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(54) **ONTOLOGY-BASED DATA STORAGE FOR DISTRIBUTED KNOWLEDGE BASES**

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(58) **Field of Classification Search**

None

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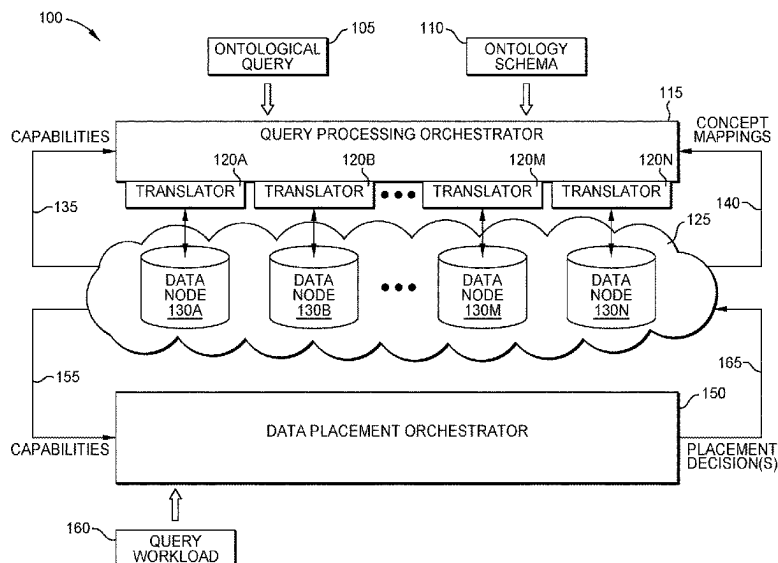
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(57) **ABSTRACT**

Techniques for distributed data placement are provided. Query workload information corresponding to a domain is determined by a data orchestrator, and the query workload information is modeled as a hypergraph, where the hypergraph includes a set of vertices and a set of hyperedges, where each vertex in the set of vertices corresponds to a concept in an ontology associated with the domain. Mappings are generated between concepts and a plurality of data nodes based on the hypergraph and based further on pre-defined capability of each of the plurality of data nodes. A distributed knowledge base is established based on the generated mappings.

22 Claims, 19 Drawing Sheets



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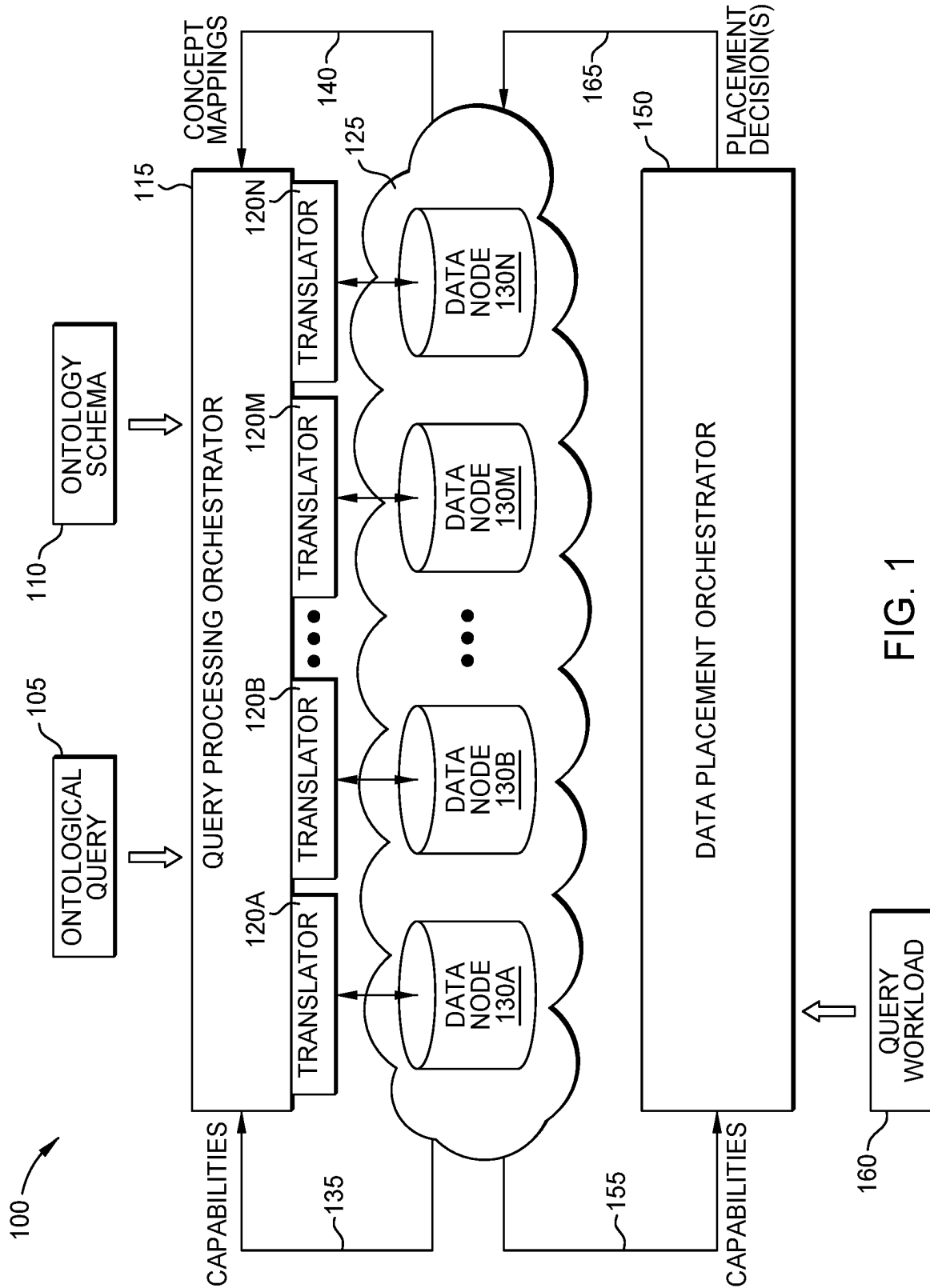
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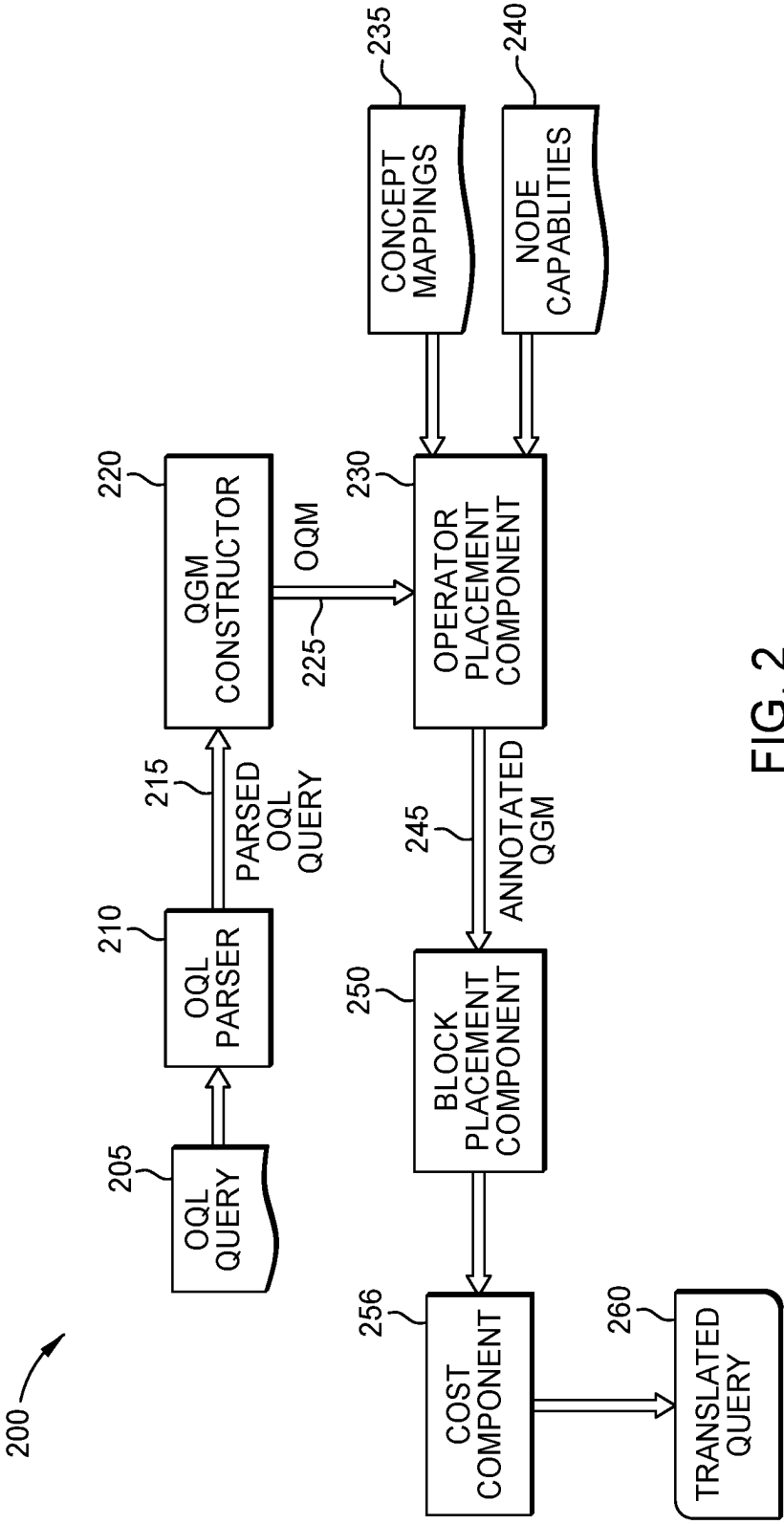


