US 20250265234A1

(19) **United States**

(12) **Patent Application Publication** (10) **Pub. No.: US 2025/0265234 A1**

Chandrahasan et al. (43) **Pub. Date: Aug. 21, 2025**

(54) **MODIFYING DATA PIPELINE AND DATASET QUALITY USING DATA OBSERVABILITY**

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(21) Appl. No.: **18/581,814**

(22) Filed: **Feb. 20, 2024**

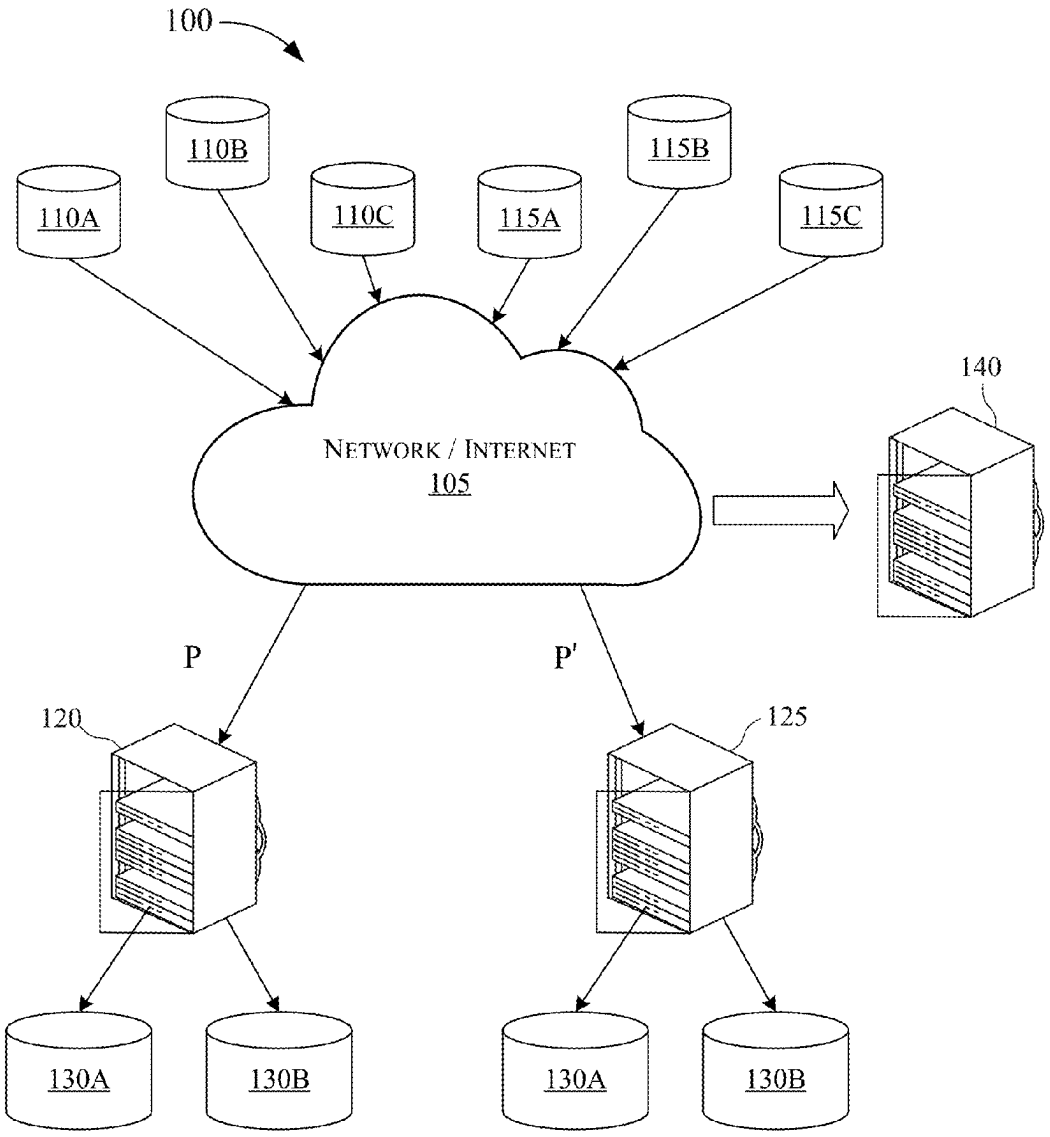
Publication Classification

(51) **Int. Cl.**
G06F 16/215 (2019.01)
G06F 16/28 (2019.01)

(52) **U.S. Cl.**
CPC ***G06F 16/215*** (2019.01); ***G06F 16/285*** (2019.01)

(57) **ABSTRACT**

A computer-implemented process for modifying one or more of a plurality of data pipelines within a computer architecture that processes data from a plurality of datasets includes the following operations. Real-time observability data regarding the plurality of data pipelines and the plurality of datasets is ingested. A dataset from the plurality of datasets is classified based upon usage and reliability to generate a classification of the dataset. Based upon the classification, a recommendation to modify at least one of the plurality of data pipelines or the quality of one of the plurality of datasets is generated.



