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(54) **MACHINE LEARNING SYSTEM FLOW AUTHORING TOOL**

(71) Applicant: **Facebook, Inc.**, Menlo Park, CA (US)

(72) Inventors: **Stuart Michael Bowers**, Menlo Park, CA (US); **Hussein Mohamed Hassan Mehanna**, Cupertino, CA (US); **Alisson Gusatti Azzolini**, San Francisco, CA (US); **Jeffrey Scott Dunn**, Seattle, WA (US); **Rodrigo Bouchardet Farnham**, Atherton, CA (US); **James Robert Paton**, Fremont, CA (US); **Aleksandr Sidorov**, Menlo Park, CA (US); **Pamela Shen Vagata**, Menlo Park, CA (US); **Xiaowen Xie**, Fremont, CA (US)

(73) Assignee: **Facebook, Inc.**, Menlo Park, CA (US)

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CPC ***G06N 20/00*** (2019.01); ***G06F 40/205*** (2020.01)

(58) **Field of Classification Search**
None
See application file for complete search history.

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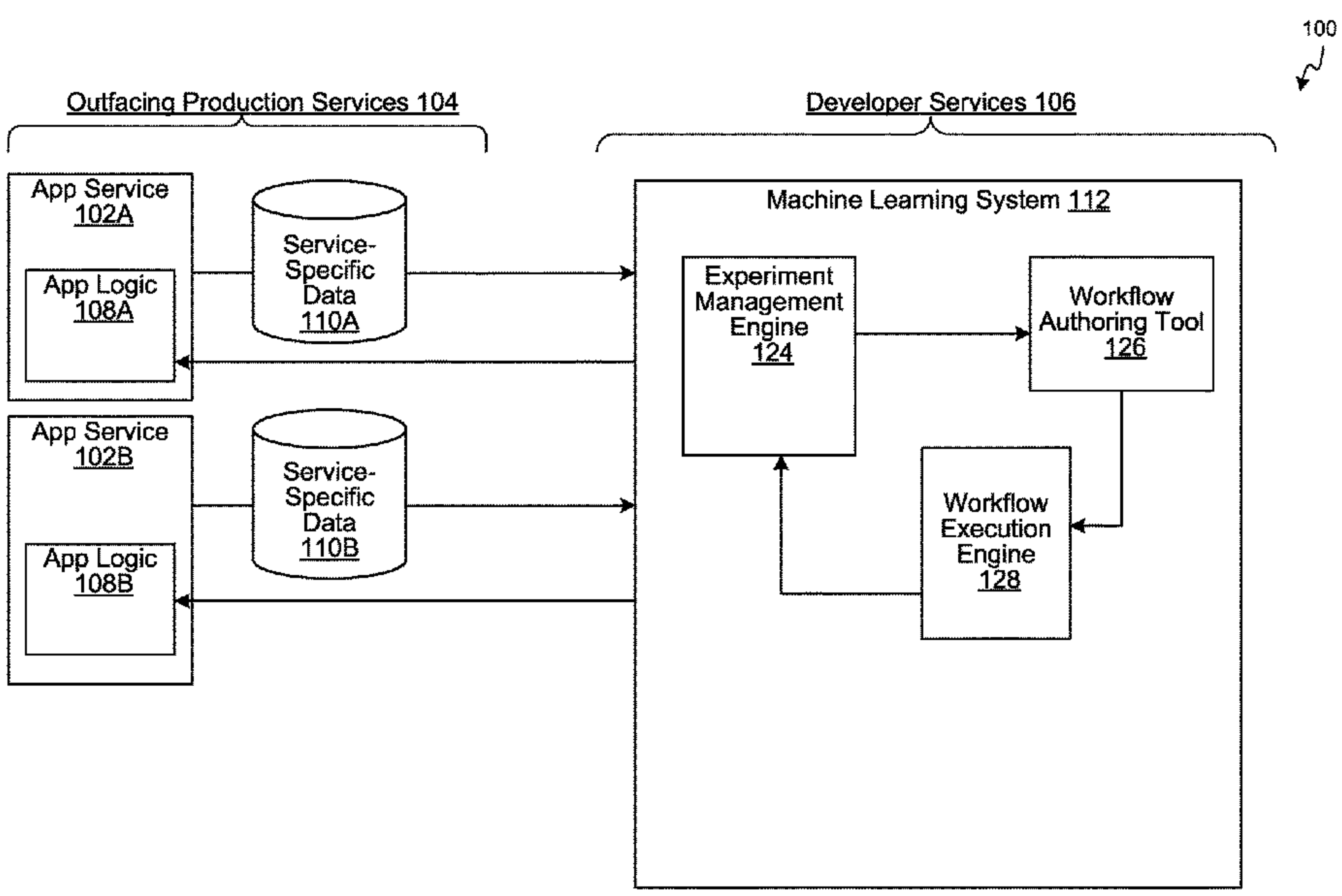
(74) *Attorney, Agent, or Firm* — Fenwick & West LLP

(57) **ABSTRACT**

Some embodiments include a workflow authoring tool that accesses a text string representation of a workflow and a text string representation of at least a data processing operator type. The workflow authoring tool enables definition of one or more data processing operator types that can be referenced in defining the machine learning workflow. When scheduling a workflow, the text string representation of the workflow can be parsed and traversed to generate an inter-dependency graph of one or more data processing operators. The text string representation of the data processing operator type can identify operator attributes associated with the data processing operator type.

18 Claims, 8 Drawing Sheets



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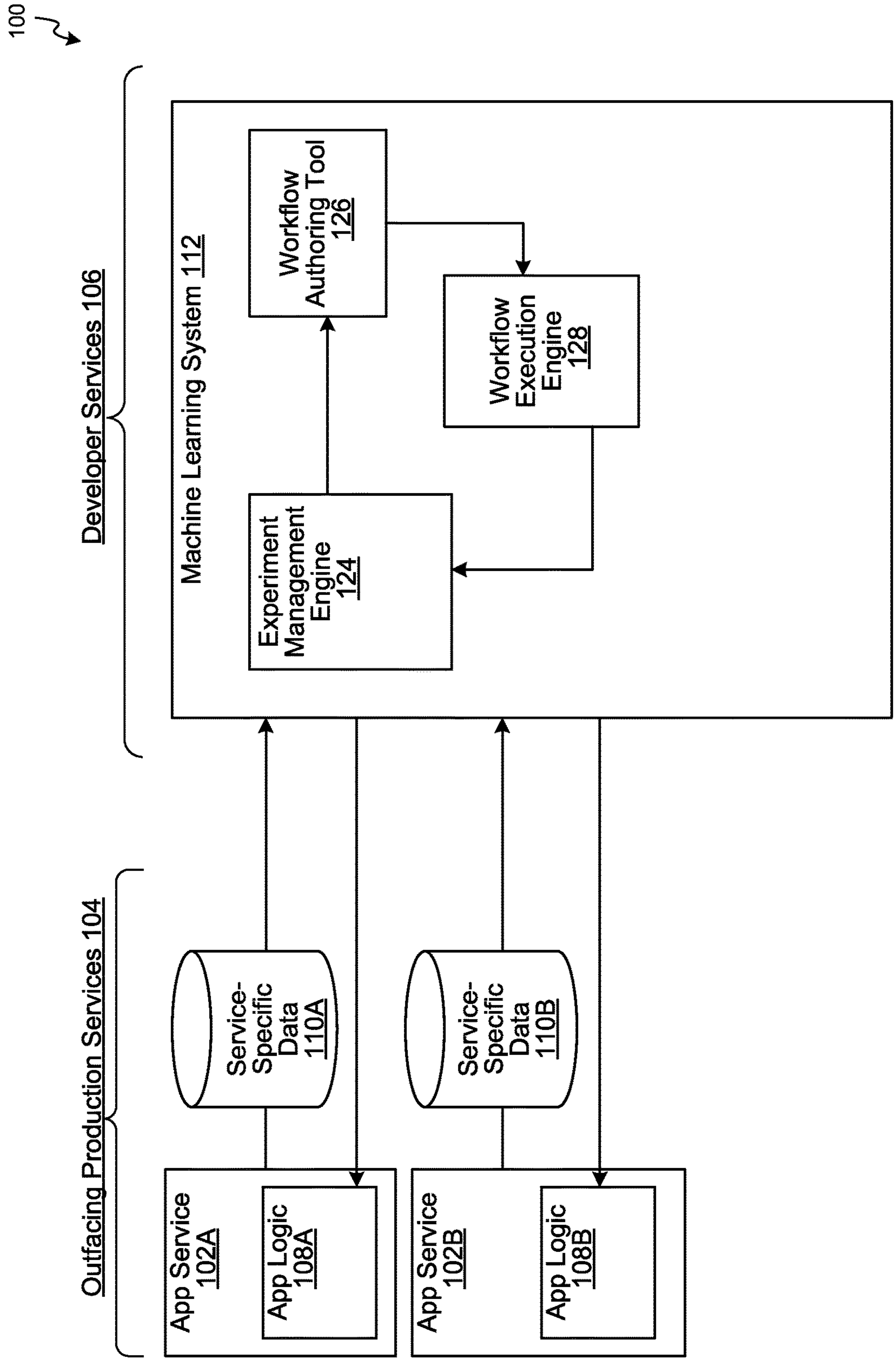
100
Developer Services 106
Machine Learning System 112
Workflow Authoring Tool 126
Workflow Execution Engine 128
Experiment Management Engine 124
Outfacing Production Services 104
Service-Specific Data 110A
Service-Specific Data 110B
App Service 102A
App Logic 108A
App Service 102B
App Logic 108B

FIG. 1

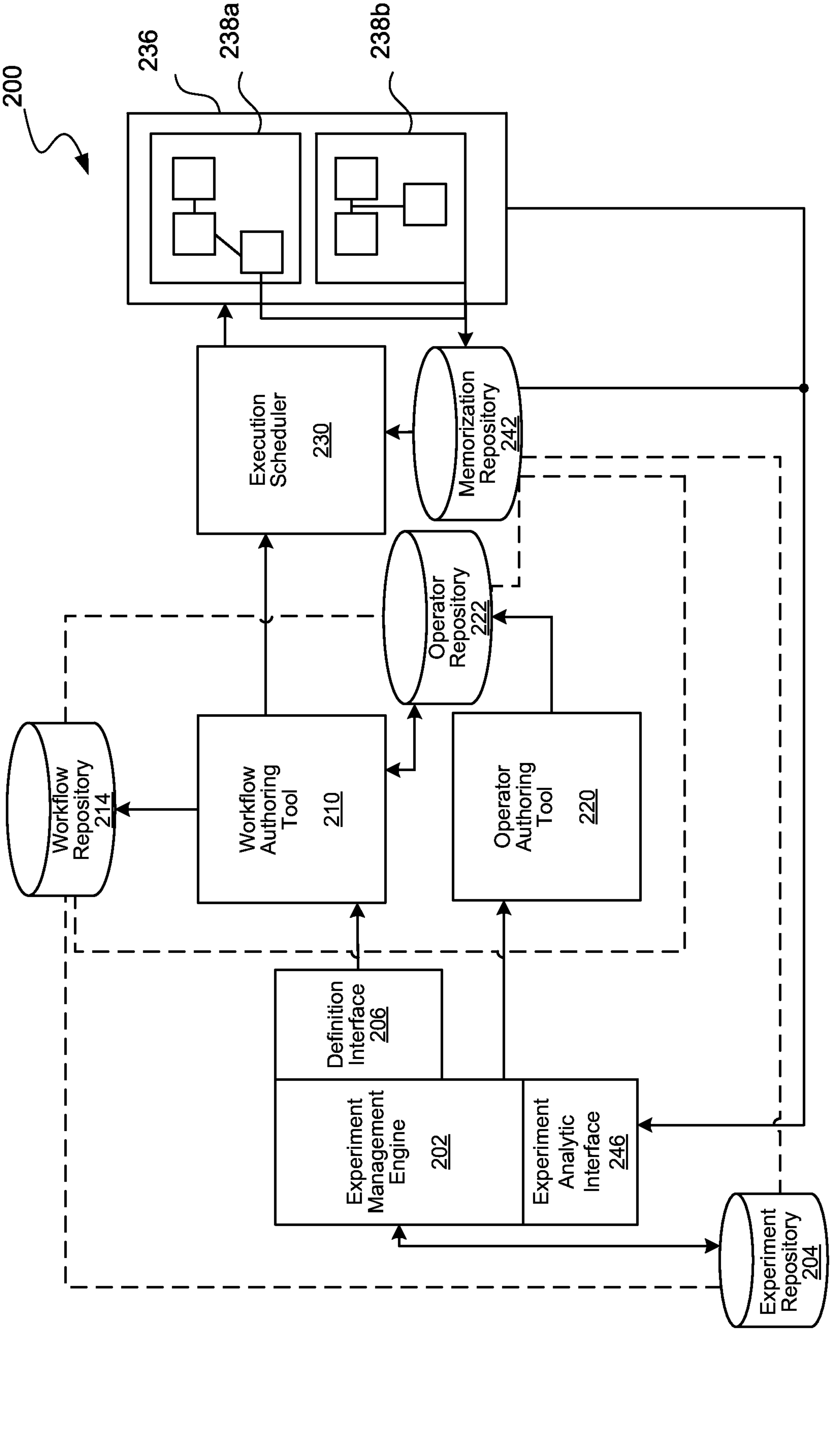
200
236
238a
238b
Execution Scheduler
230
Memorization Repository
242
Operator Repository
222
Workflow Repository
214
Workflow Authoring Tool
210
Operator Authoring Tool
220
Definition Interface
206
Experiment Management Engine
202
Experiment Analytic Interface
246
Experiment Repository
204