FIG. 2

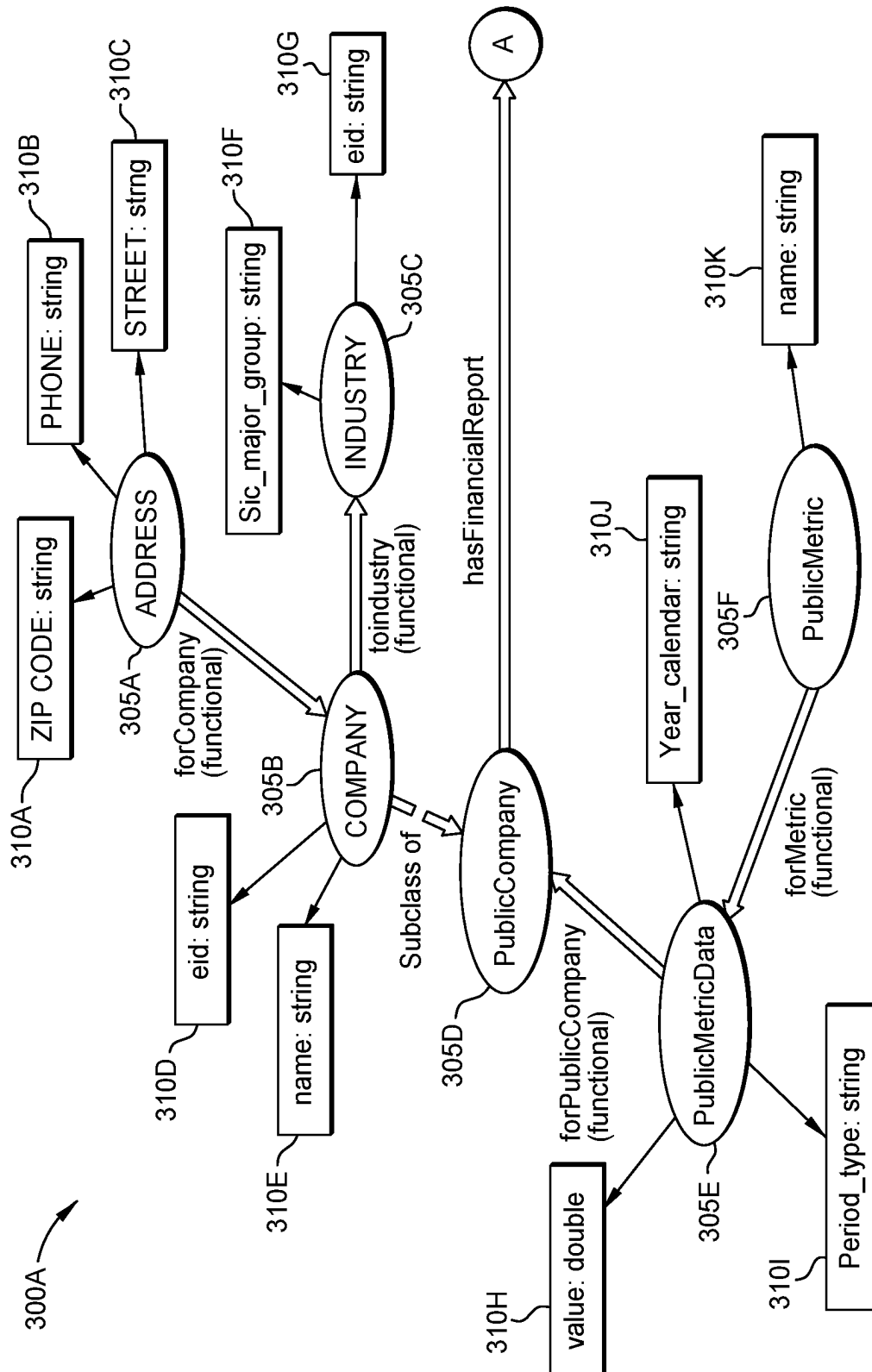


FIG. 3A

300B

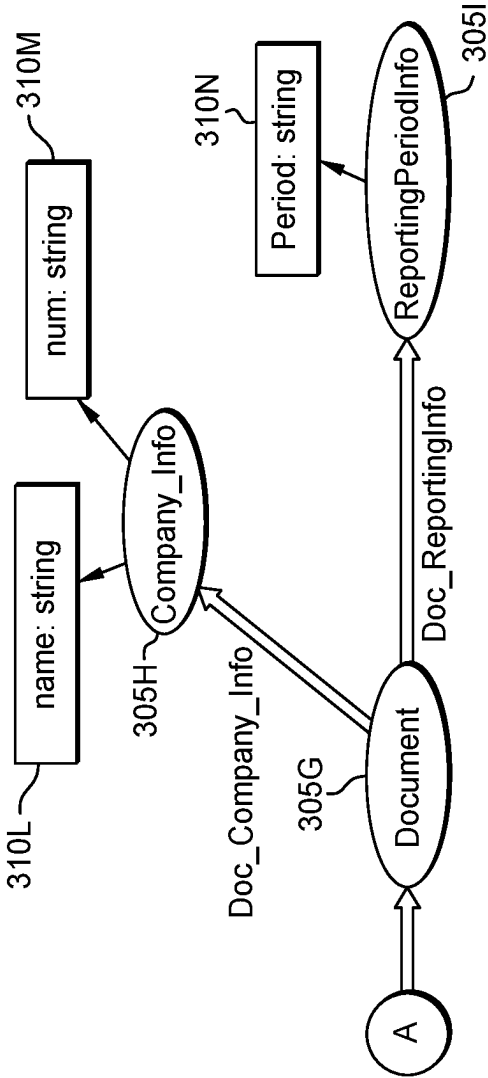


FIG. 3B

