US 20250259115A1

(19) United States

(12) Patent Application Publication (10) Pub. No.: US 2025/0259115 A1

Jeyashekar et al. (43) Pub. Date: Aug. 14, 2025

(54) **ANOMALY DETECTION METHOD FOR MODEL OUTPUTS**

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(21) Appl. No.: **19/196,702**

(22) Filed: **May 1, 2025**

Related U.S. Application Data

(63) Continuation-in-part of application No. 19/038,662, filed on Jan. 27, 2025, which is a continuation of application No. 18/781,985, filed on Jul. 23, 2024, now Pat. No. 12,210,949, which is a continuation-in-part of application No. 18/535,001, filed on Dec. 11, 2023, now Pat. No. 12,045,610, Continuation-in-part of application No. 19/061,982, filed on Feb. 24, 2025, which is a continuation-in-part of application No. 18/781,965, filed on Jul. 23, 2024, now Pat. No. 12,271,720, which is a continuation-in-part of application No. 18/535,001, filed on Dec. 11, 2023, now Pat. No. 12,045,610, Continuation-in-part of application No. PCT/US2024/051150, filed on Oct. 11, 2024, which is a continuation of application No. 18/669,421, filed on May 20, 2024, now Pat. No. 12,182,539, which is a continuation of application No. 18/535,001, filed on Dec. 11, 2023, now Pat. No. 12,045,610, which is a continuation of application No. 18/781,965, filed on Jul. 23, 2024, now Pat. No. 12,271,720, which is a continuation of application No. 18/781,977, filed on Jul. 23, 2024, now Pat. No. 12,210,858, which is a continuation of application No. 18/781,985, filed on Jul. 23, 2024, now Pat. No. 12,210,949, Continuation-in-part of application No. 18/951,120, filed on Nov. 18, 2024, which is a continuation of application No. 18/633,293, filed on Apr. 11, 2024, now Pat. No. 12,147,513, Continuation-in-part of application No. 18/907,414, filed on Oct. 4, 2024, which is a continuation of application No. 18/661,532, filed on May 10, 2024, now Pat. No. 12,111,747, which is a continuation-in-part of application No. 18/661,519, filed on May 10, 2024, now Pat. No. 12,106,205, which is a continuation-in-part of application No. 18/633,293, filed on Apr. 11, 2024, now Pat. No. 12,147,513.

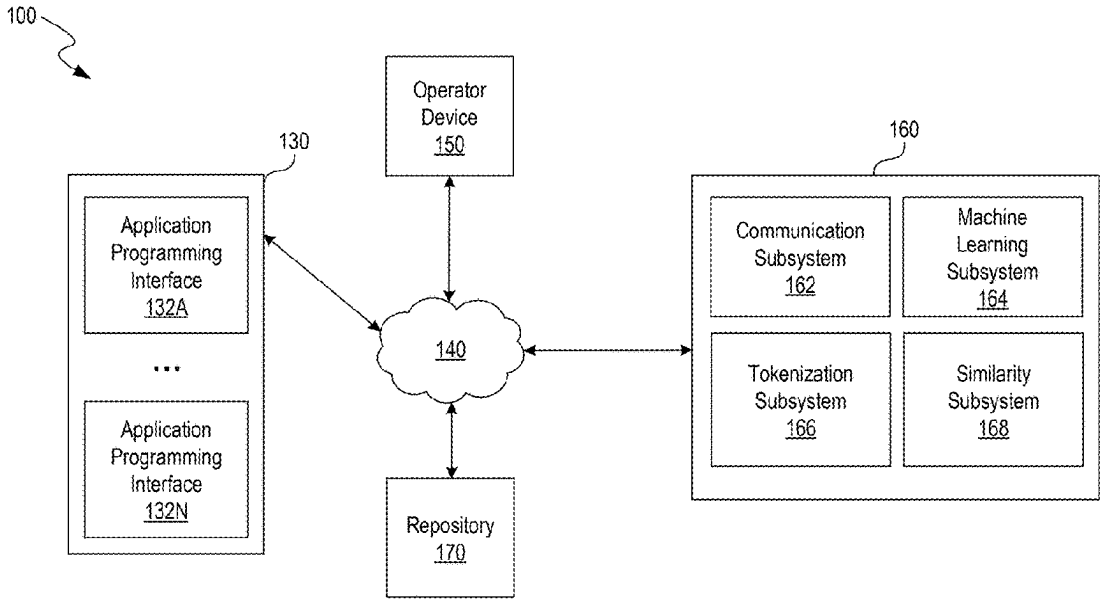
Publication Classification

(51) **Int. Cl.**
G06N 20/20 (2019.01)

(52) **U.S. Cl.**
CPC ***G06N 20/20*** (2019.01)

(57) **ABSTRACT**

Systems and methods for detecting anomalies in generative outputs are disclosed herein. The system receives a user prompt indicating a request for data over a time period. The system inputs, into a model, the user prompt to cause the model to generate an output based on the user prompt. The system then generates the first tokens based on the output. To generate the second tokens, the system retrieves, based on the user prompt, sources relating to the data requested by the user prompt. The system then generates queries to request, from the sources, the data over the time period and generates the second tokens based on the retrieved data. The system then performs a comparison of the first tokens and the second tokens and accepts or rejects the output of the model based on the comparison.



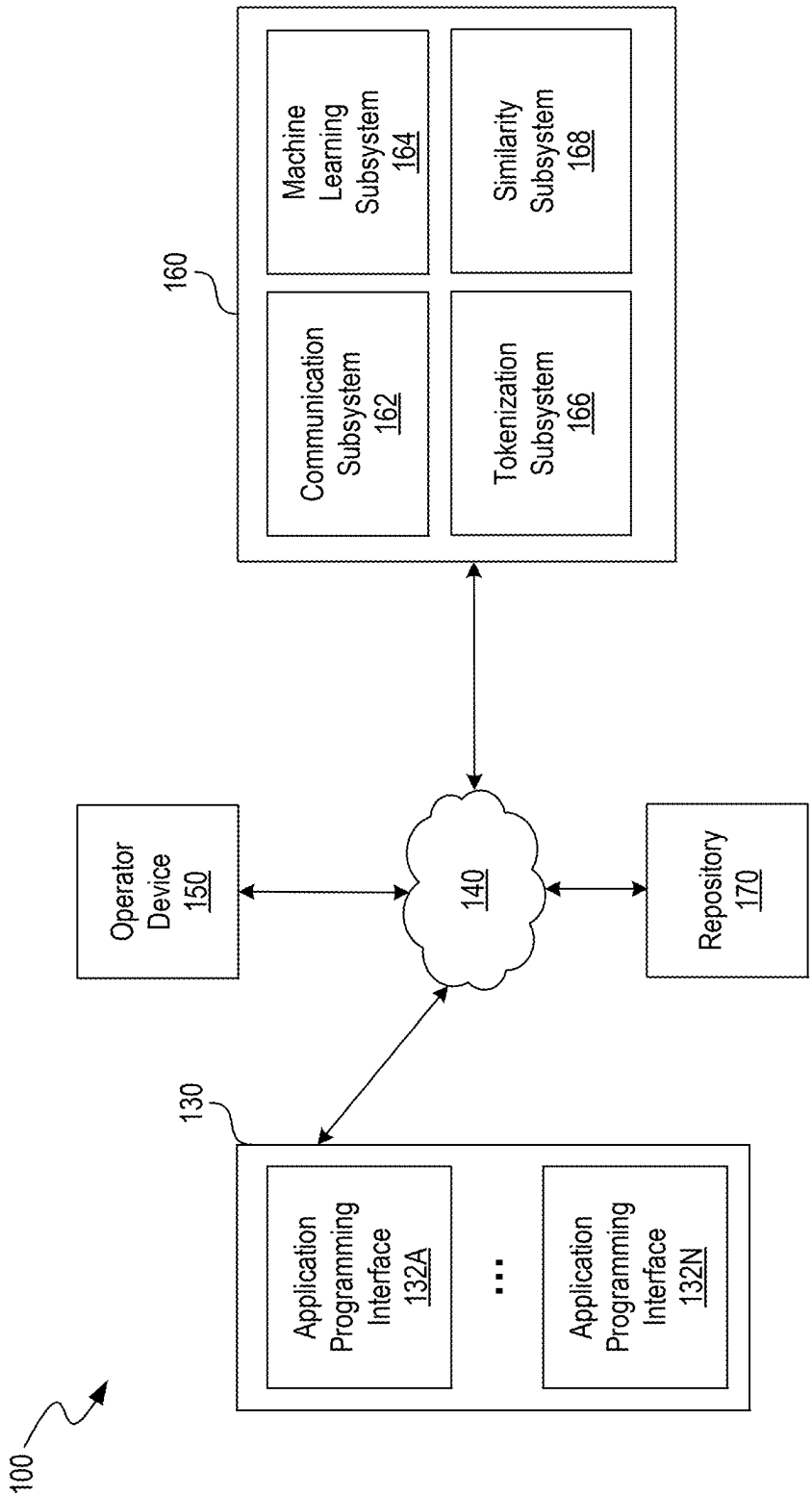

100
130
Application Programming Interface 132A
...
Application Programming Interface 132N
140
Operator Device 150
Repository 170
160
Communication Subsystem 162
Machine Learning Subsystem 164
Tokenization Subsystem 166
Similarity Subsystem 168

FIG. 1

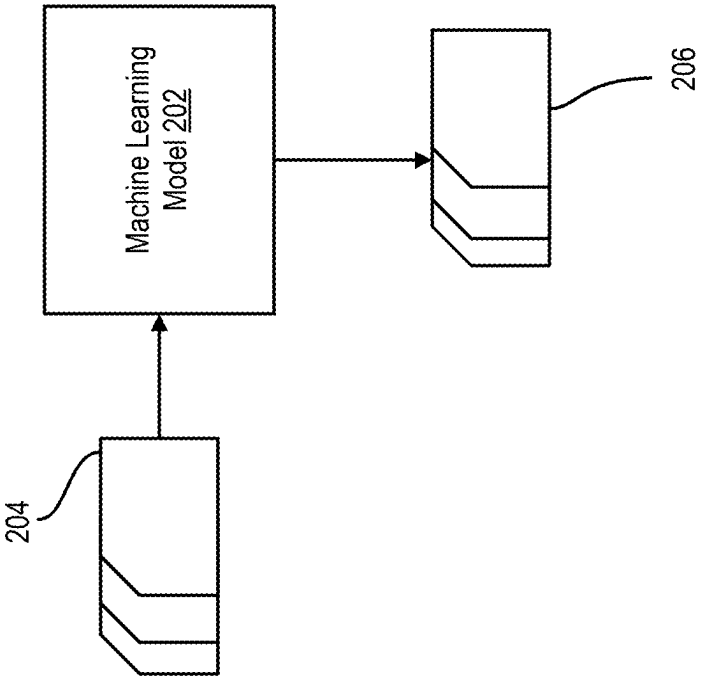


FIG. 2

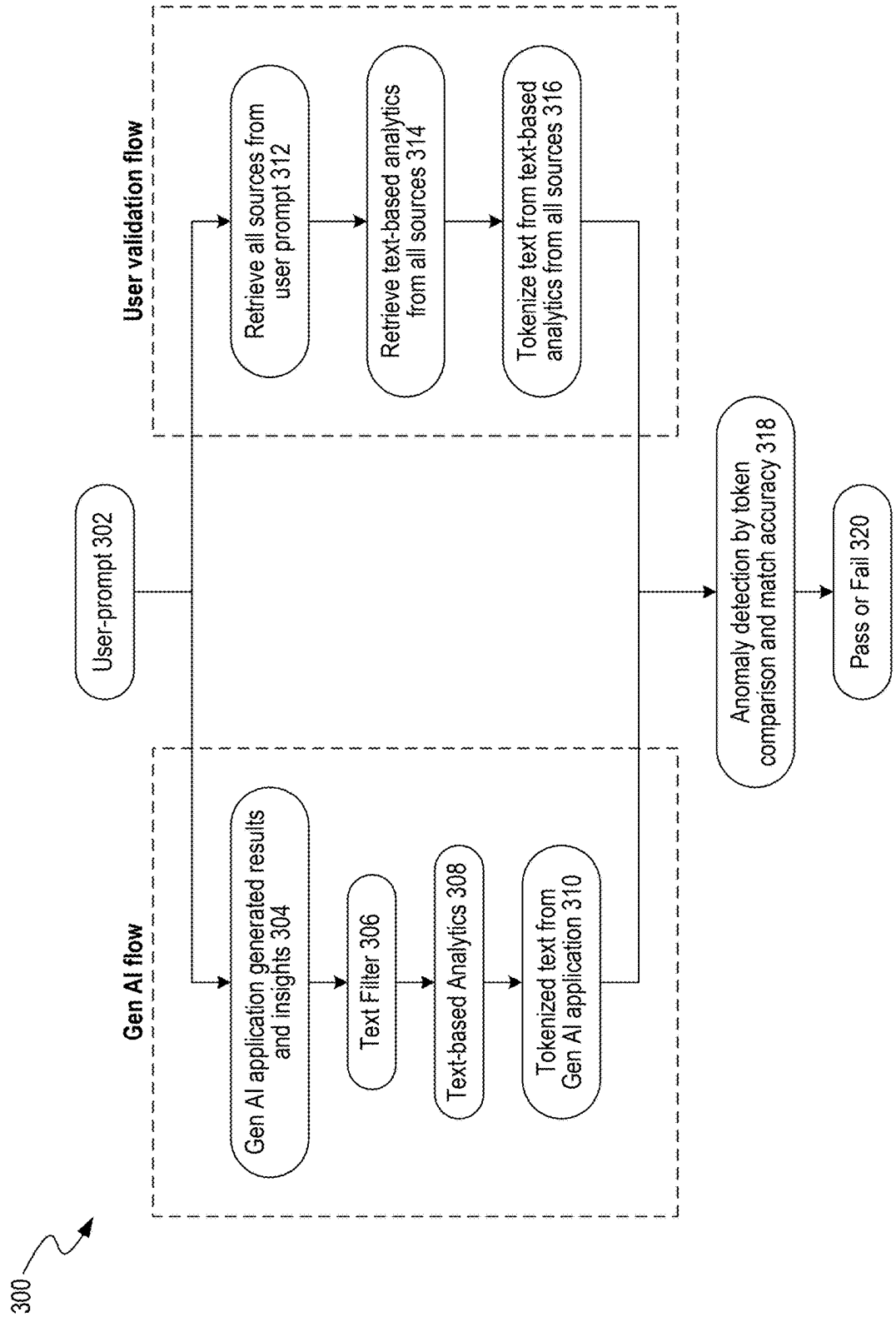

300
User-prompt 302
Gen AI flow
Gen AI application generated results and insights 304
Text Filter 306
Text-based Analytics 308
Tokenized text from Gen AI application 310
User validation flow
Retrieve all sources from user prompt 312
Retrieve text-based analytics from all sources 314
Tokenize text from text-based analytics from all sources 316
Anomaly detection by token comparison and match accuracy 318
Pass or Fail 320