FIG. 2

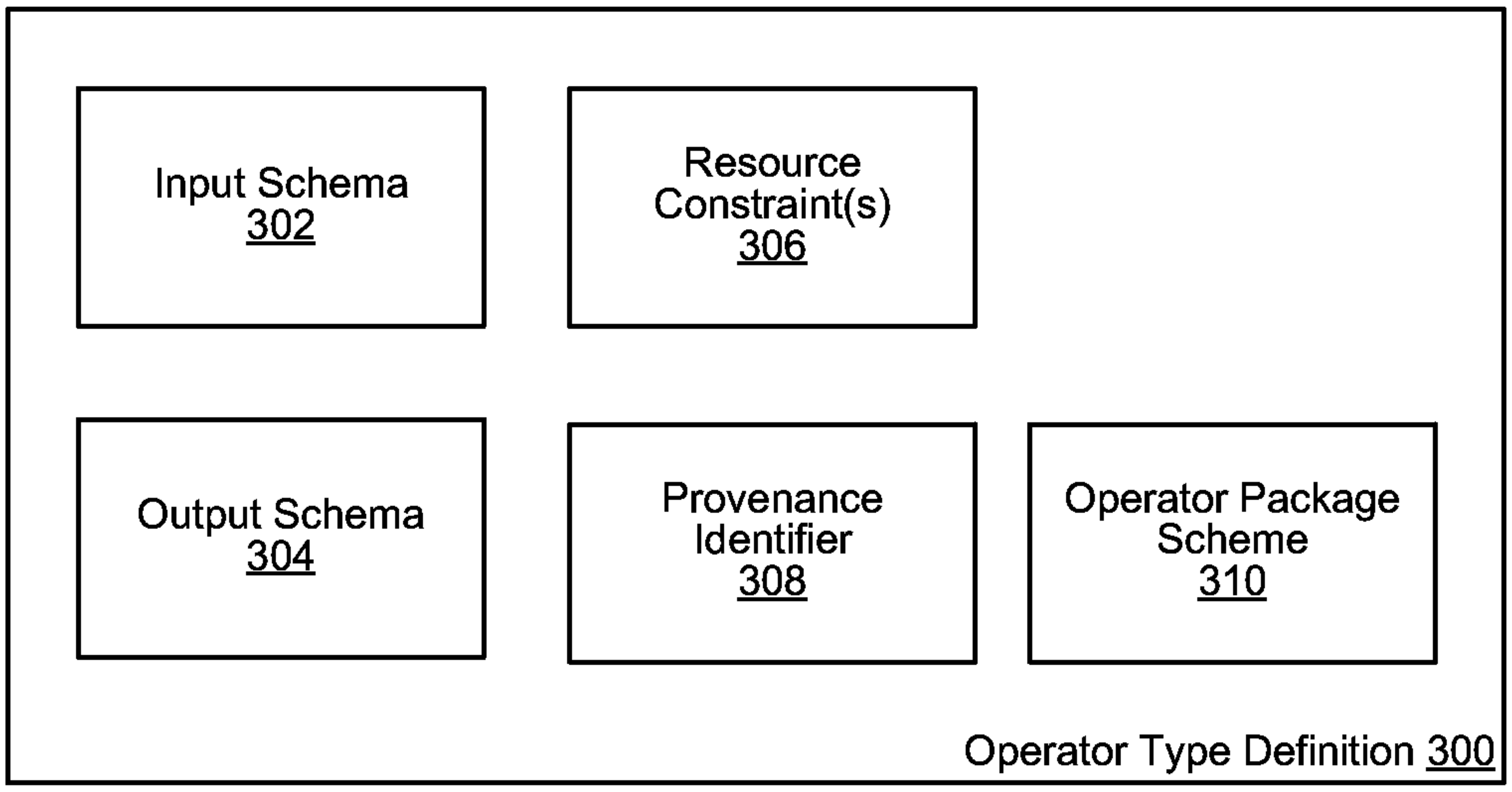
Input Schema
302
Resource Constraint(s)
306
Output Schema
304
Provenance Identifier
308
Operator Package Scheme
310
Operator Type Definition 300

FIG. 3

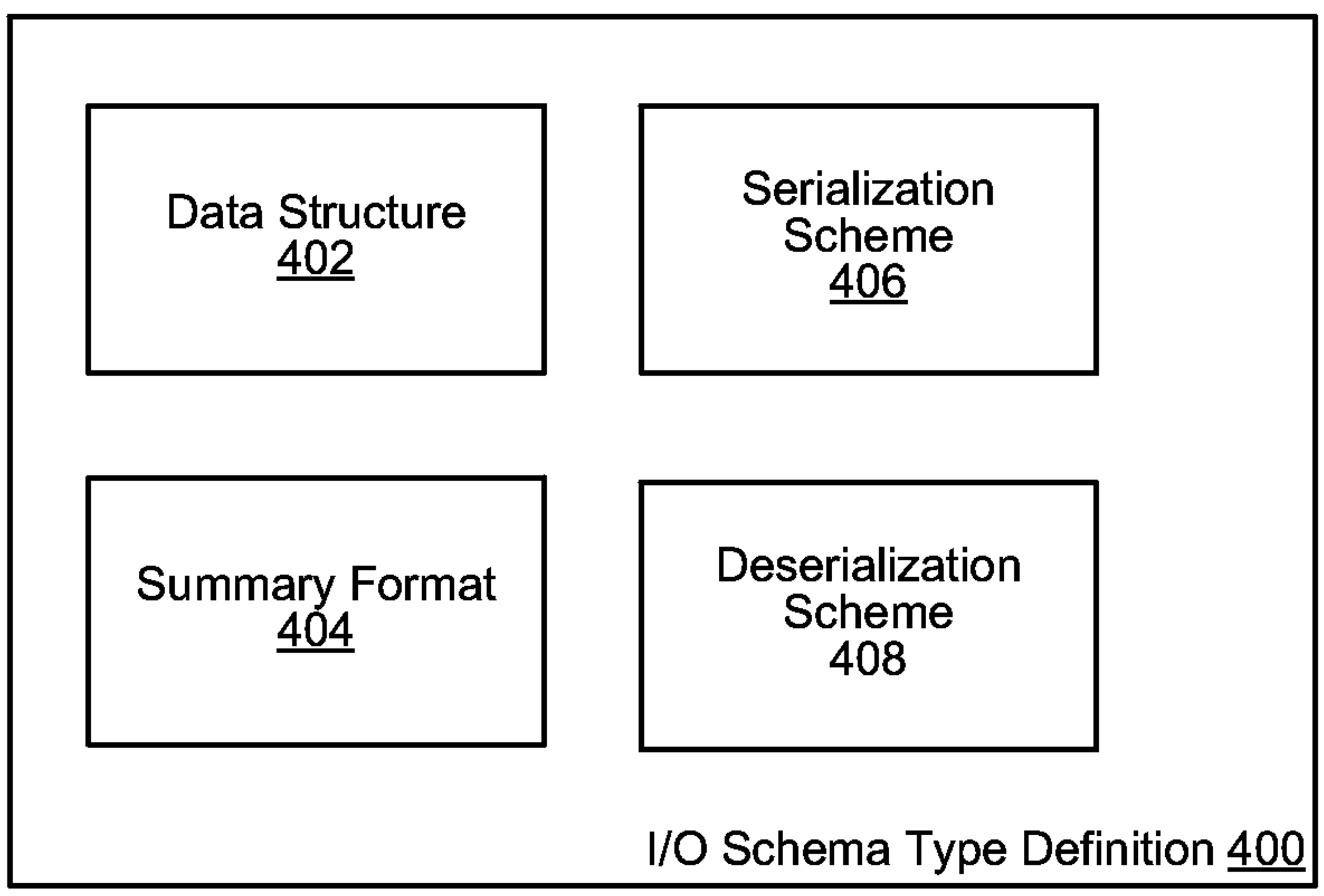
Data Structure
402
Serialization Scheme
406
Summary Format
404
Deserialization Scheme
408
I/O Schema Type Definition 400

FIG. 4

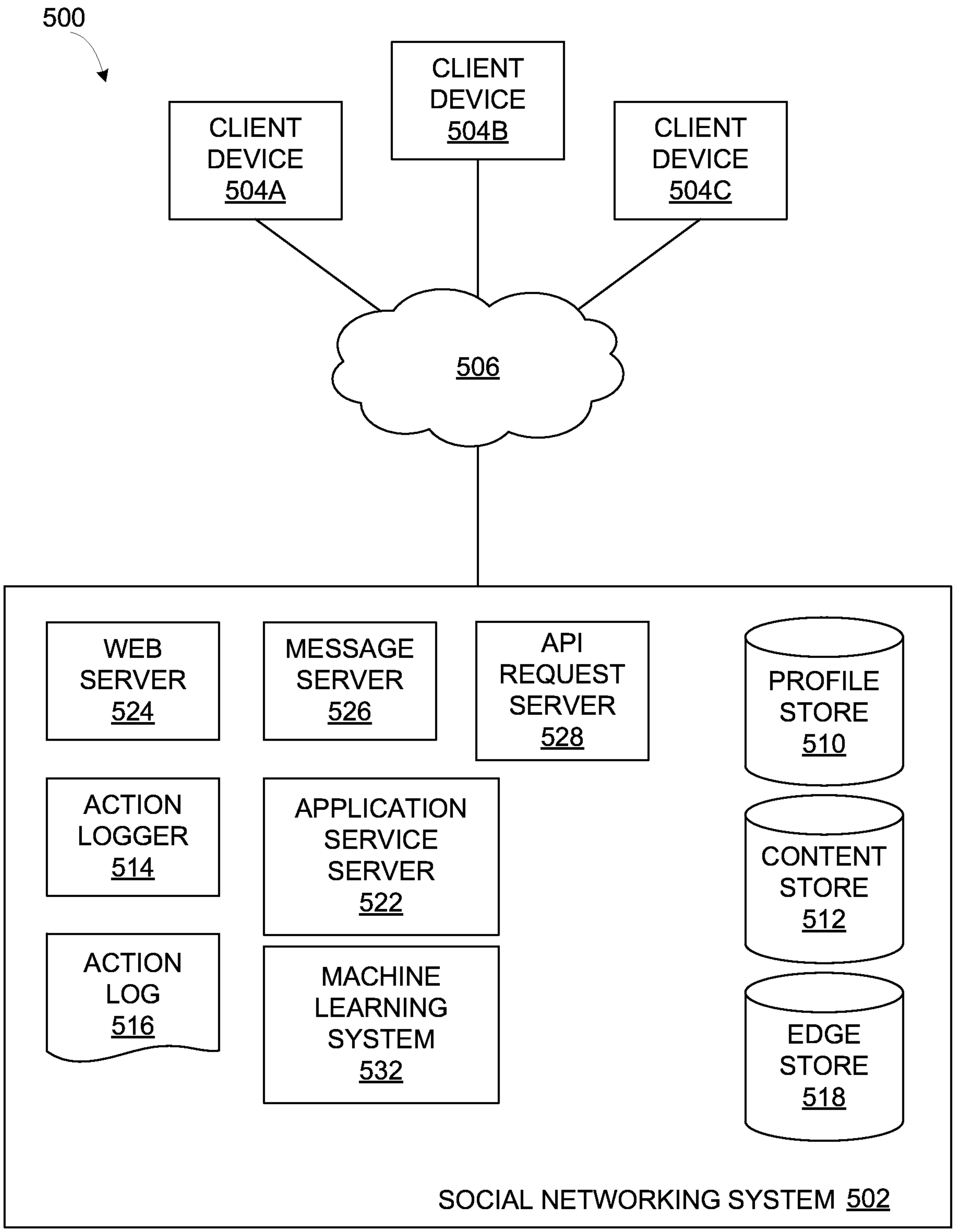
500
CLIENT DEVICE 504A
CLIENT DEVICE 504B
CLIENT DEVICE 504C
506
WEB SERVER 524
MESSAGE SERVER 526
API REQUEST SERVER 528
PROFILE STORE 510
ACTION LOGGER 514
APPLICATION SERVICE SERVER 522
CONTENT STORE 512
ACTION LOG 516
MACHINE LEARNING SYSTEM 532
EDGE STORE 518
SOCIAL NETWORKING SYSTEM 502

FIG. 5

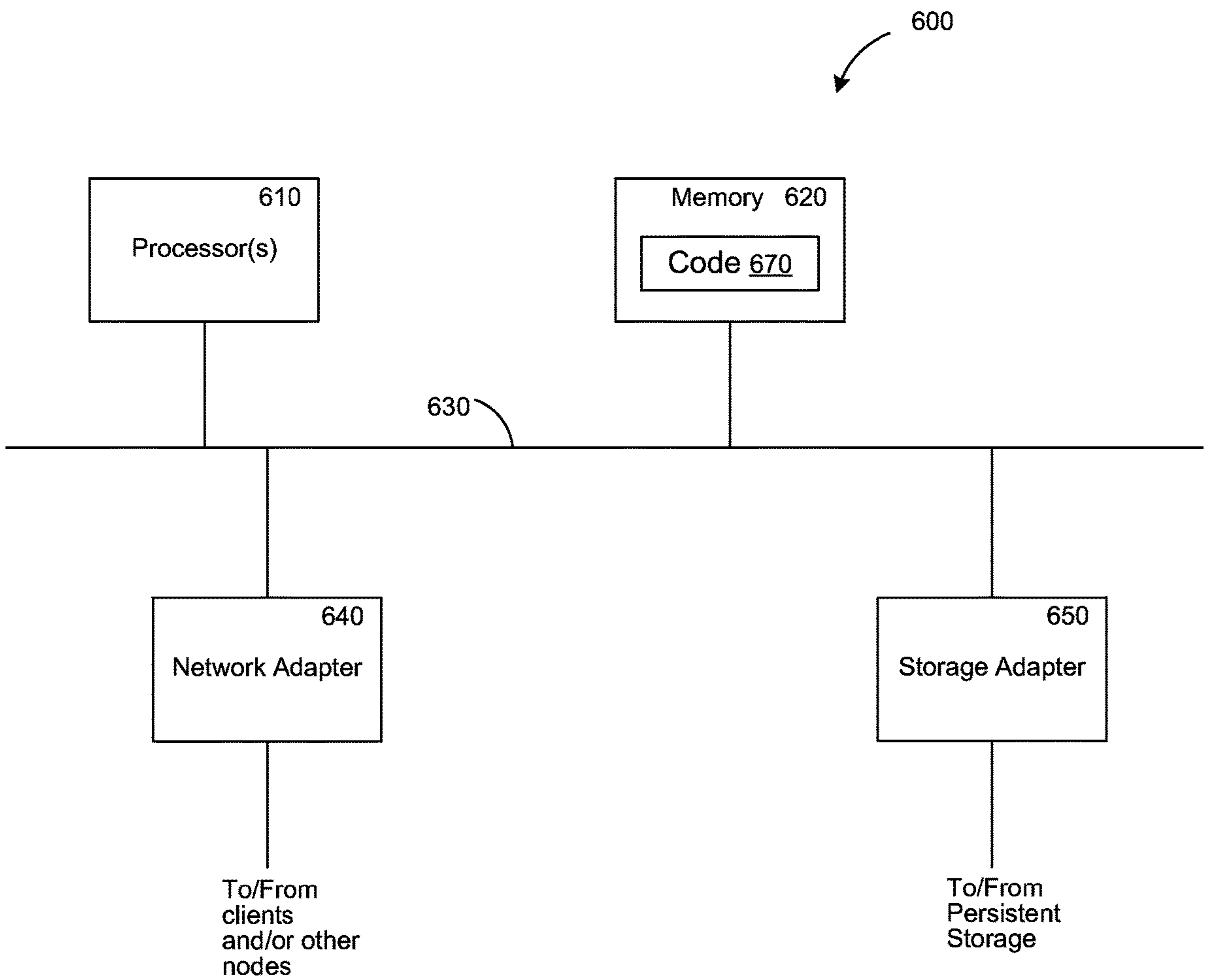
600
610
Processor(s)
Memory 620
Code 670
630
640
Network Adapter
650
Storage Adapter
To/From clients and/or other nodes
To/From Persistent Storage