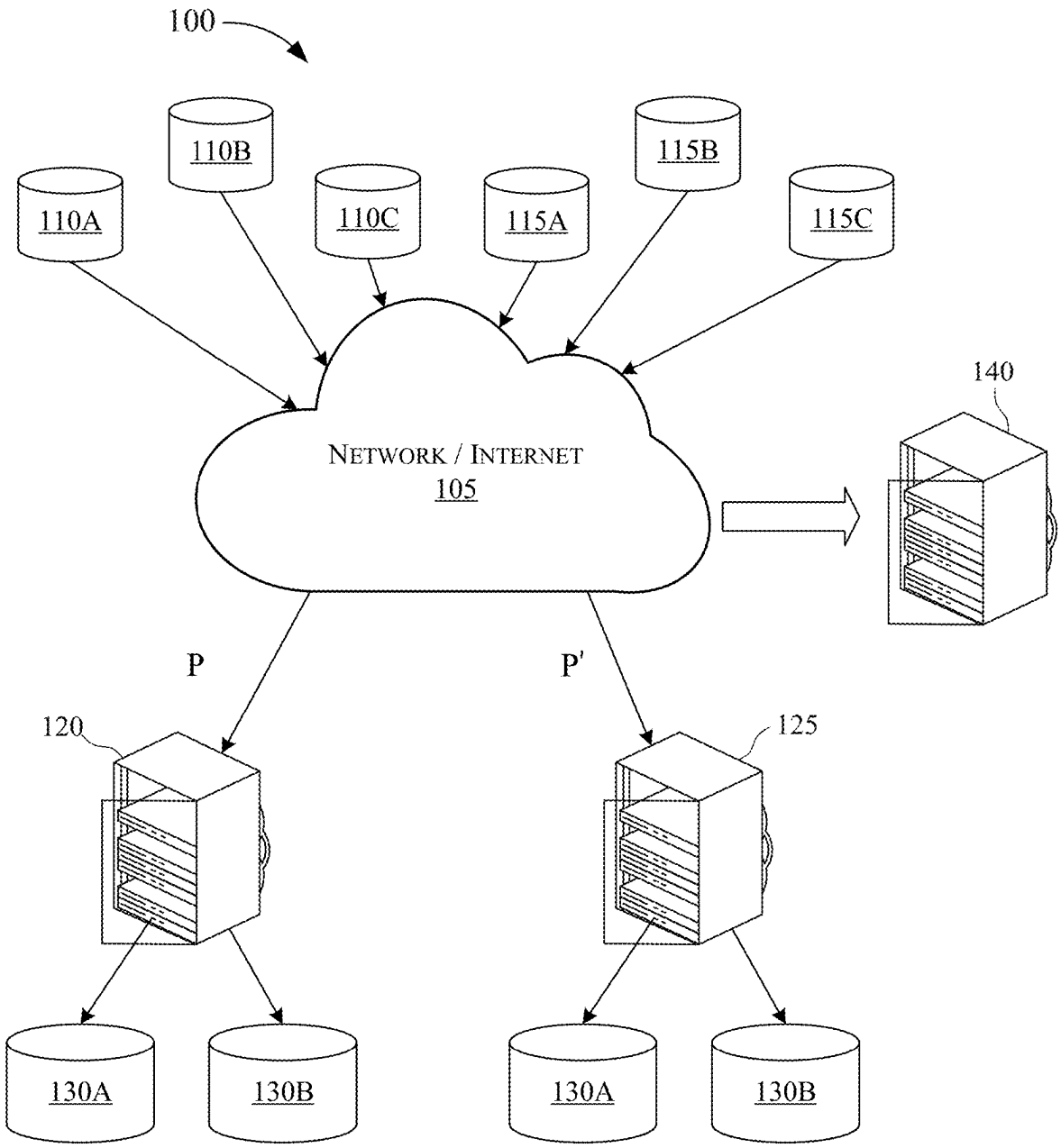

100
110A
110B
110C
115A
115B
115C
NETWORK / INTERNET
105
140
P
P'
120
125
130A
130B
130A
130B

FIG. 1A

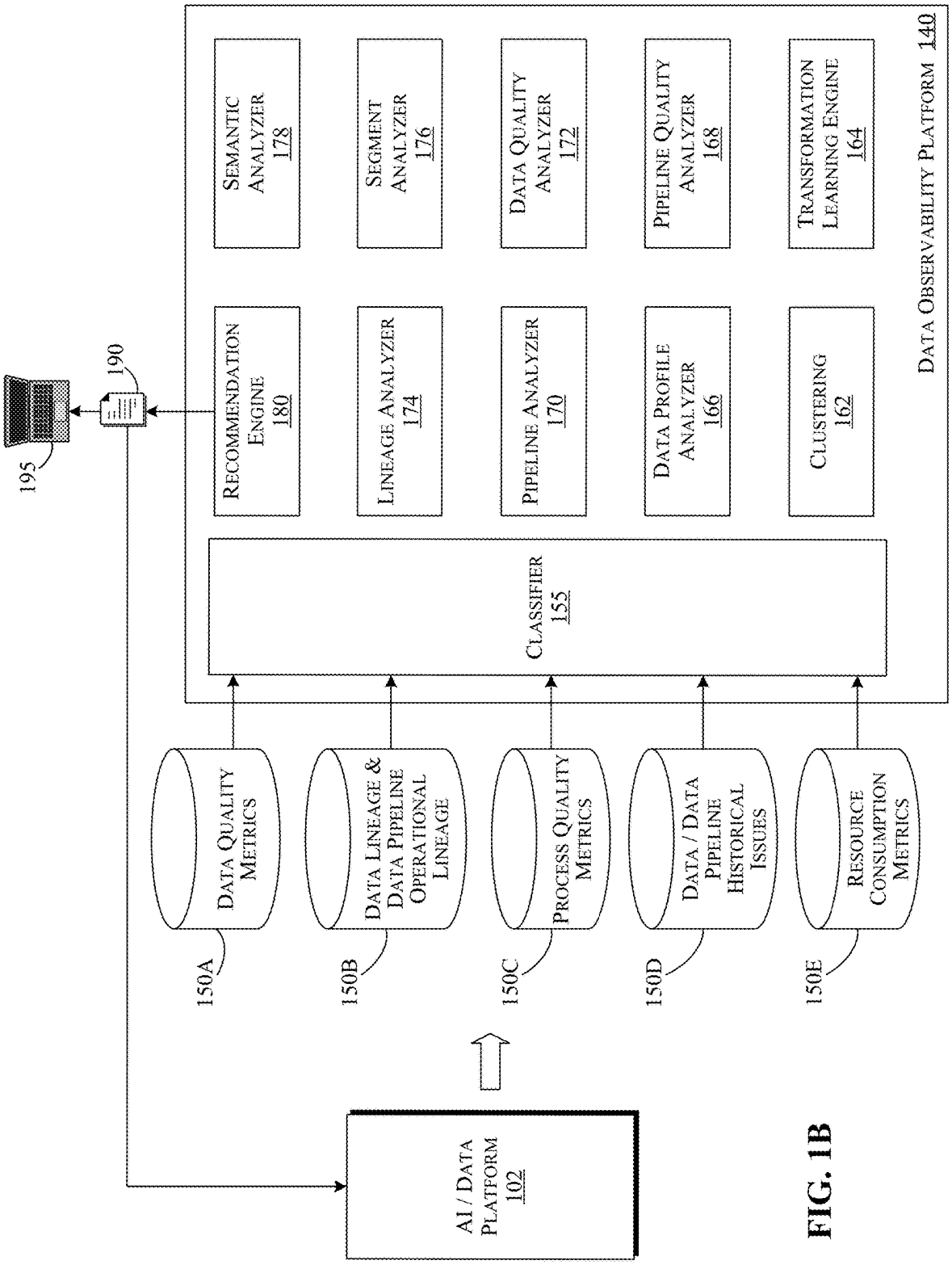

DATA OBSERVABILITY PLATFORM 140
SEMANTIC ANALYZER 178
SEGMENT ANALYZER 176
DATA QUALITY ANALYZER 172
PIPELINE QUALITY ANALYZER 168
TRANSFORMATION LEARNING ENGINE 164
RECOMMENDATION ENGINE 180
LINEAGE ANALYZER 174
PIPELINE ANALYZER 170
DATA PROFILE ANALYZER 166
CLUSTERING 162
CLASSIFIER 155
190
195
DATA QUALITY METRICS
DATA LINEAGE & DATA PIPELINE OPERATIONAL LINEAGE
PROCESS QUALITY METRICS
DATA / DATA PIPELINE HISTORICAL ISSUES
RESOURCE CONSUMPTION METRICS
150A
150B
150C
150D
150E
AI / DATA PLATFORM 102

FIG. 1B

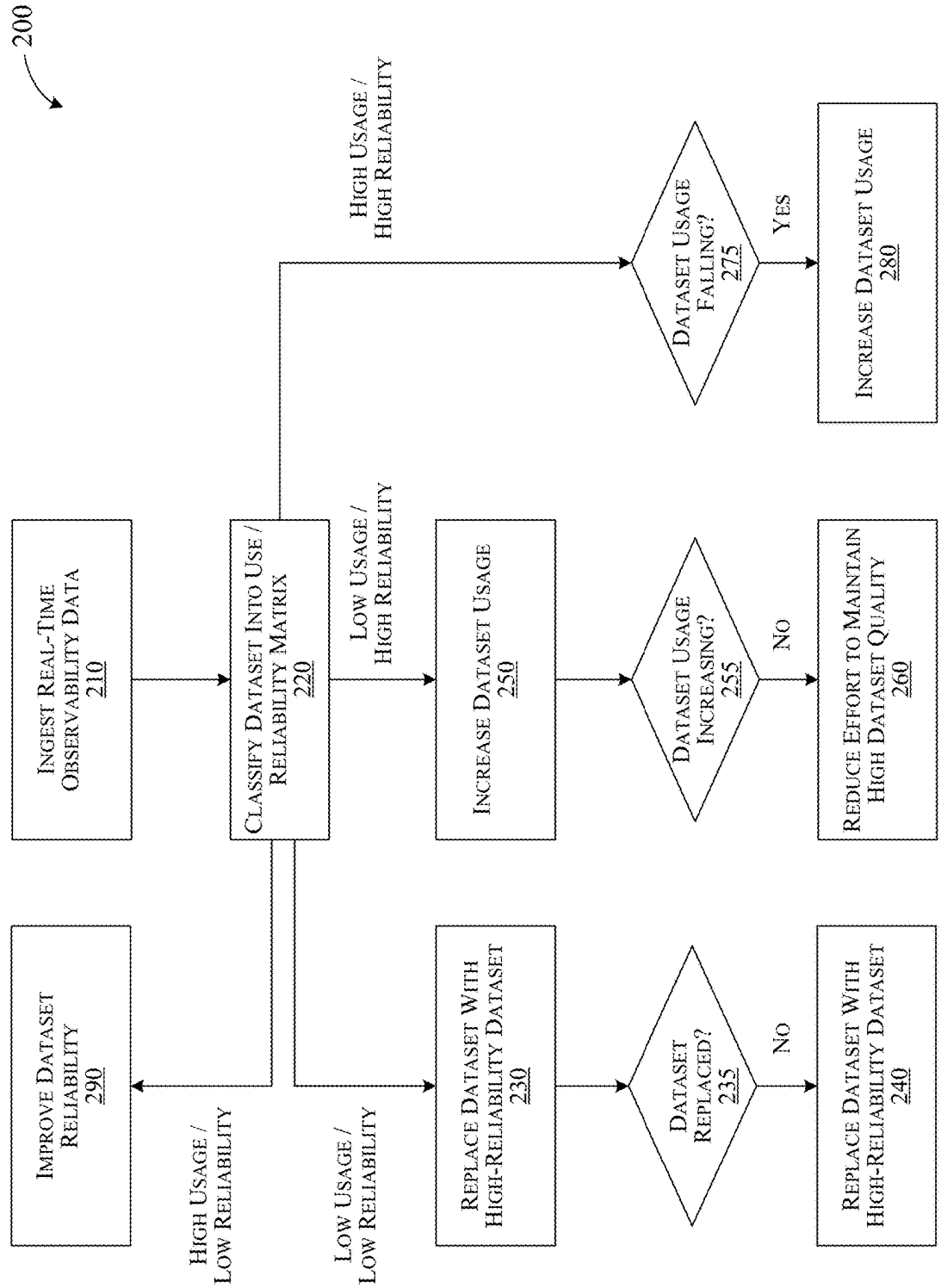

200
Ingest Real-Time Observability Data 210
Classify Dataset Into Use / Reliability Matrix 220
High Usage / High Reliability
Low Usage / High Reliability
Low Usage / Low Reliability
High Usage / Low Reliability
Dataset Usage Falling? 275
Yes
Increase Dataset Usage 280
Increase Dataset Usage 250
Dataset Usage Increasing? 255
No
Reduce Effort to Maintain High Dataset Quality 260
Replace Dataset With High-Reliability Dataset 230
Dataset Replaced? 235
No
Replace Dataset With High-Reliability Dataset 240
Improve Dataset Reliability 290

FIG. 2

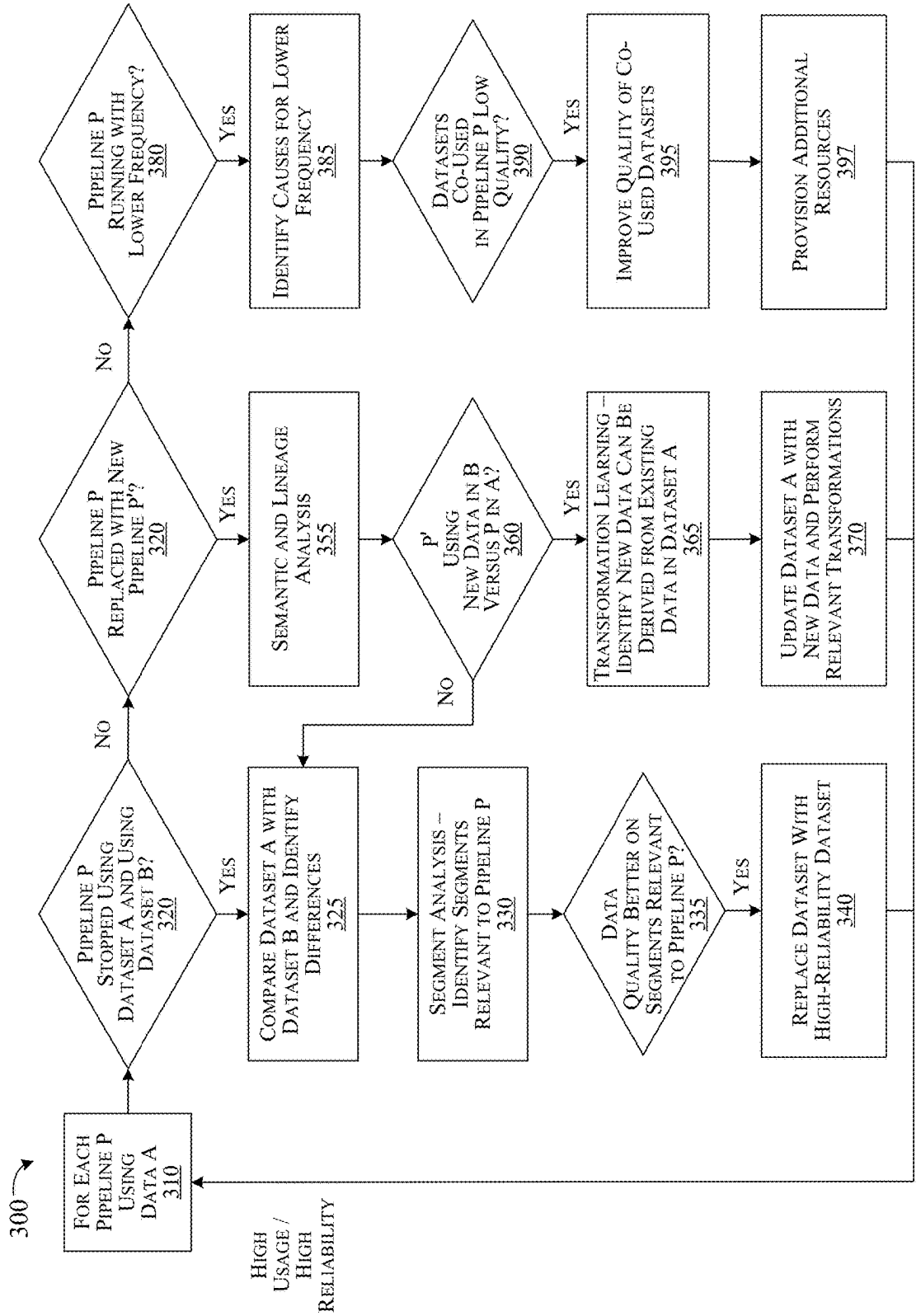

300
For Each Pipeline P Using Data A 310
High Usage / High Reliability
Pipeline P Stopped Using Dataset A and Using Dataset B? 320
Yes
No
Compare Dataset A with Dataset B and Identify Differences 325
Segment Analysis – Identify Segments Relevant to Pipeline P 330
Data Quality Better on Segments Relevant to Pipeline P? 335
Yes
Replace Dataset With High-Reliability Dataset 340
Pipeline P Replaced with New Pipeline P'? 320
Yes
No
Semantic and Lineage Analysis 355
P' Using New Data in B Versus P in A? 360
Yes
No
Transformation Learning – Identify New Data Can Be Derived from Existing Data in Dataset A 365
Update Dataset A with New Data and Perform Relevant Transformations 370
Pipeline P Running with Lower Frequency? 380
Yes
Identify Causes for Lower Frequency 385
Datasets Co-Used in Pipeline P Low Quality? 390
Yes
Improve Quality of Co-Used Datasets 395
Provision Additional Resources 397