FIG. 3

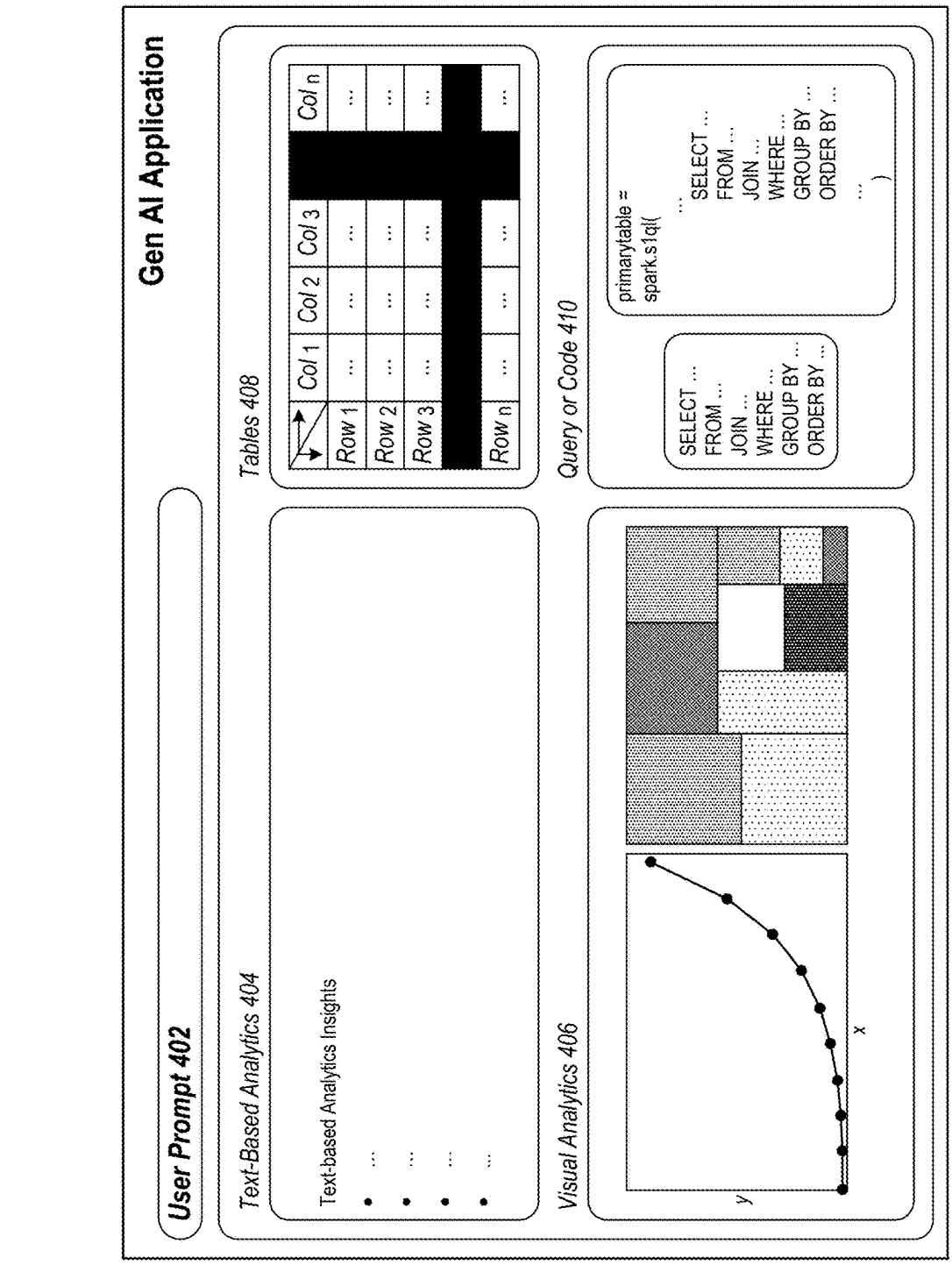

400
Gen AI Application
User Prompt 402
Text-Based Analytics 404
Text-based Analytics Insights
Tables 408
Col 1
Col 2
Col 3
Col n
Row 1
Row 2
Row 3
Row n
Visual Analytics 406
y
x
Query or Code 410
SELECT ...
FROM ...
JOIN ...
WHERE ...
GROUP BY ...
ORDER BY ...
primarytable =
spark.s1ql(
"""
SELECT ...
FROM ...
JOIN ...
WHERE ...
GROUP BY ...
ORDER BY ...
"""
)

FIG. 4

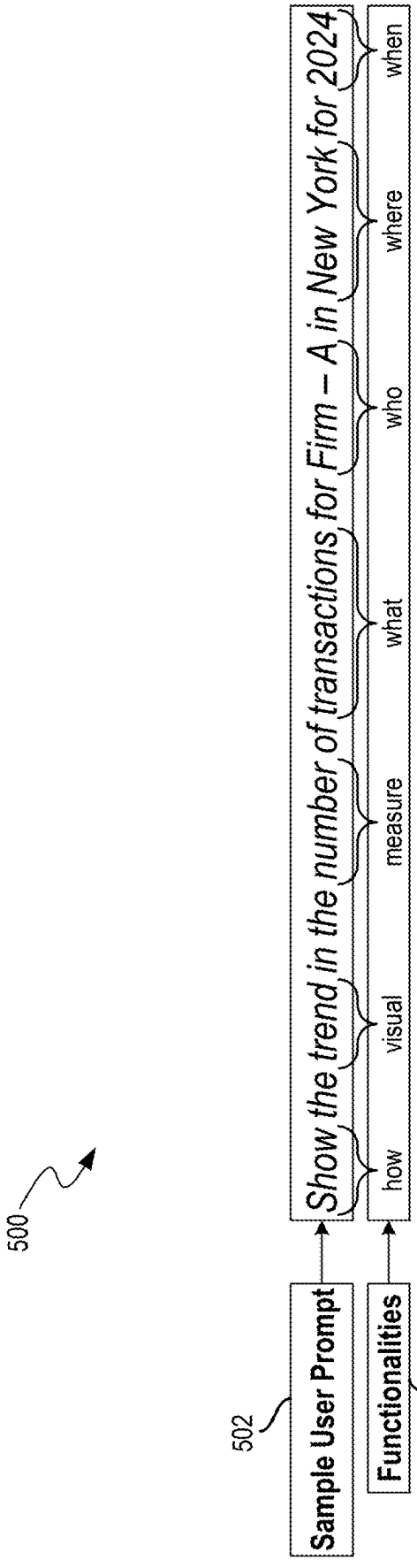

500
Sample User Prompt
502
Show the trend in the number of transactions for Firm – A in New York for 2024
Functionalities
504
how
visual
measure
what
who
where
when

FIG. 5

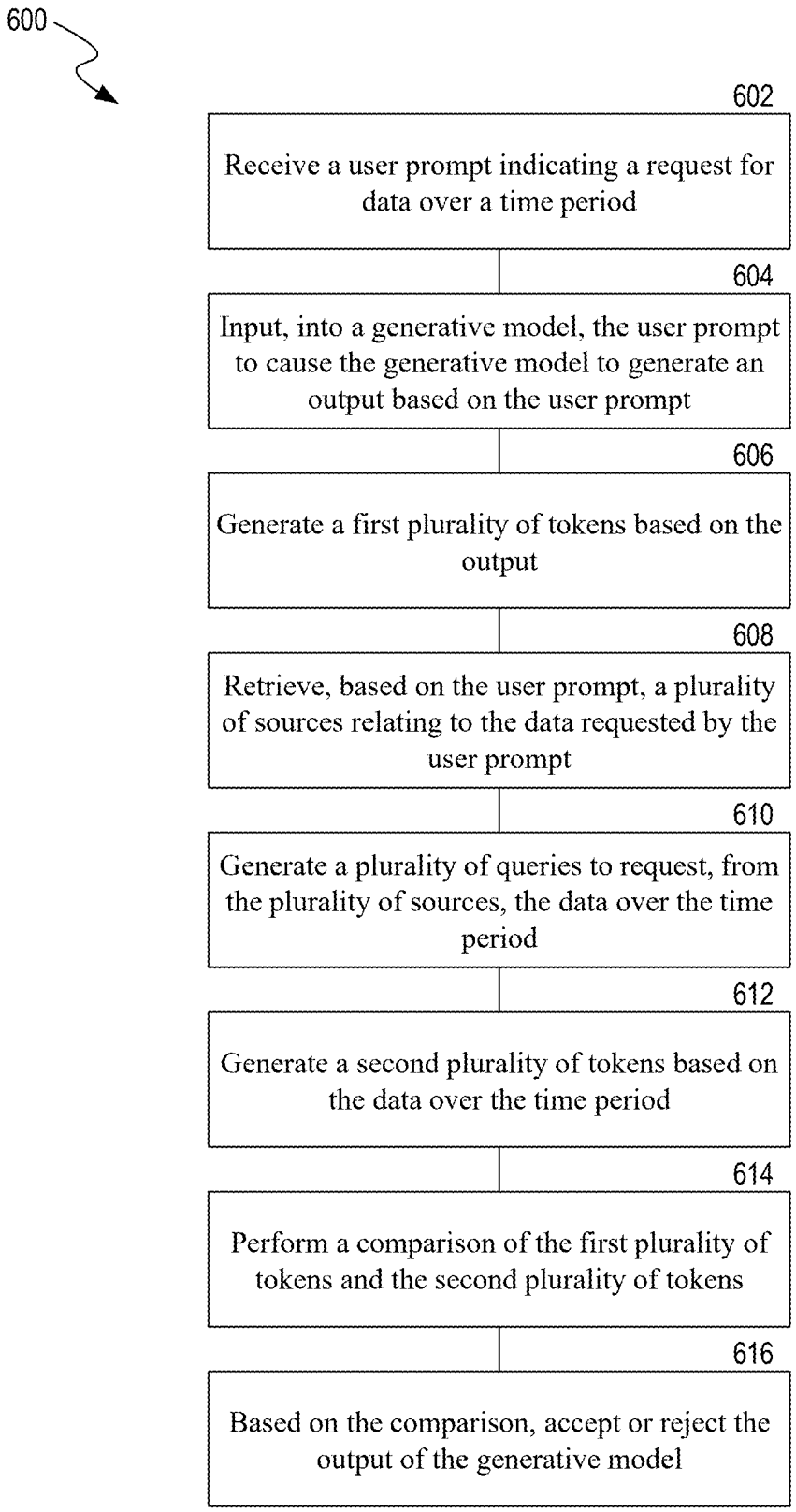

600
602
Receive a user prompt indicating a request for data over a time period
604
Input, into a generative model, the user prompt to cause the generative model to generate an output based on the user prompt
606
Generate a first plurality of tokens based on the output
608
Retrieve, based on the user prompt, a plurality of sources relating to the data requested by the user prompt
610
Generate a plurality of queries to request, from the plurality of sources, the data over the time period
612
Generate a second plurality of tokens based on the data over the time period
614
Perform a comparison of the first plurality of tokens and the second plurality of tokens
616
Based on the comparison, accept or reject the output of the generative model