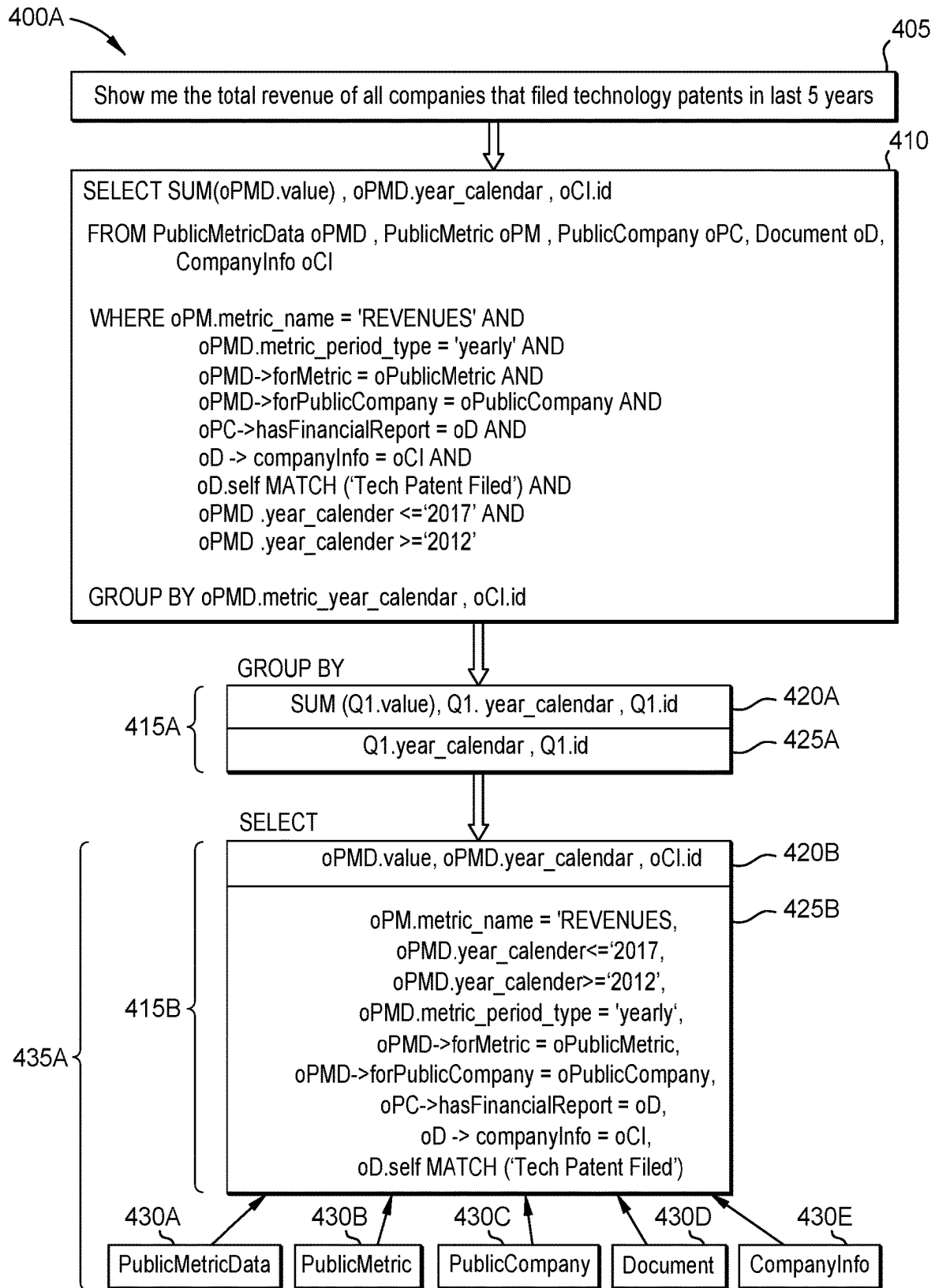


FIG. 4A

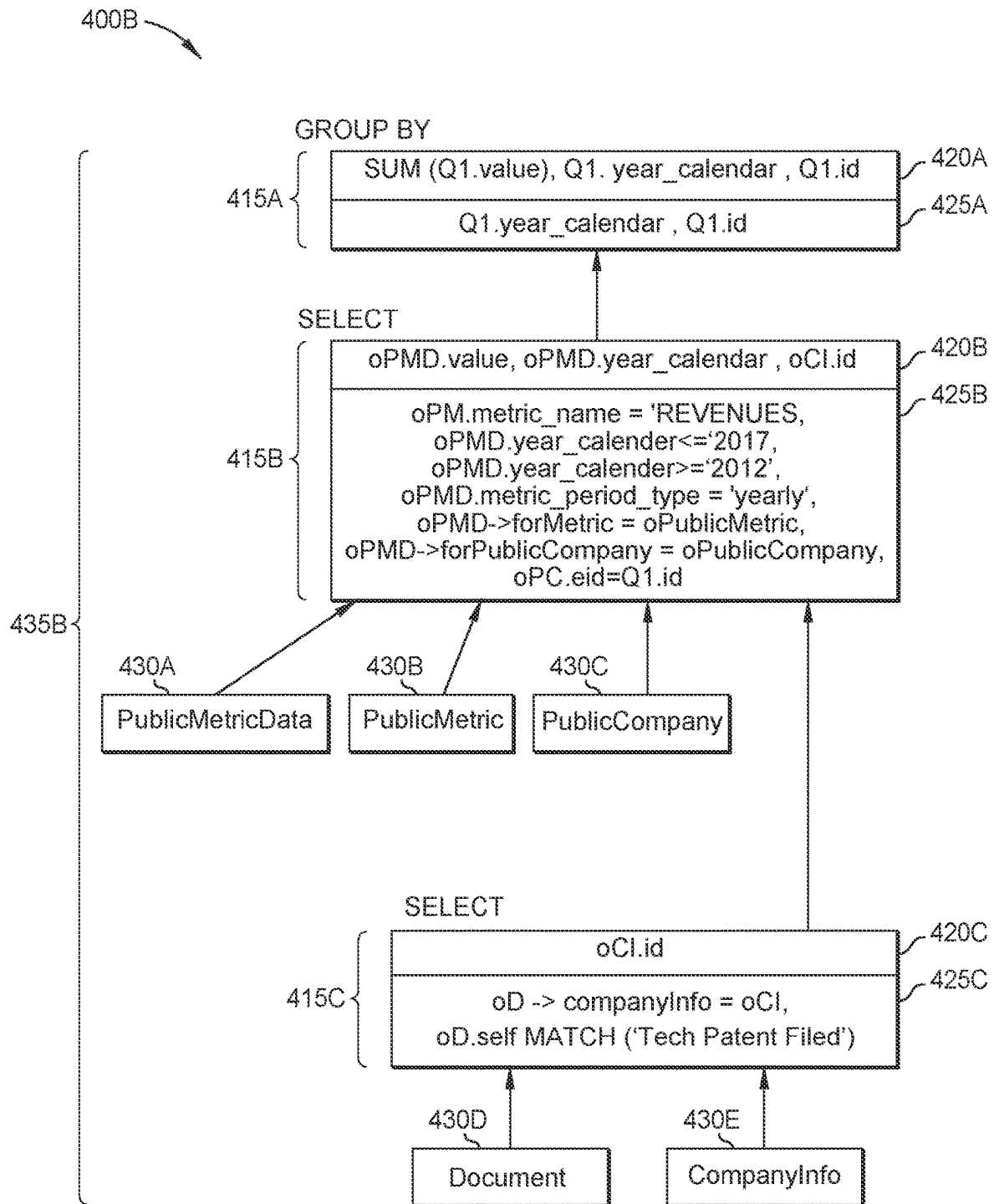


FIG. 4B

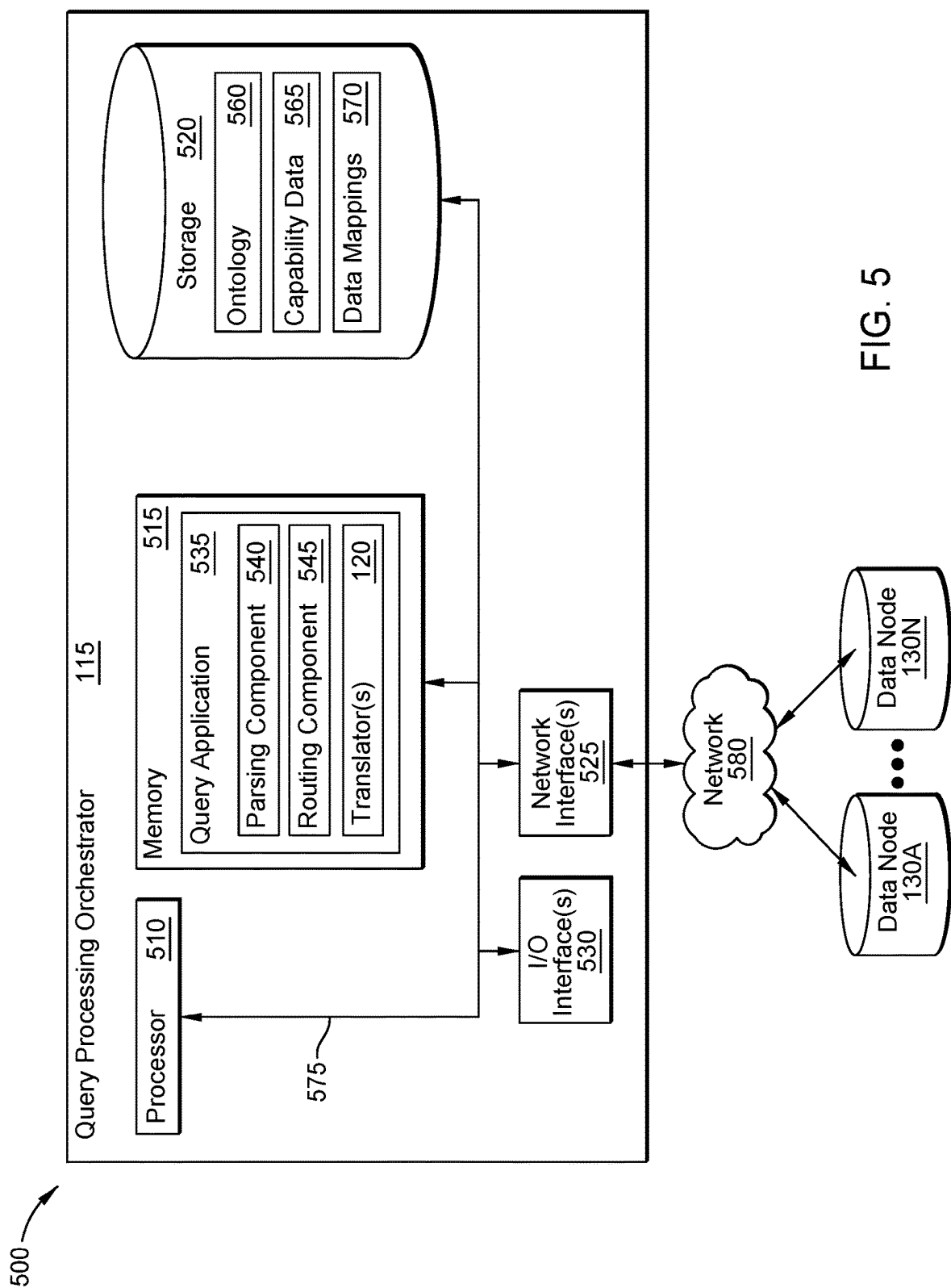