FIG. 3

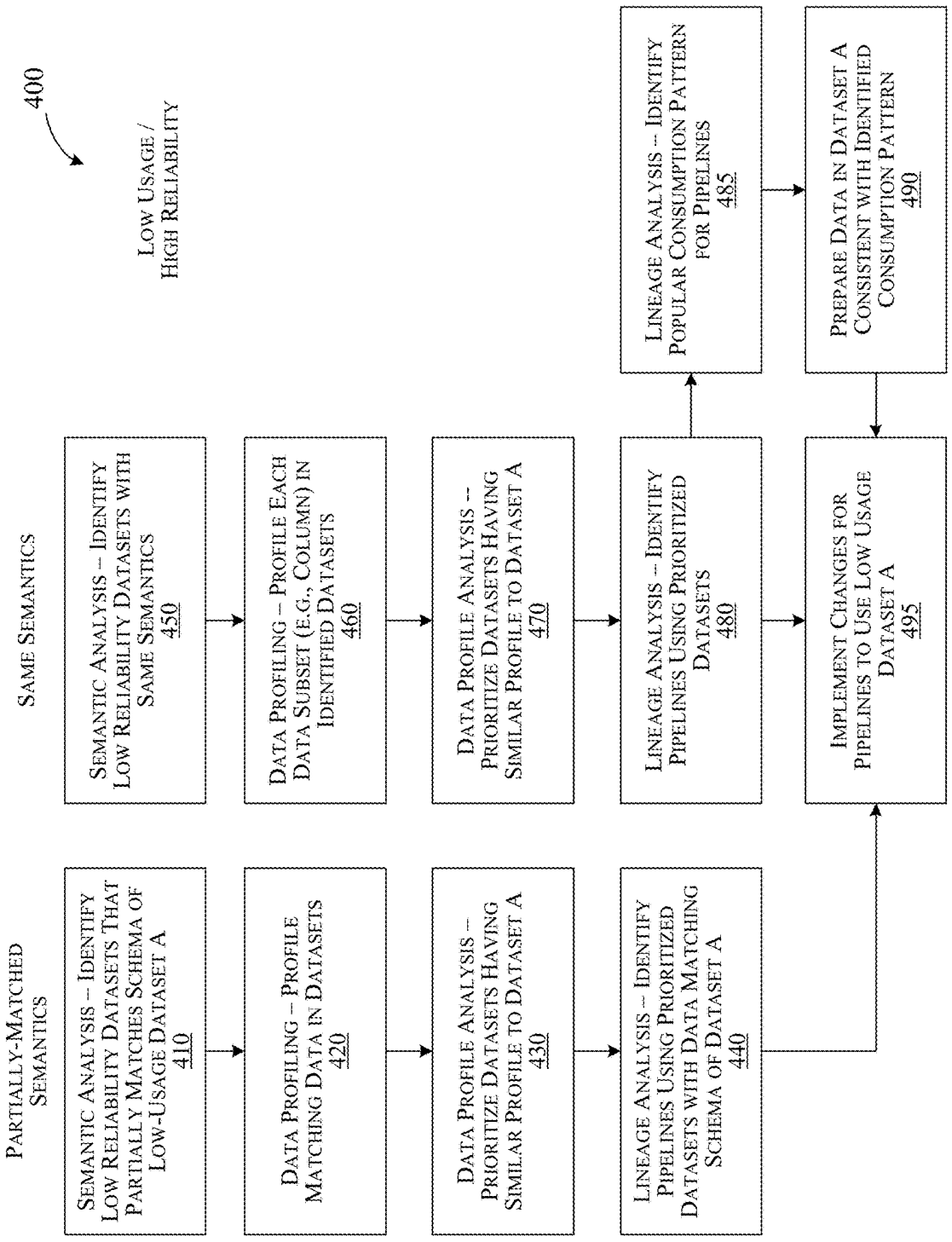

400
Low Usage / High Reliability
Same Semantics
Partially-Matched Semantics
Semantic Analysis – Identify Low Reliability Datasets That Partially Matches Schema of Low-Usage Dataset A 410
Data Profiling – Profile Matching Data in Datasets 420
Data Profile Analysis – Prioritize Datasets Having Similar Profile to Dataset A 430
Lineage Analysis – Identify Pipelines Using Prioritized Datasets with Data Matching Schema of Dataset A 440
Semantic Analysis – Identify Low Reliability Datasets with Same Semantics 450
Data Profiling – Profile Each Data Subset (e.g., Column) in Identified Datasets 460
Data Profile Analysis – Prioritize Datasets Having Similar Profile to Dataset A 470
Lineage Analysis – Identify Pipelines Using Prioritized Datasets 480
Lineage Analysis – Identify Popular Consumption Pattern for Pipelines 485
Implement Changes for Pipelines to Use Low Usage Dataset A 495
Prepare Data in Dataset A Consistent with Identified Consumption Pattern 490

FIG. 4

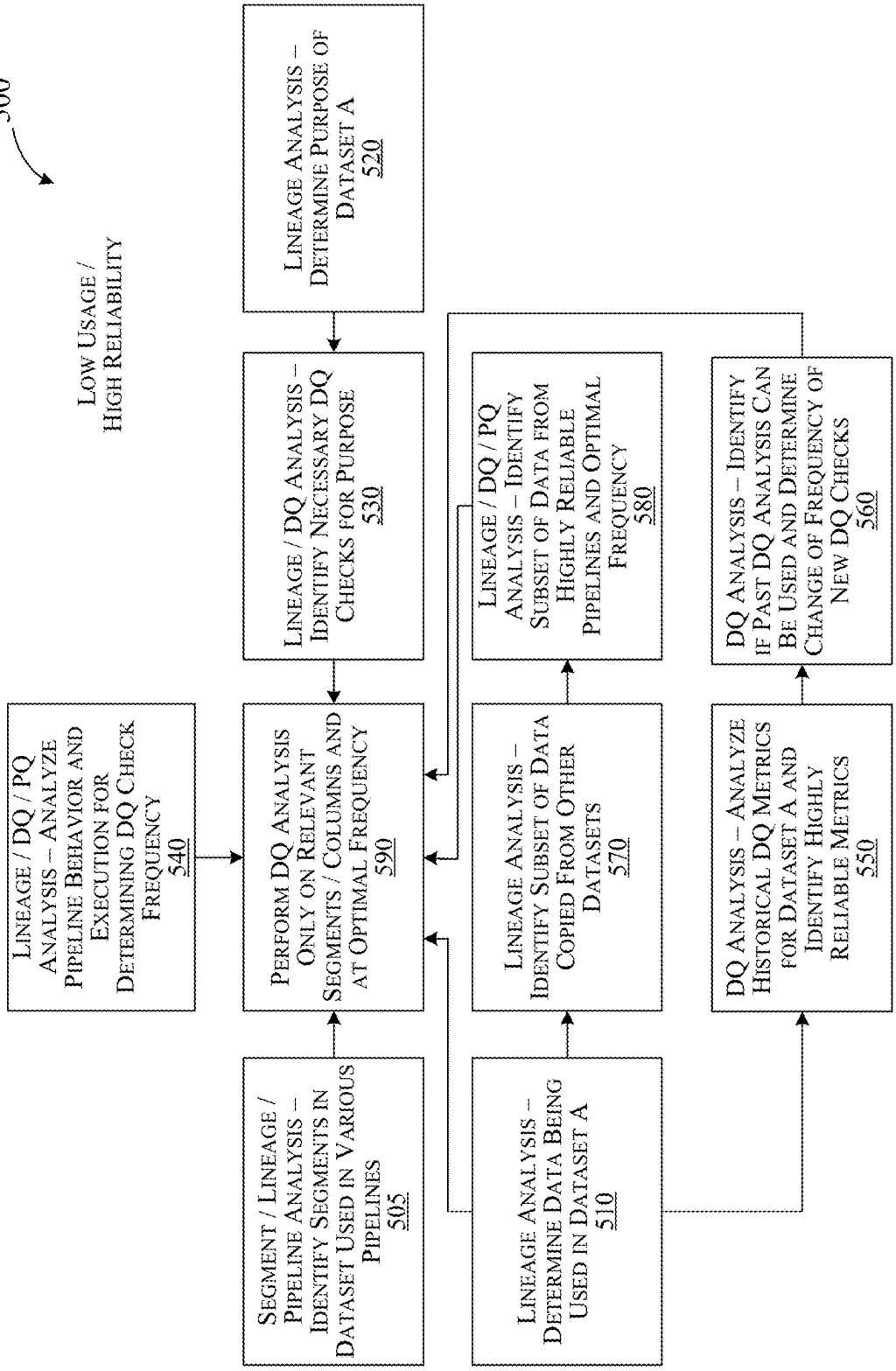

500
LOW USAGE / HIGH RELIABILITY
SEGMENT / LINEAGE / PIPELINE ANALYSIS – IDENTIFY SEGMENTS IN DATASET USED IN VARIOUS PIPELINES 505
LINEAGE ANALYSIS – DETERMINE DATA BEING USED IN DATASET A 510
LINEAGE ANALYSIS – DETERMINE PURPOSE OF DATASET A 520
LINEAGE / DQ ANALYSIS – IDENTIFY NECESSARY DQ CHECKS FOR PURPOSE 530
LINEAGE / DQ / PQ ANALYSIS – ANALYZE PIPELINE BEHAVIOR AND EXECUTION FOR DETERMINING DQ CHECK FREQUENCY 540
DQ ANALYSIS – ANALYZE HISTORICAL DQ METRICS FOR DATASET A AND IDENTIFY HIGHLY RELIABLE METRICS 550
LINEAGE ANALYSIS – IDENTIFY SUBSET OF DATA COPIED FROM OTHER DATASETS 570
LINEAGE / DQ / PQ ANALYSIS – IDENTIFY SUBSET OF DATA FROM HIGHLY RELIABLE PIPELINES AND OPTIMAL FREQUENCY 580
DQ ANALYSIS – IDENTIFY IF PAST DQ ANALYSIS CAN BE USED AND DETERMINE CHANGE OF FREQUENCY OF NEW DQ CHECKS 560
PERFORM DQ ANALYSIS ONLY ON RELEVANT SEGMENTS / COLUMNS AND AT OPTIMAL FREQUENCY 590