FIG. 6

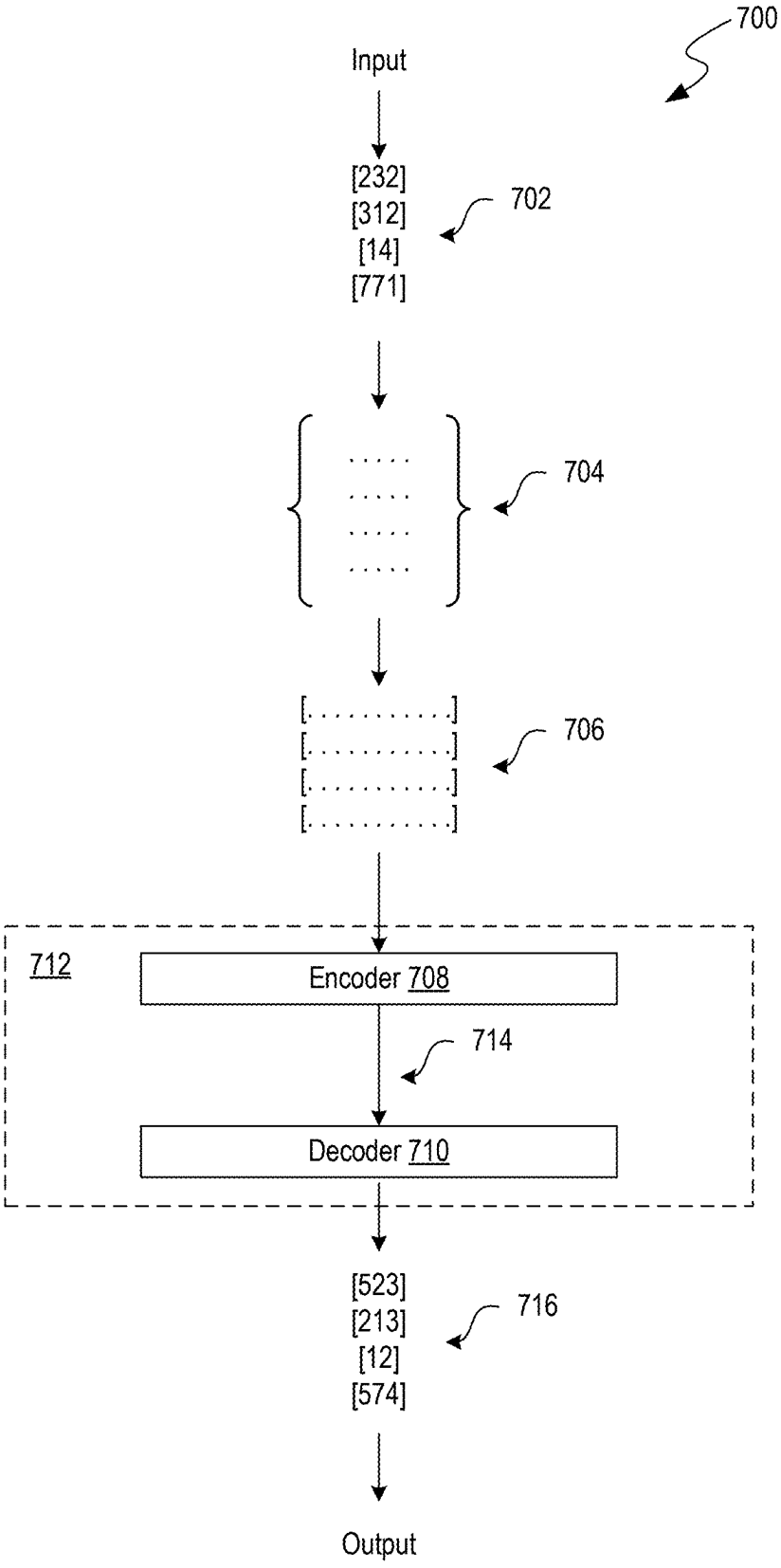

700
Input
[232]
[312]
[14]
[771]
702
704
706
712
Encoder 708
714
Decoder 710
[523]
[213]
[12]
[574]
716
Output

FIG. 7

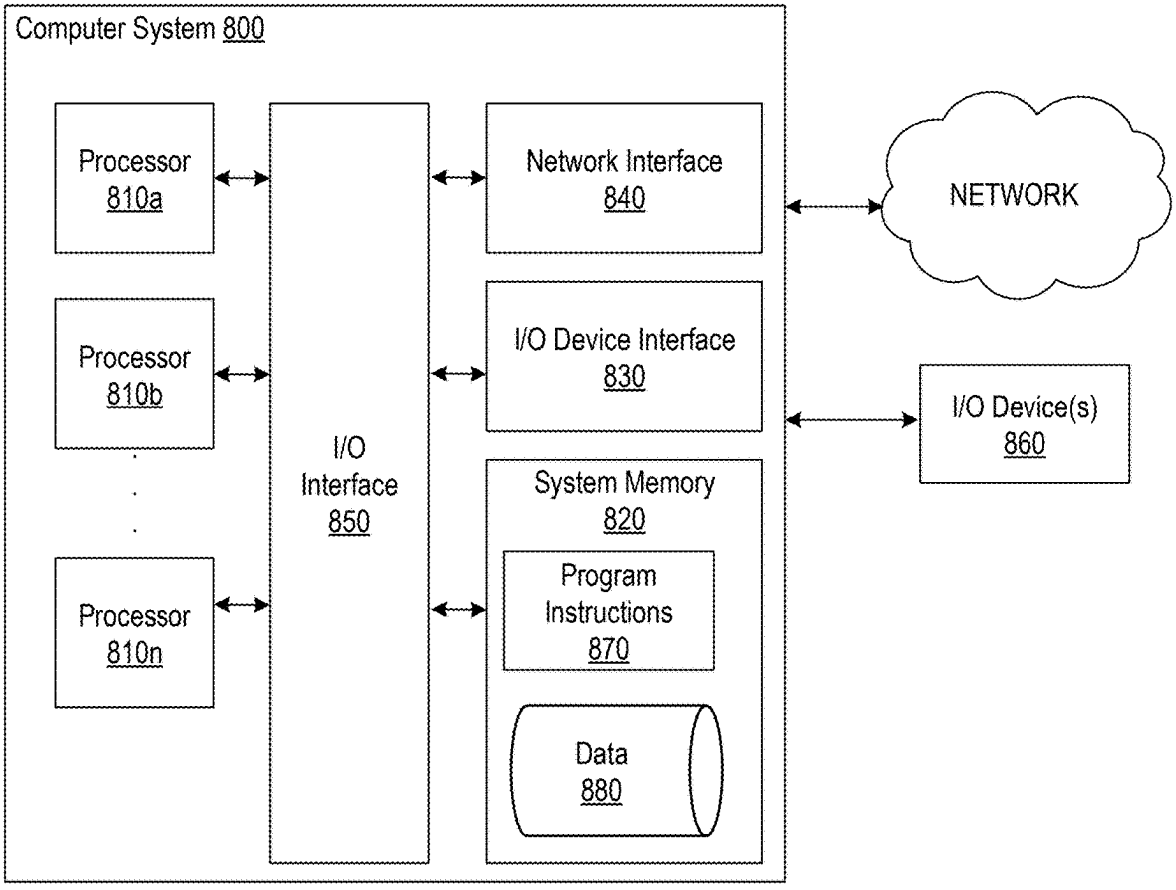

Computer System 800
Processor 810a
Processor 810b
Processor 810n
I/O Interface 850
Network Interface 840
I/O Device Interface 830
System Memory 820
Program Instructions 870
Data 880
NETWORK
I/O Device(s) 860

FIG. 8

ANOMALY DETECTION METHOD FOR MODEL OUTPUTS

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application is a continuation-in-part of U.S. patent application Ser. No. 19/038,662, filed Jan. 27, 2025, entitled "SYSTEMS AND METHODS FOR DETECTING REQUIRED RULE ENGINE UPDATED USING ARTIFICIAL INTELLIGENCE MODELS," which is a continuation of U.S. patent application Ser. No. 18/781,985, filed Jul. 23, 2024, entitled "SYSTEMS AND METHODS FOR DETECTING REQUIRED RULE ENGINE UPDATED USING ARTIFICIAL INTELLIGENCE MODELS," which is a continuation-in-part of U.S. patent application Ser. No. 18/535,001, filed Dec. 11, 2023, entitled "SYSTEMS AND METHODS FOR UPDATING RULE ENGINES DURING SOFTWARE DEVELOPMENT USING GENERATED PROXY MODELS WITH PREDEFINED MODEL DEPLOYMENT CRITERIA." U.S. patent application Ser. No. 19/038,662 is further related to U.S. patent application Ser. No. 18/669,421, filed May 20, 2024, entitled "SYSTEMS AND METHODS FOR MODIFYING DECISION ENGINES DURING SOFTWARE DEVELOPMENT USING VARIABLE DEPLOYMENT CRITERIA," which is a continuation-in-part of U.S. patent application Ser. No. 18/535,001, filed Dec. 11, 2023, entitled "SYSTEMS AND METHODS FOR UPDATING RULE ENGINES DURING SOFTWARE DEVELOPMENT USING GENERATED PROXY MODELS WITH PREDEFINED MODEL DEPLOYMENT CRITERIA."

[0002] This application is further a continuation-in-part of U.S. patent application Ser. No. 19/061,982, filed Feb. 24, 2025, entitled "SYSTEMS AND METHODS FOR GENERATING ARTIFICIAL INTELLIGENCE MODELS AND/OR RULE ENGINES WITHOUT REQUIRING TRAINING DATA THAT IS SPECIFIC TO MODEL COMPONENTS AND OBJECTIVES," which is a continuation-in-part of U.S. patent application Ser. No. 18/781,965, filed Jul. 23, 2024, entitled "SYSTEMS AND METHODS FOR DETECTING REQUIRED RULE ENGINE UPDATES USING ARTIFICIAL INTELLIGENCE MODELS," which is a continuation-in-part of U.S. patent application Ser. No. 18/535,001, filed Dec. 11, 2023, entitled "SYSTEMS AND METHODS FOR UPDATING RULE ENGINES DURING SOFTWARE DEVELOPMENT USING GENERATED PROXY MODELS WITH PREDEFINED MODEL DEPLOYMENT CRITERIA." U.S. patent application Ser. No. 19/061,982 is further related to U.S. patent application Ser. No. 19/038,662, filed Jan. 27, 2025, entitled "SYSTEMS AND METHODS FOR DETECTING REQUIRED RULE ENGINE UPDATED USING ARTIFICIAL INTELLIGENCE MODELS," which is a continuation of U.S. patent application Ser. No. 18/781,985, filed Jul. 23, 2024, entitled "SYSTEMS AND METHODS FOR DETECTING REQUIRED RULE ENGINE UPDATED USING ARTIFICIAL INTELLIGENCE MODELS," which is a continuation-in-part of U.S. patent application Ser. No. 18/535,001, filed Dec. 11, 2023, entitled "SYSTEMS AND METHODS FOR UPDATING RULE ENGINES DURING SOFTWARE DEVELOPMENT USING GENERATED PROXY MODELS WITH PREDEFINED MODEL DEPLOYMENT CRITERIA." U.S. patent application Ser. No. 19/061,982 is further related to U.S. patent application Ser. No. 18/669,421, filed May 20, 2024, entitled "SYSTEMS AND METHODS FOR MODIFYING DECISION ENGINES DURING SOFTWARE DEVELOPMENT USING VARIABLE DEPLOYMENT CRITERIA," which is a continuation-in-part of U.S. patent application Ser. No. 18/535,001, filed Dec. 11, 2023, entitled "SYSTEMS AND METHODS FOR UPDATING RULE ENGINES DURING SOFTWARE DEVELOPMENT USING GENERATED PROXY MODELS WITH PREDEFINED MODEL DEPLOYMENT CRITERIA."

[0003] This application is further a continuation-in-part of International PCT Patent Application No. PCT/US2024/051150, filed Oct. 11, 2024, which claims the benefit of priority of U.S. patent application Ser. No. 18/669,421, filed May 20, 2024, entitled "SYSTEMS AND METHODS FOR MODIFYING DECISION ENGINES DURING SOFTWARE DEVELOPMENT USING VARIABLE DEPLOYMENT CRITERIA," U.S. patent application Ser. No. 18/535,001, filed Dec. 11, 2023, entitled "SYSTEMS AND METHODS FOR UPDATING RULE ENGINES DURING SOFTWARE DEVELOPMENT USING GENERATED PROXY MODELS WITH PREDEFINED MODEL DEPLOYMENT CRITERIA," U.S. patent application Ser. No. 18/781,965, filed Jul. 23, 2024, entitled "SYSTEMS AND METHODS FOR DETECTING REQUIRED RULE ENGINE UPDATES USING ARTIFICIAL INTELLIGENCE MODELS," U.S. patent application Ser. No. 18/781,977, filed Jul. 23, 2024, entitled "SYSTEMS AND METHODS FOR DETECTING REQUIRED RULE ENGINE UPDATED USING ARTIFICIAL INTELLIGENCE MODELS," and U.S. patent application Ser. No. 18/781,985, filed Jul. 23, 2024, entitled "SYSTEMS AND METHODS FOR DETECTING REQUIRED RULE ENGINE UPDATED USING ARTIFICIAL INTELLIGENCE MODELS."

[0004] This application is further a continuation-in-part of U.S. patent application Ser. No. 18/951,120, filed Nov. 18, 2024, entitled "DYNAMIC EVALUATION OF LANGUAGE MODEL PROMPTS FOR MODEL SELECTION AND OUTPUT VALIDATION AND METHODS AND SYSTEMS OF THE SAME," which is a continuation of U.S. patent application Ser. No. 18/633,293, filed Apr. 11, 2024, entitled "DYNAMIC EVALUATION OF LANGUAGE MODEL PROMPTS FOR MODEL SELECTION AND OUTPUT VALIDATION AND METHODS AND SYSTEMS OF THE SAME."

[0005] This application is further a continuation-in-part of U.S. patent application Ser. No. 18/907,414, filed Oct. 4, 2024, entitled "DYNAMIC INPUT-SENSITIVE VALIDATION OF MACHINE LEARNING MODEL OUTPUTS AND METHODS AND SYSTEMS OF THE SAME," which is a continuation of U.S. patent application Ser. No. 18/661,532, filed May 10, 2024, entitled "DYNAMIC INPUT-SENSITIVE VALIDATION OF MACHINE LEARNING MODEL OUTPUTS AND METHODS AND SYSTEMS OF THE SAME," which is a continuation-in-part of U.S. patent application Ser. No. 18/661,519, filed May 10, 2024, entitled "DYNAMIC, RESOURCE-SENSITIVE MODEL SELECTION AND OUTPUT GENERATION AND METHODS AND SYSTEMS OF THE SAME," which is a continuation-in-part of U.S. patent application Ser. No. 18/633,293, filed Apr. 11, 2024, entitled "DYNAMIC EVALUATION OF LANGUAGE MODEL

PROMPTS FOR MODEL SELECTION AND OUTPUT VALIDATION AND METHODS AND SYSTEMS OF THE SAME."

[0006] The content of the foregoing applications is incorporated herein by reference in its entirety.

BACKGROUND

[0007] Model outputs can include the results produced by a machine learning model after it has processed and analyzed input data. These outputs can vary widely depending on the type of machine learning task being performed. In the context of machine learning model outputs, an anomaly can refer to a result or data point that deviates significantly from an expected norm. Anomalies can arise due to various factors and can be difficult to detect.

BRIEF DESCRIPTION OF THE DRAWINGS

[0008] FIG. **1** shows an illustrative system for detecting anomalies in model outputs, in accordance with one or more implementations of this disclosure.

[0009] FIG. **2** illustrates an exemplary machine learning model, in accordance with one or more implementations of this disclosure.

[0010] FIG. **3** illustrates a flow for detecting anomalies in model outputs, in accordance with one or more implementations of this disclosure.

[0011] FIG. **4** illustrates a user interface for detecting anomalies in model outputs, in accordance with one or more implementations of this disclosure.

[0012] FIG. **5** is an example of a user prompt, in accordance with one or more implementations of this disclosure.

[0013] FIG. **6** is a flowchart of operations for detecting anomalies in model outputs, in accordance with one or more implementations of this disclosure.

[0014] FIG. **7** is a block diagram of an example transformer used to detect anomalies in model outputs, in accordance with one or more implementations of this disclosure.

[0015] FIG. **8** illustrates an example computing system that can be used in accordance with some implementations of this disclosure.

[0016] The technologies described herein will become more apparent to those skilled in the art from studying the Detailed Description in conjunction with the drawings. Implementations or implementations describing aspects of the invention are illustrated by way of example, and the same references can indicate similar elements. While the drawings depict various implementations for the purpose of illustration, those skilled in the art will recognize that alternative implementations can be employed without departing from the principles of the present technologies. Accordingly, while specific implementations are shown in the drawings, the technology is amenable to various modifications.

DETAILED DESCRIPTION

[0017] As the reliance on artificial intelligence (AI) models continues to grow, there are inherent risks associated with outputs from these models. Inaccurate outputs can affect outcomes and compromise safety and efficiency. Moreover, AI models are increasingly being used in critical decision-making processes across various domains. Making decisions based on erroneous or misrepresented information included in model outputs can lead to significant consequences. For example, incorrect predictions or classifications can result in substantial losses, regulatory penalties, and damage to an organization's reputation.

[0018] Anomalies in model outputs can result in many of these consequences. Anomalies can arise from various sources and can be difficult to detect. These anomalies can manifest as outliers, unexpected patterns, or deviations from the expected results, which can compromise the reliability and accuracy of the AI system. In some implementations, anomalies include hallucinations, which occur when an AI model generates information that appears plausible but is entirely fabricated or inaccurate. These hallucinations can mislead users into believing the generated content is factual. For example, a model produces a detailed and convincing response that includes non-existent references, incorrect data, or fictitious events. The risk of hallucinations is heightened when the model is prompted with ambiguous or incomplete information, leading it to fill in gaps with invented details.