FIG. 6

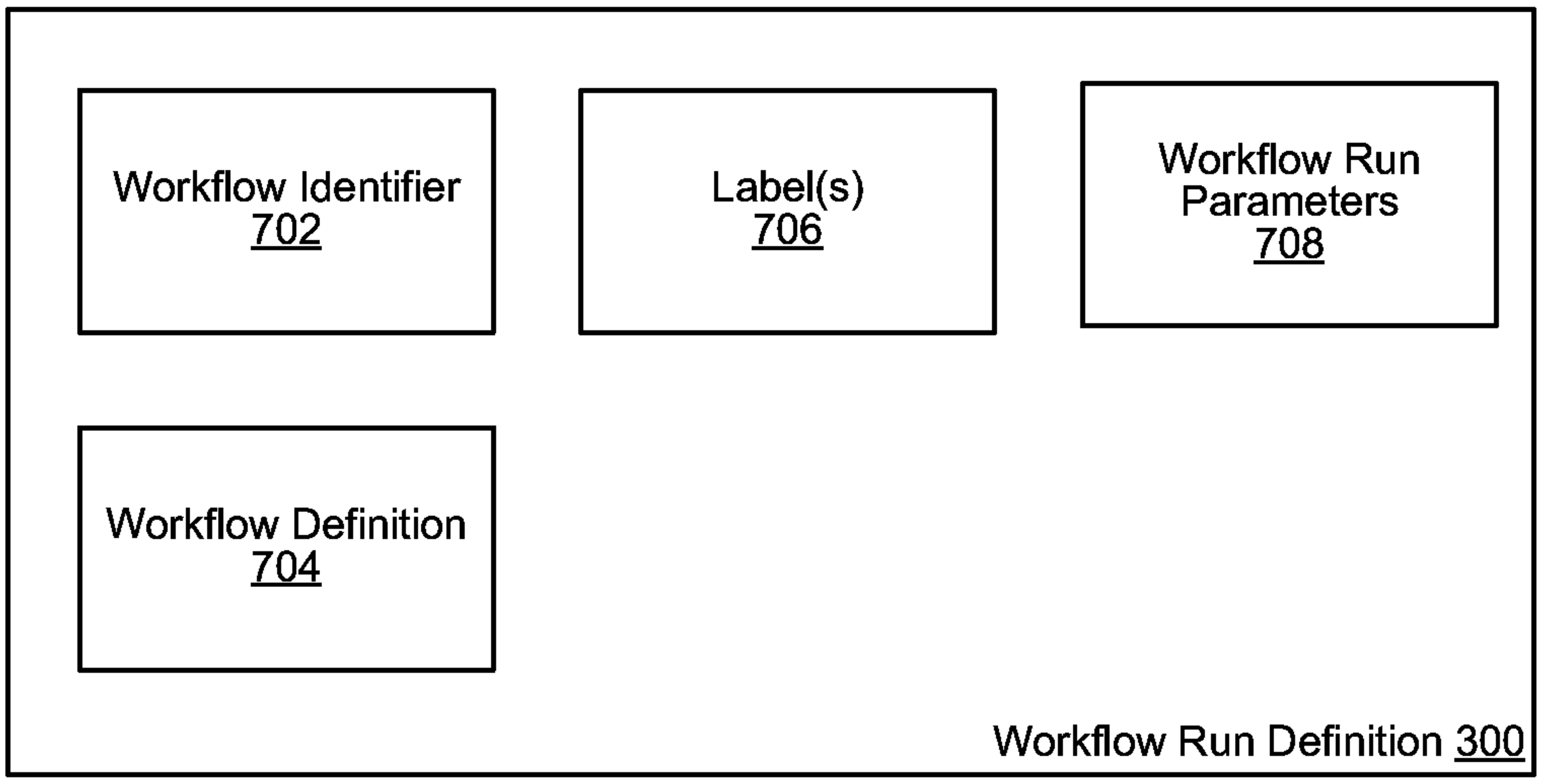
Workflow Identifier
702
Label(s)
706
Workflow Run
Parameters
708
Workflow Definition
704
Workflow Run Definition 300

FIG. 7A

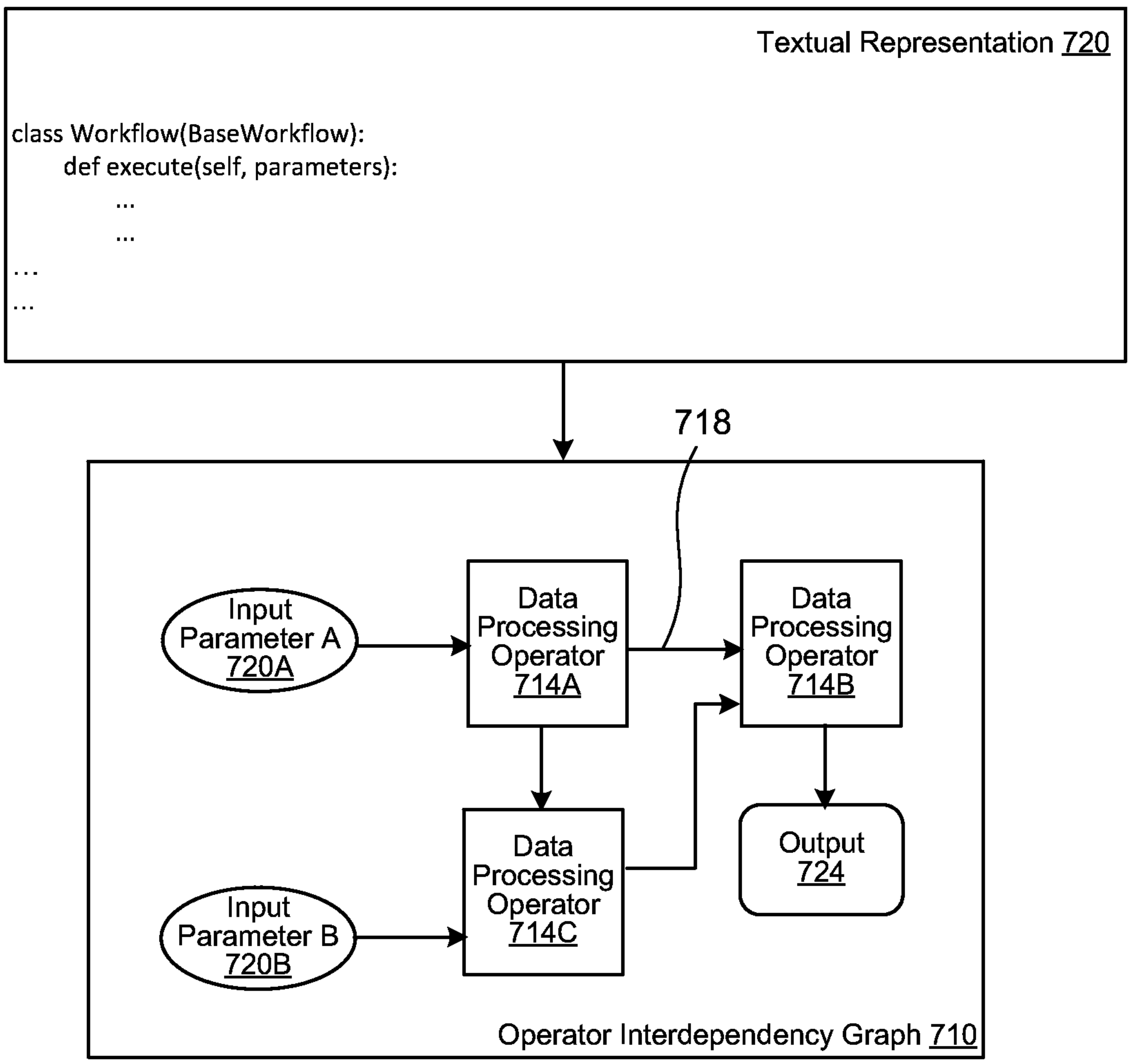
Textual Representation 720
class Workflow(BaseWorkflow):
def execute(self, parameters):
...
...
...
...
718
Input
Parameter A
720A
Data
Processing
Operator
714A
Data
Processing
Operator
714B
Data
Processing
Operator
714C
Output
724
Input
Parameter B
720B
Operator Interdependency Graph 710

FIG. 7B

Textual Representation 800

```
class Workflow(BaseWorkflow):
    def execute(self, parameters):
        big = "big"
        iters = 2 ** 16
        self.op1 = Op1(text=big, iters=iters)
        self.op2 = Op2(original=big, repeated=self.op1.outputs.text, iters=iters)
```

FIG. 8

Textual Representation 900

```
class Op1(BaseOperator):
    input_schema = types.Schema(
        text=types.TEXT,
        iters=types.INTEGER,
    )
    output_schema = types.Schema(
        text=types.TEXT
    )
    def execute(self):
    self.outputs.text = self.inputs.text * self.inputs.iters
```

FIG. 9A

Textual Representation 950

```
class Op2(BaseOperator):
    input_schema = types.Schema(
        original=types.TEXT,
        repeated=types.TEXT,
        iters=types.INTEGER,
    )
    def execute(self):
    assert len(self.inputs.repeated) == len(self.inputs.original) * self.inputs.iters
```

FIG. 9B

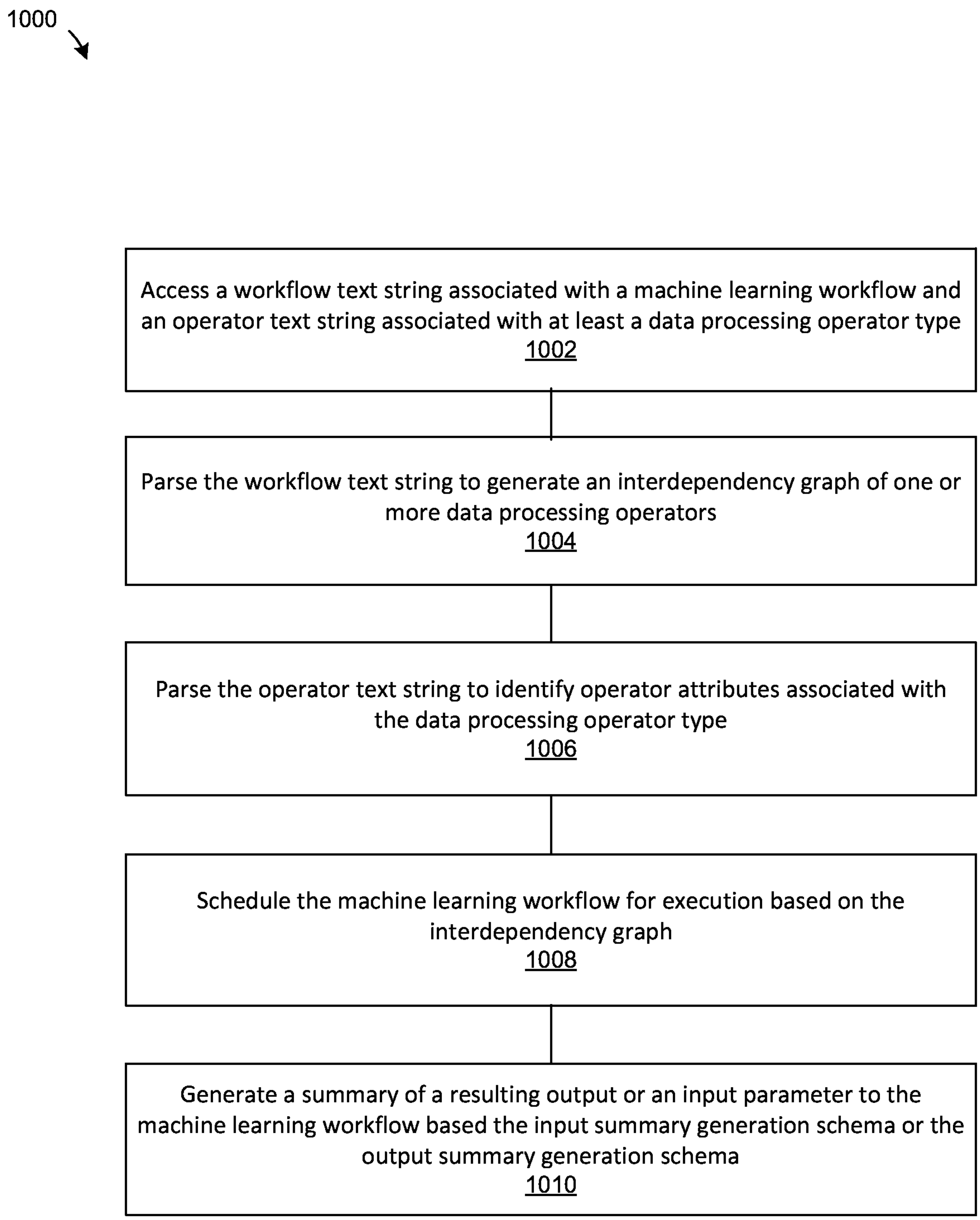
1000
Access a workflow text string associated with a machine learning workflow and an operator text string associated with at least a data processing operator type
1002
Parse the workflow text string to generate an interdependency graph of one or more data processing operators
1004
Parse the operator text string to identify operator attributes associated with the data processing operator type
1006
Schedule the machine learning workflow for execution based on the interdependency graph
1008
Generate a summary of a resulting output or an input parameter to the machine learning workflow based the input summary generation schema or the output summary generation schema
1010

FIG. 10

MACHINE LEARNING SYSTEM FLOW AUTHORING TOOL

CROSS-REFERENCE TO RELATED APPLICATIONS

This application is related to U.S. patent application Ser. No. 14/684,041, entitled "MACHINE LEARNING MODEL TRACKING PLATFORM," which was filed on Apr. 10, 2015; U.S. patent application, entitled "MACHINE LEARNING SYSTEM INTERFACE," filed on the same day as the present application; and U.S. patent application, entitled "MACHINE LEARNING SYSTEM FLOW PROCESSING," filed on the same day as the present application; all of which are incorporated by reference herein in their entirety.

BACKGROUND

"Big data" is a broad term for datasets so large or complex that traditional data processing applications are often inadequate. For example, a social networking system can run several application services that pertain to big data. The term "big data" also often refers to the use of predictive analytics or other methods to extract values from data. For example, analysis of datasets can find new correlations, trends, patterns, categories, etc. Such analyses rely on machine learning and often consumes a large amount of computational resources (e.g., memory capacity, processor capacity, and/or network bandwidth).

A typical machine learning workflow may include building a model from a sample dataset (referred to as a "training set"), evaluating the model against one or more additional sample datasets (referred to as a "validation set" and/or a "test set") to decide whether to keep the model and to benchmark how good the model is, and using the model in "production" to make predictions or decisions against live input data captured by an application service. The training set, the validation set, and/or the test set can respectively include pairs of input datasets and expected output datasets that correspond to the respective input datasets.

Various web-based or mobile applications often rely on machine learning models to process large and complex "big data" to provide application services (e.g., personalized or targeted application services) to a large number of users. There is frequently a need for higher accuracy and/or consistency models while the requirements of these models are ever evolving. Experiments involving the training and evaluation of these models nevertheless take time and are typically the manual burdens of one or more developers or analysts.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a block diagram illustrating an application service system, in accordance with various embodiments.

FIG. **2** is a block diagram illustrating a machine learning system that manages big data experiments, in accordance with various embodiments.

FIG. **3** is a block diagram illustrating an operator type definition, in accordance with various embodiments.

FIG. **4** is a block diagram illustrating an input/output (I/O) schema definition, in accordance with various embodiments.

FIG. **5** is a high-level block diagram of a system environment suitable for a social networking system, in accordance with various embodiments.

FIG. **6** is a block diagram of an example of a computing device, which may represent one or more computing device or server described herein, in accordance with various embodiments

FIG. **7**A is a block diagram illustrating a workflow run definition, in accordance with various embodiments.

FIG. **7**B is a block diagram representative of a workflow definition, in accordance with various embodiments

FIG. **8** is an example of a textual representation of a workflow, in accordance with various embodiments.

FIG. **9**A is one example of a textual representation of a data processing operator, in accordance with various embodiments.

FIG. **9**B is another example of a textual representation of a data processing operator, in accordance with various embodiments

FIG. **10** is a flow chart illustrating a method of operating a machine learning system, in accordance with various embodiments.

The figures depict various embodiments of this disclosure for purposes of illustration only. One skilled in the art will readily recognize from the following discussion that alternative embodiments of the structures and methods illustrated herein may be employed without departing from the principles of embodiments described herein.