FIG. 5

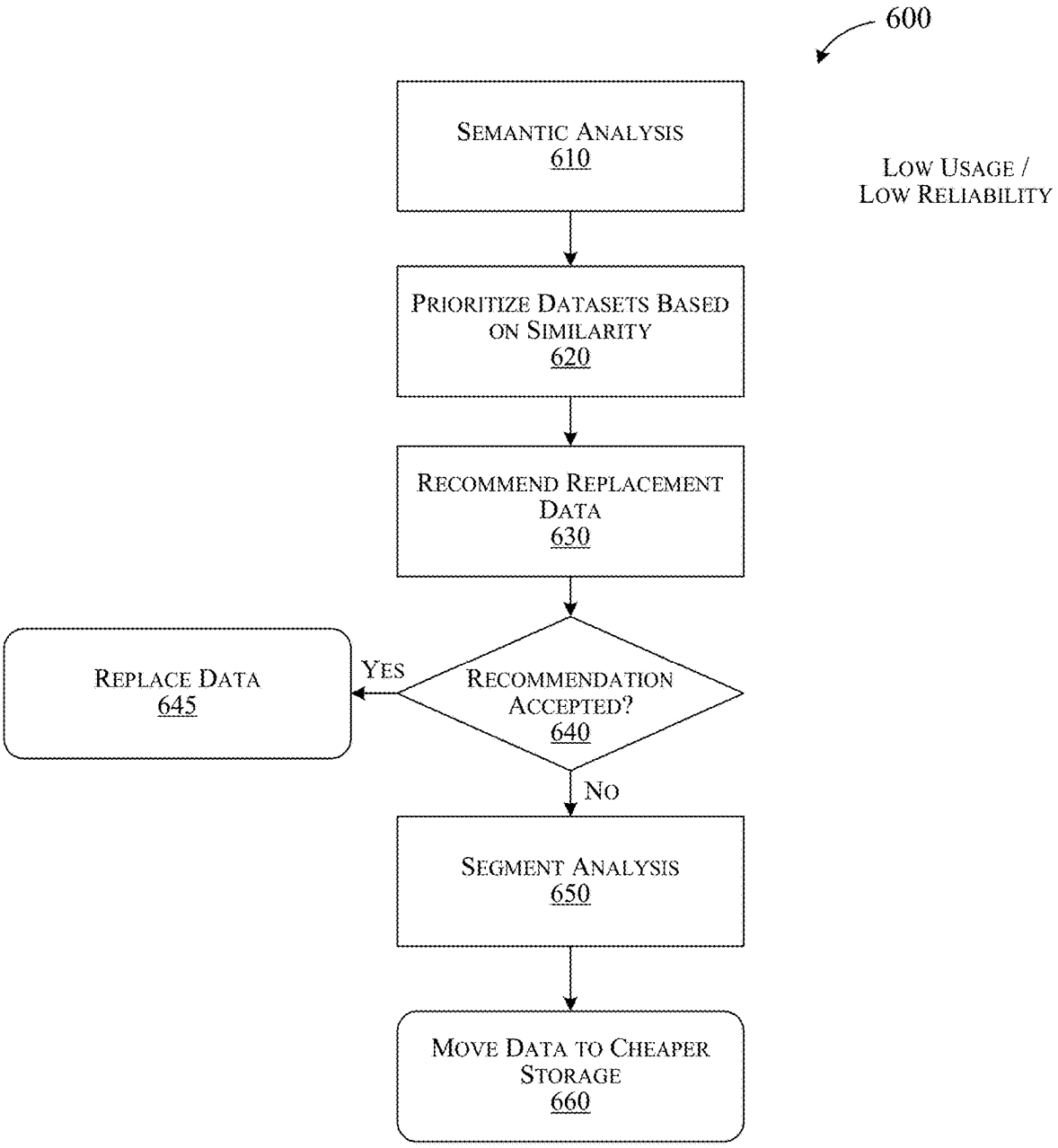

600
SEMANTIC ANALYSIS
610
LOW USAGE / LOW RELIABILITY
PRIORITIZE DATASETS BASED ON SIMILARITY
620
RECOMMEND REPLACEMENT DATA
630
REPLACE DATA
645
YES
RECOMMENDATION ACCEPTED?
640
NO
SEGMENT ANALYSIS
650
MOVE DATA TO CHEAPER STORAGE
660

FIG. 6

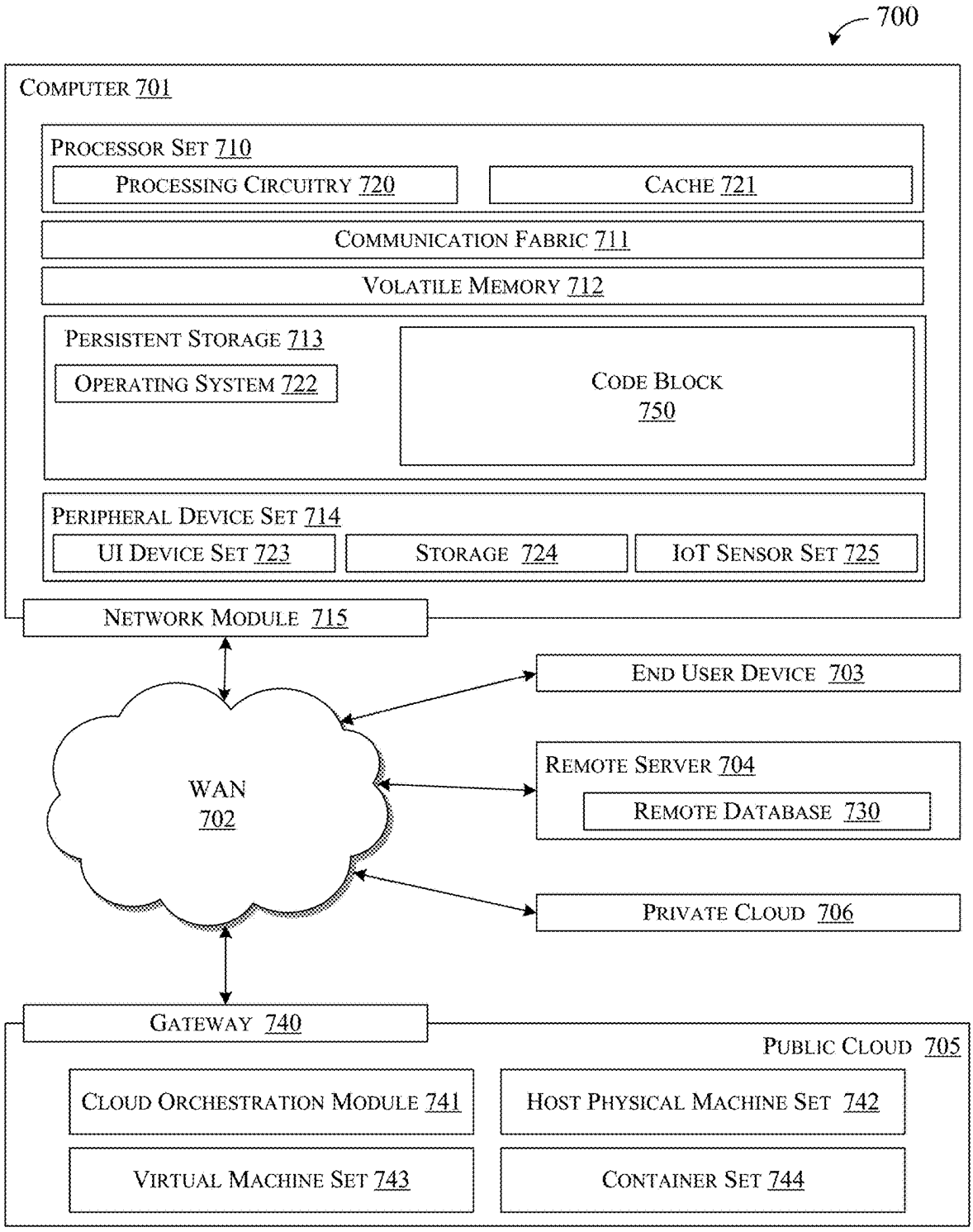

700
COMPUTER 701
PROCESSOR SET 710
PROCESSING CIRCUITRY 720
CACHE 721
COMMUNICATION FABRIC 711
VOLATILE MEMORY 712
PERSISTENT STORAGE 713
OPERATING SYSTEM 722
CODE BLOCK 750
PERIPHERAL DEVICE SET 714
UI DEVICE SET 723
STORAGE 724
IOT SENSOR SET 725
NETWORK MODULE 715
END USER DEVICE 703
WAN 702
REMOTE SERVER 704
REMOTE DATABASE 730
PRIVATE CLOUD 706
GATEWAY 740
PUBLIC CLOUD 705
CLOUD ORCHESTRATION MODULE 741
HOST PHYSICAL MACHINE SET 742
VIRTUAL MACHINE SET 743
CONTAINER SET 744

FIG. 7

MODIFYING DATA PIPELINE AND DATASET QUALITY USING DATA OBSERVABILITY

BACKGROUND

[0001] The present invention relates to data pipelines, and more specifically, to modifying data pipelines and dataset quality using real-time dataset classification and data observability analysis.

[0002] A data pipeline is a method/architecture in which raw data is ingested from various data sources and then ported to data store, such as a data lake or data warehouse, for analysis. The data is oftentimes transformed prior to being stored. Data pipelines can act as the "piping" for data science projects or business intelligence dashboards. Well-organized data pipelines provide the foundation for a range of data projects; this can include exploratory data analyses, data visualizations, and machine learning tasks.

[0003] One example of the use of a data pipeline is an exploratory data analysis (EDA), which is used by data scientists to analyze and investigate data sets and summarize their main characteristics, often employing data visualization methods. It is oftentimes helpful to determine how best to manipulate data sources to get needed answers, making it easier for data scientists to discover patterns, spot anomalies, test a hypothesis, or check assumptions. Another example of the use of a data pipeline is data visualizations, which represent data via common graphics, such as charts, plots, infographics, and even animations. These visual displays of information can communicate complex data relationships and data-driven insights in an easily-understandable manner. Yet another example of use of a data pipeline is machine learning (ML). Machine learning is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy. Through the use of statistical methods, algorithms are trained to make classifications or predictions, uncovering key insights within data mining projects.

[0004] The data (e.g., datasets) within the data sources used by a data pipeline can vary in terms of quality and usage. Generally, it is desirable to have high-quality data be used more frequently and low-quality data be used less frequently. High-quality data is usually more costly to maintain, and consequently, the use of high-quality data should be encouraged to justify the upkeep costs of the data. Consequently, there is a need to analyze data pipelines in a computer architecture (also referred to herein as data/AI platform) and recommend/implement actions for enhancing data utilization and cost efficiency trade-offs of the datasets within the data/AI platform.

SUMMARY

[0005] A computer-implemented process for modifying one or more of a plurality of data pipelines within a computer architecture that process data from a plurality of datasets includes the following operations. Real-time observability data regarding the plurality of data pipelines and the plurality of datasets is ingested. A dataset from the plurality of datasets is classified based upon usage and reliability to generate a classification of the dataset. Based upon the classification, a recommendation to modify at least one of the plurality of data pipelines is generated. The recommendation is a computer data structure that causes one or more changes/modifications to the data/AI platform.

[0006] In other aspects of the process, if the dataset is classified as low usage and low reliability, the recommendation includes replacing, for at least one of the plurality of data pipelines, the dataset with a higher-quality dataset. Alternatively, if the dataset is classified as low usage and low reliability, the recommendation includes moving a portion of the dataset into a lower cost data repository. If the dataset is classified as low usage and high reliability, the recommendation includes modifying the at least one of the plurality of data pipelines to increase usage of the dataset. Alternatively, if the dataset is classified as low usage and high reliability, the recommendation includes reducing data quality actions on the dataset. If the dataset is classified as high usage and high reliability and a determination is made that usage of the dataset is decreasing, the recommendation includes increasing usage of the dataset.

[0007] A computer hardware system for modifying one or more of a plurality of data pipelines within a computer architecture that process data from a plurality of datasets includes a hardware processor configured to perform the following executable operations. Real-time observability data regarding the plurality of data pipelines and the plurality of datasets is ingested. A dataset from the plurality of datasets is classified based upon usage and reliability to generate a classification of the dataset. Based upon the classification, a recommendation to modify at least one of the plurality of data pipelines is generated. The recommendation is a computer data structure that causes one or more changes/modifications to the data/AI platform.

[0008] In other aspects of the system, if the dataset is classified as low usage and low reliability, the recommendation includes replacing, for at least one of the plurality of data pipelines, the dataset with a higher-quality dataset. Alternatively, if the dataset is classified as low usage and low reliability, the recommendation includes moving a portion of the dataset into a lower cost data repository. If the dataset is classified as low usage and high reliability, the recommendation includes modifying the at least one of the plurality of data pipelines to increase usage of the dataset. Alternatively, if the dataset is classified as low usage and high reliability, the recommendation includes reducing data quality actions on the dataset. If the dataset is classified as high usage and high reliability and a determination is made that usage of the dataset is decreasing, the recommendation includes increasing usage of the dataset.