[0019] To mitigate these risks, systems can implement controls to ensure the accuracy of information and to detect anomalous outputs generated using AI models. This can include techniques such as anomaly detection, which involves identifying and analyzing unusual patterns in the data that may indicate potential issues. This patent document discloses systems and methods to detect anomalies in outputs generated by AI models. The system generates two sets of tokens, based on (i) GenAI outputs and (ii) sources stored in a database, and performs a token comparison between the two sets for anomaly detection in the GenAI outputs. Conventional systems often rely on the outputs of AI models without reliable methods of detecting anomalies, hallucinations, or other errors in the outputs. Anomaly detection can prevent erroneous model outputs from causing outputs to fail if they do not sufficiently align with relevant data retrieved from reliable sources.

[0020] For example, a user can input a prompt into an AI model, where the prompt requests a report or a summary of analytics over a period of time. The AI model can then generate text-based and visual analytics based on the user prompt. These analytics can be passed through a text filter to obtain only text-based analytics. The text-based analytics from the AI model can then be tokenized for comparison against actual or true information from the sources used by the AI model. The sources of requested information specified in the user prompt can be retrieved separately. The text-based analytics from these retrieved sources can also be tokenized. These tokens, representing the actual or true information from the sources, can then be compared against the tokens generated based on the outputs of the AI model. This comparison can yield a match accuracy for token comparison, providing a pass or fail result for the AI model outputs. This process can serve as an anomaly detector for AI models across many different contexts, safeguarding against the use of erroneous outputs from these models.

[0021] In particular, the system can receive a request for information or data. The system can receive a user prompt indicating a request for information or data. In some implementations, the system receives a user prompt indicating a request for a report summarizing data over a time period. For example, a user prompt can be "Show the trend in the number of transactions for Firm-A in New York for 2024." The user prompt indicates a request for data on the number of transactions for Firm-A in New York over the time period

of 2024. The system can use an AI model to generate a report summarizing the trend in the number of transactions for Firm-A in New York for 2024 and can use the methods discussed herein to detect anomalies in this output.

[0022] The system can generate two sets of tokens, which will be compared to detect any anomalies in the model output. For example, the system generates a first plurality of tokens using the AI model. The system can input, into an AI model, the user prompt to cause the AI model to generate an output based on the user prompt, the output comprising a plurality of text-based analytics and a plurality of visual analytics based on the user prompt. For example, the text-based analytics can include the number of transactions or Firm-A in New York at various points during 2024, while the visual analytics can include graphs or other images relating to this data. The system can apply a text filter to the output to generate a modified output including just the text-based analytics and excluding the visual analytics. The system can then generate the first plurality of tokens based on the text-based analytics.

[0023] The system then generates a second plurality of tokens based on the sources used by the AI model to determine the output. For example, the system retrieves, based on the user prompt, sources relating to the data requested by the user prompt. The system then generates queries to request, from the sources, the data over the time period. The system can generate the second plurality of tokens based on the data over the time period. This data, retrieved directly from the sources, is actual or true information against which the model outputs can be compared.

[0024] For example, the system can perform a comparison of the first plurality of tokens and the second plurality of tokens to determine a match accuracy. The system can use a number of techniques to assess the match accuracy between the first plurality of tokens and the second plurality of tokens. If the system determines that the match accuracy satisfies an anomaly detection threshold, the system can approve the output of the AI model. Approving the output can enable transmission of the report summarizing the data over the time period to the user. For example, the system can output a report summarizing the trend in the number of transactions for Firm-A in New York for 2024. If the match accuracy fails to satisfy the anomaly detection threshold, the system can reject the output of the AI model and refrain from outputting a report summarizing the trend in the number of transactions for Firm-A in New York for 2024.

[0025] The description and associated drawings are illustrative examples and are not to be construed as limiting. This disclosure provides certain details for a thorough understanding and enabling description of these examples. One skilled in the relevant technology will understand, however, that the invention can be practiced without many of these details. Likewise, one skilled in the relevant technology will understand that the invention can include well-known structures or features that are not shown or described in detail, to avoid unnecessarily obscuring the descriptions of examples.

[0026] FIG. **1** shows an illustrative system **100** for detecting anomalies in model outputs, in accordance with one or more implementations of this disclosure. For example, the system **100** can be used to compare outputs from AI models to verified information to detect anomalies in the outputs. In some implementations, the system **100** can utilize techniques such as applying text filters, parsing and tokenizing outputs, and performing similarity analyses in order to detect anomalies. For example, the system **100** can include an anomaly detection system **160** able to perform anomaly detection operations. The anomaly detection system **160** can include software, hardware, or a combination of the two. For example, the anomaly detection system **160** can be a physical server or a virtual server that is running on a physical computer system. In some implementations, the anomaly detection system **160** can be configured on a user device (e.g., a laptop computer, a smartphone, a desktop computer, an electronic tablet, or another suitable user device) and configured to execute instructions for detecting anomalies in model outputs. In particular, the anomaly detection system **160** can include several subsystems, each configured to perform one or more steps of the methods described herein, such as a communication subsystem **162**, a machine learning subsystem **164**, a tokenization subsystem **166**, and a similarity subsystem **168**.

[0027] As described herein, the anomaly detection system **160** can obtain data to determine whether an output is anomalous. The anomaly detection system **160** can retrieve data or sources of data from databases or data stores. As described herein, an anomaly detection system can be any system (e.g., computer, device, node, etc.) that is enabled to execute one or more tools for detecting anomalous outputs or enabled to execute tasks for which data can be passively collected. The anomaly detection system **160** can be configured to receive the data via a communication network **140** at the communication subsystem **162**. The communication network **140** can be a local area network (LAN), a wide area network (WAN; e.g., the internet), or a combination of the two. The communication subsystem **162** can include software components, hardware components, or a combination of both. For example, the communication subsystem **162** can include a network card (e.g., a wireless network card or a wired network card) that is associated with software to drive the card. The communication subsystem **162** can pass at least a portion of the data, or a pointer to the data in memory, to other subsystems, such as the machine learning subsystem **164**, the tokenization subsystem **166**, and the similarity subsystem **168**.

[0028] According to some implementations, the anomaly detection system **160** can obtain such data by generating one or more commands to execute anomaly detection operations. In some examples, the command(s) can specify a specific timeframe for obtaining the data (e.g., explicitly by identifying the timeframe via a start and an end time, or implicitly by requesting data from a current block of time). Additionally, the system **100** can include a repository **170**, which can store historic data, stored data, machine learning model parameters, and system commands. In some implementations, the repository **170** can store preconfigured commands related to detecting anomalies in model outputs, which can be used by the anomaly detection system **160** to manage anomaly detection dynamically. The repository **170** can also include metadata or tags associated with stored data, such as identifiers, policies, or patterns. The anomaly detection system **160** can retrieve data from the repository **170** to refine its predictions, optimize outcomes, and improve the accuracy of anomaly detection. Additionally, the repository **170** can store augmented datasets used to update the machine learning model based on newly collected data, ensuring adaptive and evolving predictions.

[0029] The system **100** can further include an operator device **150**, which can receive alerts generated by the

anomaly detection system **160** when a potential anomalous output is detected. The operator device **150** can be a desktop computer, mobile device, or other suitable user interface (UI) through which an operator can review system notifications and monitor outcomes, such as flagged or blocked outputs. The anomaly detection system **160** can transmit natural language explanations to the operator device **150** to provide insight into anomalous outputs and system responses.

[0030] FIG. **2** illustrates an exemplary machine learning model **202**, in accordance with one or more implementations of this disclosure. The machine learning model **202** can be an AI model, such as a generative model, or another model. According to some examples, the machine learning model can be any model, such as a model for classification. In some implementations, the machine learning model **202** can be trained to intake input **204**, including input data and requests received. As a result of inputting the input **204** into the machine learning model **202**, the machine learning model **202** can then output an output **206**. As described herein, the input data can include data such as requests or prompts. In particular, the machine learning model **202** can receive a user prompt indicating a request for a report summarizing data over a time period.

[0031] For example, the output **206** can include a plurality of text-based analytics and a plurality of visual analytics based on the user prompt. Furthermore, as described, the machine learning model **202** can be configured to output a confidence interval or other metric for certainty regarding the outputs. The machine learning model **202** can be trained on a training dataset containing a plurality of user prompts and labels, such as a degree and indication for security conditions that were identified by operators. For example, the machine learning model **202** is described in relation to FIG. **2** herein.

[0032] The output parameters can be fed back to the machine learning model **202** as input to train the machine learning model **202** (e.g., alone or in conjunction with user indications of the accuracy of outputs, labels associated with the inputs, or other reference feedback information). The machine learning model **202** can update its configurations (e.g., weights, biases, or other parameters) based on the assessment of its prediction and reference feedback information (e.g., user indication of accuracy, reference labels, or other information). Connection weights can be adjusted, for example, if the machine learning model **202** is a neural network to reconcile differences between the neural network's prediction and the reference feedback regarding conditions (e.g., anomalous behavior).

[0033] One or more neurons of the neural network can require that their respective errors are sent backward through the neural network to facilitate the update process (e.g., backpropagation of error). Updates to the connection weights may, for example, be reflective of the magnitude of error propagated backward after a forward pass has been completed. In this way, for example, the machine learning model can be trained to generate better predictions.

[0034] In some implementations, the machine learning model **202** can include an artificial neural network. In such implementations, the machine learning model **202** can include an input layer and one or more hidden layers. Each neural unit of the machine learning model **202** can be connected to one or more other neural units of the machine learning model **202**. Such connections can be enforcing or inhibitory in their effect on the activation state of connected neural units. Each individual neural unit can have a summation function that combines the values of all of its inputs together. Each connection (or the neural unit itself) can have a threshold function that a signal must surpass before it propagates to other neural units. The machine learning model **202** can be self-learning or trained rather than explicitly programmed and can perform significantly better in certain areas of problem-solving as compared to computer programs that do not use machine learning. During training, an output layer of the machine learning model **202** can correspond to a classification of the machine learning model **202**, and an input known to correspond to that classification can be input into an input layer of the machine learning model **202** during training. During testing, an input without a known classification can be input into the input layer, and a determined classification can be output.

[0035] The machine learning model **202** can include embedding layers in which each feature of a vector is converted into a dense vector representation. These dense vector representations for each feature can be pooled at one or more subsequent layers to convert the set of embedding vectors into a single vector. The machine learning model **202** can be structured as a factorization machine model. The machine learning model **202** can be a non-linear model or supervised learning model that can perform classification or regression. For example, the machine learning model **202** can be a general-purpose supervised learning algorithm that the anomaly detection system **160** uses for both classification and regression tasks. Alternatively, the machine learning model **202** can include a Bayesian model configured to perform variational inference on the graph or vector.

Transformer for Neural Network

[0036] To assist in understanding the present disclosure, some concepts relevant to neural networks and machine learning are discussed herein. Generally, a neural network includes a number of computation units (sometimes referred to as "neurons"). Each neuron receives an input value and applies a function to the input to generate an output value. The function typically includes a parameter (also referred to as a "weight") whose value is learned through the process of training. A plurality of neurons can be organized into a neural network layer (or simply "layer"), and there can be multiple such layers in a neural network. The output of one layer can be provided as input to a subsequent layer. Thus, input to a neural network can be processed through a succession of layers until an output of the neural network is generated by a final layer. This is a simplistic discussion of neural networks, and there can be more complex neural network designs that include feedback connections, skip connections, or other such possible connections between neurons or layers, which are not discussed in detail here.

[0037] A deep neural network (DNN) is a type of neural network that has multiple layers or a large number of neurons. The term DNN can encompass any neural network having multiple layers, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), multilayer perceptrons (MLPs), Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and auto-regressive models, among others.

[0038] DNNs are often used as machine learning-based models for modeling complex behaviors (e.g., human language, image recognition, object classification, etc.) in order

to improve the accuracy of outputs (e.g., more accurate predictions) such as, for example, as compared with models with fewer layers. In the present disclosure, the term "machine learning-based model" or more simply "machine learning model" can be understood to refer to a DNN. Training a machine learning model refers to a process of learning the values of the parameters (or weights) of the neurons in the layers such that the machine learning model is able to model the target behavior to a desired degree of accuracy. Training typically requires the use of a training dataset, which is a set of data that is relevant to the target behavior of the machine learning model.

[0039] As an example, to train a machine learning model that is intended to model human language (also referred to as a "language model"), the training dataset can be a collection of text documents, referred to as a "text corpus" (or simply referred to as a "corpus"). The corpus can represent a language domain (e.g., a single language), a subject domain (e.g., scientific papers), or can encompass another domain or domains, be they larger or smaller than a single language or subject domain. For example, a relatively large, multilingual, and non-subject-specific corpus can be created by extracting text from online webpages or publicly available social media posts. Training data can be annotated with ground truth labels (e.g., each data entry in the training dataset can be paired with a label) or can be unlabeled.

[0040] Training a machine learning model generally involves inputting into a machine learning model (e.g., an untrained machine learning model) training data to be processed by the machine learning model, processing the training data using the machine learning model, collecting the output generated by the machine learning model (e.g., based on the inputted training data), and comparing the output to a desired set of target values. If the training data is labeled, the desired target values can be, e.g., the ground truth labels of the training data. If the training data is unlabeled, the desired target value can be a reconstructed (or otherwise processed) version of the corresponding machine learning model input (e.g., in the case of an autoencoder), or can be a measure of some target observable effect on the environment (e.g., in the case of a reinforcement learning agent). The parameters of the machine learning model are updated based on a difference between the generated output value and the desired target value. For example, if the value outputted by the machine learning model is excessively high, the parameters can be adjusted so as to lower the output value in future training iterations. An objective function is a way to quantitatively represent how close the output value is to the target value. An objective function represents a quantity (or one or more quantities) to be optimized (e.g., minimize a loss or maximize a reward) in order to bring the output value as close to the target value as possible. The goal of training the machine learning model is typically to minimize a loss function or maximize a reward function.

[0041] The training data can be a subset of a larger data set. For example, a data set can be split into three mutually exclusive subsets: a training set, a validation (or cross-validation) set, and a testing set. The three subsets of data can be used sequentially during machine learning model training. For example, the training set can be first used to train one or more machine learning models, e.g., each machine learning model having a particular architecture, having a particular training procedure, being describable by a set of model hyperparameters, or otherwise being varied from the other of the one or more machine learning models. The validation (or cross-validation) set can then be used as input data into the trained machine learning models to, e.g., measure the performance of the trained machine learning models or compare performance between them. Where hyperparameters are used, a new set of hyperparameters can be determined based on the measured performance of one or more of the trained machine learning models, and the first step of training (e.g., with the training set) can begin again on a different machine learning model described by the new set of determined hyperparameters. In this way, these steps can be repeated to produce a more performant trained machine learning model. Once such a trained machine learning model is obtained (e.g., after the hyperparameters have been adjusted to achieve a desired level of performance), a third step of collecting the output generated by the trained machine learning model applied to the third subset (the testing set) can begin. The output generated from the testing set can be compared with the corresponding desired target values to give a final assessment of the trained machine learning model's accuracy. Other segmentations of the larger data set or schemes for using the segments for training one or more machine learning models are possible.