DETAILED DESCRIPTION

A machine learning system can be implemented by one or more computing devices to facilitate design, execution, analysis, evaluation, and/or generation of machine learning related processes (e.g., pre-processing or post-processing machine learning data, training machine learning models, testing or experimenting with machine learning models, etc.). In several embodiments, the machine learning system can implement at least an experiment management engine, a workflow authoring tool, and a workflow execution engine. Several embodiments pertain to the workflow authoring tool, including input/output schema definition.

The machine learning system can include an authorship environment (e.g., implemented by the workflow authoring tool) and an execution platform (e.g., implemented by the workflow execution engine) for developers and analysts to build machine learning pipelines with automated dependency handling, front-end process management, and built-in components for various algorithms and output formats. The machine learning system advantageously enables machine learning in a computing system (e.g., an application service system and/or a social networking system) to be more reproducible and enables collaborative authorship and execution of machine learning processes and experiments.

Experiments and workflows can be managed via a user interface (UI) or an application programming interface (API). The UI and/or API can be executed on one or more dedicated computer tiers. For example, the UI enables an operating user to associate an experiment with one or more workflows for processing one or more input data sets into at one or more outputs. An "experiment" corresponds to a run instance of at least one workflow. An experiment can have experiment parameters. For example, the experiment parameters can be a run identifier (e.g., a title/description and/or a run sequence number), an indication of one or more workflows, an indication of one or more input parameters (e.g., input datasets, input data sources and/or input data configurations for the workflows, or any combination thereof. For example, the input data configurations can define which portion of an input dataset to use. In some embodiments, an experiment parameter is a workflow run parameter.

A "workflow" is an execution pipeline in a machine learning system to create, modify, evaluate, validate, and/or utilize one or more machine learning models (e.g., including pre-processing of input data and post-processing of output data from the machine learning models). A workflow, for example, can be composed of a directed graph (DG) of data processing operators and can have an associated output schema. In some embodiments, the DG can be acyclical. In some embodiments, the DG can include iterative feedback loops and/or recursion. During each workflow run/experiment, the workflow execution engine can programmatically generate the DG from a workflow definition (e.g., textual representation or other representative format of the workflow). In some cases, different workflow runs of the same workflow can have entirely different DGs. A workflow can inherit attributes from another workflow. In one example, all workflows can inherit attributes from a basic workflow. Workflows can accept one or more input parameters (e.g., functional arguments). Workflows can expose its data processing operators as members, elements of member lists, or elements of member dictionaries.

A workflow can utilize a pipeline of data processing operators and be configured to process one or more input datasets consistent with an input schema into one or more outputs consistent with an output schema. The input datasets can be passed in as or identified by at least one of the input parameters. In some embodiments, the DG of the data processing operators represent interdependencies of the data processing operators, where each directed edge represents an output of a data processing operator feeding into an input of another data processing operator. In several embodiments, more than one instance of a single data processing operator can be represented in the DG. For example, a data processing operator that normalizes a dataset can be used multiple times in the pipeline. In some embodiments, the input schema and the output schema are defined in the workflow. For example, the input schema is defined by a data processing operator at the front of the pipeline and the output schema is defined by a data processing operator at the end of the pipeline.

A data processing operator type is a computational unit. Instances of the data processing operator type can be scheduled to run on a single host device or a single operating environment (e.g., a virtual device) in an indivisible manner. Data processing operator types are the building blocks for workflows and are reusable across workflows. Different instances of the same data processing operator types can be used in the same workflow. Some operators can be used to run programmable scripts. For example, a "Bash" operator or an "R" operator which can be used to run an arbitrary bash script or R script respectively. Each data processing operator exposes an input schema defining one or more types of data it expects as its one or more inputs. Each data processing operator can also define an output schema defining one or more types of data it produces as its one or more outputs. Inputs to a data processing operator may be outputs from another data processing operator. The workflow execution engine can automatically handle scheduling data processing operators appropriately such that a data processing operator will not run until all of its inputs have been materialized by one or more data processing operators that produce them.

Data processing operators and/or workflows can expose output schemas describing the set of items they produce. In some embodiments, an input or output (I/O) schema can be associated with a serialization format. In some embodiments, each workflow with a defined output schema and corresponding serialization format can automatically upload its outputs according to the serialization format to a memorization database of operator outputs. This enables the machine learning system to automatically produce visualizations of outputs and reuse outputs that another data processing operator or workflow would otherwise have to re-calculate.

In some embodiments, a data processing operator defines an input summary format and an output summary format. In turn, the data processing operator at the front of the pipeline for a workflow can define the input summary format of the workflow. Likewise, the data processing operator at the end of the pipeline can define the output summary format of the workflow. An input summary format can describe the look and feel of a summary of the input datasets of the data processing operator and an output summary format can describe the look and feel of a summary of the outputs of the data processing operator.

When the machine learning system runs an experiment based on a workflow, the machine learning system can generate visualizations of the inputs and outputs of the experiment according to the input summary format and the output summary format. In some embodiments, the visualizations or representations of the visualizations are stored on the machine learning system and can be accessed by the user. In some embodiments, the visualizations are presented to the user automatically (e.g., when the visualizations are generated) as part of an experiment tracking dashboard. In some embodiments, the machine learning system sends the visualizations to one or more associated operating users of an experiment, in response to detecting that the experiment has finished running. The summary formats can describe to the machine learning system how to compute summary data, how to render the summary data, how to present the summary data (e.g., dimensionalities to present, whether to remove outliers, what colors to use, size of the visualization, etc.), in what form to render the data (e.g., a pie chart, a linear graph, a comparison table, etc.), and whether and/or how to sample the data prior to presentation.

One or more resource constraints can be associated with one or more data processing operators in the workflow. For example, the resource constraints can include a memory capacity threshold, a number of CPUs threshold, a number of GPUs threshold, a network bandwidth restriction, a geographic region restriction (e.g., relative or absolute), a network location restriction (e.g., relative or absolute), or any combination thereof.

In some embodiments, the workflow authorship tool can include an integrated development environment to define a workflow utilizing a workflow definition language. An authoring user can define one or more data processing operators for a workflow using the workflow definition language. In some cases, the authoring user can create and edit the workflow within the integrated development environment. In other cases, the authoring user can create and edit the workflow externally as a text formatted in the workflow definition language and import the text into the machine learning system.

A data processing operator definition can associate at least one input schema and at least one output schema with a data processing operator type. The authoring user can select an input schema or an output schema from the existing I/O schemas in the machine learning system or by defining a new I/O schema. An I/O schema can be associated with a data structure format (e.g., during run-time in operating memory), a serialization schema (e.g., for cross-device delivery and/or for memorization in a database), a deserialization schema, a summary format for a potential dataset that may qualify under the I/O schema, or any combination thereof. The summary format can define how the experiment management engine would render the potential dataset in its user interface. In some embodiments, an I/O schema can reference one or more automatic data conversion operators. The machine learning system can maintain an operator library/repository for frequently used functionalities for machine learning.

Referring now to the figures, FIG. **1** is a block diagram illustrating an application service system **100**, in accordance with various embodiments. The application service system **100** provides one or more application services (e.g., an application service **102**A and an application service **102**B, collectively as the "application services **102**") to client devices over one or more networks (e.g., a local area network and/or a wide area network). The application service system **100** can provide the application services **102** via an application programming interface (API), a Web server, a mobile service server (e.g., a server that communicates with client applications running on mobile devices), or any combination thereof. In some embodiments, the application service system **100** can be a social networking system (e.g., the social networking system **502** of FIG. **5**). The application services **102** can process client requests in real-time. The client requests can be considered "live traffic." For example, the application services **102** can include a search engine, a photo editing tool, a location-based tool, an advertisement platform, a media service, an interactive content service, a messaging service, a social networking service, or any combination thereof.

The application service system **100** can include one or more outfacing production services **104** that are exposed to the client devices, directly or indirectly, and one or more developer services **106** that are not exposed to the client devices. The developer services **106** can be used by operators of the application service system **100** to monitor, maintain, or improve the application services **102**. In one example, at least one of the outfacing production services **104** can directly communicate with the client devices and respond to client requests from the client devices. In another example, a first outfacing production service can indirectly provide its service to the client devices by servicing a second outfacing production service. The second outfacing production service, in turn, can either directly provide its service to the client devices or provide its service to a third outfacing production service that directly provides its service to the client devices. That is, the outfacing production services **104** may be chained when providing their services to the client devices.

The application services **102** may be part of the outfacing production services **104**. Each of the application services **102** can include an application logic module (e.g., executable code, binary, or script) that may be executed by a computer server (e.g., the computing device **600** of FIG. **6**) hosting an application service. For example, the application service **102**A can include an application logic module **108**A and the application service **102**B can include an application logic module **108**B (e.g., collectively as the "application logic modules **108**"). An application logic module provides the decision-making logic when responding to service requests (e.g., client requests or service requests from other application services). The service requests to the application logic modules and the corresponding responses generated by the application logic modules can be tracked and/or stored in a service-specific database. The service-specific database can also store metadata and/or analysis associated with each application service. For example, the application service **102**A can maintain a service-specific data repository **110**A and the application service **102**B can maintain a service-specific data repository **110**B. The service-specific data repositories **110**A and **110**B can be collectively referred to as "the service-specific data repositories **110**."

In various situations, the decision-making logic can be improved over time via data analysis of user data in the service-specific data repositories **110**. Several embodiments provides a machine learning system **112** that implements a platform to facilitate improvement of these decision-making logics via running machine learning experiments. These experiments can be based on real-time or aggregated user data in the service-specific data repositories **110**. In several embodiments, the developer services **106** include the machine learning system **112**. The machine learning system **112** provides a platform that facilitates big data experiments on the application service system **100**. For example, the machine learning system **112** can include an experiment management engine **124**, a workflow authoring tool **126**, and a workflow execution engine **128**.

The experiment management engine **124** can facilitate creation of new experiments. Each experiment can correspond to at least one workflow. A workflow can be defined by one or more data processing operators working together in a pipeline (e.g., represented by a directed acyclic graph) to process one or more input datasets into one or more outputs. The workflow can also define a summary format to facilitate analysis (e.g., comparative analysis, statistical analysis, evaluative analysis, or any combination thereof) of the outputs or the input datasets. For example, the summary format can describe how to post process the outputs to generate an illustrative presentation (e.g., an image, a table, a graph, or other media objects). In some embodiments, a workflow or a data processing operator in a workflow can define one or more resource constraints for running itself. The resource constraints can be defined by a user during creation of the workflow or the data processing operator or automatically estimated by the workflow authoring tool **126**. The resource constraints, for example, can include a memory requirement (e.g., persistent data storage capacity requirement and/or run-time data storage capacity requirement), a processing power requirement, a network bandwidth requirement, or any combination thereof.

In some embodiments, the workflow authoring tool **126** can include or be coupled to an operator authoring tool to define or modify one or more data processing operators in a workflow. The workflow authoring tool **126** can provide a user interface such that an operating user can search and reference one or more known workflows, known data processing operators, and known resource constraints to associate with a workflow being authored.

The workflow authoring tool **126** facilitates compilation of a workflow. Here, "compilation of a workflow" does not necessarily refer to transforming a source code written in a programming language into a machine executable language. Rather, "compilation of the workflow" refers to the analysis of an arrangement of data processing operators to synthesize information that can be used by the workflow execution engine **128** to schedule distributed tasks to a pool of computing devices.

When an operating user finishes authoring a workflow, the workflow authoring tool **126** can compile the workflow into a workflow execution format manageable by the workflow execution engine **128**. The workflow execution format can indicate analysis performed on the workflow by the workflow authoring tool **126**. For example, as part of the compilation, the workflow authoring tool **126** can identify interdependencies amongst one or more data processing operators, flag potential inconsistencies in inputs or outputs of the data processing operators, identify one or more code packages associated with the data processing operators and interdependencies of the code packages, identify resource constraints for computing devices that will run the data processing operators, or any combination thereof.

The workflow execution engine **128** can facilitate execution of a workflow associated with an experiment. The workflow execution engine **128** can manage and schedule execution of code packages in accordance with the workflow execution format. For example, the workflow execution engine **128** can select computing devices to run data processing operators of the workflow, distribute code packages corresponding to the data processing operators, distribute references or links to input datasets of the workflow, and/or schedule execution of the code packages on the computing devices. The workflow execution engine **128** can also ensure load-balancing and resource consumption minimization when scheduling the workflow for execution on the selected computing devices (e.g., by managing the selection of the computing devices, distributing appropriate code packages, and/or streaming the input datasets or links thereto ahead of execution schedule while minimizing network bandwidth). The workflow execution engine **128** can schedule execution of the workflow by analysis of the workflow indicated in the workflow execution format to avoid bottlenecks, errors, and inconsistencies. The workflow execution engine **128** can also schedule the execution of the workflow based on statuses of currently running experiments, health data and operation states of the outfacing production services **104** (e.g., as a source of determining when input data will be available) and the developer services **106** (e.g., as entities potentially competing for the same computational resources), and/or scheduled execution times of scheduled experiments. For example, the workflow execution engine **128** can ensure that a data processing operator, which requires the output of another data processing operator to execute, is not executed in parallel with that other data processing operator.

In some embodiments, an experiment analytic interface may be generated by the experiment management engine **124**. The experiment analytic interface can be part of the experiment management engine **124**. The experiment analytic interface can present results of an experiment to operating users (e.g., developers or analysts) of the application service system **100**. The results can be presented according to one or more summary formats defined by a workflow of the experiment.

A workflow of an experiment can include preprocessing of an input dataset, training a machine learning model, validating the machine learning model, processing a test dataset through the machine learning model to compute test results, post-processing the test results for analysis, or any combination thereof. In some examples, the workflow can include post-processing the input dataset for analysis. Post-processing for analysis can include computing statistical measures, computing comparative measures (e.g., between the test results and expected results), computing an evaluative measure (e.g., based on an evaluation algorithm), or any combination thereof.

Social Networking System Overview

Several embodiments of the application service system **100** utilize or are part of a social networking system. Social networking systems commonly provide mechanisms enabling users to interact with objects and other users both within and external to the context of the social networking system. A social networking system user may be an individual or any other entity, e.g., a business or other non-person entity. The social networking system may utilize a web-based interface or a mobile interface comprising a series of inter-connected pages displaying and enabling users to interact with social networking system objects and information. For example, a social networking system may display a page for each social networking system user comprising objects and information entered by or related to the social networking system user (e.g., the user's "profile").

Social networking systems may also have pages containing pictures or videos, dedicated to concepts, dedicated to users with similar interests ("groups"), or containing communications or social networking system activity to, from or by other users. Social networking system pages may contain links to other social networking system pages, and may include additional capabilities, e.g., search, real-time communication, content-item uploading, purchasing, advertising, and any other web-based inference engine or ability. It should be noted that a social networking system interface may be accessible from a web browser or a non-web browser application, e.g., a dedicated social networking system application executing on a mobile computing device or other computing device. Accordingly, "page" as used herein may be a web page, an application interface or display, a widget displayed over a web page or application, a box or other graphical interface, an overlay window on another page (whether within or outside the context of a social networking system), or a web page external to the social networking system with a social networking system plug in or integration capabilities.