[0009] A computer program product includes a computer readable storage medium having stored therein program code for modifying one or more of a plurality of data pipelines within a computer architecture that process data from a plurality of datasets. The program code, which when executed by a computer hardware system, cause the computer hardware system to perform the following. Real-time observability data regarding the plurality of data pipelines and the plurality of datasets is ingested. A dataset from the plurality of datasets is classified based upon usage and reliability to generate a classification of the dataset. Based upon the classification, a recommendation to modify at least one of the plurality of data pipelines is generated. The recommendation is a computer data structure that causes one or more changes/modifications to the data/AI platform.

[0010] In other aspects of the computer program product, if the dataset is classified as low usage and low reliability,

the recommendation includes replacing, for at least one of the plurality of data pipelines, the dataset with a higher-quality dataset. Alternatively, if the dataset is classified as low usage and low reliability, the recommendation includes moving a portion of the dataset into a lower cost data repository. If the dataset is classified as low usage and high reliability, the recommendation includes modifying the at least one of the plurality of data pipelines to increase usage of the dataset. Alternatively, if the dataset is classified as low usage and high reliability, the recommendation includes reducing data quality actions on the dataset. If the dataset is classified as high usage and high reliability and a determination is made that usage of the dataset is decreasing, the recommendation includes increasing usage of the dataset.

[0011] This Summary section is provided merely to introduce certain concepts and not to identify any key or essential features of the claimed subject matter. Other features of the inventive arrangements will be apparent from the accompanying drawings and from the following detailed description.

BRIEF DESCRIPTION OF THE DRAWINGS

[0012] FIG. **1**A is a block diagram of a data/AI platform according to an aspect of the present invention.

[0013] FIG. **1**B is a block diagram further illustrating the architecture of a data observability platform according to an aspect of the present invention.

[0014] FIG. **2** illustrates a methodology of employing the data observability platform of FIG. **1**B according to an aspect of the present invention.

[0015] FIG. **3** illustrates a methodology of generating a recommendation upon classifying a dataset as high usage and high reliability according to an aspect of the present invention.

[0016] FIG. **4** illustrates a methodology of generating a recommendation to increase usage upon classifying a dataset as low usage and high reliability according to an aspect of the present invention.

[0017] FIG. **5** illustrates a methodology of generating a recommendation to reduce data quality efforts upon classifying a dataset as low usage and high reliability according to an aspect of the present invention.

[0018] FIG. **6** illustrates a methodology of generating a recommendation upon classifying a dataset as low usage and low reliability according to an aspect of the present invention.

[0019] FIG. **7** is a block diagram illustrating an example of computer hardware system for implementing the deep context disambiguation system of FIG. **1**.

DETAILED DESCRIPTION

[0020] Reference is made to FIGS. **1**A-**1**B and **2**, which respectively illustrate an architecture **100** and methodology **200** and for enhancing data utilization of a data/AI platform **102** within the architecture **100** using a data observability platform **140**. More specifically, a computer-implemented process **200** for modifying one or more of a plurality of data pipelines P, P' within a computer architecture **100** that process data from a plurality of datasets **110**A-C, **115**A-C includes the following operations. Real-time observability data **150**A-E regarding the plurality of data pipelines P, P' and the plurality of datasets **110**A-C, **115**A-C is ingested. A dataset **110**A from the plurality of datasets **110**A-C, **115**A-C is classified based upon usage and reliability to generate a classification of the dataset **110**A. Based upon the classification, a recommendation **190** to modify at least one of the plurality of data pipelines P, P' is generated. The recommendation **190** is a computer data structure that causes one or more changes/modifications to a data/AI platform within the computer architecture **100** that improves the functionality/usability of the computer architecture **100**.

[0021] In other aspects of the process, if the dataset **110**A is classified as low usage and low reliability, the recommendation **190** includes replacing, for at least one of the plurality of data pipelines P, P', the dataset **110**A with a higher-quality dataset **110**B. Alternatively, if the dataset **110**A is classified as low usage and low reliability, the recommendation **190** includes moving a portion of the dataset **110**A into a lower cost data repository. If the dataset **110**A is classified as low usage and high reliability, the recommendation **190** includes modifying the at least one of the plurality of data pipelines P, P' to increase usage of the dataset **110**A. Alternatively, if the dataset **110**A is classified as low usage and high reliability, the recommendation **190** includes reducing data quality actions on the dataset **110**A. If the dataset **110**A is classified as high usage and high reliability and a determination is made that usage of the dataset **110**A is decreasing, the recommendation **190** includes increasing usage of the dataset **110**A.

[0022] A computer hardware system **140** for modifying one or more of a plurality of data pipelines P, P' within a computer architecture **100** that process data from a plurality of datasets **110**A-C, **115**A-C includes a hardware processor configured to perform the following executable operations. Real-time observability data **150**A-E regarding the plurality of data pipelines P, P' and the plurality of datasets **110**A-C, **115**A-C is ingested. A dataset **110**A from the plurality of datasets **110**A-C, **115**A-C is classified based upon usage and reliability to generate a classification of the dataset **110**A. Based upon the classification, a recommendation **190** to modify at least one of the plurality of data pipelines P, P' is generated. The recommendation **190** is a computer data structure that causes one or more changes/modifications to a data/AI platform within the computer architecture **100** that improves the functionality/usability of the computer architecture **100**.

[0023] In other aspects of the system, if the dataset **110**A is classified as low usage and low reliability, the recommendation **190** includes replacing, for at least one of the plurality of data pipelines P, P', the dataset **110**A with a higher-quality dataset **110**B. Alternatively, if the dataset **110**A is classified as low usage and low reliability, the recommendation **190** includes moving a portion of the dataset **110**A into a lower cost data repository. If the dataset **110**A is classified as low usage and high reliability, the recommendation **190** includes modifying the at least one of the plurality of data pipelines P, P' to increase usage of the dataset **110**A. Alternatively, if the dataset **110**A is classified as low usage and high reliability, the recommendation **190** includes reducing data quality actions on the dataset **110**A. If the dataset **110**A is classified as high usage and high reliability and a determination is made that usage of the dataset **110**A is decreasing, the recommendation **190** includes increasing usage of the dataset **110**A.

[0024] A computer program product includes a computer readable storage medium having stored therein program code for modifying one or more of a plurality of data pipelines P, P' within a computer architecture **100** that

process data from a plurality of datasets **110**A-C, **115**A-C. The program code, which when executed by a computer hardware system **140**, cause the computer hardware system **140** to perform the following. Real-time observability data **150**A-E regarding the plurality of data pipelines P, P' and the plurality of datasets **110**A-C, **115**A-C is ingested. A dataset **110**A from the plurality of datasets **110**A-C, **115**A-C is classified based upon usage and reliability to generate a classification of the dataset **110**A. Based upon the classification, a recommendation **190** to modify at least one of the plurality of data pipelines P, P' is generated. The recommendation **190** is a computer data structure that causes one or more changes/modifications to a data/AI platform within the computer architecture **100** that improves the functionality/usability of the computer architecture **100**.

[0025] In other aspects of the computer program product, if the dataset **110**A is classified as low usage and low reliability, the recommendation **190** includes replacing, for at least one of the plurality of data pipelines P, P', the dataset **110**A with a higher-quality dataset **110**B. Alternatively, if the dataset **110**A is classified as low usage and low reliability, the recommendation **190** includes moving a portion of the dataset **110**A into a lower cost data repository. If the dataset **110**A is classified as low usage and high reliability, the recommendation **190** includes modifying the at least one of the plurality of data pipelines P, P' to increase usage of the dataset **110**A. Alternatively, if the dataset **110**A is classified as low usage and high reliability, the recommendation **190** includes reducing data quality actions on the dataset **110**A. If the dataset **110**A is classified as high usage and high reliability and a determination is made that usage of the dataset **110**A is decreasing, the recommendation **190** includes increasing usage of the dataset **110**A. An example of a tool for implementing such a data/AI platform **102** is IBM® DataStage®. Although the data observability platform **140** is illustrated as including storage and functional components **150-180**, one or more of these storage and functional components **150-190** may be external to the data observability platform **140**. For example, one or more of the observability data storage **150**A-E could be located in the cloud, as described in more detail with regard to FIG. **7**.

[0026] Referring to FIG. **1**A, the data observability platform **140** collects real-time observability data **150**A-E from one or more data pipelines P, P'. In broad terms, a data pipeline P, P', is a well-known type of architecture/methodology in which raw data is ingested from one or more data sources **110**A-C, **115**A-C and ported to one or more data repositories **130**A-B, **140**A-B. Additionally, prior to the data being stored within the data repositories **130**A-B, **140**A-B, the data typically undergoes some type of data processing, such as filtering, masking, and aggregation. Additionally, the data repositories **130**A-B, **140**A-B oftentimes have a defined schema, which can require that new data be aligned, as necessary, with the previously-stored data. As used herein, the term "pipeline" can include the one or more data sources **110**A-C, **115**A-C and/or the one or more data repositories **130**A-B, **140**A-B.

[0027] The types of data sources **110**A-C, **115**A-C are not limited and can includes a wide variety of formats such as APIs, SQL and NoSQL databases, files, et cetera. The data can include various data structures (e.g., structured and unstructured data). The data from these data sources **110**A-C, **115**A-C is typically ingested (i.e., received) by one or more server systems **120**, **125** configured to do so. Once received, the data is processed/transformed into a format needed for the destination data repositories **130**A-B, **140**A-B. This can also be performed by the one or more server systems **120**, **125**. For example, a data stream may come in a nested JSON format, and the data transformation stage will aim to unroll that JSON to extract the key fields for analysis. Once transformed, the transformed data is stored within the one or more data repositories **130**A-B, **140**A-B. This data can then be exposed to various stakeholders.

[0028] Referring to FIG. **1**B, the data observability platform **140** includes a classifier **155** that classifies datasets in the data sources **110**A-C, **115**A-C based upon the real-time observability data **150**A-E gathered from the one or more data pipelines P, P'. As discussed in greater detail with regard to FIGS. **2-6**, the data observability platform **140** employs one or more functional modules **162-180** to generate a recommendation **190** for use with the data/AI platform. As used herein, a recommendation **190** is a computer data structure that causes one or more changes/modifications to the data/AI platform. The recommendation **190**, for example, can be visually outputted to a user **195** or be used to automatically modify the data/AI platform **102**.

[0029] Referring specifically to FIG. **2**, the process **200** of employing the data observability platform **140** involves, in **210**, the data observability platform **140** ingesting the real-time observability data **150**A-E. Examples of real-time observability data includes data quality (DQ) metrics **150**A, data lineage and data pipeline operational lineage **150**B, process quality metrics **150**C for each of the data pipelines P, P' (e.g., run-duration, data-volume processed and output), data/data pipeline historical issues **150**D such as history of errors encountered on data pipelines P, P' and history of various data quality issues encountered on the datasets, and resource consumption metrics **150**E. The real-time observability data **150**A-E is not limited to the types of data discussed above. For example, the real-time observability data **150**A-E can also include details of identified root causes of various data pipeline failures among others.

[0030] The data observability platform **140** is not limited in the manner in which the real-time observability data **150**A-E is collected. For example, individual components of the data/AI platform **102** can be instrumented to generate the metrics found with the real-time observability data **150**A-E and push those metrics to the data observability platform **140**.

[0031] In **220**, the classifier **155** is configured to classify the dataset into one of four different classifications: (i) low use/low reliability, (ii) low usage/high reliability, (iii) high usage/high reliability, and (iv) high usage/low reliability. Whether a dataset is classified as high/low reliability and high/low usage can be based upon predetermined standards that may vary depending upon the type of data/AI platform being evaluated. In addition to or alternatively, the standards for determining high/low reliability and high/low usage can be determined using a machine learning engine (not illustrated) with changes in real-time observability data **150**A-E resulting from changes to the data/AI platform **102** being used as feedback to the machine learning engine.

