comprise word embedding featurization vectors;
the new mathematical representation generated for the new name of the new metric comprises a new word embedding featurization vector; and
identifying the similar mathematical representation for the new mathematical representation comprises:
computing a cosine distance between the new word embedding featurization vector and each word embedding featurization vector in the word embedding featurization vectors; and
determining that the respective metric associated with the similar mathematical representation has a lowest cosine distance.

5. The method of claim 1, wherein the score generated for each metric of the metrics based on the precision parameter and the recall parameter comprises an F-score.

6. The method of claim 1, wherein the predefined time period and the other predefined time period are established based on the particular type of incident.

7. The method of claim 6, wherein the predefined time period is from two to six hours and the other predefined time period is from two to six hours.

8. The method of claim 1, wherein a dynamic anomaly detection algorithm is used to determine whether the first value for each metric of the metrics is above or below the first threshold value and to determine whether the second value for each metric of the metrics is above or below the second threshold value.

9. The method of claim 1, further comprising:
mapping the similar mathematical representation to multiple different scores for a same metric encountered in multiple different workspaces configured by multiple different customers; and
averaging the multiple scores to calculate the new score.

10. A system comprising:
a processing system; and
a computer-readable storage medium storing instructions that, when executed by the processing system, cause the system to perform operations comprising:
accessing data associated with incidents of a particular type of incident, wherein the data includes:
respective times at which the incidents occur;
respective values for metrics; and
respective names for the metrics;
generating training data useable to determine a score for each metric of the metrics, wherein:
the score indicates relevance of the metric to the particular type of incident; and
generating the training data includes, for each incident of the incidents:
determining whether a first value for each metric of the metrics is above or below a first threshold value within a predefined time period immediately before a respective time at which the incident occurs;
adding, to a positive dataset in the training data, a first portion of the metrics for which corresponding first values are determined to be above or below the first threshold value within the predefined time period;
determining whether a second value for each metric of the metrics is above or below a second threshold value within another predefined time period immediately before the predefined time period; and
adding, to a negative dataset in the training data, a second portion of the metrics for which corresponding second values are determined to be above or below the second threshold value before the other predefined time period;
determining, based on the training data, a precision parameter and a recall parameter for each metric of the metrics;
generating a score for each metric of the metrics based on the precision parameter and the recall parameter; and
generating, using a natural language processing algorithm, a mathematical representation for a respective name of each of the metrics.

11. The system of claim 10, wherein the operations further comprise, in association with a new incident:
receiving a new metric with a new name;
generating, using the natural language processing algorithm, a new mathematical representation for the new name of the new metric;
identifying, from the mathematical representations respectively generated for the names of the metrics, a similar mathematical representation for the new mathematical representation;
retrieving a score for a respective metric associated with the similar mathematical representation; and
assigning the score to the new metric.

12. The system of claim 11, wherein the assigned score is useable to reduce a number of metrics to be queried as part of a root-cause analysis of the new incident.

13. The system of claim 11, wherein:
the incidents occur in a first workspace of a first customer;
the respective names for the metrics are defined by the first customer;
the new incident occurs in a second workspace of a second customer; and
the new name for the new metric is defined by the second customer.

14. The system of claim 11, wherein:
the natural language processing algorithm comprises term frequency-inverse document frequency (TF-IDF);
the mathematical representations generated for the respective names of the metrics comprise word embedding featurization vectors;
the new mathematical representation generated for the new name of the new metric comprises a new word embedding featurization vector; and
identifying the similar mathematical representation for the new mathematical representation comprises:
computing a cosine distance between the new word embedding featurization vector and each word embedding featurization vector in the word embedding featurization vectors; and

determining that the respective metric associated with the similar mathematical representation has a lowest cosine distance.

15. The system of claim **11**, wherein the score generated for each metric of the metrics based on the precision parameter and the recall parameter comprises an F-score.

16. The system of claim **11**, wherein the predefined time period and the other predefined time period are established based on the particular type of incident.

17. The system of claim **11** wherein a dynamic anomaly detection algorithm is used to determine whether the first value for each metric of the metrics is above or below the first threshold value and to determine whether the second value for each metric of the metrics is above or below the second threshold value.

18. A computer-readable storage medium storing instructions that, when executed by a processing system, cause a system to perform operations comprising:

accessing data associated with incidents of a particular type of incident, wherein the data includes:

respective times at which the incidents occur;

respective values for metrics; and

respective names for the metrics;

generating training data useable to determine a score for each metric of the metrics, wherein:

the score indicates relevance of the metric to the particular type of incident; and

generating the training data includes, for each incident of the incidents:

determining whether a first value for each metric of the metrics is above or below a first threshold value within a predefined time period immediately before a respective time at which the incident occurs;

adding, to a positive dataset in the training data, a first portion of the metrics for which corresponding first values are determined to be above or below the first threshold value within the predefined time period;

determining whether a second value for each metric of the metrics is above or below a second threshold value within another predefined time period immediately before the predefined time period; and

adding, to a negative dataset in the training data, a second portion of the metrics for which corresponding second values are determined to be above or below the second threshold value before the other predefined time period;

determining, based on the training data, a precision parameter and a recall parameter for each metric of the metrics;

generating a score for each metric of the metrics based on the precision parameter and the recall parameter; and

generating, using a natural language processing algorithm, a mathematical representation for a respective name of each of the metrics.

19. The computer-readable storage medium of claim **18**, wherein the operations further comprise, in association with a new incident:

receiving a new metric with a new name;

generating, using the natural language processing algorithm, a new mathematical representation for the new name of the new metric;

identifying, from the mathematical representations respectively generated for the names of the metrics, a similar mathematical representation for the new mathematical representation;

retrieving a score for a respective metric associated with the similar mathematical representation; and

assigning the score to the new metric.

20. The computer-readable storage medium of claim **19**, wherein:

the incidents occur in a first workspace of a first customer;

the respective names for the metrics are defined by the first customer;

the new incident occurs in a second workspace of a second customer; and

the new name for the new metric is defined by the second customer.

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