FIG. 5

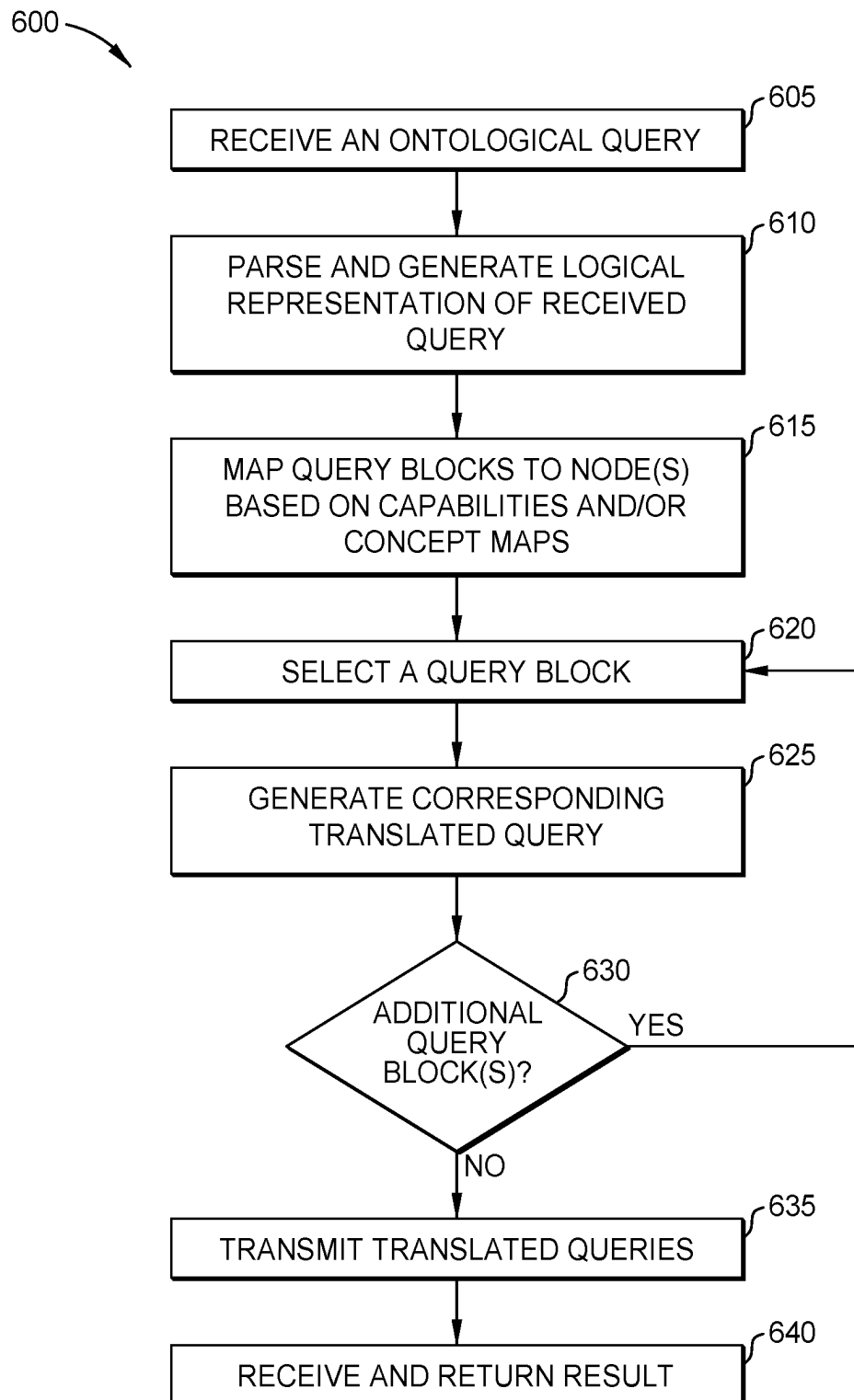


FIG. 6

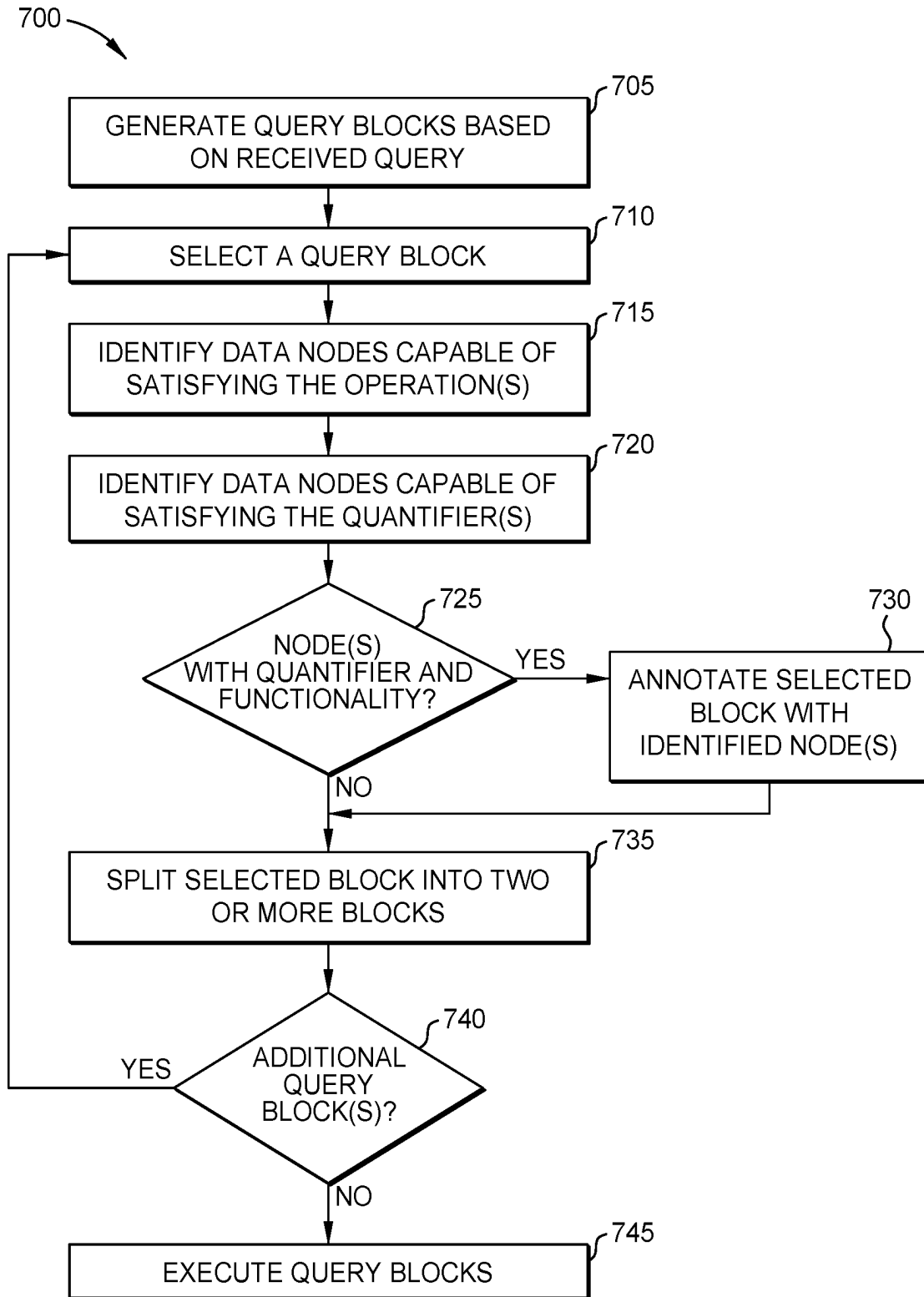