[0032] Based upon the classification of the dataset, in **220**, the process **200** proceeds down one of four different paths. If the dataset is classified as low usage/low reliability, in **230**, a recommendation **190** can be made to replace the prior dataset with a higher-reliability dataset. In addition to or alternatively, if it is determined that the dataset is not

replaced, in **235**, a recommendation **190** can be made, in **240**, to reduce the storage cost of the dataset. This path **600** is discussed in more detail with regard to the FIG. **6**.

[0033] If the dataset is classified as low usage/high reliability, in **250**, the recommendation engine **180** can generate a recommendation **190** to increase dataset usage. This path **400** is discussed in more detail with regard to the FIG. **4**. In addition to or alternatively, if it is determined that the dataset usage is decreasing or not increasing, in **255**, a recommendation **190** can be made, in **260**, to reduce efforts to maintain high dataset quality. This path **500** is discussed in more detail with regard to the FIG. **5**.

[0034] If the dataset is classified as high usage/high reliability, then dataset usage is determined to be optimal. However, in **275**, if a determination is made that dataset usage is falling, a recommendation **190** can be made, in **280**, to increase dataset usage. This path **300** is discussed in more detail with regard to the FIG. **3**.

[0035] If the dataset is classified as high usage/low reliability, then the process proceeds to **290** in which a recommendation is made to improve dataset reliability **290**. There are many known ways to increase dataset reliability **290** and the process **200** is not limited as to any particular approach for doing so.

[0036] Referring to FIG. **3**, the illustrated process **300** can be performed when the classifier **155** classifies a dataset as high usage/high reliability. The process **300** begins, in **310**, by looking at each data pipeline (e.g., P) using a particular dataset (e.g., **110**A) and performing a number of different causal analysis **320**, **350**, **380** to determine why usage of the particular dataset **110**A is dropping. Although illustrated being performed in series, each causal analysis **320**, **350**, **380** can be performed in parallel or in a different order than depicted.

[0037] The causal analysis of **320** includes a determination as to whether the data pipeline P has stopped using dataset **110**A and is instead using a new dataset **110**B. If so, an assumption can be made that no changes were made to the data pipeline P and that the new dataset **110**B has the same schema as (or is a superset of) the prior dataset **110**A. Also, in **325**, a comparison can be made between the prior dataset **110**A and the new dataset **110**B to identify the differences there between.

[0038] In **330**, the segment analyzer **176** is configured to identify segments of the new dataset **110**B that are relevant to the data pipeline P. In **335**, a determination is made as to whether the data quality on these identified segments of the new dataset **110**B, which are relevant to the data pipeline P, are better. If the determination is made that the data quality is better, then remediation methods are applied to those identified segments contained in the prior dataset **110**A. For example, the remediation can be to improve quality of the identified segments in the prior dataset **110**A. Additionally, this causal analysis **320** can determine whether new data classes exist in the new dataset **110**B. If so, the specification of the new data can be specified, and the recommendation engine **180** can generate a recommendation **190** to update the dataset **110**B. For example, the recommendation can be to check if the prior dataset **110**A can be updated to reflect the new data classes.

[0039] The causal analysis of **350** includes a determination as to whether the prior data pipeline P has been replaced with a new data pipeline P' or the prior data pipeline P has been replaced with a new version of the prior data pipeline P. If so, an assumption can be made that P' (or the new revision of P) includes a new dataset **115**B in which the schema has been changed. Also, in **355**, the semantic analyzer **178** and lineage analyzer **174** performs a semantic and lineage analysis to determine if the new data pipeline P' is using new data (e.g., new columns) in the new dataset **115**B that are not found in the dataset **110**A used by the prior data pipeline P. If new data is not being used, the causal analysis of **350** proceeds to **325**.

[0040] If new data is being used in the new dataset **115**, in **365**, a transformation learning engine **365** (e.g., a type of machine learning engine), is configured to determine if the new data in the new dataset **115**B can be derived from existing data in the dataset **110**A in the prior pipeline P. In **370**, the recommendation engine **180** generates a recommendation to update the old dataset **110**A to include the new data and/or update the prior data pipeline P to perform a transformation on the existing data in the dataset **110**A to the extent that the new data can be derived from existing data in the dataset **110**A.

[0041] The causal analysis of **380** includes a determination as to whether the data pipeline P is operating at a lower frequency. If so, in **385**, potential causes for the lower frequency are identified, and the recommendation engine **180** can generate a recommendation **190** to remediate those causes. Also, in **390**, a determination can be made whether any of the other datasets **110**A-C used by the data pipeline P are classified as low quality. If so, in **395**, the recommendation engine **180** can generate a recommendation **190** to improve the quality of the datasets **110**A-C determined to be low quality.

[0042] Referring to FIG. **4**, the illustrated process **400** can be performed upon the classifier **155** classifying a dataset **110**A as low usage/high reliability and an intent is to increase usage of the dataset **110**A. The process **300** can go down two paths. In **410**, **450**, a semantic analysis is performed by the semantic analyzer **176** on the dataset **110**A to identify low reliability (either high or low usage) dataset(s) that have the same semantics as the initial dataset **110**A or having a subset of data (e.g., columns) that matches the schema of the initial dataset **110**A. If the dataset **110**A cannot be analyzed by the semantic analyzer **160** (i.e., the dataset **110**A is not discoverable), various semantic metadata can be added to the dataset **110**A. For example, business terms can be added at a column level and/or at an asset level. Additionally, tags can be added to the data and natural language expansion can be performed on the columns.

[0043] If the low reliability dataset(s) has the same semantics, the process **400** continues from **450**. In **460**, the data profile analyzer **166**, profiles each data subset (e.g., columns) in the identified low reliability dataset(s), and in **470**, the data profile analyzer **166** prioritizes the identified low reliability dataset(s) based upon the similarity to the initial dataset **110**A. Next, in **480**, the lineage analyzer **174** performs an analysis that identifies pipelines P' that use the identified low reliability dataset(s). In **495**, the recommendation engine **180** generates a recommendation **190** for the identified pipelines P' to use the low usage/high reliability dataset.

[0044] In **485**, the lineage analyzer **174** can perform an additional analysis whereby similar datasets with high usage are identified. Once identified these similar datasets with high usage are analyzed to determine how the data contained therein is consumed. From this analysis, popular (i.e., high

usage) consumption patterns are determined. In **490**, the recommendation engine **180** generates a recommendation **190** to modify the initial dataset **110**A in a manner (e.g., change the schema—for example, instead of an address, the schema may require that the street name, city, and zip code be divided out) such that the initial dataset **110**A is more attractive to be used according to these identified popular consumption patterns.

[0045] Alternative, if in **410**, a determination is made that the low reliability dataset(s) have certain subsets (e.g., columns) of data that matches the schema of the initial dataset **110**, the process proceeds to **420**. Operations **420**, **430**, **440** are similar to operations **460**, **470**, **480** except the analysis is only performed on those subsets of the of the low reliability datasets(s) that match the schema of the initial dataset **110**.

[0046] Referring to FIG. **5**, the illustrated process **500** can be performed when the classifier **155** classifies a dataset **110**A as low usage/high reliability and an intent is to reduce the effort (cost) of maintain the data quality of the dataset **110**A. There are a number of different paths that can be taken depending upon an initial assumption regarding the dataset **110**. For example, if a determination is made that only some segments in the dataset **110**A are being used, the process proceeds to **505**, in which the segment analyzer **176** identifies those segments in the dataset **110**A being used, the lineage analyzer **174** and the pipeline analyzer **170** determines what pipelines P, P' are using the segments in the dataset **110**A. Based upon this analysis, in **590**, the recommendation engine **180** can generate a recommendation **190** that data quality checks be performed (and at what frequency) only for those segments in the dataset **110**A that are being used.

[0047] For example, a dataset **110**A that includes address and various cities (e.g., San Jose, Dallas, Austin), but the pipelines P, P' only use San Jose and Dallas. In this instance data quality need not be maintained for segments of data not belonging to the San Jose and Dallas locations.

[0048] As another example, a determination can be made that only certain subsets (e.g., columns) of the dataset **110**A are being used. In this instance, the process begins at **500**, in which lineage analyzer **174** determines what subsets of the dataset **110**A are being used. Based upon this analysis, in **590**, the recommendation engine **180** can generate a recommendation that data quality actions (e.g., checks) be performed (and at what frequency) only for those subsets in the dataset **110**A that are being used.

[0049] In **520**, the lineage analyzer **174** can perform a lineage analysis on the dataset **110**A to determine for what purpose the dataset **110**A is being used. Next, in **530**, the lineage analyzer **174** can interact with the data quality analyzer **172** to determine what subset of data quality operations are relevant to the purpose identified in **520**. Based upon this analysis, in **590**, the recommendation engine **180** can generate a recommendation **190** what data quality checks should be performed (and at what frequency) that are relevant to the purpose.

[0050] In **540**, the lineage analyzer **174**, the data quality analyzer **172**, and the pipeline quality analyzer **168** can operate together to determine pipeline behavior to support the recommendation engine **180** making a recommendation **190** based upon that analysis. For example, assume the pipelines P, P' run at 12 AM daily and the pipelines P, P' use the past 6 hours and it is determine that data batches arrive every 30 minutes. In this instance, the recommendation engine **180** can make a recommendation that data quality need only be maintained for the 6 hour period the precedes the checking of data at 12 AM. In this instance, the recommendation **190** is to maintain the data that arrives between 6 PM and 12 AM daily and there is no need to maintain the data during other time periods.

[0051] Using the data from **510**, in which segments being used in the dataset **110**A are identified, in **550**, the data quality analyzer **172** can determine what historical data quality metrics for the dataset **110**A are highly-reliable. If the data quality metrics are highly-reliable, then the frequency of those checks can be reduced in **560** using the data quality analyzer **172**. For example, if a first reading of the data quality metric is 100% (with a threshold of 90% required by the pipelines P, P') and second reading of the data quality metric is 97%, then the frequency in which the data quality of the dataset **110**A is checked can be reduced. However, if a subsequent data check reveals that the required threshold has not been reached, the frequency of in which the data quality of the data **110**A is checked can be increased. As another example, if ten consecutive data batches have 100% accuracy and a 90% threshold is needed, an assumption can be made that even if the 11th batch is completely in error, then the 90% threshold will still be reached. Consequently, a data check need not be performed on the 11th batch. Based upon this analysis, in **590**, the recommendation engine **180** can generate a recommendation **190** that the frequency in which data quality checks are performed be changed.

[0052] Alternatively, using the data from **510**, in which segments being used in the dataset **110**A are identified, in **570**, the lineage analyzer **174** can determine if any subsets (e.g., columns) of data **110**A have been copied from other datasets **110**B, **110**C. In **540**, the lineage analyzer **174**, the data quality analyzer **172**, and the pipeline quality analyzer **168** can operate together to determine which of those previously-identified subset of data from **570** are from highly-reliable datasets **110**B, **110**C. For those subsets of data from highly-reliable datasets **110**B, **110**C, the data quality metrics associated with those highly-reliable datasets **110**B, **110**C can be used as data quality metrics for the initial dataset **110**A. Based upon this analysis, in **590**, the recommendation engine **180** can generate a recommendation **190** that changes the frequency in which data quality checks are performed on the initial dataset **110**A to reflect that the dataset **110**A contains data from already highly-reliable datasets **110**B, **110**C.

[0053] Referring to FIG. **6**, the illustrated process **600** can be performed when the classifier **155** classifies a particular dataset as low usage/low reliability. Based upon this classification, the data observability platform is configured to replace the particular dataset with a higher reliability data and/or move the particular dataset into cheaper storage. The process **600** begins, in **610**, with the semantic analyzer **178** performing a semantic analysis on the particular dataset (e.g., **110**A) determined to be low reliability. A semantic analysis is also performed on different datasets (e.g., **110**B, **110**C) determined to be of higher reliability.