As discussed above, a social graph can include a set of nodes (representing social networking system objects, also known as social objects) interconnected by edges (representing interactions, activity, or relatedness). A social networking system object may be a social networking system user, nonperson entity, content item, group, social networking system page, location, application, subject, concept or other social networking system object, e.g., a movie, a band, or a book. Content items can include anything that a social networking system user or other object may create, upload, edit, or interact with, e.g., messages, queued messages (e.g., email), text and SMS (short message service) messages, comment messages, messages sent using any other suitable messaging technique, an HTTP link, HTML files, images, videos, audio clips, documents, document edits, calendar entries or events, and other computer-related files. Subjects and concepts, in the context of a social graph, comprise nodes that represent any person, place, thing, or idea.

A social networking system may enable a user to enter and display information related to the user's interests, education and work experience, contact information, demographic information, and other biographical information in the user's profile page. Each school, employer, interest (for example, music, books, movies, television shows, games, political views, philosophy, religion, groups, or fan pages), geographical location, network, or any other information contained in a profile page may be represented by a node in the social graph. A social networking system may enable a user to upload or create pictures, videos, documents, songs, or other content items, and may enable a user to create and schedule events. Content items and events may be represented by nodes in the social graph.

A social networking system may provide various means to interact with nonperson objects within the social networking system. For example, a user may form or join groups, or become a fan of a fan page within the social networking system. In addition, a user may create, download, view, upload, link to, tag, edit, or play a social networking system object. A user may interact with social networking system objects outside of the context of the social networking system. For example, an article on a news web site might have a "like" button that users can click. In each of these instances, the interaction between the user and the object may be represented by an edge in the social graph connecting the node of the user to the node of the object. A user may use location detection functionality (such as a GPS receiver on a mobile device) to "check in" to a particular location, and an edge may connect the user's node with the location's node in the social graph.

A social networking system may provide a variety of communication channels to users. For example, a social networking system may enable a user to email, instant message, or text/SMS message, one or more other users; may enable a user to post a message to the user's wall or profile or another user's wall or profile; may enable a user to post a message to a group or a fan page; or may enable a user to comment on an image, wall post or other content item created or uploaded by the user or another user. In least one embodiment, a user posts a status message to the user's profile indicating a current event, state of mind, thought, feeling, activity, or any other present-time relevant communication. A social networking system may enable users to communicate both within and external to the social networking system. For example, a first user may send a second user a message within the social networking system, an email through the social networking system, an email external to but originating from the social networking system, an instant message within the social networking system, and an instant message external to but originating from the social networking system. Further, a first user may comment on the profile page of a second user, or may comment on objects associated with a second user, e.g., content items uploaded by the second user.

Social networking systems enable users to associate themselves and establish connections with other users of the social networking system. When two users (e.g., social graph nodes) explicitly establish a social connection in the social networking system, they become "friends" (or, "connections") within the context of the social networking system. For example, a friend request from a "John Doe" to a "Jane Smith," which is accepted by "Jane Smith," is a social connection. The social connection is a social network edge. Being friends in a social networking system may allow users access to more information about each other than would otherwise be available to unconnected users. For example, being friends may allow a user to view another user's profile, to see another user's friends, or to view pictures of another user. Likewise, becoming friends within a social networking system may allow a user greater access to communicate with another user, e.g., by email (internal and external to the social networking system), instant message, text message, phone, or any other communicative interface. Being friends may allow a user access to view, comment on, download, endorse or otherwise interact with another user's uploaded content items. Establishing connections, accessing user information, communicating, and interacting within the context of the social networking system may be represented by an edge between the nodes representing two social networking system users.

In addition to explicitly establishing a connection in the social networking system, users with common characteristics may be considered connected (such as a soft or implicit connection) for the purposes of determining social context for use in determining the topic of communications. In at least one embodiment, users who belong to a common network are considered connected. For example, users who attend a common school, work for a common company, or belong to a common social networking system group may be considered connected. In at least one embodiment, users with common biographical characteristics are considered connected. For example, the geographic region users were born in or live in, the age of users, the gender of users and the relationship status of users may be used to determine whether users are connected. In at least one embodiment, users with common interests are considered connected. For example, users' movie preferences, music preferences, political views, religious views, or any other interest may be used to determine whether users are connected. In at least one embodiment, users who have taken a common action within the social networking system are considered connected. For example, users who endorse or recommend a common object, who comment on a common content item, or who RSVP to a common event may be considered connected. A social networking system may utilize a social graph to determine users who are connected with or are similar to a particular user in order to determine or evaluate the social context between the users. The social networking system can utilize such social context and common attributes to facilitate content distribution systems and content caching systems to predictably select content items for caching in cache appliances associated with specific social network accounts.

FIG. **2** is a block diagram illustrating a machine learning system **200** (e.g., the machine learning system **112** of FIG. **1**) that manages big data experiments, in accordance with various embodiments. The machine learning system **200** can facilitate running of machine learning related processes in an application service system (e.g., the application service system **100** of FIG. **1**). The application service system can run multiple application services and produce multiple streams of input data based on the service requests and service responses of the application services.

The machine learning system **200** includes an experiment management engine **202** (e.g., the experiment management engine **124** of FIG. **1**). The experiment management engine **202** can manage an experiment repository **204** storing data of one or more previously executed or currently running experiments. The data for an experiment can include references to one or more workflows used in the experiment (e.g., including references to workflow related data in a workflow repository **214**), one or more input datasets used in the experiment, one or more output results of the experiment (e.g., including references to output results in an memorization repository **242**), rendered illustrations (e.g., video or still image representations) of the output results (e.g., including rendered illustrations in the memorization repository **242**), or any combination thereof.

The experiment management engine **202** can generate a definition interface **206** to define an experiment. In some embodiments, the experiment management engine **202** can present the definition interface **206** as an internal website accessible to developers and analysts of the application service system. The definition interface **206** can query an operating user to define an experiment by indicating a title of the experiment, a description of the experiment, one or more application services associated with the experiment, a workflow for the experiment, or any combination thereof. The definition interface **206** can also create an experiment by querying the operating user to select a previous experiment from the experiment repository **204** to clone. Once a previous experiment is cloned into a new experiment, the definition interface **206** can receive modifications to the experiment parameters cloned from the selected previous experiment. In some embodiments, the definition interface **206** can create an experiment by querying the operating user to select an existing workflow from the workflow repository **214**. Once an existing workflow is cloned into the new experiment, the definition interface **206** can receive modifications to the workflow attributes cloned from the selected existing workflow. The operating user can also fill in other experiment parameters other than the definition of a workflow.

In some embodiments, the definition interface **206** includes a search widget capable of identifying one or more workflows based on a user query of an input schema, an output schema, an input summary format, an output summary format, a title keyword, a description keyword, a tag keyword, a data processing operator keyword, or any combination thereof. The definition interface **206** can present one or more workflows for reviewing, editing, or cloning, that match or are associated with the user query. In some embodiments, the same or a different search widget is capable of identifying one or more data processing operators based on a user query of an input dataset, an input data source, an input schema, an output schema, an input summary format, an output summary format, or any combination thereof, that match one or more respective parameters of the identified data processing operators. The identified workflow and/or data processing operators can be selected to define and/or modify an experiment or a workflow.

A workflow can be defined through a workflow authoring tool **210** (e.g., the workflow authoring tool **126** of FIG. **1**). For example, the workflow authoring tool **210** can generate an integrated development environment for scripting a workflow definition in text. In some embodiments, the workflow authoring tool **210** can import a workflow definition from a text file or based on one or more user selections. The workflow authoring tool **210** can compile the imported workflow definition into a workflow execution format (e.g., including interdependency graph of operators and associated code packages and resource constraints). In some embodiments, the workflow authoring tool **210** can import one or more experiment parameters and/or one or more workflow attributes from a text file or based on one or more user selections. The workflow authoring tool **210** can facilitate creation of a workflow from scratch or by cloning an existing workflow in the workflow repository **214** and making modifications to it.

To create a workflow, an operating user can indicate relationships between one or more data processing operators via the user interface of the workflow authoring tool **210**. In some embodiments, the operating user can identify the data processing operators and indicate their relationships in a text file and import that to the workflow authoring tool **210**. That is, the workflow authoring tool **210** can be used to add or remove data processing operators from a workflow and specify relationships between the data processing operators in the workflow. A relationship can be a directed relationship where one or more outputs of a first data processing operator is passed to a second data processing operator as one or more of its inputs. In some embodiments, more than one instance of a data processing operator can be defined within the workflow.

In several embodiments, the machine learning system **200** includes also an operator authoring tool **220**. In some embodiments, the operator authoring tool **220** is part of the workflow authoring tool **210**. In other embodiments, the operator authoring tool **220** is coupled to the workflow authoring tool **210** whenever an operating user indicates an intention to edit or create a data processing operator. The operator authoring tool **220** can also include a user interface (e.g., an IDE or a text editor) to facilitate definition of a data processing operator. For example, operator parameters that can be defined in the operator authoring tool **220** include an input schema, an output schema, an input summary format, an output summary format, a resource constraint (e.g., run-time memory requirement or network bandwidth requirement), data processing logics, code package requirements (e.g., these parameters can be device/operating system dependent), programming language indicator, code compiling parameters (e.g., these parameters can be dependent on the programming language used), or any combination thereof. A data processing operator can be an ephemeral operator that is defined specific for a particular workflow or a particular experiment. The operator authoring tool **220** can also set a data processing operator as a "production operator" for inclusion into other workflows or experiments with or without modifications. In some embodiments, all of the data processing operators are stored and tracked in the operator repository **222**. In some embodiments, only the production operators are stored and tracked in the operator repository **222**.

In several embodiments, an experiment in the experiment repository **204** can reference one or more workflows in the workflow repository **214** or vice versa (e.g., a workflow can make a reference to an experiment). In several embodiments, an experiment in the experiment repository **204** can reference one or more outputs or illustrations in the memorization repository **242**, or vice versa (e.g., an output or illustration can make a reference to an experiment). In several embodiments, a workflow in the workflow repository **214** can reference one or more data processing operators in the operator repository **222**, or vice versa (e.g., an operator can make a reference to a workflow).

After a workflow is defined, the workflow authoring tool **210** can compile the workflow definition into a workflow execution format (e.g., as previously described). The machine learning system **200** can include an execution scheduler engine (e.g., part of the workflow execution engine **128** of FIG. **1**). The execution scheduler engine **230** can schedule to execute an experiment associated with one or more workflows. For each workflow, the execution scheduler engine **230** can select one or more computing environments in a backend computation pool **236** to execute the workflow. In some embodiments, the backend computation pool **236** can include multiple server farms (e.g., a server farm **238**A, a server farm **238**B, etc., collectively as the "server farms **238**"). Each of the server farms **238** can be housed in a different data center and include one or more computing devices. The computing environments can be computing devices (e.g., instances of the computing device **600** of FIG. **6**) or virtualized operating systems. The execution scheduler engine **230** can determine, based on the workflow execution format, which of the data processing operators are executed by which of the computing environments in the backend computation pool **236** and the order and constraints of executing the data processing operators. The execution scheduler engine **230** can also determine how data is to be shared amongst the data processing operators.

One or more data outputs produced from a computing environment executing at least one data processing operator can be stored in a memorization repository **242**. Prior to committing resources to execute a data processing operator, the execution scheduler engine **230** can check with the memorization repository **242** to determine whether the process has already been run. The matching performed by the execution scheduler engine **230** can be exact, or with built-in flexibilities. For example, when exact matching is required, the execution scheduler engine **230** can determine whether or not an output stored in the memorization repository **242** is associated with the same input and the same version of the data processing operator. When flexible matching is allowed, the execution scheduler engine **230** can determine a match when the same or similar input is passed into the same version or a different version of the data processing operator to produce the memorized output. The memorized output can be output data or a rendered visualization/illustration. In some embodiments, the memorized outputs in the memorization repository **242** can make references to the associated workflow in the workflow repository **214** and/or the associated data processing operator in the operator repository **222**, or vice versa (e.g., an operator and/or a workflow can make a reference to a memorized output).

In some embodiments, the experiment management engine **202** can generate and present an experiment analytic interface **246** to operating users to track one or more experiments. The experiment analytic interface **246** can present results of an experiment to the operating users. The results can be presented according to one or more summary formats defined by a workflow of the experiment. The results can be extracted by the memorization repository **242**.

In some embodiments, upon completing a workflow of an experiment, the experiment analytic interface **246** can present interactive elements to trigger re-run of the experiment (e.g., without modification), creation of another experiment (e.g., a brand new experiment or a new experiment based on the original experiment with one or more modifications to its workflow attributes), or any combination thereof. In some embodiments, the experiment analytic interface **246** can present an interactive element to trigger deployment of the workflow as part of or a replacement for an application logic module. In some embodiments, the experiment analytic interface **246** can present an interactive element to trigger deployment of one or more data processing operators in the workflow to replace or to become part of an application logic module, or any combination thereof.

Functional components (e.g., engines, modules, and databases) associated with the application service system **100** and/or the machine learning system **200** can be implemented as circuitry, firmware, software, or other functional instructions. For example, the functional components can be implemented in the form of special-purpose circuitry, in the form of one or more appropriately programmed processors, a single board chip, a field programmable gate array, a network-capable computing device, a virtual machine, a cloud computing environment, or any combination thereof. For example, the functional components described can be implemented as instructions on a tangible storage memory capable of being executed by a processor or other integrated circuit chip. The tangible storage memory may be volatile or non-volatile memory. In some embodiments, the volatile memory may be considered "non-transitory" in the sense that it is not a transitory signal. Memory space and storages described in the figures can be implemented with the tangible storage memory as well, including volatile or non-volatile memory.

Each of the functional components may operate individually and independently of other functional components. Some or all of the functional components may be executed on the same host device or on separate devices. The separate devices can be coupled through one or more communication channels (e.g., wireless or wired channel) to coordinate their operations. Some or all of the functional components may be combined as one component. A single functional component may be divided into sub-components, each sub-component performing separate method step or method steps of the single component.

In some embodiments, at least some of the functional components share access to a memory space. For example, one functional component may access data accessed by or transformed by another functional component. The functional components may be considered "coupled" to one another if they share a physical connection or a virtual connection, directly or indirectly, allowing data accessed or modified by one functional component to be accessed in another functional component. In some embodiments, at least some of the functional components can be upgraded or modified remotely (e.g., by reconfiguring executable instructions that implements a portion of the functional components). The systems, engines, or devices described may include additional, fewer, or different functional components for various applications.

Type System in Work Authoring Tool

A machine learning system (e.g., the machine learning system **200** of FIG. **2**) can implement a type system in a work authoring tool (e.g., the workflow authoring tool **126** of FIG. **2**). Developers of the machine learning system can define and execute machine learning processes represented by one or more workflows. A workflow can be represented as a directed graph of data processing operators. The type system enables the developers to describe input schemas and output schemas of the data processing operators as platform-level types that are reproducible and comparable. A data processing operator can reference a predefined type as an I/O schema (e.g., an input schema or as an output schema). In several embodiments, the I/O schemas are programming language independent.

The type system enables the work authoring tool to parse textual representation of a workflow (e.g., a machine learning workflow). For example, the type system enables the work authoring tool to identify potential data sources or known data sets that can be used as one or more inputs to a data processing operator in a workflow. For another example, the type system enables the work authoring tool to identify comparable results from different workflows having the same I/O schema. For example, by matching output schemas of some data processing operators to input schemas of subsequent data processing operators, a workflow execution engine can accurately generate an interdependency graph of the data processing operators in the workflow to facilitate scheduling of the workflow in a distributed computing network. For example, the workflow execution engine can interrogate the underlying textual syntax of a textual representation of a workflow to determine one or more edges in the interdependency graph. Each edge can represent a promised object (e.g., according to an I/O schema) from one data processing operator to another.