FIG. 7

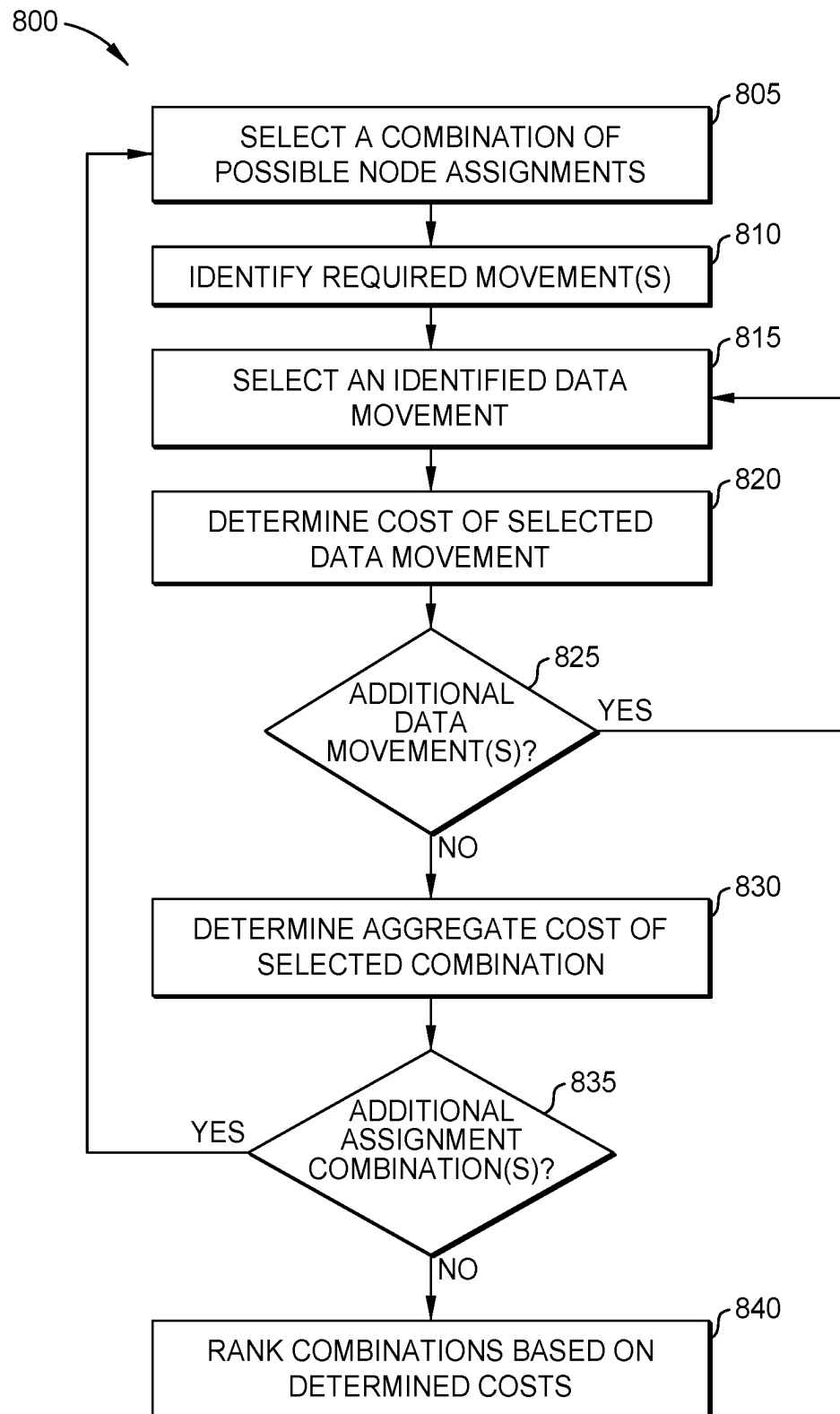


FIG. 8

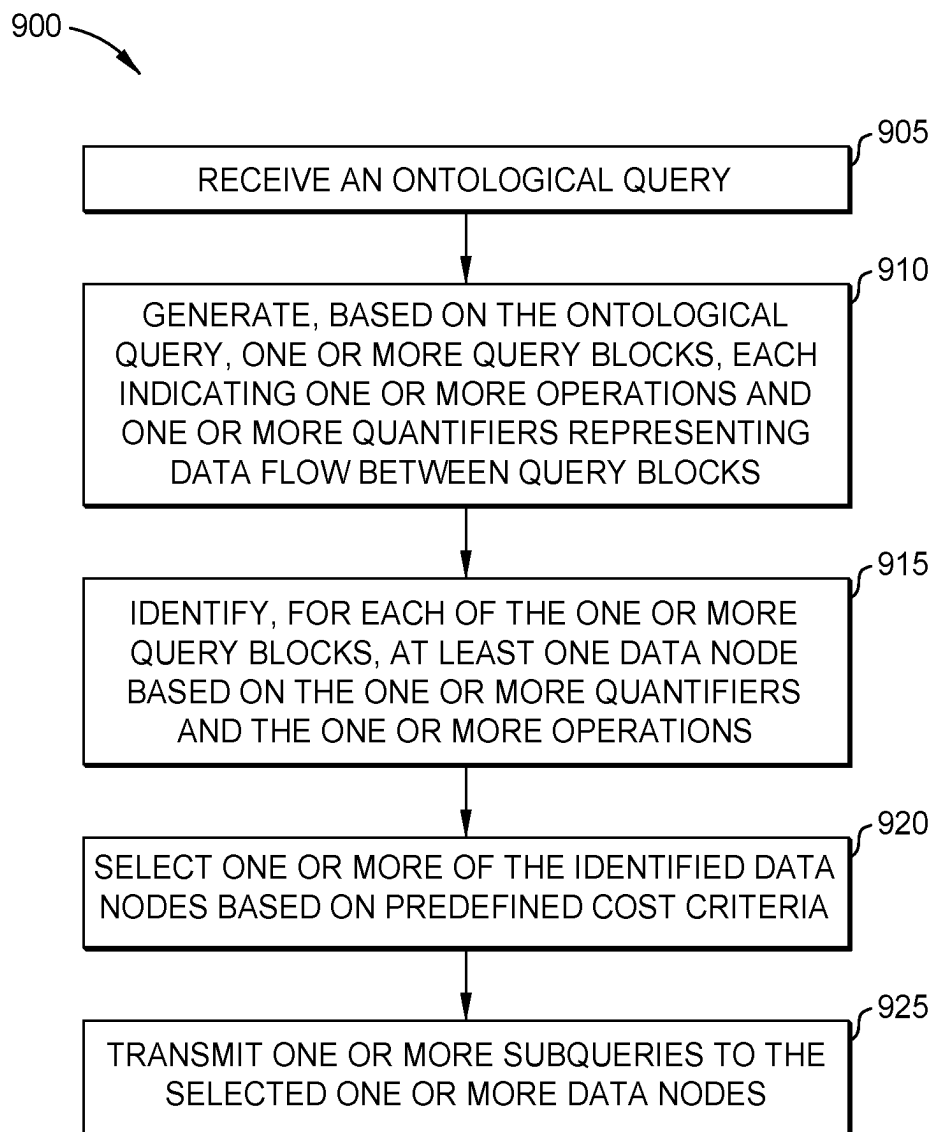


FIG. 9