[0054] In **620**, based upon the semantic analysis, the other datasets **110**B, **110**C are compared to the initial dataset **110**A and those datasets **110**B, **110**C that are more similar to the initial dataset **110**A are prioritized. In **630**, based upon prioritization of the other datasets **110**B, **110**C, the recom-

mendation engine **180** generates a recommendation **190** to replace the initial dataset **110**A with one of the other datasets **110**B, **110**C. The prioritization of the other datasets **110**B, **110**C is not limited as to a particular approach. However, one approach for prioritizing the other datasets can include identifying those datasets **110**B, **110**C that are being co-used in the pipeline P. Another approach to prioritizing the other datasets can include identifying datasets **115**A-C in an important pipeline P' in which the quality of the datasets **115**A-C used therein are anticipated to be maintained at a high level.

[0055] In **645**, if the recommendation **190** is determined to be accepted in **640**, the initial dataset **110**A is replaced with one of the other datasets **110**B, **110**C. In **580**, the lineage analyzer **174**, the data quality analyzer **172**, and the pipeline quality analyzer **168** can operate together can operation together to determine pipeline behavior to support the recommendation engine **180** making a recommendation **190** based upon that analysis.

[0056] In **650**, the process **600** can also include the segment analyzer **176** performing an analysis on the initial dataset **110**A to determine what segments of the initial dataset **110** are being used. Since the initial dataset **110**A was classified as low usage, an assumption can be made that those segments of the initial dataset—other than those segments being used—are unlikely to be used. In **660**, the recommendation engine **180** generates a recommendation **190** to move those segments that are determined to be unlikely to be used into a less expensive data repositories (e.g., data repository **130**B may be less expensive than data repository **130**A).

[0057] As defined herein, the term "responsive to" means responding or reacting readily to an action or event. Thus, if a second action is performed "responsive to" a first action, there is a causal relationship between an occurrence of the first action and an occurrence of the second action, and the term "responsive to" indicates such causal relationship.

[0058] As defined herein, the term "real time" means a level of processing responsiveness that a user or system senses as sufficiently immediate for a particular process or determination to be made, or that enables the processor to keep up with some external process.

[0059] As defined herein, the term "automatically" means without user intervention.

[0060] Referring to FIG. **7**, computing environment **700** contains an example of an environment for the execution of at least some of the computer code involved in performing the inventive methods, such as code block **750** for implementing the operations of the data observability platform **140**. Computing environment **700** includes, for example, computer **701**, wide area network (WAN) **702**, end user device (EUD) **703**, remote server **704**, public cloud **705**, and private cloud **706**. In certain aspects, computer **701** includes processor set **710** (including processing circuitry **720** and cache **721**), communication fabric **711**, volatile memory **712**, persistent storage **713** (including operating system **722** and method code block **750**), peripheral device set **714** (including user interface (UI), device set **723**, storage **724**, and Internet of Things (IoT) sensor set **725**), and network module **715**. Remote server **704** includes remote database **730**. Public cloud **705** includes gateway **740**, cloud orchestration module **741**, host physical machine set **742**, virtual machine set **743**, and container set **744**.

[0061] Computer **701** may take the form of a desktop computer, laptop computer, tablet computer, smart phone, smart watch or other wearable computer, mainframe computer, quantum computer or any other form of computer or mobile device now known or to be developed in the future that is capable of running a program, accessing a network or querying a database, such as remote database **730**. As is well understood in the art of computer technology, and depending upon the technology, performance of a computer-implemented method may be distributed among multiple computers and/or between multiple locations. However, to simplify this presentation of computing environment **700**, detailed discussion is focused on a single computer, specifically computer **701**. Computer **701** may or may not be located in a cloud, even though it is not shown in a cloud in FIG. **7** except to any extent as may be affirmatively indicated.

[0062] Processor set **710** includes one, or more, computer processors of any type now known or to be developed in the future. As defined herein, the term "processor" means at least one hardware circuit (e.g., an integrated circuit) configured to carry out instructions contained in program code. Examples of a processor include, but are not limited to, a central processing unit (CPU), an array processor, a vector processor, a digital signal processor (DSP), a field-programmable gate array (FPGA), a programmable logic array (PLA), an application specific integrated circuit (ASIC), programmable logic circuitry, and a controller. Processing circuitry **720** may be distributed over multiple packages, for example, multiple, coordinated integrated circuit chips. Processing circuitry **720** may implement multiple processor threads and/or multiple processor cores. Cache **721** is memory that is located in the processor chip package(s) and is typically used for data or code that should be available for rapid access by the threads or cores running on processor set **710**. Cache memories are typically organized into multiple levels depending upon relative proximity to the processing circuitry. Alternatively, some, or all, of the cache for the processor set may be located "off chip." In certain computing environments, processor set **710** may be designed for working with qubits and performing quantum computing.

[0063] Computer readable program instructions are typically loaded onto computer **701** to cause a series of operational steps to be performed by processor set **710** of computer **701** and thereby effect a computer-implemented method, such that the instructions thus executed will instantiate the methods specified in flowcharts and/or narrative descriptions of computer-implemented methods discussed above in this document (collectively referred to as "the inventive methods"). These computer readable program instructions are stored in various types of computer readable storage media, such as cache **721** and the other storage media discussed below. The program instructions, and associated data, are accessed by processor set **710** to control and direct performance of the inventive methods. In computing environment **700**, at least some of the instructions for performing the inventive methods may be stored in code block **750** in persistent storage **713**.

[0064] A computer program product embodiment ("CPP embodiment" or "CPP") is a term used in the present disclosure to describe any set of one, or more, storage media (also called "mediums") collectively included in a set of one, or more, storage devices that collectively include machine readable code corresponding to instructions and/or data for performing computer operations specified in a given CPP

claim. A "storage device" is any tangible, hardware device that can retain and store instructions for use by a computer processor. Without limitation, the computer readable storage medium may be an electronic storage medium, a magnetic storage medium, an optical storage medium, an electromagnetic storage medium, a semiconductor storage medium, a mechanical storage medium, or any suitable combination of the foregoing. Some known types of storage devices that include these mediums include: diskette, hard disk, random access memory (RAM), read-only memory (ROM), erasable programmable read-only memory (EPROM or Flash memory), static random access memory (SRAM), compact disc read-only memory (CD-ROM), digital versatile disk (DVD), memory stick, floppy disk, mechanically encoded device (such as punch cards or pits/lands formed in a major surface of a disc) or any suitable combination of the foregoing.

[0065] A computer readable storage medium, as that term is used in the present disclosure, is not to be construed as storage in the form of transitory signals per se, such as radio waves or other freely propagating electromagnetic waves, electromagnetic waves propagating through a waveguide, light pulses passing through a fiber optic cable, electrical signals communicated through a wire, and/or other transmission media. As will be understood by those of skill in the art, data is typically moved at some occasional points in time during normal operations of a storage device, such as during access, de-fragmentation or garbage collection, but this does not render the storage device as transitory because the data is not transitory while it is stored.

[0066] Communication fabric **711** is the signal conduction paths that allow the various components of computer **701** to communicate with each other. Typically, this communication fabric **711** is made of switches and electrically conductive paths, such as the switches and electrically conductive paths that make up busses, bridges, physical input/output ports and the like. Other types of signal communication paths may be used for the communication fabric **711**, such as fiber optic communication paths and/or wireless communication paths.

[0067] Volatile memory **712** is any type of volatile memory now known or to be developed in the future. Examples include dynamic type random access memory (RAM) or static type RAM. Typically, the volatile memory **712** is characterized by random access, but this is not required unless affirmatively indicated. In computer **701**, the volatile memory **712** is located in a single package and is internal to computer **701**. In addition to alternatively, the volatile memory **712** may be distributed over multiple packages and/or located externally with respect to computer **701**.

[0068] Persistent storage **713** is any form of non-volatile storage for computers that is now known or to be developed in the future. The non-volatility of the persistent storage **713** means that the stored data is maintained regardless of whether power is being supplied to computer **701** and/or directly to persistent storage **713**. Persistent storage **713** may be a read only memory (ROM), but typically at least a portion of the persistent storage **713** allows writing of data, deletion of data and re-writing of data. Some familiar forms of persistent storage **713** include magnetic disks and solid state storage devices. Operating system **722** may take several forms, such as various known proprietary operating systems or open source Portable Operating System Interface type operating systems that employ a kernel. The code included in code block **750** typically includes at least some of the computer code involved in performing the inventive methods.

[0069] Peripheral device set **714** includes the set of peripheral devices for computer **701**. Data communication connections between the peripheral devices and the other components of computer **701** may be implemented in various ways, such as Bluetooth connections, Near-Field Communication (NFC) connections, connections made by cables (such as universal serial bus (USB) type cables), insertion type connections (for example, secure digital (SD) card), connections made though local area communication networks and even connections made through wide area networks such as the internet.

[0070] In various aspects, UI device set **723** may include components such as a display screen, speaker, microphone, wearable devices (such as goggles and smart watches), keyboard, mouse, printer, touchpad, game controllers, and haptic devices. Storage **724** is external storage, such as an external hard drive, or insertable storage, such as an SD card. Storage **724** may be persistent and/or volatile. In some aspects, storage **724** may take the form of a quantum computing storage device for storing data in the form of qubits. In aspects where computer **701** is required to have a large amount of storage (for example, where computer **701** locally stores and manages a large database) then this storage **724** may be provided by peripheral storage devices designed for storing very large amounts of data, such as a storage area network (SAN) that is shared by multiple, geographically distributed computers. Internet-of-Things (IoT) sensor set **725** is made up of sensors that can be used in IoT applications. For example, one sensor may be a thermometer and another sensor may be a motion detector.

[0071] Network module **715** is the collection of computer software, hardware, and firmware that allows computer **701** to communicate with other computers through a Wide Area Network (WAN) **702**. Network module **715** may include hardware, such as modems or Wi-Fi signal transceivers, software for packetizing and/or de-packetizing data for communication network transmission, and/or web browser software for communicating data over the internet. In certain aspects, network control functions and network forwarding functions of network module **715** are performed on the same physical hardware device. In other aspects (for example, aspects that utilize software-defined networking (SDN)), the control functions and the forwarding functions of network module **715** are performed on physically separate devices, such that the control functions manage several different network hardware devices. Computer readable program instructions for performing the inventive methods can typically be downloaded to computer **701** from an external computer or external storage device through a network adapter card or network interface included in network module **715**.

[0072] WAN **702** is any Wide Area Network (for example, the internet) capable of communicating computer data over non-local distances by any technology for communicating computer data, now known or to be developed in the future. In some aspects, the WAN **702** may be replaced and/or supplemented by local area networks (LANs) designed to communicate data between devices located in a local area, such as a Wi-Fi network. The WAN **702** and/or LANs typically include computer hardware such as copper trans-

mission cables, optical transmission fibers, wireless transmission, routers, firewalls, switches, gateway computers and edge servers.

[0073] End user device (EUD) **703** is any computer system that is used and controlled by an end user (for example, a customer of an enterprise that operates computer **701**), and may take any of the forms discussed above in connection with computer **701**. EUD **703** typically receives helpful and useful data from the operations of computer **701**. For example, in a hypothetical case where computer **701** is designed to provide a recommendation to an end user, this recommendation would typically be communicated from network module **715** of computer **701** through WAN **702** to EUD **703**. In this way, EUD **703** can display, or otherwise present, the recommendation to an end user. In certain aspects, EUD **703** may be a client device, such as thin client, heavy client, mainframe computer, desktop computer and so on.