[0042] Backpropagation is an algorithm for training a machine learning model. Backpropagation is used to adjust (e.g., update) the value of the parameters in the machine learning model with the goal of optimizing the objective function. For example, a defined loss function is calculated by forward propagation of an input to obtain an output of the machine learning model and a comparison of the output value with the target value. Backpropagation calculates a gradient of the loss function with respect to the parameters of the machine learning model, and a gradient algorithm (e.g., gradient descent) is used to update (e.g., "learn") the parameters to reduce the loss function. Backpropagation is performed iteratively so that the loss function is converged or minimized. Other techniques for learning the parameters of the machine learning model can be used. The process of updating (or learning) the parameters over many iterations is referred to as training. Training can be carried out iteratively until a convergence condition is met (e.g., a predefined maximum number of iterations has been performed, or the value outputted by the machine learning model is sufficiently converged with the desired target value), after which the machine learning model is considered to be sufficiently trained. The values of the learned parameters can then be fixed and the machine learning model can be deployed to generate output in real-world applications (also referred to as "inference").

[0043] In some examples, a trained machine learning model can be fine-tuned, meaning that the values of the learned parameters can be adjusted slightly in order for the machine learning model to better model a specific task. Fine-tuning of a machine learning model typically involves further training the machine learning model on a number of data samples (which can be smaller in number/cardinality than those used to train the model initially) that closely target the specific task. For example, a machine learning model for generating natural language, e.g., for alerts to operators, or commands that have been trained generically on publicly available text corpora can be, e.g., fine-tuned by further training using specific training samples. The specific training samples can be used to generate language in a certain style or in a certain format. For example, the machine

learning model can be trained to generate a blog post having a particular style and structure with a given topic.

[0044] Some concepts in machine learning-based language models are now discussed. It can be noted that, while the term "language model" has been commonly used to refer to a machine learning-based language model, there could exist non-machine learning language models. In the present disclosure, the term "language model" can refer to a machine learning-based language model (e.g., a language model that is implemented using a neural network or other machine learning architecture), unless stated otherwise. For example, unless stated otherwise, the "language model" encompasses LLMs.

[0045] A language model can use a neural network (typically a DNN) to perform natural language processing (NLP) tasks. A language model can be trained to model how words relate to each other in a textual sequence, based on probabilities. A language model can contain hundreds of thousands of learned parameters or, in the case of an LLM, can contain millions or billions of learned parameters or more. As non-limiting examples, a language model can generate text, translate text, summarize text, answer questions, write code (e.g., Python, JavaScript, or other programming languages), classify text (e.g., to identify spam emails), create content for various purposes (e.g., social media content, factual content, or marketing content), or create personalized content for a particular individual or group of individuals. Language models can also be used for chatbots (e.g., virtual assistance).

[0046] A type of neural network architecture, referred to as a "transformer," can be used for language models. For example, the Bidirectional Encoder Representations from Transformers (BERT) model, the Transformer-XL model, and the Generative Pre-trained Transformer (GPT) models are types of transformers. A transformer is a type of neural network architecture that uses self-attention mechanisms in order to generate predicted output based on input data that has some sequential meaning (i.e., the order of the input data is meaningful, which is the case for most text input). Although transformer-based language models are described herein, it should be understood that the present disclosure can be applicable to any machine learning-based language model, including language models based on other neural network architectures such as RNN-based language models.

[0047] FIG. **3** illustrates a flow **300** for detecting anomalies in model outputs, in accordance with one or more implementations of this disclosure. As shown in FIG. **3**, the flow **300** can include both a generative AI flow ("Gen AI flow") and a validation flow ("User validation flow"). A user prompt **302** can feed into both of these flows, and the results of both flows can be compared to determine whether to approve or reject the model output (e.g., Pass or Fail **320**). For example, in the "Gen AI flow," the user prompt **302** can be processed by an AI model to produce an initial output (e.g., Gen AI application-generated results and insights **304**). This output can include various forms of analytics, such as text-based summaries, statistical analyses, and visual representations of data. The AI model leverages its training on extensive datasets to generate a comprehensive response that addresses the specifics of the user prompt. Simultaneously, in the "User validation flow," the same user prompt **302** can be used to retrieve relevant data from trusted sources. This data can be processed and analyzed independently to create a benchmark output. The benchmark output serves as a reference point for validating the AI model's output. Once both the model output and the benchmark output are available and correctly formatted, the anomaly detection system can compare the two (e.g., anomaly detection by token comparison and match accuracy **318**). The anomaly detection system can identify any discrepancies, anomalies, or deviations that can indicate potential errors or inaccuracies in the model output. If the comparison reveals that the model output aligns closely with the benchmark output, the system can approve the model output for user consumption. However, if significant discrepancies are detected, the system can reject the model output and flag it for further review. This ensures that only accurate and reliable information is presented to the user.

[0048] In particular, the anomaly detection system receives a user prompt (e.g., the user prompt **302**) indicating a request for data over a time period. As an illustrative example, the user prompt can include "Show the trend in the number of transactions for Firm-A in New York for 2024." In some implementations, the user prompt requests a report summarizing the data over a time period. For example, the user prompt can request a type of report or summary or can specify certain formats for the outputs. The anomaly detection system can accommodate various user preferences by allowing customization of the report format, such as including specific data visualizations like graphs or charts, or focusing on particular metrics or key performance indicators (KPIs).

[0049] FIG. **4** illustrates a UI **400** for detecting anomalies in model outputs, in accordance with one or more implementations of this disclosure. As shown in FIG. **4**, the UI **400** can include a field for a user to input a user prompt **402**, a portion of the UI dedicated to displaying text-based analytics **404**, portions of the UI dedicated to displaying visual analytics **406** or tables **408**, and query or code **410**. In some implementations, the text-based analytics **404**, the visual analytics **406**, and the tables **408** are analyzed for anomalies using the methods discussed herein before being generated for display on the UI **400**. In some implementations, the text-based analytics **404** are analyzed for anomalies using the methods discussed herein, and once the anomaly detection system verifies that the text-based analytics **404** do not include any anomalies, the anomaly detection system generates the visual analytics **406** and the tables **408** (e.g., based on the text-based analytics **404**) for display. In some implementations, the query or code **410** can include a query or code used by the AI model to retrieve data for generating an output (e.g., discussed in greater detail below). In some implementations, the UI **400** includes other information or other configurations.

[0050] When the anomaly detection system receives the user prompt, the anomaly detection system can generate a first plurality of tokens. For example, as shown in FIG. **3**, the "Gen AI flow" can be used to generate the first plurality of tokens. These first tokens reflect the model outputs, which must be analyzed for anomalies. In particular, the anomaly detection system can input the user prompt into an AI model (e.g., machine learning model **202**, as shown in FIG. **2**). This can cause the AI model to generate an output based on the user prompt (e.g., Gen AI application generated results and insights **304**, as shown in FIG. **3**). The output can include a plurality of text-based analytics and a plurality of visual analytics based on the user prompt. As shown in FIG. **4**, the outputs can include the text-based analytics **404**, the visual

analytics **406**, and other information. For example, the AI model can produce a detailed report that includes textual summaries of transaction trends, statistical analyses, and key insights derived from the data. Additionally, the output can feature visual elements such as graphs, charts, and heatmaps that illustrate the trends and patterns in the data over the specified time period.

[0051] The anomaly detection system can apply a text filter to the output from the AI model to generate a modified output. The modified output can include the plurality of text-based analytics and excluding the plurality of visual analytics. For example, the text filter can be designed to identify and extract only the textual content from the AI model's output, disregarding any visual elements such as graphs, charts, and images. The text filter can work by parsing the output and recognizing specific tags or markers that differentiate text-based content from visual content. It can then isolate the sections of the output that contain textual information, such as summaries, explanations, and statistical analyses. The filter can also remove any references to visual elements to ensure that the modified output is purely text-based. Additionally, the text filter can be configured to enhance the readability and coherence of the extracted text. This can involve reformatting text, correcting any grammatical errors, and ensuring that the extracted content flows logically. The result can be a clean, text-only version of the AI model's output that retains all the relevant analytical insights while excluding any visual components (e.g., text-based analytics **308**, as shown in FIG. **3**).

[0052] Techniques for applying a text filter are described in U.S. application Ser. No. 18/669,421, titled "Systems and Methods for Modifying Decision Engines During Software Development Using Variable Deployment Criteria" and filed on May 20, 2024, which is hereby incorporated by reference. For example, a filter can employ a variety of techniques and technologies to identify content within outputs. The filter can use keyword filtering, where filters scan text-based content for specific keywords, phrases, or patterns. Additionally or alternatively, the filter can analyze images and videos to identify the content. This can involve image recognition, facial detection, or algorithms that recognize the content of images or videos. Additionally or alternatively, the filter can categorize text into predefined categories. The system can set filtering rules based on these categories. The filter can include models that can be trained to recognize patterns within outputs. They can adapt and improve their filtering capabilities over time.

[0053] Once the anomaly detection system has generated a modified output including the text-based analytics generated by the model, the anomaly detection system can generate the first plurality of tokens based on the plurality of text-based analytics (e.g., tokenized text from Gen AI application **310**, as shown in FIG. **3**). For example, to generate the first plurality of tokens, the anomaly detection system can tokenize the output from the AI model or the plurality of text-based analytics to extract a first plurality of keywords. Tokens can be words, phrases, symbols, or other meaningful elements that are used to break down and analyze text. Tokenizing is the process of converting a sequence of text into these smaller, manageable units called tokens. This process involves segmenting the text into individual components, which can then be used for various analytical purposes. In the context of the anomaly detection system, tokenizing the output means breaking down the text-based analytics into discrete tokens. This can involve identifying and extracting keywords, phrases, or other significant elements from the text. The anomaly detection system can use these tokens to perform further analysis, such as comparing them against tokens derived from reliable data sources to verify the accuracy and consistency of the information.

[0054] The anomaly detection system can then generate a second plurality of tokens. For example, as shown in FIG. **3**, the "User validation flow" can be used to generate the second plurality of tokens. This flow can involve the anomaly detection system retrieving, based on the user prompt, a plurality of sources relating to the data requested by the user prompt (e.g., retrieve all sources from user prompt **312**, as shown in FIG. **3**). For example, the anomaly detection system can identify and access various databases, repositories, and information sources pertinent to the user prompt, such as academic journals, industry reports, government databases, and news articles. The anomaly detection system can query external APIs provided by trusted organizations and data providers to ensure real-time access to up-to-date information. For sources not available through APIs or databases, web scraping techniques can be employed to collect data from relevant websites and online publications, adhering to legal guidelines.

[0055] In some implementations, the anomaly detection system generates a plurality of queries to request, from the plurality of sources, the data over the time period. For example, the anomaly detection system can begin by analyzing the user prompt to identify key parameters such as the specific data required, the relevant time period, and any pertinent keywords or entities. Based on this analysis, the anomaly detection system can construct a series of structured queries tailored to each source's data retrieval protocols. The anomaly detection system can use predefined templates for different types of sources, such as financial databases, news archives, and social media platforms. These templates can include placeholders for the identified parameters, ensuring that each query is customized to retrieve the most relevant data. For instance, a query template for a financial database might include placeholders for the company's stock ticker symbol, the date range, and the specific financial metrics required (e.g., daily closing prices, trading volumes).

[0056] Once the templates are populated with the appropriate parameters, the anomaly detection system can generate the actual queries. This process can involve converting the structured templates into the specific query languages or formats required by each source. For example, a query to a SQL-based financial database might be formatted as an SQL SELECT statement, while a query to a RESTful API might be formatted as an HTTP GET request with query parameters. The anomaly detection system can also incorporate error handling and validation mechanisms into the query generation process. This can include checks to ensure that the generated queries are syntactically correct and that they adhere to any constraints or limitations imposed by the data sources. For example, the anomaly detection system can validate that date ranges are within acceptable limits and that required fields are not left empty. After generating the queries, the anomaly detection system can execute them in parallel to retrieve the data over the time period from the various sources (e.g., retrieve text-based analytics from all sources **314**, as shown in FIG. **3**). The retrieved data can then

be aggregated and processed to create a comprehensive dataset that covers the specified time period.

[0057] FIG. **5** is an example of a user prompt **500**, in accordance with one or more implementations of this disclosure. As shown in FIG. **5**, a sample user prompt **502** is "Show the trend in the number of transactions for Firm-A in New York for 2024." The anomaly detection system can break down this prompt by functionalities **504** into key parameters. For example, "Show" is a parameter indicating "how" to generate the prompt, "trend" is indicative of a visual output, "number" indicates a request for a measure, "transactions" is the parameter for which the user is requesting the measure, "Firm-A" is the "who," "New York" indicates "where," and "2024" indicates "when," or the time period. As discussed above, the anomaly detection system can use these key parameters and their functionalities **504** to populate queries for the sources. As an example, query or code **410**, as shown in FIG. **4**, can include templates or sample code for querying the sources, and the anomaly detection system can utilize the query or code **410** in conjunction with the key parameters and functionalities, as shown in FIG. **3**, to generate the queries.

[0058] Once the anomaly detection system has executed the queries to the sources and received the data, the anomaly detection system can generate the second plurality of tokens based on the data over the time period (e.g., tokenize text from text-based analytics from all sources **316**, as shown in FIG. **3**). For example, the anomaly detection system can tokenize the data over the time period to extract a second plurality of keywords within the data over the time period. As previously discussed, the tokens can be words, phrases, symbols, or other meaningful elements that are used to break down and analyze text. Tokenizing the retrieved data can involve breaking down the data over the time period into discrete tokens. This can involve identifying and extracting keywords, phrases, or other significant elements from the text. The anomaly detection system can use these tokens to perform a comparison of the first plurality of tokens and the second plurality of tokens. Based on the comparison, the anomaly detection system can accept or reject the output of the AI model.

[0059] Validation techniques relating to LLMs are described in U.S. patent application Ser. No. 18/907,414, filed Oct. 4, 2024, entitled "DYNAMIC INPUT-SENSITIVE VALIDATION OF MACHINE LEARNING MODEL OUTPUTS AND METHODS AND SYSTEMS OF THE SAME," and U.S. patent application Ser. No. 18/951,120, filed Nov. 18, 2024, entitled "DYNAMIC EVALUATION OF LANGUAGE MODEL PROMPTS FOR MODEL SELECTION AND OUTPUT VALIDATION AND METHODS AND SYSTEMS OF THE SAME," which are hereby incorporated by reference. For example, the system can evaluate an LLM output for accuracy, security, safety (e.g., with respect to associated policies, requirements, or criteria), compliance (e.g., compliance with regulations, rules, guidelines, etc.), and/or other requirements/recommendations. In response to validating the generated output, the data generation platform can transmit this information to an associated data store or deployment system (e.g., any relevant consumer of the generated data, such as a server that is accessible to the user). The anomaly detection system can use any of these techniques to validate or assess outputs from the AI model.