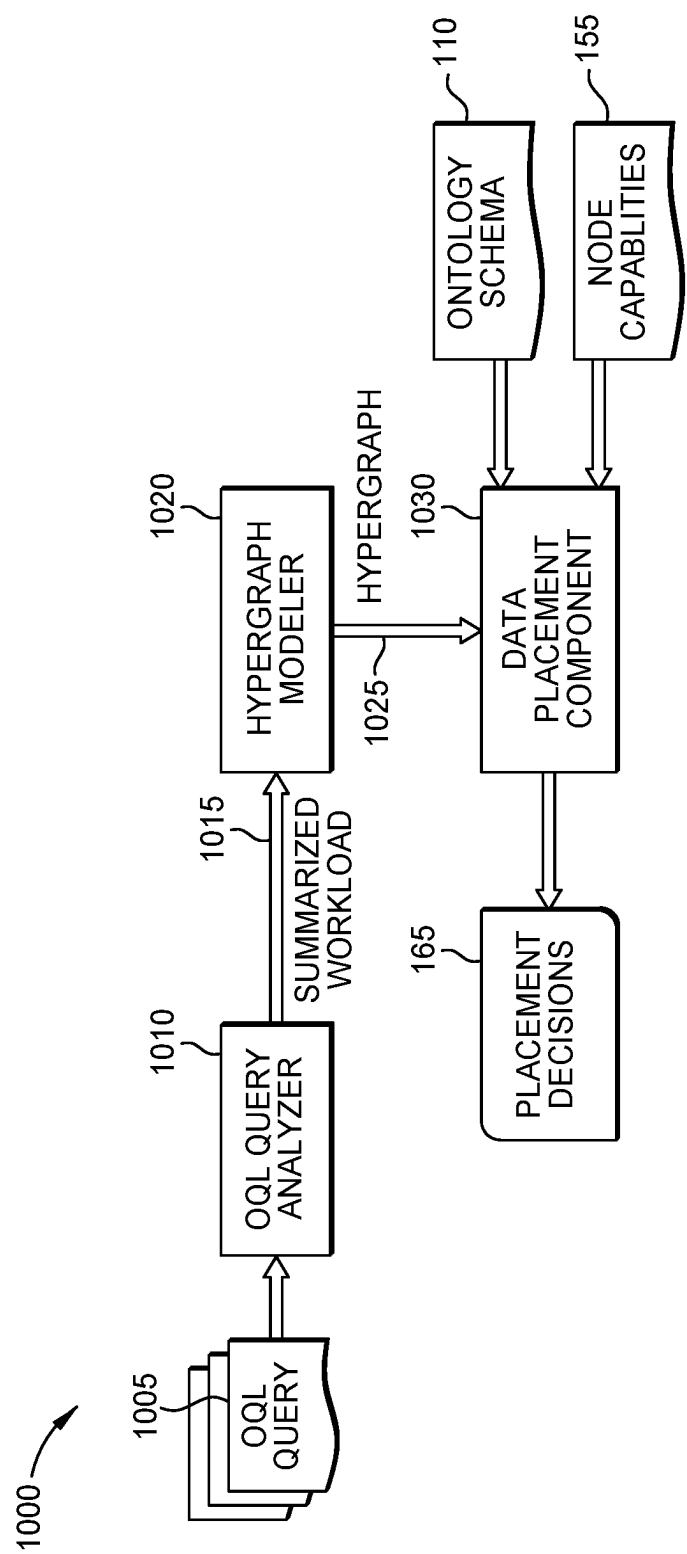


FIG. 10

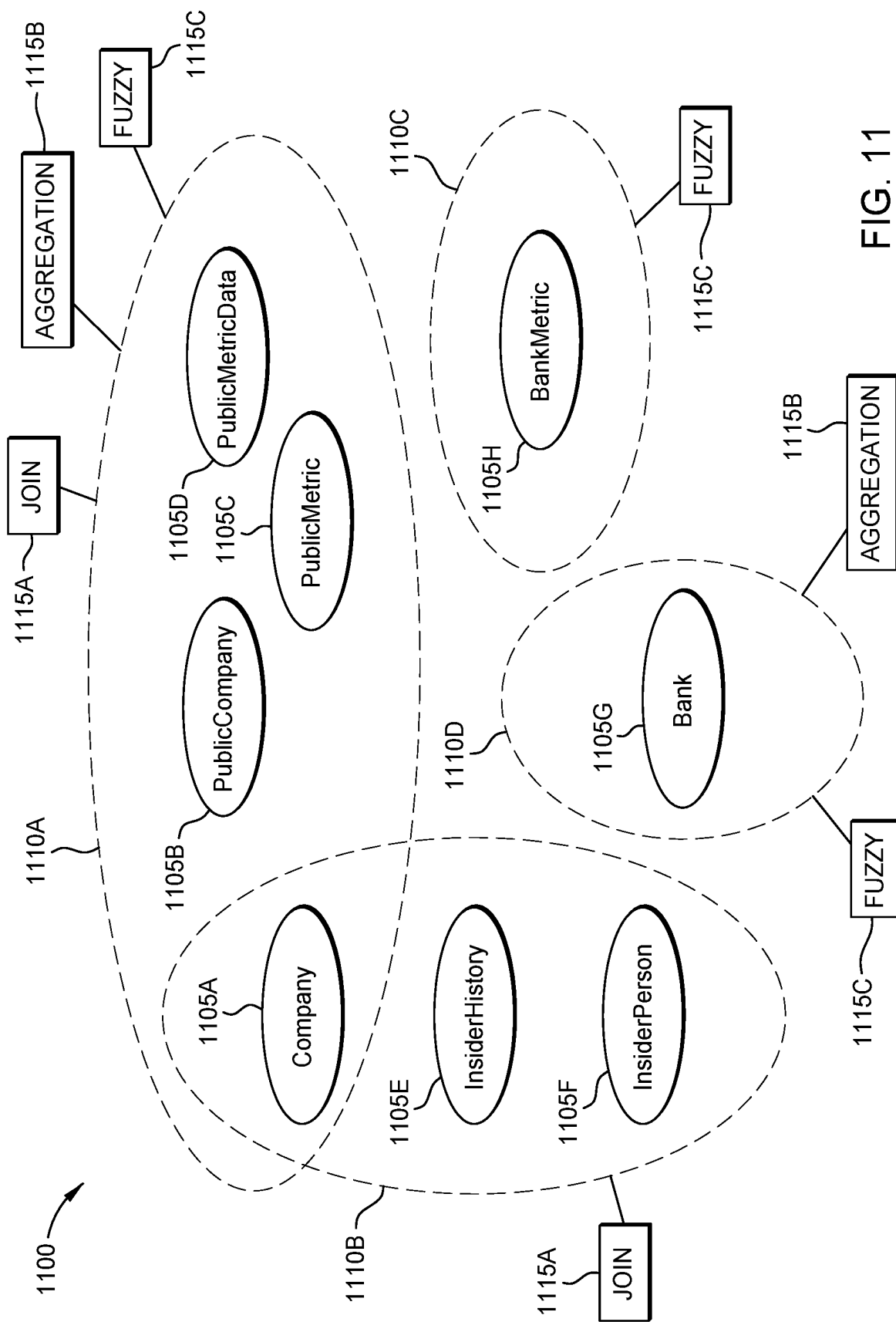
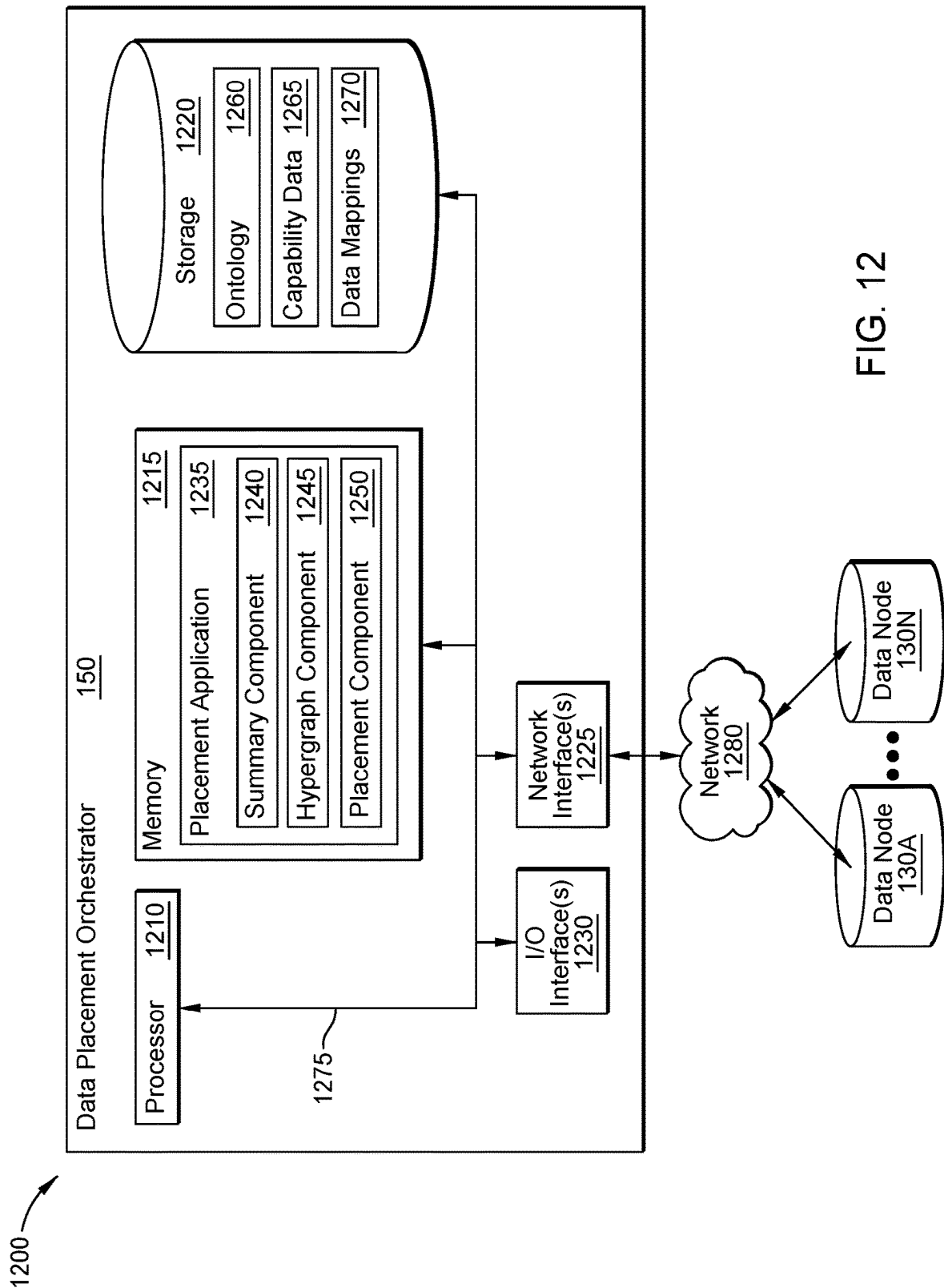