The type system can resolve several technical problems faced in a machine learning system concerning big data. Because a developer user can arbitrarily create input types and output types, the type system increases the applicability of the machine learning system to process large volume datasets having complex data structures. Further, by matching output schemas of some data processing operators into input schemas of other data processing operators, the work authoring tool can automatically detect errors in a workflow.

For example, the work authoring tool can raise a warning flag in its user interface when an output schema of a workflow does not match an input schema that the output schema feeds into, according to the operator interdependency graph of the workflow.

The type system can also advantageously create dataset types that describe how it can be summarized and/or presented. For example, an input schema or an output schema can have a corresponding input summary generation schema or a corresponding output summary generation schema. A I/O summary generation schema can indicate how to sample, aggregate, and analyze a data set matching the corresponding I/O schema to produce a summary. This summary can include a set of one or more numbers and/or data strings, a table, or an illustration. For example, the I/O summary can include a bar graph, a line graph, a histogram, a pie chart, a learning curve, other graph or illustration type, or any combination thereof. The I/O summary can include feature statistics including statistical values (e.g., mean, standard deviation, range, variance, median, mode, or any combination thereof) of features (e.g., individual measurable properties of a phenomenon being observed in machine learning) used. The I/O summary can include feature importance and/or coverage (e.g., percent of rows in a data set that contains a particular type of feature). For example, the I/O summary can include a representative example of a data set that matches an I/O schema.

In some embodiments, an I/O schema can represent a logical unit instead of a passive data unit. For example, a data processing operator can specify an output schema describing a type corresponding to data processing operators. In one specific example, a data processing operator can be a machine learning model optimizer that optimizes effectiveness of other operators or workflows pertaining to a machine learning application. The model optimizer can take in test data and/or evaluative metrics (e.g., how well the existing operators or workflows perform) as inputs. The model optimizer can produce a data processing operator or a modified workflow as its output. This capability advantageously enables machine learning model training, testing, and optimization in the machine learning system. This introduces reproducibility and comparability (e.g., capability to be indexed, searched, or compared) of model optimizers (e.g., a data processing operator that optimizes other workflows and/or operators).

In several embodiments, the type system can include implicit type conversion operators. An implicit type conversion operator can translate a first I/O schema to a second I/O schema. For example, the workflow authoring tool can detect mismatching I/O schemas (e.g., an output schema of a precedent operator feeding into an input schema of a subsequent operator) on an edge of an interdependency graph of a workflow. The workflow authoring tool can determine whether there is an implicit type conversion operator that can convert the output schema to the input schema in question. If an implicit type conversion operator is identified, the workflow authoring tool can insert the implicit type conversion operator into the interdependency graph between the precedent operator and the subsequent operator without raising a warning flag. If an implicit type conversion operator cannot be identified, the workflow authoring tool can raise a warning flag in its user interface.

In some embodiments, the implicit type conversion operator can bring in additional data during the conversion process that neither matches the first I/O schema nor the second I/O schema. In some embodiments, the implicit type conversion operator can trigger a request to download data from an external source, a request to cache data that is being converted, an execution request for one or more other data processing operators (e.g., data normalization or sampling) on the data being converted, or any combination thereof.

In several embodiments, the type system enables self-documentation of data processing operator types and/or I/O schema types. Various attributes of the data processing operator types and the I/O schema types can be indexed in an operator repository. This enables an operating user to search for operator types and/or I/O schema types matching one or more operator type attributes and schema type attributes. For example, an operating user can search for all operator types that take in a particular I/O schema as an input. In response, the workflow authoring tool can present the matching operator types in its user interface. In another example, an operating user can request the workflow authoring tool to present all I/O schemas involved in executing a workflow. The indexed storage of the operator types and I/O schema types in the operator repository facilitates reproducibility, comparability, and reusability of already defined operators and I/O schemas. For example, the indexing can enable an experiment management engine to generate automatic comparisons between inputs and outputs of similar or identical data processing operator types or between similar or identical I/O schemas.

FIG. **3** is a block diagram illustrating an operator type definition **300**, in accordance with various embodiments. The operator type definition **300** stores one or more operator attributes representing a data processing operator. Multiple instances of the operator type definition **300** can be included in a workflow (e.g., the workflow represented by the workflow definition of FIG. **7**B). In some embodiments, the operator type definition **300** can be constructed based on a text string received through the user interface or an API of a workflow authoring tool (e.g., the workflow authoring tool **126** of FIG. **1**). The workflow authoring tool can build the operator type definition **300** from a textual representation of the operator (e.g., the textual representation **900** of FIG. **9**A or the textual representation **950** of FIG. **9**B). FIG. **9**A is one example of a textual representation **900** of a data processing operator, in accordance with various embodiments. FIG. **9**B is another example of a textual representation **950** of a data processing operator, in accordance with various embodiments.

The operator type definition **300** can include an input schema **302**, an output schema **304**, a resource constraint **306**, a version provenance identifier **308**, an operator package scheme **310**, or any combination thereof. The input schema **302** defines what data can potentially be fed into the data processing operator for processing or to configure the data processing operator. The input schema **302** can correspond to one or more I/O schema types (e.g., the I/O schema type definition **400** in FIG. **4**) that feed data into the data processing operator. The output schema **304** defines what data is produced from running the data processing operator. The output schema **304** can correspond to one or more I/O schema types.

The resource constraint **306** can define what kind of operating environment and/or computing device can execute the data processing operator. In some embodiments, the resource constraint **306** is defined as part of the operator type definition **300**. In some embodiments, the resource constraint **306** is defined when a data processing operator is instantiated as a part of a workflow definition or a workflow run/experiment definition. For example, the resource constraint **306** can include a memory capacity threshold, a number of CPUs threshold, a number of GPUs threshold, a network bandwidth restriction, a geographic region restriction (e.g., relative or absolute), a network location restriction (e.g., relative or absolute), or any combination thereof.

The version provenance identifier **308** identifies the operator type defined by the operator type definition **300** relative to other operator types. For example, the version provenance identifier **308** can indicate that the data processing operator of its type is part of a family of data processing operator types previously defined in the machine learning system (e.g., the machine learning system **200** of FIG. **2**).

The operator package scheme **310** defines how an operator instance of the operator type defined by the operator type definition **300** can be distributed to a computing environment/device for execution. For example, the operator package scheme **310** can define how to serialize and/or deserialize executable code or logics associated with the operator type. In another example, the operator package scheme **310** can define whether any executable libraries (e.g., of one or more programming language or for one or more operating environments) are to be distributed together with a serialized package of the operator logics.

FIG. **4** is a block diagram illustrating an I/O schema type definition **400**, in accordance with various embodiments. The I/O schema type definition **400** defines an I/O schema type. One or more I/O schema types can be referenced in a data processing operator type. The I/O schema type definition **400** stores one or more I/O schema attributes. For example, the I/O schema type definition **400** can include a data structure **402**, a summary format **404**, a serialization scheme **406**, a deserialization scheme **408**, or any combination thereof. The data structure **402** can define one or more data objects that are accessible in a dataset matching the I/O schema type. The data structure **402** can also define how the data objects can be stored during run-time in operating memory.

The summary format **404** can describe how to generate a summary of a data set matching the I/O schema type. For example, the summary format **404** can describe how to compute summary data from the data structure **402**, how to render the summary data (e.g., via an illustration or a visualization), how to present the summary data, in what form to render the summary data (e.g., a pie chart, a linear graph, a comparison table, etc.), whether and/or how to sample the dataset prior to presenting the rendered summary, or any combination thereof. The summary format **404** can pertain to a textual summary, a graphical summary, a multimedia summary, or any combination thereof.

The serialization scheme **406** can include logics of how to convert the data structure **402** (e.g., with one or more independent data elements) matching the I/O schema type into a serialized string. The serialized string can be used for data transference or for storage in a database. The deserialization scheme **408** can include logics of how to convert the serialized string back to the data structure **402**.

FIG. **7**A is a block diagram illustrating a workflow run definition **700**, in accordance with various embodiments. The workflow run definition **700** defines a workflow run. The workflow run can be associated with an experiment being run on the machine learning system. In some embodiments, the workflow run definition **700** can be constructed as a user interface receives one or more inputs from an operating user. In some embodiments, the workflow run definition **700** can be constructed based on a text string imported through the user interface or an API of a workflow authoring tool (e.g., the workflow authoring tool **126** of FIG. **1**).

The workflow run definition **700** can include a workflow identifier **702** referencing a workflow definition **704**, one or more labels **706**, and one or more workflow run parameters **708**. The workflow identifier **702** can indicate to an experiment management engine (e.g., the experiment management engine **124** of FIG. **1**) which workflow to execute as part of the experiment. The workflow identifier **702** can reference one or more workflow definitions (e.g., the workflow definition **704**). The workflow definition **704** can be copied or stored as part of the workflow run definition **700**, or be stored in a workflow repository (e.g., the workflow repository **214** of FIG. **2**) and referenced by the workflow run definition.

The workflow identifier **702** can be a user selection of a workflow from amongst workflows stored in a workflow repository (e.g., the workflow repository **214** of FIG. **2**). In some embodiments, a user interface for defining a workflow run (e.g., the definition interface **206** of FIG. **2**) can present a list of workflows for an operating user to select. In some embodiments, the user interface can provide a typeahead query box that generates a dynamic list of workflows satisfying a user's query. The workflow authoring tool can match the user's query against labels of available workflows and place workflows that match the user's query in the dynamic list.

The labels **706** can facilitate operating users to search, clone, modify, edit, and/or review the workflow definition **704**. For example, the labels **706** can include a workflow run name, one or more searchable tags, operating-user-defined notes, or any combination thereof. The workflow run parameters **708** are parameters to configure the workflow run. For example, the workflow run parameters **708** can include input parameters to front-line data processing operators.

For example, FIG. **7**B is a block diagram representative of a workflow definition (e.g., the workflow definition **704** of FIG. **7**A), in accordance with various embodiments. A workflow execution engine (e.g., the workflow execution engine **128** of FIG. **1**) can execute the workflow run. For example, the workflow execution engine can locate the workflow definition **704** based on the workflow identifier **702**. The workflow definition **704** can correspond to a textual representation **720** (e.g., a textual representation **800** of FIG. **8**). FIG. **8** is an example of the textual representation **800** of a workflow, in accordance with various embodiments. The workflow execution engine can parse and traverses the textual representation **720** to produce an operator interdependency graph **710**. The operator interdependency graph **710** describes the interdependencies of one or more data processing operators (e.g., a data processing operator **714**A, a data processing operator **714**B, a data processing operator **714**C, etc., collectively as the "data processing operators **714**"). The operator interdependency graph **710** can be a directed graph. For example, a directed edge **718** can represent that the data processing operator **714**B depends from the data processing operator **714**A. That is, an input to the data processing operator **714**B is a promise of an output from the data processing operator **714**A.

In the example in FIG. **7**B, the data processing operator **714**B also depends on an output of the data processing operator **714**C, which in turn depends on an output of the data processing operator **714**A (e.g., the same or different output that feeds into the data processing operator **714**B). In the example, the workflow takes in the workflow run parameters **708** (e.g., an input parameter **720**A, an input parameter **720**B, etc.). The input parameters can include input datasets, identifier/network address of input datasets, input configuration, other static or dynamically defined values, or any combination thereof. In the example, the data processing operator **714**A can be considered an independent operator because it does not depend on the output of any other data processing operators. In the example, the data processing operator **714**B produces an output **724**, which is also the output for the workflow.

In some embodiments, the workflow execution engine can generate the operator interdependency graph **710** in real-time when a workflow run as initiated. In some embodiments, the workflow authoring tool can precompile the operator interdependency graph **710** prior to initiating a workflow run. In some embodiments, when the operator interdependency graph **710** is generated, the workflow authoring tool and/or the workflow execution engine can identify one or more front-line data processing operators responsible for taking in the workflow run parameters **708** (e.g., the data processing operator **714**A and the data processing operator **714**C). The workflow execution engine or the workflow authoring tool can also identify independent data processing operators (e.g., the data processing operator **714**A) that do depend from other operators in the operator interdependency graph **710**. In some embodiments, the textual representation **720** can explicitly indicate which are the front-line data processing operators that take in the workflow run parameters **708**. In some embodiments, when the operator interdependency graph **710** is generated, the workflow authoring tool and/or the workflow execution engine can identify tail-end data processing operators (e.g., the data processing operator **714**B) responsible for producing outputs of the workflow run. For example, the tail-end data processing operators can be one or more operators that no other operators depend from. In some embodiments, the textual representation **720** can explicitly indicate what are the outputs of the workflow.

FIG. **10** is a flow chart illustrating a method **1000** of operating a machine learning system (e.g., the machine learning system **200** of FIG. **2**), in accordance with various embodiments. The machine learning system can be part of an application service system (e.g., the application service system **100** of FIG. **1**). At step **1002**, the machine learning system can access a workflow text string associated with a machine learning workflow and an operator text string associated with at least a data processing operator type. At step **1004**, the machine learning system can parse the workflow text string to generate an interdependency graph of one or more data processing operators. At least one of the data processing operators can be an instance of the data processing operator type.

In one example, step **1004** can include the machine learning system identifying a data processing operator of the data processing operator type as a receiver of the input parameter to the machine learning workflow. The machine learning system can ensure that the input parameter matches at least one data structure in the input schema of the data processing operator type. In another example, step **1004** can include the machine learning system identifying a data processing operator of the data processing operator type as a source of the resulting output upon the execution of the machine learning workflow. The machine learning system can ensure that the resulting output matches at least one data structure of the output schema of the data processing operator type.

In some embodiments, parsing the workflow text string includes traversing the workflow text string to match an output of a first data processing operator as an input of a second data processing operator; and updating the interdependency graph to indicate that the second data processing operator depends on the output of the first data processing operator. The interdependency graph is not only advantageous in partitioning tasks for automatic workflow execution (e.g., scheduling the workflow for parallel and/or sequential processing), but also for error detection. For example, the machine learning system can determine whether the output of first data processing operator has the same schema type as the input of the second data processing operator. The machine learning system can then generate a warning alert in response to determining that the output of the first data processing operator is not of the same schema type as the input of the second data processing operator. In some embodiments, the machine learning system can implement a way of inserting implicit type conversion operators to resolve potential errors. For example, the machine learning system can determine an implicit type conversion operator corresponding to a first schema type of the output of the first data processing operator and a second schema type of the input of the second data processing operator. The machine learning system can then insert the implicit type conversion operator between the first data processing operator and the second data processing operator in the interdependency graph.

At step **1006**, the machine learning system can parse the operator text string to identify operator attributes associated with the data processing operator type. The operator attributes can comprise an input schema and an output schema. The input schema can identify a data structure of one or more independent data elements that is able to be referenced as one or more inputs to the computational logics of the data processing operator type. The output schema can identify a data structure of one or more independent data elements that is able to be referenced as one or more outputs from the computational logics of the data processing operator type. In some embodiments, the input schema includes an input summary generation schema. In some embodiments, the output schema includes an output summary generation schema. The input summary generation schema can define how to convert a data structure of the input schema into a summary format. The output summary generation schema can define how to convert a data structure of the output schema into a summary format. The operator text string can identify computational logics that is executable on a single host operating environment as a single unit.