[0060] In some implementations, the anomaly detection system can perform a comparison of the first plurality of tokens and the second plurality of tokens to determine a match accuracy. In some implementations, the anomaly detection system uses one-to-one matching of tokens. One-to-one matching between tokens involves directly comparing each token from the first set of tokens to a corresponding token in the second set to determine if they are identical or sufficiently similar. This method ensures that each token in one set has a unique counterpart in the other set. The process begins by aligning the tokens based on their positions or predefined criteria, ensuring that the first token in the first set is compared to the first token in the second set, the second token to the second token, and so on. This alignment can be particularly useful in structured data where the order of tokens is significant, such as in time-series data or sequences of events. Once aligned, each pair of tokens is compared using exact matching or similarity metrics like cosine similarity, Jaccard similarity, or Levenshtein distance. Exact matching checks if the tokens are identical, while similarity metrics allow for a degree of variation, accounting for minor differences in spelling or phrasing. One-to-one matching is highly effective in scenarios where the sequence and position of tokens are crucial, as it preserves the structural integrity of the data. However, it can be less flexible in handling cases where tokens can be reordered or where there are insertions or deletions.

[0061] In some implementations, to perform the comparison, the anomaly detection system can compare a first plurality of keywords extracted from the output or the plurality of text-based analytics and a second plurality of keywords extracted from the data over the time period. These keywords represent the most significant terms and concepts within the text, providing a basis for comparison. Next, the anomaly detection system can apply various text analysis techniques to refine the keyword extraction process. This can include removing stop words (common words that do not carry significant meaning, such as "and," "the," "is"), stemming or lemmatizing words to their root forms (e.g., "running" to "run"), and identifying named entities (e.g., company names, locations, dates). By refining the keywords in this manner, the anomaly detection system ensures that the comparison focuses on the most relevant and meaningful terms.

[0062] Once the keywords are extracted and refined, the anomaly detection system can perform a similarity analysis to compare the first plurality of keywords (e.g., from the output) with the second plurality of keywords (e.g., from the sources). This can involve calculating various similarity metrics, such as cosine similarity, Jaccard similarity, or Levenshtein distance. These metrics quantify the degree of overlap or similarity between the two sets of keywords, providing a measure of match accuracy. For example, cosine similarity measures the cosine of the angle between two non-zero vectors of an inner product space, which in this case are the keyword vectors. A cosine similarity score close to 1 indicates a high degree of similarity, while a score close to 0 indicates low similarity. Jaccard similarity measures the size of the intersection divided by the size of the union of the two sets of keywords, providing a ratio that reflects the overlap between the sets. Levenshtein distance calculates the minimum number of single-character edits (insertions, deletions, or substitutions) required to change one word into the other, providing a measure of the difference between the

keywords. By applying these similarity metrics, the anomaly detection system can determine the match accuracy between the first and second pluralities of keywords. A high match accuracy indicates that the output closely aligns with the data retrieved over the time period, suggesting that the information is consistent and reliable. Conversely, a low match accuracy can indicate discrepancies or anomalies, prompting further investigation or validation.

[0063] In some implementations, the anomaly detection system can categorize the keywords according to importance or other criteria. The anomaly detection system can begin by categorizing the extracted keywords based on their contextual relevance and importance. For example, the first category of keywords might include critical terms such as company names, product names, or specific financial metrics that are directly related to the user prompt. The anomaly detection system can then identify the first subset of keywords from the output and the second subset of keywords from the data that belong to this first category. Using similarity metrics such as cosine similarity or Jaccard similarity, the anomaly detection system can calculate the first similarity score between these two subsets. This score is then compared against a predefined first similarity threshold, which represents the minimum acceptable level of similarity for the keywords in this category. If the first similarity score meets or exceeds the threshold, it indicates that the keywords in the first category are sufficiently aligned between the output and the data.

[0064] Similarly, to determine a second category of keywords for which a second similarity between a third subset of keywords of the first plurality of keywords and a fourth subset of keywords of the second plurality of keywords must satisfy a second similarity threshold, the third subset of keywords and the fourth subset of keywords belonging to the second category, the anomaly detection system can categorize another set of keywords based on different contextual criteria. The second category might include supporting terms such as dates, locations, or general descriptors that provide additional context but are not as critical as the first category. The anomaly detection system can then identify the third subset of keywords from the output and the fourth subset of keywords from the data that belong to this second category. The second similarity score is calculated between these two subsets using the same or different similarity metrics. This score is compared against a predefined second similarity threshold, which can be set at a different level (e.g., a lower level) than the first threshold to reflect the varying importance of the categories. Meeting or exceeding this threshold indicates that the keywords in the second category are adequately aligned.

[0065] To perform the comparison, the anomaly detection system can perform a first comparison between the first similarity of keywords in the first category with the first similarity threshold. This involves evaluating whether the calculated first similarity score for the first category of keywords meets or exceeds the predefined first similarity threshold. If the score meets the threshold, it suggests that the critical keywords are consistent between the output and the data. Next, the anomaly detection system can perform a second comparison between the second similarity and the second similarity threshold. This involves evaluating whether the calculated second similarity score for the second category of keywords meets or exceeds the predefined second similarity threshold. If this score meets the threshold, it indicates that the supporting keywords are also consistent. Finally, the anomaly detection system can determine the match accuracy based on the results of the first comparison and the second comparison. If both comparisons indicate that the similarity scores meet or exceed their respective thresholds, the overall match accuracy is considered high, suggesting that the output is reliable and consistent with the data. If either comparison fails to meet the threshold, the match accuracy is considered lower, indicating potential discrepancies or anomalies that can require further investigation. This multi-tiered comparison approach ensures a comprehensive evaluation of the output's alignment with the data, enhancing the reliability and accuracy of the anomaly detection process.

[0066] In addition to similarity metrics like cosine similarity, Jaccard similarity, and Levenshtein distance, there are several other methods to determine whether the first and second pluralities of tokens match. One approach is to use semantic similarity techniques, which involve understanding the meaning of the words rather than just their syntactic similarity. Techniques such as Word2Vec, GloVe, or BERT embeddings can be employed to convert words into high-dimensional vectors that capture their semantic context. By calculating the cosine similarity between these vectors, the system can determine how closely related the meanings of the tokens are. Another method is to use fuzzy matching algorithms, which can handle minor typographical errors and variations in spelling. Additionally, the use of ontology-based matching can be beneficial, where tokens are mapped to concepts in a predefined ontology or knowledge graph. This allows the system to recognize that different terms can refer to the same underlying concept (e.g., "car" and "automobile"). Contextual analysis can also be applied, where the surrounding words and phrases are analyzed to determine if the tokens are used in a similar context. This can be achieved through techniques like n-gram analysis or using advanced language models that consider the entire sentence or paragraph.

[0067] In some implementations, once the anomaly detection system performs the comparison, the anomaly detection system determines whether the match accuracy satisfies an anomaly detection threshold. This threshold represents the minimum level of similarity required for the data to be considered consistent and free of anomalies. The anomaly detection system can use various comparison techniques to calculate the match accuracy, such as those discussed above or a combination of techniques. In some implementations, the anomaly detection threshold is specific to the method or analysis used to assess the match accuracy. For example, if the anomaly detection system uses cosine similarity, it calculates the cosine of the angle between the vectors representing the first and second pluralities of tokens. A cosine similarity score close to **1** indicates a high degree of similarity, suggesting that the tokens are closely aligned. If this score meets or exceeds the predefined anomaly detection threshold, the data is considered consistent. Conversely, a score lower than the threshold indicates potential anomalies, prompting further investigation. Similarly, if the anomaly detection system employs Jaccard similarity, it measures the size of the intersection divided by the size of the union of the two sets of tokens. A high Jaccard similarity score indicates substantial overlap between the sets, while a low score suggests discrepancies. The anomaly detection system compares this score against the anomaly detection

threshold to determine if the data is reliable. Using Levenshtein distance, the anomaly detection system calculates the minimum number of single-character edits required to transform one token set into the other. A low Levenshtein distance indicates high similarity, while a high distance points to significant differences. The anomaly detection system assesses whether the calculated distance falls within the acceptable range defined by the anomaly detection threshold.

[0068] Based on the match accuracy failing to satisfy the anomaly detection threshold, the anomaly detection system can reject the output of the AI model. This rejection process involves several steps to ensure that the output is thoroughly evaluated and the reasons for rejection are clearly documented. First, the anomaly detection system can log the specific areas where the output failed to meet a threshold, such as discrepancies in key data points, inconsistencies in the information, or significant deviations from the validated sources. For example, if the AI model's output includes financial metrics that do not align with the data retrieved from trusted financial databases, the anomaly detection system can highlight these discrepancies. The subsystem can then generate a detailed report outlining the reasons for rejection, including the specific tokens or data points that contributed to the low match accuracy. This report can be used for further analysis and review by human experts, who can investigate the anomalies and determine the appropriate corrective actions. Additionally, the anomaly detection system can provide feedback to the AI model, indicating the areas that need improvement. This feedback loop can help refine the model's training and improve its future outputs. By rejecting outputs that fail to meet the anomaly detection threshold, the anomaly detection system ensures that only accurate and reliable information is included in the final report, maintaining the integrity and trustworthiness of the data.

[0069] Based on the match accuracy satisfying the anomaly detection threshold, the anomaly detection system can approve the output of the AI model for inclusion in the report requested by the user prompt. This approval process involves validating that the output meets the required standards of accuracy and consistency. Once the match accuracy is confirmed to be above the threshold, the subsystem can generate a summary of the validation process, including the similarity scores and the comparison techniques used. For example, if the output includes a trend analysis of stock prices, the anomaly detection system can document the cosine similarity scores between the generated output and the validated financial data. The approved output can then be formatted and integrated into the final report, ensuring that it aligns with the user's requirements and the overall structure of the report. The anomaly detection system can also store the approved output and the validation summary in a structured repository, making it available for future reference and audits. This repository can include metadata such as the date of approval, the user prompt, and the sources used for validation. By approving outputs that meet the anomaly detection threshold, the anomaly detection system ensures that the final report is comprehensive, accurate, and reliable.

[0070] FIG. **6** is a flowchart **600** of operations for detecting anomalies in model outputs, in accordance with one or more implementations of this disclosure. The operations of FIG. **6** can use components described in relation to FIG. **6**. In some implementations, the anomaly detection system **160** can include one or more components of computer system **800**, as shown in FIG. **8**.

[0071] At operation **602**, the anomaly detection system **160** (e.g., using one or more of processors **810***a*-**810***n*) can receive a user prompt indicating a request for data over a time period. For example, a user can input a prompt such as "Show the trend in the number of transactions for Firm-A in New York for 2024." This prompt specifics the type of data requested (number of transactions), the entity of interest (Firm-A), the location (New York), and the time period (2024). One or more of processors **810***a*-**810***n* can receive the user prompt over the communication network **140** using network interface **640**.

[0072] At operation **604**, the anomaly detection system **160** (e.g., using one or more of processors **810***a*-**810***n*) can input, into an AI model, the user prompt to cause the AI model to generate an output based on the user prompt. For example, if the user prompt is "Show the trend in the number of transactions for Firm-A in New York for 2024," the system can feed this prompt into the AI model. The output can include a narrative description of the transaction trends, statistical summaries, and visualizations such as graphs or charts. For instance, the model can produce a line graph showing the monthly transaction volumes for Firm-A in New York throughout 2024, accompanied by a textual analysis highlighting any significant trends or anomalies observed in the data. The AI model can also incorporate relevant contextual information to enhance the output. For example, it can include insights on external factors that could have influenced the transaction trends, such as economic conditions, regulatory changes, or significant events related to Firm-A.

[0073] At operation **606**, the anomaly detection system **160** (e.g., using one or more of processors **810***a*-**810***n*) can generate a first plurality of tokens based on the output. This process involves breaking down the generated output into smaller, manageable units of information, known as tokens. These tokens can represent individual words, phrases, or key data points that capture the essential elements of the output. For example, if the output is a detailed report on the trend in the number of transactions for Firm-A in New York for 2024, the tokens can include terms like "Firm-A," "New York," "2024," "transactions," "trend," and specific numerical values or dates mentioned in the report.

[0074] At operation **608**, the anomaly detection system **160** (e.g., using one or more of processors **810***a*-**810***n*) can retrieve, based on the user prompt, a plurality of sources relating to the data requested by the user prompt. This retrieval process involves accessing various databases, repositories, and information sources that are relevant to the parameters specified in the user prompt. For example, if the user prompt requests data on the trend in the number of transactions for Firm-A in New York for **2024**, the system can query financial databases, transaction logs, and business intelligence platforms to gather the necessary data.

[0075] At operation **610**, the anomaly detection system **160** (e.g., using one or more of processors **810***a*-**810***n*) can generate a plurality of queries to request, from the plurality of sources, the data over the time period. This can involve creating specific and structured queries tailored to each data source's format and retrieval protocols. For example, if the user prompt is to analyze the trend in the number of transactions for Firm-A in New York for 2024, the system

can generate SQL queries for relational databases, API requests for web services, and web scraping scripts for online articles and reports.

[0076] At operation **612**, the anomaly detection system **160** (e.g., using one or more of processors **810***a*-**810***n*) can generate a second plurality of tokens based on the data over the time period. This can involve breaking down the retrieved data into smaller, manageable units of information, known as tokens. These tokens can represent individual words, phrases, or key data points that capture the essential elements of the data. For example, if the retrieved data includes transaction records for Firm-A in New York for 2024, the tokens can include terms like "Firm-A," "New York," "2024," "transactions," specific transaction counts, and dates.

[0077] At operation **614**, the anomaly detection system **160** (e.g., using one or more of processors **810***a*-**810***n*) can perform a comparison of the first plurality of tokens and the second plurality of tokens. This comparison process involves evaluating the similarity and alignment between the tokens generated from the AI model's output and the tokens generated from the retrieved data. The system can use various similarity metrics and algorithms to perform this comparison, such as cosine similarity, Jaccard similarity, and Levenshtein distance.

[0078] At operation **616**, the anomaly detection system **160** (e.g., using one or more of processors **810***a*-**810***n*) can, based on the comparison, accept or reject the output of the AI model. This decision is made by evaluating whether the match accuracy between the first plurality of tokens (from the AI model's output) and the second plurality of tokens (from the retrieved data) meets the predefined anomaly detection threshold. If the match accuracy satisfies the threshold, indicating that the output is consistent and reliable, the system can accept the output. This accepted output can then be included in the final report or used for further analysis as requested by the user prompt.

[0079] FIG. **7** is a block diagram **700** of an example transformer **712** used to detect anomalies in generative outputs, in accordance with one or more implementations of this disclosure. A transformer is a type of neural network architecture that uses self-attention mechanisms to generate predicted output based on input data that has some sequential meaning (e.g., the order of the input data is meaningful, which is the case for most text input). Self-attention is a mechanism that relates different positions of a single sequence to compute a representation of the same sequence. Although transformer-based language models are described herein, the present disclosure can be applicable to any machine learning-based language model, including language models based on other neural network architectures, such as RNN-based language models.