[0074] As defined herein, the term "client device" means a data processing system that requests shared services from a server, and with which a user directly interacts. Examples of a client device include, but are not limited to, a workstation, a desktop computer, a computer terminal, a mobile computer, a laptop computer, a netbook computer, a tablet computer, a smart phone, a personal digital assistant, a smart watch, smart glasses, a gaming device, a set-top box, a smart television and the like. Network infrastructure, such as routers, firewalls, switches, access points and the like, are not client devices as the term "client device" is defined herein. As defined herein, the term "user" means a person (i.e., a human being).

[0075] Remote server **704** is any computer system that serves at least some data and/or functionality to computer **701**. Remote server **704** may be controlled and used by the same entity that operates computer **701**. Remote server **704** represents the machine(s) that collect and store helpful and useful data for use by other computers, such as computer **701**. For example, in a hypothetical case where computer **701** is designed and programmed to provide a recommendation based on historical data, then this historical data may be provided to computer **701** from remote database **730** of remote server **704**. As defined herein, the term "server" means a data processing system configured to share services with one or more other data processing systems.

[0076] Public cloud **705** is any computer system available for use by multiple entities that provides on-demand availability of computer system resources and/or other computer capabilities, especially data storage (cloud storage) and computing power, without direct active management by the user. Cloud computing typically leverages sharing of resources to achieve coherence and economies of scale. The direct and active management of the computing resources of public cloud **705** is performed by the computer hardware and/or software of cloud orchestration module **741**. The computing resources provided by public cloud **705** are typically implemented by virtual computing environments that run on various computers making up the computers of host physical machine set **742**, which is the universe of physical computers in and/or available to public cloud **705**.

[0077] The virtual computing environments (VCEs) typically take the form of virtual machines from virtual machine set **743** and/or containers from container set **744**. It is understood that these VCEs may be stored as images and may be transferred among and between the various physical machine hosts, either as images or after instantiation of the VCE. Cloud orchestration module **741** manages the transfer and storage of images, deploys new instantiations of VCEs and manages active instantiations of VCE deployments. Gateway **740** is the collection of computer software, hardware, and firmware that allows public cloud **705** to communicate through WAN **702**.

[0078] VCEs can be stored as "images," and a new active instance of the VCE can be instantiated from the image. Two familiar types of VCEs are virtual machines and containers. A container is a VCE that uses operating-system-level virtualization. This refers to an operating system feature in which the kernel allows the existence of multiple isolated user-space instances, called containers. These isolated user-space instances typically behave as real computers from the point of view of programs running in them. A computer program running on an ordinary operating system can utilize all resources of that computer, such as connected devices, files and folders, network shares, CPU power, and quantifiable hardware capabilities. However, programs running inside a container can only use the contents of the container and devices assigned to the container, a feature which is known as containerization.

[0079] Private cloud **706** is similar to public cloud **705**, except that the computing resources are only available for use by a single enterprise. While private cloud **706** is depicted as being in communication with WAN **702**, in other aspects, a private cloud **706** may be disconnected from the internet entirely (e.g., WAN **702**) and only accessible through a local/private network. A hybrid cloud is a composition of multiple clouds of different types (for example, private, community or public cloud types), often respectively implemented by different vendors. Each of the multiple clouds remains a separate and discrete entity, but the larger hybrid cloud architecture is bound together by standardized or proprietary technology that enables orchestration, management, and/or data/application portability between the multiple constituent clouds. In this aspect, public cloud **705** and private cloud **706** are both part of a larger hybrid cloud.

[0080] Various aspects of the present disclosure are described by narrative text, flowcharts, block diagrams of computer systems and/or block diagrams of the machine logic included in computer program product (CPP) embodiments. With respect to any flowcharts, depending upon the technology involved, the operations can be performed in a different order than what is shown in a given flowchart. For example, again depending upon the technology involved, two operations shown in successive flowchart blocks may be performed in reverse order, as a single integrated step, concurrently, or in a manner at least partially overlapping in time.

[0081] As another example, two blocks shown in succession may, in fact, be accomplished as one step, executed concurrently, substantially concurrently, in a partially or wholly temporally overlapping manner, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved. It will also be noted that each block of the block diagrams and/or flowchart illustration, and combinations of blocks in the block diagrams and/or flowchart illustration, can be implemented by special purpose hardware-based systems that perform the specified functions or acts or carry out combinations of special purpose hardware and computer instructions. Each block in

the flowchart or block diagrams may represent a module, segment, or portion of instructions, which comprises one or more executable instructions for implementing the specified logical function(s).

[0082] The terminology used herein is for the purpose of describing particular embodiments only and is not intended to be limiting of the invention. As used herein, the singular forms "a," "an," and "the" are intended to include the plural forms as well, unless the context clearly indicates otherwise. It will be further understood that the terms "includes," "including," "comprises," and/or "comprising," when used in this disclosure, specify the presence of stated features, integers, steps, operations, elements, and/or components, but do not preclude the presence or addition of one or more other features, integers, steps, operations, elements, components, and/or groups thereof.

[0083] Reference throughout this disclosure to "one embodiment," "an embodiment," "one arrangement," "an arrangement," "one aspect," "an aspect," or similar language means that a particular feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment described within this disclosure. Thus, appearances of the phrases "one embodiment," "an embodiment," "one arrangement," "an arrangement," "one aspect," "an aspect," and similar language throughout this disclosure may, but do not necessarily, all refer to the same embodiment.

[0084] The term "plurality," as used herein, is defined as two or more than two. The term "another," as used herein, is defined as at least a second or more. The term "coupled," as used herein, is defined as connected, whether directly without any intervening elements or indirectly with one or more intervening elements, unless otherwise indicated. Two elements also can be coupled mechanically, electrically, or communicatively linked through a communication channel, pathway, network, or system. The term "and/or" as used herein refers to and encompasses any and all possible combinations of one or more of the associated listed items. It will also be understood that, although the terms first, second, etc. may be used herein to describe various elements, these elements should not be limited by these terms, as these terms are only used to distinguish one element from another unless stated otherwise or the context indicates otherwise.

[0085] The term "if" may be construed to mean "when" or "upon" or "in response to determining" or "in response to detecting," depending on the context. Similarly, the phrase "if it is determined" or "if [a stated condition or event] is detected" may be construed to mean "upon determining" or "in response to determining" or "upon detecting [the stated condition or event]" or "in response to detecting [the stated condition or event]," depending on the context. As used herein, the terms "if," "when," "upon," "in response to," and the like are not to be construed as indicating a particular operation is optional. Rather, use of these terms indicate that a particular operation is conditional. For example and by way of a hypothetical, the language of "performing operation A upon B" does not indicate that operation A is optional. Rather, this language indicates that operation A is conditioned upon B occurring.

[0086] The foregoing description is just an example of embodiments of the invention, and variations and substitutions. While the disclosure concludes with claims defining novel features, it is believed that the various features described herein will be better understood from a consideration of the description in conjunction with the drawings. The process(es), machine(s), manufacture(s) and any variations thereof described within this disclosure are provided for purposes of illustration. Any specific structural and functional details described are not to be interpreted as limiting, but merely as a basis for the claims and as a representative basis for teaching one skilled in the art to variously employ the features described in virtually any appropriately detailed structure. Further, the terms and phrases used within this disclosure are not intended to be limiting, but rather to provide an understandable description of the features described.

What is claimed is:

1. A computer-implemented method for modifying one or more of a plurality of data pipelines within a computer architecture that process data from a plurality of datasets, comprising:

ingesting real-time observability data regarding the plurality of data pipelines and the plurality of datasets;

classifying a dataset from the plurality of datasets based upon usage and reliability to generate a classification of the dataset; and

generating, based upon the classification, a recommendation to modify at least one of the plurality of data pipelines.

2. The method of claim **1**, wherein

the dataset is classified as low usage and low reliability, and

the recommendation includes replacing, for at least one of the plurality of data pipelines, the dataset with a higher-quality dataset.

3. The method of claim **1**, wherein

the dataset is classified as low usage and low reliability, and

the recommendation includes moving a portion of the dataset into a lower cost data repository.

4. The method of claim **1**, wherein

the dataset is classified as low usage and high reliability, and

the recommendation includes modifying the at least one of the plurality of data pipelines to increase usage of the dataset.

5. The method of claim **1**, wherein

the dataset is classified as low usage and high reliability, and

the recommendation includes reducing data quality actions on the dataset.

6. The method of claim **1**, wherein

the dataset is classified as high usage and high reliability,

a determination is made that usage of the dataset is decreasing,

the recommendation includes increasing usage of the dataset.

7. The method of claim **1**, wherein

the recommendation is a computer data structure that causes one or more changes/modifications to a data/AI platform within the computer architecture.

8. A computer hardware system for modifying one or more of a plurality of data pipelines within a computer architecture that process data from a plurality of datasets, comprising:

a hardware processor configured to perform the following executable operations:

ingesting real-time observability data regarding the plurality of data pipelines and the plurality of datasets;

classifying a dataset from the plurality of datasets based upon usage and reliability to generate a classification of the dataset; and

generating, based upon the classification, a recommendation to modify at least one of the plurality of data pipelines.

9. The system of claim **8**, wherein

the dataset is classified as low usage and low reliability, and

the recommendation includes replacing, for at least one of the plurality of data pipelines, the dataset with a higher-quality dataset.

10. The system of claim **8**, wherein

the dataset is classified as low usage and low reliability, and

the recommendation includes moving a portion of the dataset into a lower cost data repository.

11. The system of claim **8**, wherein

the dataset is classified as low usage and high reliability, and

the recommendation includes modifying the at least one of the plurality of data pipelines to increase usage of the dataset.

12. The system of claim **8**, wherein

the dataset is classified as low usage and high reliability, and

the recommendation includes reducing data quality actions on the dataset.

13. The system of claim **8**, wherein

the dataset is classified as high usage and high reliability,

a determination is made that usage of the dataset is decreasing,

the recommendation includes increasing usage of the dataset.

14. The system of claim **8**, wherein

the recommendation is a computer data structure that causes one or more changes/modifications to a data/AI platform within the computer architecture.

15. A computer program product, comprising:

a computer readable storage medium having stored therein program code for modifying one or more of a plurality of data pipelines within a computer architecture that process data from a plurality of datasets,

the program code, which when executed by a computer hardware system, causes the computer hardware system to perform:

ingesting real-time observability data regarding the plurality of data pipelines and the plurality of datasets;

classifying a dataset from the plurality of datasets based upon usage and reliability to generate a classification of the dataset; and

generating, based upon the classification, a recommendation to modify at least one of the plurality of data pipelines, wherein

the recommendation is a computer data structure that causes one or more changes/modifications to the data/AI platform.

16. The computer program product of claim **15**, wherein

the dataset is classified as low usage and low reliability, and

the recommendation includes replacing, for at least one of the plurality of data pipelines, the dataset with a higher-quality dataset.

17. The computer program product of claim **15**, wherein

the dataset is classified as low usage and low reliability, and

the recommendation includes moving a portion of the dataset into a lower cost data repository.

18. The computer program product of claim **15**, wherein

the dataset is classified as low usage and high reliability, and

the recommendation includes modifying the at least one of the plurality of data pipelines to increase usage of the dataset.

19. The computer program product of claim **15**, wherein

the dataset is classified as low usage and high reliability, and

the recommendation includes reducing data quality actions on the dataset.

20. The computer program product of claim **15**, wherein

the dataset is classified as high usage and high reliability,

a determination is made that usage of the dataset is decreasing,

the recommendation includes increasing usage of the dataset.

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