FIG. 11



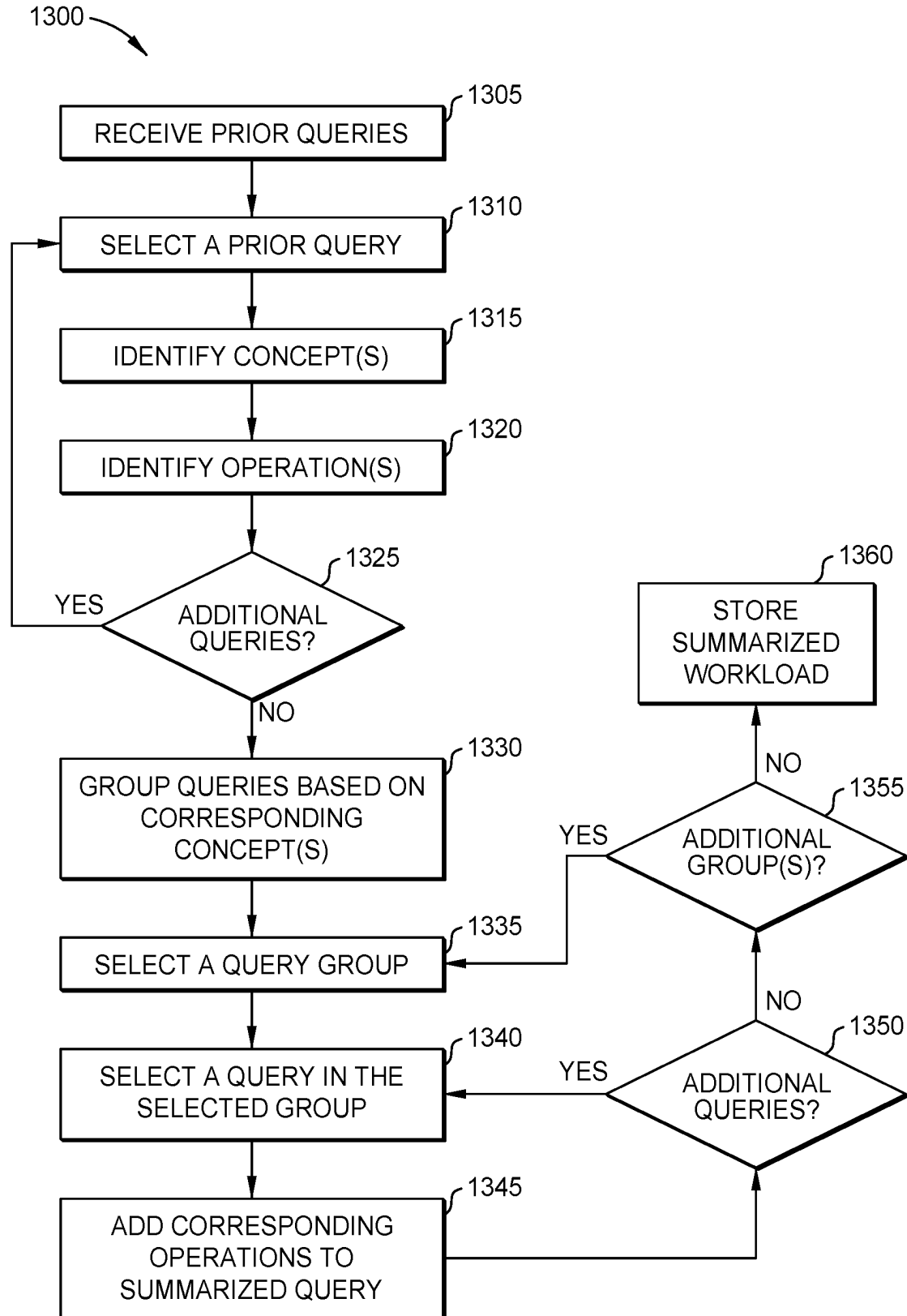


FIG. 13