[0080] The transformer **712** includes an encoder **708** (which can include one or more encoder layers/blocks connected in series) and a decoder **710** (which can include one or more decoder layers/blocks connected in series). Generally, the encoder **708** and the decoder **710** each include multiple neural network layers, at least one of which can be a self-attention layer. The parameters of the neural network layers can be referred to as the parameters of the language model.

[0081] The transformer **712** can be trained to perform certain functions on a natural language input. Examples of the functions include summarizing existing content, brainstorming ideas, writing a rough draft, fixing spelling and grammar, and translating content. Summarizing can include extracting key points or themes from existing content in a high-level summary. Brainstorming ideas can include generating a list of ideas based on provided input. For example, the machine learning model can generate a list of names for a startup or costumes for an upcoming party. Writing a rough draft can include generating writing in a particular style that could be useful as a starting point for the user's writing. The style can be identified as, e.g., an email, a blog post, a social media post, or a poem. Fixing spelling and grammar can include correcting errors in an existing input text. Translating can include converting an existing input text into a variety of different languages. In some implementations, the transformer **712** is trained to perform certain functions on input formats other than natural language input. For example, the input can include objects, images, audio content, or video content, or a combination thereof.

[0082] The transformer **712** can be trained on a text corpus that is labeled (e.g., annotated to indicate verbs, nouns) or unlabeled. LLMs can be trained on a large unlabeled corpus. The term "language model," as used herein, can include a machine learning-based language model (e.g., a language model that is implemented using a neural network or other machine learning architecture), unless stated otherwise. Some LLMs can be trained on a large multi-language, multi-domain corpus to enable the model to be versatile at a variety of language-based tasks such as generative tasks (e.g., generating human-like natural language responses to natural language input).

[0083] FIG. **7** illustrates an example block diagram **700** of how the transformer **712** can process textual input data. Input to a language model (whether transformer-based or otherwise) typically is in the form of natural language that can be parsed into tokens. The term "token" in the context of language models and NLP has a different meaning from the use of the same term in other contexts, such as data security. Tokenization, in the context of language models and NLP, refers to the process of parsing textual input (e.g., a character, a word, a phrase, a sentence, a paragraph) into a sequence of shorter segments that are converted to numerical representations referred to as tokens (or "compute tokens"). Typically, a token can be an integer that corresponds to the index of a text segment (e.g., a word) in a vocabulary dataset. Often, the vocabulary dataset is arranged by frequency of use. Commonly occurring text, such as punctuation, can have a lower vocabulary index in the dataset and thus be represented by a token having a smaller integer value than less commonly occurring text. Tokens frequently correspond to words, with or without white space appended. In some implementations, a token can correspond to a portion of a word.

[0084] For example, the word "greater" can be represented by a token for [great] and a second token for [er]. In another example, the text sequence "write a summary" can be parsed into the segments [write], [a], and [summary], each of which can be represented by a respective numerical token. In addition to tokens that are parsed from the textual sequence (e.g., tokens that correspond to words and punctuation), there can also be special tokens to encode non-textual information. For example, a [CLASS] token can be a special token that corresponds to a classification of the textual sequence (e.g., can classify the textual sequence as a list, a paragraph), an [EOT] token can be another special token that

indicates the end of the textual sequence, other tokens can provide formatting information, etc.

[0085] As shown in the example **700**, a short sequence of tokens **702** corresponding to the input text is illustrated as input to the transformer **712**. Tokenization of the text sequence into the tokens **702** can be performed by some pre-processing tokenization module such as, for example, a byte-pair encoding tokenizer (the "pre" referring to the tokenization occurring prior to the processing of the tokenized input by the LLM), which is not shown in FIG. **6** for brevity. In general, the token sequence that is inputted to the transformer **712** can be of any length up to a maximum length defined based on the dimensions of the transformer **712**. Each token **702** in the token sequence is converted into an embedding **706** (also referred to as "embedding vector").

[0086] An embedding **706** is a learned numerical representation (such as, for example, a vector) of a token that captures some semantic meaning of the text segment represented by the token **702**. The embedding **706** represents the text segment corresponding to the token **702** in a way such that embeddings corresponding to semantically related text are closer to each other in a vector space than embeddings corresponding to semantically unrelated text. For example, assuming that the words "write," "a," and "summary" each correspond to, respectively, a "write" token, an "a" token, and a "summary" token when tokenized, the embedding **706** corresponding to the "write" token will be closer to another embedding corresponding to the "jot down" token in the vector space as compared to the distance between the embedding **706** corresponding to the "write" token and another embedding corresponding to the "summary" token.

[0087] The vector space can be defined by the dimensions and values of the embedding vectors. Various techniques can be used to convert a token **702** to an embedding **706**. For example, another trained machine learning model can be used to convert the token **702** into an embedding **706**. In particular, another trained machine learning model can be used to convert the token **702** into an embedding **706** in a way that encodes additional information into the embedding **706** (e.g., a trained machine learning model can encode positional information about the position of the token **702** in the text sequence into the embedding **706**). In some implementations, the numerical value of the token **702** can be used to look up the corresponding embedding in an embedding matrix **704**, which can be learned during training of the transformer **712**.

[0088] The generated embeddings, e.g., such as the embedding **706**, are input into the encoder **708**. The encoder **708** serves to encode the embedding **706** into feature vectors **714** that represent the latent features of the embedding **706**. The encoder **708** can encode positional information (i.e., information about the sequence of the input) in the feature vectors **714**. The feature vectors **714** can have very high dimensionality (e.g., on the order of thousands or tens of thousands), with each clement in a feature vector corresponding to a respective feature. The numerical weight of each clement in a feature vector represents the importance of the corresponding feature. The space of all possible feature vectors, e.g., such as the feature vectors **714**, that can be generated by the encoder **708** can be referred to as a latent space or feature space.

[0089] Conceptually, the decoder **710** is designed to map the features represented by the feature vectors **714** into meaningful output, which can depend on the task that was assigned to the transformer **712**. For example, if the transformer **712** is used for a translation task, the decoder **710** can map the feature vectors **714** into text output in a target language different from the language of the original tokens **702**. Generally, in a generative language model, the decoder **710** serves to decode the feature vectors **714** into a sequence of tokens. The decoder **710** can generate output tokens **716** one by one. Each output token **716** can be fed back as input to the decoder **710** in order to generate the next output token **716**. By feeding back the generated output and applying self-attention, the decoder **710** can generate a sequence of output tokens **716** that has sequential meaning (e.g., the resulting output text sequence is understandable as a sentence and obeys grammatical rules). The decoder **710** can generate output tokens **716** until a special [EOT] token (indicating the end of the text) is generated. The resulting sequence of output tokens **716** can then be converted to a text sequence in post-processing. For example, each output token **716** can be an integer number that corresponds to a vocabulary index. By looking up the text segment using the vocabulary index, the text segment corresponding to each output token **716** can be retrieved, the text segments can be concatenated together, and the final output text sequence can be obtained.

[0090] In some implementations, the input provided to the transformer **712** includes instructions to perform a function on an existing text. The output can include, for example, a modified version of the input text and instructions to modify the text. The modification can include summarizing, translating, correcting grammar or spelling, changing the style of the input text, lengthening or shortening the text, or changing the format of the text (e.g., adding bullet points or checkboxes). As an example, the input text can include meeting notes prepared by a user and the output can include a high-level summary of the meeting notes. In other examples, the input provided to the transformer includes a question or a request to generate text. The output can include a response to the question, text associated with the request, or a list of ideas associated with the request. For example, the input can include the question "What is the weather like in San Francisco?" and the output can include a description of the weather in San Francisco. As another example, the input can include a request to brainstorm names for a flower shop and the output can include a list of relevant names.

[0091] Although a general transformer architecture for a language model and its theory of operation have been described above, this is not intended to be limiting. Existing language models include language models that are based only on the encoder of the transformer or only on the decoder of the transformer. An encoder-only language model encodes the input text sequence into feature vectors that can then be further processed by a task-specific layer (e.g., a classification layer). BERT is an example of a language model that can be considered to be an encoder-only language model. A decoder-only language model accepts embeddings as input and can use auto-regression to generate an output text sequence. Transformer-XL and GPT-type models can be language models that are considered to be decoder-only language models.

[0092] Because GPT-type language models tend to have a large number of parameters, these language models can be considered LLMs. An example of a GPT-type LLM is GPT-**3**. GPT-**3** is a type of GPT language model that has been trained (in an unsupervised manner) on a large corpus

derived from documents available online to the public. GPT-3 has a very large number of learned parameters (on the order of hundreds of billions), can accept a large number of tokens as input (e.g., up to 2,047 input tokens), and is able to generate a large number of tokens as output (e.g., up to 2,047 tokens). GPT-3 has been trained as a generative model, meaning that it can process input text sequences to predictively generate a meaningful output text sequence. ChatGPT is built on top of a GPT-type LLM and has been fine-tuned with training datasets based on text-based chats (e.g., chatbot conversations). ChatGPT is designed for processing natural language, receiving chat-like inputs, and generating chat-like outputs.

[0093] A computer system can access a remote language model (e.g., a cloud-based language model), such as ChatGPT or GPT-3, via a software interface (e.g., an API). Additionally or alternatively, such a remote language model can be accessed via a network such as the internet. In some implementations, such as, for example, potentially in the case of a cloud-based language model, a remote language model can be hosted by a computer system that can include a plurality of cooperating (e.g., cooperating via a network) computer systems that can be in, for example, a distributed arrangement. Notably, a remote language model can employ multiple processors (e.g., hardware processors such as, for example, processors of cooperating computer systems). Indeed, processing of inputs by an LLM can be computationally expensive or can involve a large number of operations (e.g., many instructions can be executed/large data structures can be accessed from memory), and providing output in a required timeframe (e.g., real time or near real time) can require the use of a plurality of processors/cooperating computing devices as discussed above.

[0094] Input(s) to an LLM can be referred to as a prompt, which is a natural language input that includes instructions to the LLM to generate a desired output. A computer system can generate a prompt that is provided as input to the LLM via an API. As described above, the prompt can optionally be processed or pre-processed into a token sequence prior to being provided as input to the LLM via its API. A prompt can include one or more examples of the desired output, which provides the LLM with additional information to enable the LLM to generate output according to the desired output. Additionally or alternatively, the examples included in a prompt can provide inputs (e.g., example inputs) corresponding to/as can be expected to result in the desired outputs provided. A one-shot prompt refers to a prompt that includes one example, and a few-shot prompt refers to a prompt that includes multiple examples. A prompt that includes no examples can be referred to as a zero-shot prompt.

[0095] Although the present invention has been described in detail for the purpose of illustration based on what is currently considered to be the most practical and preferred implementations, it is to be understood that such detail is solely for that purpose and that the invention is not limited to the disclosed implementations, but, on the contrary, is intended to cover modifications and equivalent arrangements that are within the scope of the appended claims. For example, it is to be understood that the present invention contemplates that, to the extent possible, one or more features of any implementation can be combined with one or more features of any other implementation.

[0096] The above-described implementations of the present disclosure are presented for purposes of illustration, not of limitation, and the present disclosure is limited only by the claims which follow. Furthermore, it should be noted that the features and limitations described in any one implementation can be applied to any other implementation herein, and flowcharts or examples relating to one implementation can be combined with any other implementation in a suitable manner, done in different orders, or done in parallel. In addition, the systems and methods described herein can be performed in real time. It should also be noted that the systems or methods described above can be applied to, or used in accordance with, other systems or methods.

[0097] FIG. **8** shows an example computing system that can be used in accordance with some implementations of this disclosure. In some instances, computing system **800** is referred to as a computer system **800**. A person skilled in the art would understand that those terms can be used interchangeably. The components of FIG. **8** can be used to perform some or all operations discussed in relation to FIGS. **1-7**. Furthermore, various portions of the systems and methods described herein can include or be executed on one or more computer systems similar to computing system **800**. Further, processes and modules described herein can be executed by one or more processing systems similar to that of computing system **800**.

[0098] Computing system **800** can include one or more processors (e.g., processors **810***a*-**810***n*) coupled to system memory **820**, an input/output (I/O) device interface **830**, and a network interface **840** via an I/O interface **850**. A processor can include a single processor or a plurality of processors (e.g., distributed processors). A processor can be any suitable processor capable of executing or otherwise performing instructions. A processor can include a central processing unit (CPU) that carries out program instructions to perform the arithmetical, logical, and I/O operations of computing system **800**. A processor can execute code (e.g., processor firmware, a protocol stack, a database management system, an operating system, or a combination thereof) that creates an execution environment for program instructions.

[0099] A processor can include a programmable processor. A processor can include general or special purpose microprocessors. A processor can receive instructions and data from a memory (e.g., system memory **820**). Computing system **800** can be a uni-processor system including one processor (e.g., processor **810***a*), or a multiprocessor system including any number of suitable processors (e.g., **810***a*-**810***n*). Multiple processors can be employed to provide for parallel or sequential execution of one or more portions of the techniques described herein. Processes, such as logic flows, described herein can be performed by one or more programmable processors executing one or more computer programs to perform functions by operating on input data and generating corresponding output. Processes described herein can be performed by, and apparatus can also be implemented as, special purpose logic circuitry, e.g., an FPGA (field-programmable gate array) or an ASIC (application-specific integrated circuit). Computing system **800** can include a plurality of computing devices (e.g., distributed computer systems) to implement various processing functions.

[0100] V/O device interface **830** can provide an interface for connection of one or more I/O devices **860** to computer system **800**. I/O devices can include devices that receive

input (e.g., from a user) or output information (e.g., to a user). I/O devices **860** can include, for example, a graphical user interface presented on displays (e.g., a cathode ray tube (CRT) or liquid crystal display (LCD) monitor), pointing devices (e.g., a computer mouse or trackball), keyboards, keypads, touchpads, scanning devices, voice recognition devices, gesture recognition devices, printers, audio speakers, microphones, cameras, or the like. I/O devices **860** can be connected to computer system **800** through a wired or wireless connection. I/O devices **860** can be connected to computer system **800** from a remote location. I/O devices **860** located on remote computer systems, for example, can be connected to computer system **800** via a network and network interface **840**.

[0101] The I/O device interface **830** and I/O devices **860** can be used to enable manipulation of the three-dimensional model as well. For example, the user can be able to use I/O devices such as a keyboard and touchpad to indicate specific selections for nodes, adjust values for nodes, select from the history of machine learning models, select specific inputs or outputs, or the like. Alternatively or additionally, the user can use their voice to indicate specific nodes, specific models, or the like via the voice recognition device or microphones.