In some embodiments, the input summary generation schema identifies a sampling process to reduce number of individual data units in an input dataset matching the input schema and the input summary generation schema identifies a sampling process to reduce number of individual data units in an output dataset matching the output schema. In some embodiments, the input summary generation schema identifies a statistical analysis to produce a statistical summary of an input dataset matching the input schema and the output summary generation schema identifies a statistical analysis to produce a statistical summary of an output dataset matching the output schema. The statistical summary of either the input dataset or the output dataset can include range, mean, median, mode, standard deviation, spread, or any combination thereof, of the input dataset or the output dataset. In some embodiments, the input summary generation schema identifies a visualization rendering process to produce a visual summary of an input dataset matching the input schema and the output summary generation schema identifies a visualization rendering process to produce a visual summary of an output dataset matching the output schema.

The operator attributes can include a resource constraint for running the data processing operator type. In some embodiments, the resource constraint includes memory capacity requirement, processing power requirement, network bandwidth requirement, operating environment requirement, software library requirement, or any combination thereof. In some embodiments, the resource constraint includes an absolute geographical location of where to run an instance of the data processing operator type. In some embodiments, the resource constraint includes a relative location requirement of where to run a first instance of the data processing operator type. In one example, the relative location requirement can be relative to where to run a second instance of another data processing operator type that is connected to the first instance in the interdependency graph. In another example, the relative location requirement can enforce a proximity threshold for where to run the first instance of the data processing operator type relative to a location of a computing device storing an input dataset for the first instance of the data processing operator type.

In several embodiments, parsing of the operator text string enables the machine learning system to implement a type system. The type system not only enables automatic workflow scheduling and execution, but is also a self-documenting type system that exposes the interfaces and logics of data processing operators for analysis and comparison. For example, the machine learning system can automatically index newly defined data processing operator types based on their operator attributes. The machine learning system can track where (e.g., which workflow and/or workflow runs) the data processing operator types are being used. The machine learning system can implement a version control system for the data processing operator types and provide a visual summary of the version evolution of the data processing operator types. For example, a user interface can be implemented for an operating user of the machine learning system to search for a data processing operator type based on one or more attributes of a data processing operator type. Similarly, the type system can be implemented for a workflow. Because a workflow is comprised of interdependent operators, the machine learning system can also automatically index the workflow based on the input parameters of the workflow and operator attributes of its interdependent operators.

At step **1008**, the machine learning system can schedule the machine learning workflow for execution based on the interdependency graph. At step **1010**, the machine learning system can generate a summary of a resulting output or an input parameter to the machine learning workflow based the input summary generation schema or the output summary generation schema.

While processes or blocks are presented in a given order in this disclosure, alternative embodiments may perform routines having steps, or employ systems having blocks, in a different order, and some processes or blocks may be deleted, moved, added, subdivided, combined, and/or modified to provide alternative or subcombinations. Each of these processes or blocks may be implemented in a variety of different ways. In addition, while processes or blocks are at times shown as being performed in series, these processes or blocks may instead be performed in parallel, or may be performed at different times. When a process or step is "based on" a value or a computation, the process or step should be interpreted as based at least on that value or that computation.

FIG. **5** is a high-level block diagram of a system environment **500** suitable for a social networking system **502**, in accordance with various embodiments. The system environment **500** shown in FIG. **5** includes the social networking system **502** (e.g., the application service system **100** of FIG. **1**), a client device **504**A, and a network channel **506**. The system environment **500** can include other client devices as well, e.g., a client device **504**B and a client device **504**C. In other embodiments, the system environment **500** may include different and/or additional components than those shown by FIG. **5**. The machine learning system **200** of FIG. **2** can be implemented in the social networking system **502**.

Social Networking System Environment and Architecture

The social networking system **502**, further described below, comprises one or more computing devices storing user profiles associated with users (i.e., social networking accounts) and/or other objects as well as connections between users and other users and/or objects. Users join the social networking system **502** and then add connections to other users or objects of the social networking system to which they desire to be connected. Users of the social networking system **502** may be individuals or entities, e.g., businesses, organizations, universities, manufacturers, etc. The social networking system **502** enables its users to interact with each other as well as with other objects maintained by the social networking system **502**. In some embodiments, the social networking system **502** enables users to interact with third-party websites and a financial account provider.

Based on stored data about users, objects and connections between users and/or objects, the social networking system **502** generates and maintains a "social graph" comprising multiple nodes interconnected by multiple edges. Each node in the social graph represents an object or user that can act on another node and/or that can be acted on by another node. An edge between two nodes in the social graph represents a particular kind of connection between the two nodes, which may result from an action that was performed by one of the nodes on the other node. For example, when a user identifies an additional user as a friend, an edge in the social graph is generated connecting a node representing the first user and an additional node representing the additional user. The generated edge has a connection type indicating that the users are friends. As various nodes interact with each other, the social networking system **502** adds and/or modifies edges connecting the various nodes to reflect the interactions.

The client device **504**A is a computing device capable of receiving user input as well as transmitting and/or receiving data via the network channel **506**. In at least one embodiment, the client device **504**A is a conventional computer system, e.g., a desktop or laptop computer. In another embodiment, the client device **504**A may be a device having computer functionality, e.g., a personal digital assistant (PDA), mobile telephone, a tablet, a smart-phone or similar device. In yet another embodiment, the client device **504**A can be a virtualized desktop running on a cloud computing service. The client device **504**A is configured to communicate with the social networking system **502** via a network channel **506** (e.g., an intranet or the Internet). In at least one embodiment, the client device **504**A executes an application enabling a user of the client device **504**A to interact with the social networking system **502**. For example, the client device **504**A executes a browser application to enable interaction between the client device **504**A and the social networking system **502** via the network channel **506**. In another embodiment, the client device **504**A interacts with the social networking system **502** through an application programming interface (API) that runs on the native operating system of the client device **504**A, e.g., IOS® or ANDROID™

The client device **504**A is configured to communicate via the network channel **506**, which may comprise any combination of local area and/or wide area networks, using both wired and wireless communication systems. In at least one embodiment, the network channel **506** uses standard communications technologies and/or protocols. Thus, the network channel **506** may include links using technologies, e.g., Ethernet, 802.11, worldwide interoperability for microwave access (WiMAX), 3G, 4G, CDMA, digital subscriber line (DSL), etc. Similarly, the networking protocols used on the network channel **506** may include multiprotocol label switching (MPLS), transmission control protocol/Internet protocol (TCP/IP), User Datagram Protocol (UDP), hypertext transport protocol (HTTP), simple mail transfer protocol (SMTP) and file transfer protocol (FTP). Data exchanged over the network channel **506** may be represented using technologies and/or formats including hypertext markup language (HTML) or extensible markup language (XML). In addition, all or some of links can be encrypted using conventional encryption technologies, e.g., secure sockets layer (SSL), transport layer security (TLS), and Internet Protocol security (IPsec).

The social networking system **502** includes a profile store **510**, a content store **512**, an action logger **514**, an action log **516**, an edge store **518**, an application service server **522**, a web server **524**, a message server **526**, an application service interface (API) request server **528**, a machine learning system **532**, or any combination thereof. In other embodiments, the social networking system **502** may include additional, fewer, or different modules for various applications.

User of the social networking system **502** can be associated with a user profile, which is stored in the profile store **510**. The user profile is associated with a social networking account. A user profile includes declarative information about the user that was explicitly shared by the user, and may include profile information inferred by the social networking system **502**. In some embodiments, a user profile includes multiple data fields, each data field describing one or more attributes of the corresponding user of the social networking system **502**. The user profile information stored in the profile store **510** describes the users of the social networking system **502**, including biographic, demographic, and other types of descriptive information, e.g., work experience, educational history, gender, hobbies or preferences, location and the like. A user profile may also store other information provided by the user, for example, images or videos. In some embodiments, images of users may be tagged with identification information of users of the social networking system **502** displayed in an image. A user profile in the profile store **510** may also maintain references to actions by the corresponding user performed on content items (e.g., items in the content store **512**) and stored in the edge store **518** or the action log **516**.

A user profile may be associated with one or more financial accounts, enabling the user profile to include data retrieved from or derived from a financial account. In some embodiments, information from the financial account is stored in the profile store **510**. In other embodiments, it may be stored in an external store.

A user may specify one or more privacy settings, which are stored in the user profile, that limit information shared through the social networking system **502**. For example, a privacy setting limits access to cache appliances associated with users of the social networking system **502**.

The content store **512** stores content items (e.g., images, videos, or audio files) associated with a user profile. The content store **512** can also store references to content items that are stored in an external storage or external system. Content items from the content store **512** may be displayed when a user profile is viewed or when other content associated with the user profile is viewed. For example, displayed content items may show images or video associated with a user profile or show text describing a user's status. Additionally, other content items may facilitate user engagement by encouraging a user to expand his connections to other users, to invite new users to the system or to increase interaction with the social networking system by displaying content related to users, objects, activities, or functionalities of the social networking system **502**. Examples of social networking content items include suggested connections or suggestions to perform other actions, media provided to, or maintained by, the social networking system **502** (e.g., pictures or videos), status messages or links posted by users to the social networking system, events, groups, pages (e.g., representing an organization or commercial entity), and any other content provided by, or accessible via, the social networking system.

The content store **512** also includes one or more pages associated with entities having user profiles in the profile store **510**. An entity can be a non-individual user of the social networking system **502**, e.g., a business, a vendor, an organization, or a university. A page includes content associated with an entity and instructions for presenting the content to a social networking system user. For example, a page identifies content associated with the entity's user profile as well as information describing how to present the content to users viewing the brand page. Vendors may be associated with pages in the content store **512**, enabling social networking system users to more easily interact with the vendor via the social networking system **502**. A vendor identifier is associated with a vendor's page, thereby enabling the social networking system **502** to identify the vendor and/or to retrieve additional information about the vendor from the profile store **510**, the action log **516** or from any other suitable source using the vendor identifier. In some embodiments, the content store **512** may also store one or more targeting criteria associated with stored objects and identifying one or more characteristics of a user to which the object is eligible to be presented.

The action logger **514** receives communications about user actions on and/or off the social networking system **502**, populating the action log **516** with information about user actions. Such actions may include, for example, adding a connection to another user, sending a message to another user, uploading an image, reading a message from another user, viewing content associated with another user, attending an event posted by another user, among others. In some embodiments, the action logger **514** receives, subject to one or more privacy settings, content interaction activities associated with a user. In addition, a number of actions described in connection with other objects are directed at particular users, so these actions are associated with those users as well. These actions are stored in the action log **516**.

In accordance with various embodiments, the action logger **514** is capable of receiving communications from the web server **524** about user actions on and/or off the social networking system **502**. The action logger **514** populates the action log **516** with information about user actions to track them. This information may be subject to privacy settings associated with the user. Any action that a particular user takes with respect to another user is associated with each user's profile, through information maintained in a database or other data repository, e.g., the action log **516**. Such actions may include, for example, adding a connection to the other user, sending a message to the other user, reading a message from the other user, viewing content associated with the other user, attending an event posted by another user, being tagged in photos with another user, liking an entity, etc.

The action log **516** may be used by the social networking system **502** to track user actions on the social networking system **502**, as well as external website that communicate information to the social networking system **502**. Users may interact with various objects on the social networking system **502**, including commenting on posts, sharing links, and checking-in to physical locations via a mobile device, accessing content items in a sequence or other interactions. Information describing these actions is stored in the action log **516**. Additional examples of interactions with objects on the social networking system **502** included in the action log **516** include commenting on a photo album, communications between users, becoming a fan of a musician, adding an event to a calendar, joining a groups, becoming a fan of a brand page, creating an event, authorizing an application, using an application and engaging in a transaction. Additionally, the action log **516** records a user's interactions with advertisements on the social networking system **502** as well as applications operating on the social networking system **502**. In some embodiments, data from the action log **516** is used to infer interests or preferences of the user, augmenting the interests included in the user profile, and enabling a more complete understanding of user preferences.

Further, user actions that happened in particular context, e.g., when the user was shown or was seen accessing particular content on the social networking system **502**, can be captured along with the particular context and logged. For example, a particular user could be shown/not-shown information regarding candidate users every time the particular user accessed the social networking system **502** for a fixed period of time. Any actions taken by the user during this period of time are logged along with the context information (i.e., candidate users were provided/not provided to the particular user) and are recorded in the action log **516**. In addition, a number of actions described below in connection with other objects are directed at particular users, so these actions are associated with those users as well.

The action log **516** may also store user actions taken on external websites services associated with the user. The action log **516** records data about these users, including viewing histories, advertisements that were engaged, purchases or rentals made, and other patterns from content requests and/or content interactions.

In some embodiments, the edge store **518** stores the information describing connections between users and other objects on the social networking system **502** in edge objects. The edge store **518** can store the social graph described above. Some edges may be defined by users, enabling users to specify their relationships with other users. For example, users may generate edges with other users that parallel the users' real-life relationships, e.g., friends, co-workers, partners, and so forth. Other edges are generated when users interact with objects in the social networking system **502**, e.g., expressing interest in a page or a content item on the social networking system, sharing a link with other users of the social networking system, and commenting on posts made by other users of the social networking system. The edge store **518** stores edge objects that include information about the edge, e.g., affinity scores for objects, interests, and other users. Affinity scores may be computed by the social networking system **502** over time to approximate a user's affinity for an object, interest, and other users in the social networking system **502** based on the actions performed by the user. Multiple interactions of the same type between a user and a specific object may be stored in one edge object in the edge store **518**, in at least one embodiment. In some embodiments, connections between users may be stored in the profile store **510**. In some embodiments, the profile store **510** may reference or be referenced by the edge store **518** to determine connections between users. Users may select from predefined types of connections, or define their own connection types as needed.

The web server **524** links the social networking system **502** via a network to one or more client devices; the web server **524** serves web pages, as well as other web-related content, e.g., Java, Flash, XML, and so forth. The web server **524** may communicate with the message server **526** that provides the functionality of receiving and routing messages between the social networking system **502** and client devices. The messages processed by the message server **526** can be instant messages, email messages, text and SMS (short message service) messages, photos, or any other suitable messaging technique. In some embodiments, a message sent by a user to another user can be viewed by other users of the social networking system **502**, for example, by the connections of the user receiving the message. An example of a type of message that can be viewed by other users of the social networking system besides the recipient of the message is a wall post. In some embodiments, a user can send a private message to another user that can only be retrieved by the other user.

The API request server **528** enables external systems to access information from the social networking system **502** by calling APIs. The information provided by the social network may include user profile information or the connection information of users as determined by their individual privacy settings. For example, a system interested in predicting the probability of users forming a connection within a social networking system may send an API request to the social networking system **502** via a network. The API request server **528** of the social networking system **502** receives the API request. The API request server **528** processes the request by determining the appropriate response, which is then communicated back to the requesting system via a network.

The application service server **522** can implement at least one application service, for example, one of the application services **102** of FIG. **1**. In several embodiments, the social networking system **502** can include multiple application service servers implementing multiple application services.

The machine learning system **532** can be the machine learning system **200** of FIG. **2**. The machine learning system **532** can enable developer/analyst users to define, modify, track, schedule, execute, compare, analyze, evaluate, and/or deploy one or more workflows associated with running machine learning training and experiments corresponding to one or more application services of the social networking system **502**. The machine learning system **532** can also enable developer/analyst users to modularly produce new workflows to refine machine learning models and to evaluate the efficacy of the machine learning models.