[0102] Network interface **840** can include a network adapter that provides for connection of computer system **800** to a network. Network interface **840** can facilitate data exchange between computer system **800** and other devices connected to the network. Network interface **840** can support wired or wireless communication. The network can include an electronic communication network, such as the internet, a LAN, a WAN, a cellular communications network, or the like.

[0103] System memory **820** can be configured to store program instructions **870** or data **880**. Program instructions **870** can be executable by a processor (e.g., one or more of processors **810***a*-**810***n*) to implement one or more implementations of the present techniques. Program instructions **870** can include modules of computer program instructions for implementing one or more techniques described herein with regard to various processing modules. Program instructions can include a computer program (which in certain forms is known as a program, software, software application, script, or code). A computer program can be written in a programming language, including compiled or interpreted languages, or declarative or procedural languages. A computer program can include a unit suitable for use in a computing environment, including as a stand-alone program, a module, a component, or a subroutine. A computer program can correspond to a file in a file system. A program can be stored in a portion of a file that holds other programs or data (e.g., one or more scripts stored in a markup language document), in a single file dedicated to the program in question, or in multiple coordinated files (e.g., files that store one or more modules, subprograms, or portions of code). A computer program can be deployed to be executed on one or more computer processors located locally at one site or distributed across multiple remote sites and interconnected by a communication network.

[0104] System memory **820** can include a tangible program carrier having program instructions stored thereon. A tangible program carrier can include a non-transitory, computer-readable storage medium. A non-transitory, computer-readable storage medium can include a machine-readable storage device, a machine-readable storage substrate, a memory device, or any combination thereof. A non-transitory, computer-readable storage medium can include non-volatile memory (e.g., flash memory, ROM, PROM, EPROM, EEPROM), volatile memory (e.g., random access memory (RAM), static random access memory (SRAM), synchronous dynamic RAM (SDRAM)), bulk storage memory (e.g., CD-ROM or DVD-ROM, hard drives), or the like. System memory **820** can include a non-transitory, computer-readable storage medium that can have program instructions stored thereon that are executable by a computer processor (e.g., one or more of processors **810***a*-**810***n*) to cause the subject matter and the functional operations described herein. A memory (e.g., system memory **820**) can include a single memory device or a plurality of memory devices (e.g., distributed memory devices).

[0105] I/O interface **850** can be configured to coordinate I/O traffic between processors **810***a*-**810***n*, system memory **820**, network interface **840**, I/O devices **860**, or other peripheral devices. I/O interface **850** can perform protocol, timing, or other data transformations to convert data signals from one component (e.g., system memory **820**) into a format suitable for use by another component (e.g., processors **810***a*-**810***n*). I/O interface **850** can include support for devices attached through various types of peripheral buses, such as a variant of the Peripheral Component Interconnect (PCI) bus standard or the Universal Serial Bus (USB) standard.

[0106] Implementations of the techniques described herein can be implemented using a single instance of computer system **800** or multiple computer systems **800** configured to host different portions or instances of implementations. Multiple computer systems **800** can provide for parallel or sequential processing/execution of one or more portions of the techniques described herein.

[0107] Those skilled in the art will appreciate that computer system **800** is merely illustrative and is not intended to limit the scope of the techniques described herein. Computer system **800** can include any combination of devices or software that can perform or otherwise provide for the performance of the techniques described herein. For example, computer system **800** can include or be a combination of a cloud-computing system, a data center, a server rack, a server, a virtual server, a desktop computer, a laptop computer, a tablet computer, a server device, a client device, a mobile telephone, a personal digital assistant (PDA), a mobile audio or video player, a game console, a vehicle-mounted computer, a Global Positioning System (GPS), or the like. Computer system **800** can also be connected to other devices that are not illustrated or can operate as a stand-alone system. In addition, the functionality provided by the illustrated components may, in some implementations, be combined in fewer components, or be distributed in additional components. Similarly, in some implementations, the functionality of some of the illustrated components may not be provided, or other additional functionality can be available.

Conclusion

[0108] Unless the context clearly requires otherwise, throughout the description and the claims, the words "comprise," "comprising," and the like are to be construed in an inclusive sense, as opposed to an exclusive or exhaustive sense; that is to say, in the sense of "including, but not

limited to." As used herein, the terms "connected," "coupled," or any variant thereof means any connection or coupling, either direct or indirect, between two or more elements; the coupling or connection between the elements can be physical, logical, or a combination thereof. Additionally, the words "herein," "above," "below," and words of similar import, when used in this application, refer to this application as a whole and not to any particular portions of this application. Where the context permits, words in the above Detailed Description using the singular or plural number can also include the plural or singular number, respectively. The word "or," in reference to a list of two or more items, covers all of the following interpretations of the word: any of the items in the list, all of the items in the list, and any combination of the items in the list.

[0109] The above Detailed Description of examples of the technology is not intended to be exhaustive or to limit the technology to the precise form disclosed above. While specific examples of the technology are described above for illustrative purposes, various equivalent modifications are possible within the scope of the technology, as those skilled in the relevant art will recognize. For example, while processes or blocks are presented in a given order, alternative implementations can perform routines having steps, or employ systems having blocks, in a different order, and some processes or blocks can be deleted, moved, added, subdivided, combined, and/or modified to provide alternative or sub-combinations. Each of these processes or blocks can be implemented in a variety of different ways. Also, while processes or blocks are at times shown as being performed in series, these processes or blocks can instead be performed or implemented in parallel, or can be performed at different times. Further, any specific numbers noted herein are only examples: alternative implementations can employ differing values or ranges.

[0110] The teachings of the technology provided herein can be applied to other systems, not necessarily the system described above. The elements and acts of the various examples described above can be combined to provide further implementations of the technology. Some alternative implementations of the technology not only can include additional elements to those implementations noted above, but also can include fewer elements.

[0111] These and other changes can be made to the technology in light of the above Detailed Description. While the above description describes certain examples of the technology, and describes the best mode contemplated, no matter how detailed the above appears in text, the technology can be practiced in many ways. Details of the system can vary considerably in its specific implementation, while still being encompassed by the technology disclosed herein. As noted above, specific terminology used when describing certain features or aspects of the technology should not be taken to imply that the terminology is being redefined herein to be restricted to any specific characteristics, features, or aspects of the technology with which that terminology is associated. In general, the terms used in the following claims should not be construed to limit the technology to the specific examples disclosed in the specification, unless the above Detailed Description section explicitly defines such terms. Accordingly, the actual scope of the technology encompasses not only the disclosed examples, but also all equivalent ways of practicing or implementing the technology under the claims.

[0112] To reduce the number of claims, certain aspects of the technology are presented below in certain claim forms, but the applicant contemplates the various aspects of the technology in any number of claim forms. For example, while only one aspect of the technology is recited as a computer-readable medium claim, other aspects can likewise be embodied as a computer-readable medium claim, or in other forms, such as being embodied in a means-plus-function claim. Any claims intended to be treated under 35 U.S.C. § 112 (f) will begin with the words "means for," but use of the term "for" in any other context is not intended to invoke treatment under 35 U.S.C. § 112 (f). Accordingly, the applicant reserves the right to pursue additional claims after filing this application to pursue such additional claim forms, either in this application or in a continuing application.

We claim:

1. One or more non-transitory, computer-readable storage medium comprising instructions recorded thereon, wherein the instructions, when executed by at least one data processor of a system, cause the system to:

receive a user prompt indicating a request for a report summarizing data over a time period;

generate a first plurality of tokens by causing the system to:

input, into a generative model, the user prompt to cause the generative model to generate an output based on the user prompt, the output comprising a plurality of text-based analytics and a plurality of visual analytics based on the user prompt;

apply a text filter to the output to generate a modified output comprising the plurality of text-based analytics and excluding the plurality of visual analytics; and

generate the first plurality of tokens based on the plurality of text-based analytics;

generate a second plurality of tokens by causing the system to:

retrieve, based on the user prompt, a plurality of sources relating to the data requested by the user prompt;

generate a plurality of queries to request, from the plurality of sources, the data over the time period; and

generate the second plurality of tokens based on the data over the time period;

perform a comparison of the first plurality of tokens and the second plurality of tokens to determine a match accuracy;

determine whether the match accuracy satisfies an anomaly detection threshold; and

based on the match accuracy failing to satisfy the anomaly detection threshold, reject the output of the generative model.

2. The one or more non-transitory, computer-readable storage medium of claim **1**, wherein the system is further caused to, based on the match accuracy satisfying the anomaly detection threshold, approve the output of the generative model for inclusion in the report requested by the user prompt.

3. The one or more non-transitory, computer-readable storage medium of claim **1**, wherein, to generate the first plurality of tokens, the instructions further cause the system

to tokenize the plurality of text-based analytics to extract a first plurality of keywords within the plurality of text-based analytics.

4. The one or more non-transitory, computer-readable storage medium of claim **1**, wherein, to generate the second plurality of tokens, the instructions further cause the system to tokenize the data over the time period to extract a second plurality of keywords within the data over the time period.

5. The one or more non-transitory, computer-readable storage medium of claim **1**, wherein, to perform the comparison, the instructions further cause the system to compare a first plurality of keywords extracted from the plurality of text-based analytics and a second plurality of keywords extracted from the data over the time period.

6. The one or more non-transitory, computer-readable storage medium of claim **5**, wherein the instructions further cause the system to:

determine a first category of keywords for which a first similarity between a first subset of keywords of the first plurality of keywords and a second subset of keywords of the second plurality of keywords must satisfy a first similarity threshold, the first subset of keywords and the second subset of keywords belonging to the first category;

determine a second category of keywords for which a second similarity between a third subset of keywords of the first plurality of keywords and a fourth subset of keywords of the second plurality of keywords must satisfy a second similarity threshold, the third subset of keywords and the fourth subset of keywords belonging to the second category; and

wherein, to perform the comparison, the instructions further cause the system to:

perform a first comparison between the first similarity and the first similarity threshold;

perform a second comparison between the second similarity and the second similarity threshold; and

determine the match accuracy based on the first comparison and the second comparison.

7. A method comprising:

receiving a user prompt indicating a request for data over a time period;

generating a first plurality of tokens by:

inputting, into a generative model, the user prompt to cause the generative model to generate an output based on the user prompt, the output comprising a plurality of text-based analytics and a plurality of visual analytics based on the user prompt;

applying a text filter to the output to generate a modified output comprising the plurality of text-based analytics and excluding the plurality of visual analytics; and

generating the first plurality of tokens based on the plurality of text-based analytics;

generating a second plurality of tokens by:

retrieving, based on the user prompt, a plurality of sources relating to the data requested by the user prompt;

generating a plurality of queries to request, from the plurality of sources, the data over the time period; and

generating the second plurality of tokens based on the data over the time period;

performing a comparison of the first plurality of tokens and the second plurality of tokens; and

based on the comparison, accepting or rejecting the output of the generative model.

8. The method of claim **7**, wherein performing the comparison further comprises:

determining, based on the comparison, a match accuracy between the first plurality of tokens and the second plurality of tokens; and

determining whether the match accuracy satisfies an anomaly detection threshold,

wherein accepting or rejecting the output of the generative model based on the comparison comprises accepting or rejecting the output based on whether the match accuracy satisfies the anomaly detection threshold.

9. The method of claim **7**, wherein generating the first plurality of tokens comprises tokenizing the plurality of text-based analytics to extract a first plurality of keywords within the plurality of text-based analytics.

10. The method of claim **7**, wherein generating the second plurality of tokens comprises tokenizing the data over the time period to extract a second plurality of keywords within the data over the time period.

11. The method of claim **7**, wherein performing the comparison comprises comparing a first plurality of keywords extracted from the plurality of text-based analytics and a second plurality of keywords extracted from the data over the time period.

12. The method of claim **11**, further comprising:

determine a first category of keywords for which a first similarity between a first subset of keywords of the first plurality of keywords and a second subset of keywords of the second plurality of keywords must satisfy a first similarity threshold, the first subset of keywords and the second subset of keywords belonging to the first category; and

determine a second category of keywords for which a second similarity between a third subset of keywords of the first plurality of keywords and a fourth subset of keywords of the second plurality of keywords must satisfy a second similarity threshold, the third subset of keywords and the fourth subset of keywords belonging to the second category.

13. The method of claim **12**, wherein performing the comparison comprises:

performing a first comparison between the first similarity and the first similarity threshold;

performing a second comparison between the second similarity and the second similarity threshold; and

determine a match accuracy based on the first comparison and the second comparison.

14. A system for determining preferred routes for transferring virtual resources between nodes across networks, the system comprising:

a storage device; and

one or more processors communicatively coupled to the storage device storing instructions thereon, that cause the one or more processors to:

receive a request for data over a time period;

generate a first plurality of tokens by causing the system to:

input, into an artificial intelligence (AI) model, the user prompt to cause the AI model to generate an output based on the user prompt;

generate the first plurality of tokens based on the output;

generate a second plurality of tokens by causing the system to:

retrieve, based on the user prompt, a plurality of sources relating to the data requested by the user prompt;

generate a plurality of queries to request, from the plurality of sources, the data over the time period; and

generate the second plurality of tokens based on the data over the time period;

perform a comparison of the first plurality of tokens and the second plurality of tokens; and

based on the comparison, accept or reject the output of the AI model.

15. The system of claim **14**, wherein, to perform the comparison, the instructions further cause the one or more processors to:

determine, based on the comparison, a match accuracy between the first plurality of tokens and the second plurality of tokens; and

determine whether the match accuracy satisfies an anomaly detection threshold,

wherein, to accept or reject the output of the AI model based on the comparison, the instructions further cause the one or more processors to accept or reject the output based on whether the match accuracy satisfies the anomaly detection threshold.

16. The system of claim **14**, wherein, to generate the first plurality of tokens, the instructions further cause the one or more processors to tokenize the output to extract a first plurality of keywords within the output.

17. The system of claim **14**, wherein, to generate the second plurality of tokens, the instructions further cause the one or more processors to tokenize the data over the time period to extract a second plurality of keywords within the data over the time period.

18. The system of claim **14**, wherein, to perform the comparison, the instructions further cause the one or more processors to compare a first plurality of keywords extracted from the output and a second plurality of keywords extracted from the data over the time period.

19. The system of claim **18**, wherein the instructions further cause the one or more processors to:

determine a first category of keywords for which a first similarity between a first subset of keywords of the first plurality of keywords and a second subset of keywords of the second plurality of keywords must satisfy a first similarity threshold, the first subset of keywords and the second subset of keywords belonging to the first category; and

determine a second category of keywords for which a second similarity between a third subset of keywords of the first plurality of keywords and a fourth subset of keywords of the second plurality of keywords must satisfy a second similarity threshold, the third subset of keywords and the fourth subset of keywords belonging to the second category.

20. The system of claim **19**, wherein, to perform the comparison, the instructions further cause the one or more processors to:

perform a first comparison between the first similarity and the first similarity threshold;

perform a second comparison between the second similarity and the second similarity threshold; and

determine a match accuracy based on first comparison and the second comparison.

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