Functional components (e.g., circuits, devices, engines, modules, and data storages, etc.) associated with the application service system **100** of FIG. **1**, the machine learning system **200** of FIG. **2**, and/or the social networking system **502** of FIG. **5**, can be implemented as a combination of circuitry, firmware, software, or other functional instructions. For example, the functional components can be implemented in the form of special-purpose circuitry, in the form of one or more appropriately programmed processors, a single board chip, a field programmable gate array, a network-capable computing device, a virtual machine, a cloud computing environment, or any combination thereof. For example, the functional components described can be implemented as instructions on a tangible storage memory capable of being executed by a processor or other integrated circuit chip. The tangible storage memory may be volatile or non-volatile memory. In some embodiments, the volatile memory may be considered "non-transitory" in the sense that it is not a transitory signal. Memory space and storages described in the figures can be implemented with the tangible storage memory as well, including volatile or non-volatile memory.

Each of the functional components may operate individually and independently of other functional components. Some or all of the functional components may be executed on the same host device or on separate devices. The separate devices can be coupled through one or more communication channels (e.g., wireless or wired channel) to coordinate their operations. Some or all of the functional components may be combined as one component. A single functional component may be divided into sub-components, each sub-component performing separate method step or method steps of the single component.

In some embodiments, at least some of the functional components share access to a memory space. For example, one functional component may access data accessed by or transformed by another functional component. The functional components may be considered "coupled" to one another if they share a physical connection or a virtual connection, directly or indirectly, allowing data accessed or modified by one functional component to be accessed in another functional component. In some embodiments, at least some of the functional components can be upgraded or modified remotely (e.g., by reconfiguring executable instructions that implements a portion of the functional components). Other arrays, systems and devices described above may include additional, fewer, or different functional components for various applications.

FIG. **6** is a block diagram of an example of a computing device **600**, which may represent one or more computing device or server described herein, in accordance with various embodiments. The computing device **600** can be one or more computing devices that implement the application service system **100** of FIG. **1** and/or the machine learning system **200** of FIG. **2**. The computing device **600** can execute at least part of the method **1000** of FIG. **10**. The computing device **600** includes one or more processors **610** and memory **620** coupled to an interconnect **630**. The interconnect **630** shown in FIG. **6** is an abstraction that represents any one or more separate physical buses, point-to-point connections, or both connected by appropriate bridges, adapters, or controllers. The interconnect **630**, therefore, may include, for example, a system bus, a Peripheral Component Interconnect (PCI) bus or PCI-Express bus, a HyperTransport or industry standard architecture (ISA) bus, a small computer system interface (SCSI) bus, a universal serial bus (USB), IIC (I2C) bus, or an Institute of Electrical and Electronics Engineers (IEEE) standard 1394 bus, also called "Firewire".

The processor(s) **610** is/are the central processing unit (CPU) of the computing device **600** and thus controls the overall operation of the computing device **600**. In certain embodiments, the processor(s) **610** accomplishes this by executing software or firmware stored in memory **620**. The processor(s) **610** may be, or may include, one or more programmable general-purpose or special-purpose microprocessors, digital signal processors (DSPs), programmable controllers, application specific integrated circuits (ASICs), programmable logic devices (PLDs), trusted platform modules (TPMs), or the like, or a combination of such devices.

The memory **620** is or includes the main memory of the computing device **600**. The memory **620** represents any form of random access memory (RAM), read-only memory (ROM), flash memory, or the like, or a combination of such devices. In use, the memory **620** may contain a code **670** containing instructions according to the mesh connection system disclosed herein.

Also connected to the processor(s) **610** through the interconnect **630** are a network adapter **640** and a storage adapter **650**. The network adapter **640** provides the computing device **600** with the ability to communicate with remote devices, over a network and may be, for example, an Ethernet adapter or Fibre Channel adapter. The network adapter **640** may also provide the computing device **600** with the ability to communicate with other computers. The storage adapter **650** enables the computing device **600** to access a persistent storage, and may be, for example, a Fibre Channel adapter or SCSI adapter.

The code **670** stored in memory **620** may be implemented as software and/or firmware to program the processor(s) **610** to carry out actions described above. In certain embodiments, such software or firmware may be initially provided to the computing device **600** by downloading it from a remote system through the computing device **600** (e.g., via network adapter **640**).

The techniques introduced herein can be implemented by, for example, programmable circuitry (e.g., one or more microprocessors) programmed with software and/or firmware, or entirely in special-purpose hardwired circuitry, or in a combination of such forms. Special-purpose hardwired circuitry may be in the form of, for example, one or more application-specific integrated circuits (ASICs), programmable logic devices (PLDs), field-programmable gate arrays (FPGAs), etc.

Software or firmware for use in implementing the techniques introduced here may be stored on a machine-readable storage medium and may be executed by one or more general-purpose or special-purpose programmable microprocessors. A "machine-readable storage medium," as the term is used herein, includes any mechanism that can store information in a form accessible by a machine (a machine may be, for example, a computer, network device, cellular phone, personal digital assistant (PDA), manufacturing tool, any device with one or more processors, etc.). For example, a machine-accessible storage medium includes recordable/non-recordable media (e.g., read-only memory (ROM); random access memory (RAM); magnetic disk storage media; and/or optical storage media; flash memory devices), etc.

The term "logic," as used herein, can include, for example, programmable circuitry programmed with specific software and/or firmware, special-purpose hardwired circuitry, or a combination thereof.

Some embodiments of the disclosure have other aspects, elements, features, and steps in addition to or in place of what is described above. These potential additions and replacements are described throughout the rest of the specification. Reference in this specification to "various embodiments" or "some embodiments" means that a particular feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment of the disclosure. Alternative embodiments (e.g., referenced as "other embodiments") are not mutually exclusive of other embodiments. Moreover, various features are described which may be exhibited by some embodiments and not by others. Similarly, various requirements are described which may be requirements for some embodiments but not other embodiments. Reference in this specification to where a result of an action is "based on" another element or feature means that the result produced by the action can change depending at least on the nature of the other element or feature.

For example, some embodiments include a workflow authoring system. The work authoring system can comprise an operator repository storing serialized definitions of one or more operators; a workflow authoring tool configured to receive a workflow text string associated with a machine learning workflow and an operator text string associated with at least a data processing operator type; and an execution scheduler engine configured to parse the workflow text string to generate an interdependency graph of one or more data processing operators and to parse the operator text string to identify operator attributes associated with the data processing operator type. The operator attributes can comprise an input schema and an output schema. The input schema and/or the output schema can include a summary generation schema. The operator text string can identify computational logics that is executable on a single host operating environment as a single unit. The execution scheduler engine can further be configured to schedule the machine learning workflow for execution based on the interdependency graph. The workflow authoring system can also include an experiment analytic interface that is configured to generate a summary of a resulting output or an input parameter to the machine learning workflow based the summary generation schema.

Some embodiments include a computer readable data storage memory storing computer-executable instructions. The computer-executable instructions, when executed by a computer system, can cause the computer system to perform a computer-implemented method. The computer implemented method can include having the computer system to receive an operator definition of an operator type associated with operator attributes. The operator attributes can identify computational logics that is executable on a single host operating environment as a single unit, an input schema, and an output schema. The input schema or the output schema includes a summary generation schema. The computer implemented method can further include instructions for the computer system to receive a text string representation of a workflow including one or more references to one or more data processing operators of one or more operator types including the operator type. The computer-implemented method further include instructions for the computer system to traverse through the text string representation of the workflow to determine a set of expected promises made between the operator types. The expected promises can indicate interdependencies between the operator types. The extraction of the expected promises enable the computer system to determine the interdependencies without live input data. The computer-implemented method then further includes instructions for scheduling execution of the workflow by at least assigning executing instances of the operator types to one or more computing environments and passing data between the computing environments based on the interdependencies. In some embodiments, the computer implemented method can include instructions for identifying a first data processing operator as being depended on a second data processing operator by matching an output schema of the second data processing operator to an input schema of the first data processing operator.

What is claimed is:

1. A computer-implemented method, comprising:

accessing a workflow text string that is a textual representation of a machine learning workflow, the machine learning workflow comprising an execution pipeline in a machine learning system for creating, modifying, evaluating, validating, or utilizing one or more machine learning models, and an operator text string associated with at least a data processing operator type, the textual representation of the machine learning workflow generated using a workflow definition language;

parsing the workflow text string to generate an interdependency graph of one or more data processing operators, the parsing generating an interdependency graph that is a cyclic directed graph of the one or more data processing operators, wherein at least one of the data processing operators is an instance of the data processing operator type, where parsing the workflow text string comprises:

traversing the workflow text string to match an output of a first data processing operator as an input of a second data processing operator, and

updating the interdependency graph to indicate that the second data processing operator depends on the output of the first data processing operator;

parsing the operator text string to identify operator attributes associated with the data processing operator type, wherein the operator attributes comprise an input schema and an output schema, wherein the input schema or the output schema includes a summary generation schema; and wherein the operator text string identifies computational logic that is executable on a single host operating environment as a single unit;

scheduling the machine learning workflow for execution based on the interdependency graph; and

generating a summary of a resulting output or an input parameter to the machine learning workflow based the summary generation schema.

2. The computer-implemented method of claim **1**, wherein the input schema or the output schema identifies a data structure definition of one or more independent data elements that is able to be referenced as one or more inputs or one or more outputs to the computational logics of the data processing operator type.

3. The computer-implemented method of claim **1**, wherein parsing the workflow text string includes identifying a data processing operator of the data processing operator type as a receiver of the input parameter to the machine learning workflow.

4. The computer-implemented method of claim **1**, wherein parsing the workflow text string associated with the machine learning workflow includes identifying a data processing operator of the data processing operator type as a source of the resulting output upon the execution of the machine learning workflow.

5. The computer-implemented method of claim **1**, wherein the summary generation schema defines how to convert a data structure of the input schema or the output schema into a summary format.

6. The computer-implemented method of claim **5**, wherein the summary generation schema identifies a sampling process to reduce number of individual data units in an input dataset matching the input schema or in an output dataset matching the output schema.

7. The computer-implemented method of claim **5**, wherein the summary generation schema identifies a statistical analysis to produce a statistical summary of an input dataset matching the input schema or of an output dataset matching the output schema.

8. The computer-implemented method of claim **7**, wherein the statistical summary includes range, mean, median, mode, standard deviation, spread, or any combination thereof, of the input dataset or the output dataset.

9. The computer-implemented method of claim **1**, wherein the summary generation schema identifies a visualization rendering process to produce a visual summary of an input dataset matching the input schema or of an output dataset matching the output schema.

10. The computer-implemented method of claim **1**, further comprising:

determining whether the output of the first data processing operator has the same schema type as the input of the second data processing operator; and

generating warning alert in response to determining that the output of the first

data processing operator is not of the same schema type as the input of the second

data processing operator.

11. The computer-implemented method of claim **1**, further comprising: determining an implicit type conversion operator corresponding to a first schema type of the output of the first data processing operator and a second schema type of the input of the second data processing operator; and

inserting the implicit type conversion operator between the first data processing operator and the second data processing operator in the interdependency graph.

12. The computer-implemented method of claim **1**, wherein the operator attributes includes a resource constraint for running the data processing operator type.

13. The computer-implemented method of claim **12**, wherein the resource constraint includes an absolute geographical location of where to run an instance of the data processing operator type.

14. The computer-implemented method of claim **12**, wherein the resource constraint includes a relative location requirement of where to run a first instance of the data processing operator type, wherein the relative location requirement is relative to where to run a second instance of another data processing operator type that is connected to the first instance in the interdependency graph.

15. The computer-implemented method of claim **14**, wherein the relative location requirement enforces a proximity threshold for where to run the first instance of the data processing operator type relative to a location of a computing device storing an input dataset for the first instance of the data processing operator type.

16. The computer-implemented method of claim **12**, wherein the resource constraint includes memory capacity requirement, processing power requirement, network bandwidth requirement, operating environment requirement, software library requirement, or any combination thereof.

17. A non-transitory computer readable data memory storing computer-executable instructions that, when executed by a computer system, cause the computer system to perform a computer-implemented method, the instructions comprising:

instructions for receiving an operator definition of an operator type associated with operator attributes that identify computational logics that is executable on a single host operating environment as a single unit, an input schema, and an output schema, wherein the input schema or the output schema includes a summary generation schema;

instructions for receiving a text string representation that is a textual representation of a machine learning workflow including one or more references to one or more data processing operators of one or more operator types including the operator type, the textual representation of the machine learning workflow generated using a workflow definition language, the machine learning workflow comprising an execution pipeline in a machine learning system for creating, modifying, evaluating, validating, or utilizing one or more machine learning models;

instructions for parsing the text string representation to generate an interdependency graph of one or more data processing operators, the parsing generating an interdependency graph that is an acyclic directed graph of the one or more data processing operators, the parsing comprising traversing through the text string representation of the workflow to determine a set of expected promises made between the operator types, wherein the expected promises indicate interdependencies between the operator types, the instructions for traversing comprising instructions for identifying a first data processing operator as being dependent on a second data processing operator by matching an output schema of the second data processing operator to an input schema of the first data processing operator;

instructions for parsing the text string representation to generate an interdependency graph of one or more data processing operators, the parsing generating an interdependency graph that is a cyclic directed graph of the one or more data processing operators, the parsing comprising traversing through the text string representation of the workflow to determine a set of expected promises made between the operator types, wherein the expected promises indicate interdependencies between the operator types, the instructions for traversing comprising instructions for identifying a first data processing operator as being dependent on a second data processing operator by matching an output schema of the second data processing operator to an input schema of the first data processing operator; and

instructions for scheduling execution of the workflow by at least assigning executing instances of the operator types to one or more computing environments and passing data between the computing environments based on the interdependencies.

18. A computer program product comprising a non-transitory computer readable storage medium having instructions encoded therein that, when executed by a processor cause the processor to:

receive an operator definition of a data processing operator type associated with operator attributes that identify computational logics that is executable on a single host operating environment as a single unit, an input schema, and an output schema, wherein the input schema or the output schema includes a summary generation schema;

access a workflow text string that is a textual representation of a machine learning workflow, the textual representation of the machine learning workflow generated using a workflow definition language, the machine learning workflow comprising an execution pipeline in a machine learning system for creating, modifying, evaluating, validating, or utilizing one or more machine learning models, and an operator text string associated with at least a data processing operator type;

parse the workflow text string to generate an interdependency graph of one or more data processing operators, the parse generating an interdependency graph that is an acyclic directed graph of the one or more data processing operators, wherein at least one of the data processing operators is an instance of the data processing operator type, where parsing the workflow text string comprises:

traversing the workflow text string to match an output of a first data processing operator as an input of a second data processing operator, and

updating the interdependency graph to indicate that the second data processing operator depends on the output of the first data processing operator;

parse the workflow text string to generate an interdependency graph of one or more data processing operators, the parse generating an interdependency graph that is a cyclic directed graph of the one or more data processing operators, wherein at least one of the data processing operators is an instance of the data processing operator type, where parsing the workflow text string comprises:

traversing the workflow text string to match an output of a first data processing operator as an input of a second data processing operator, and

updating the interdependency graph to indicate that the second data processing operator depends on the output of the first data processing operator;

parse the operator text string to identify operator attributes associated with the data processing operator type, wherein the operator attributes comprise an input schema and an output schema, wherein the input schema or the output schema includes a summary generation schema; and wherein the operator text string identifies computational logic that is executable on a single host operating environment as a single unit;

schedule the machine learning workflow for execution based on the interdependency graph; and

generate a summary of a resulting output or an input parameter to the machine learning workflow based the summary generation schema.

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