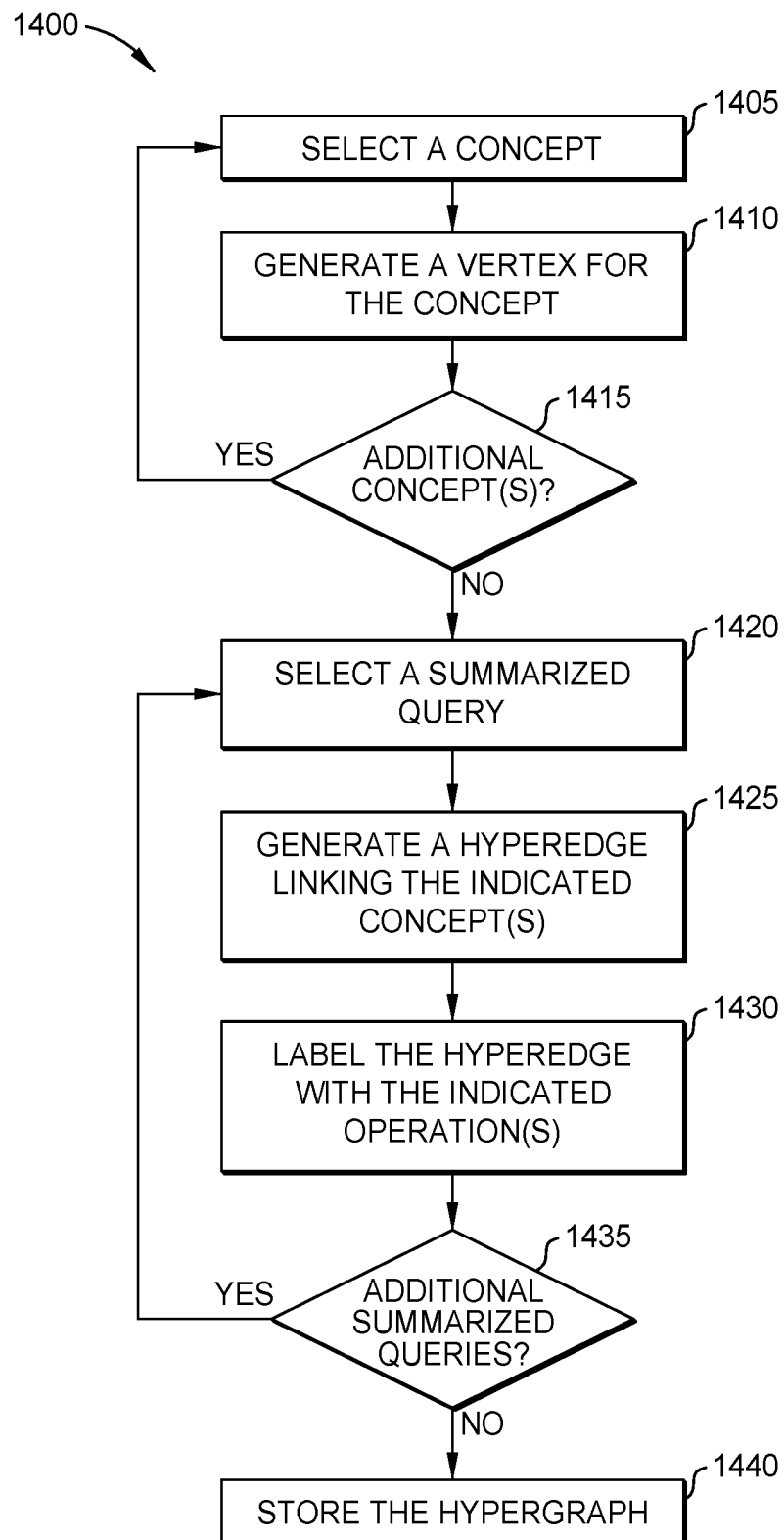
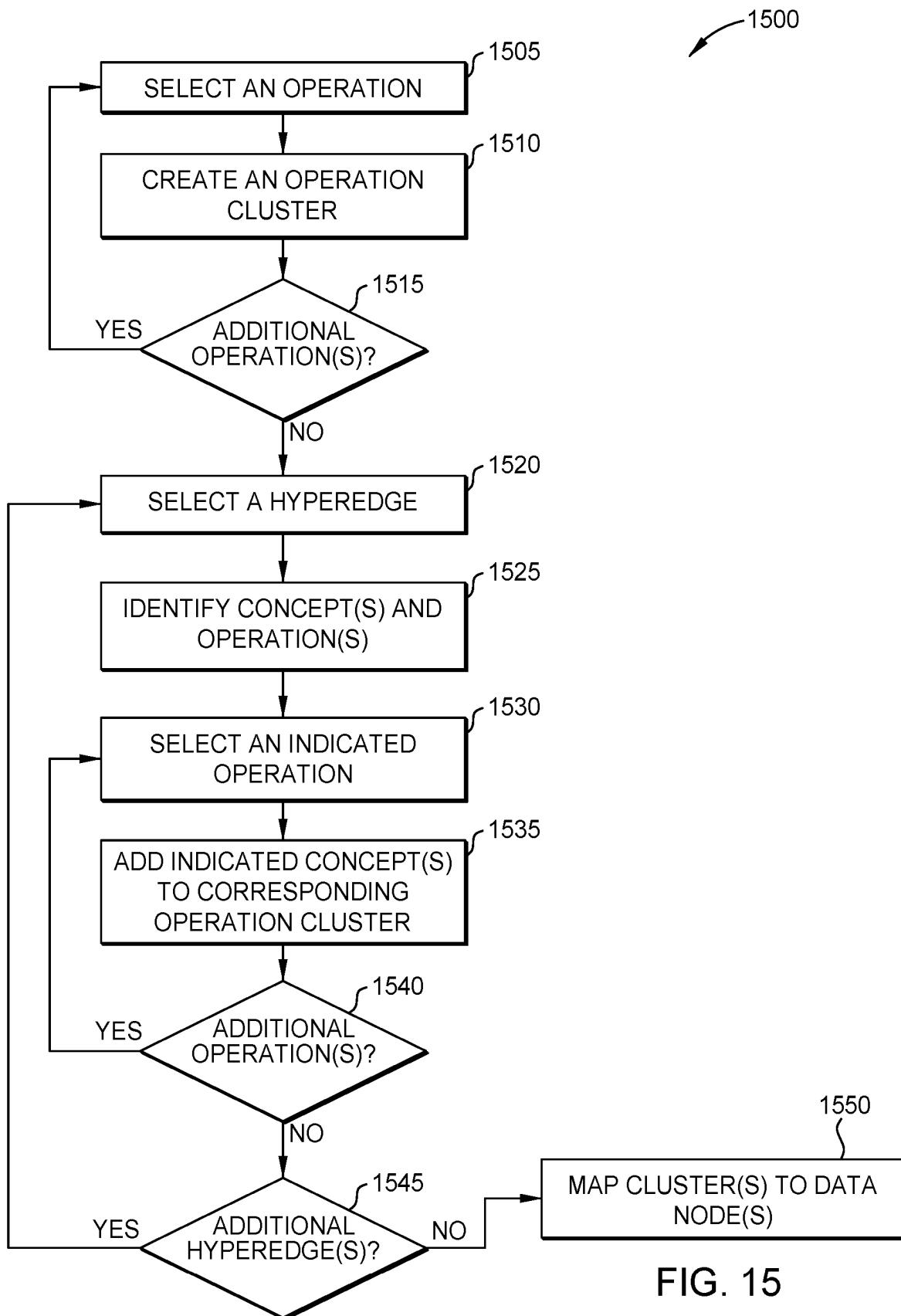


FIG. 14



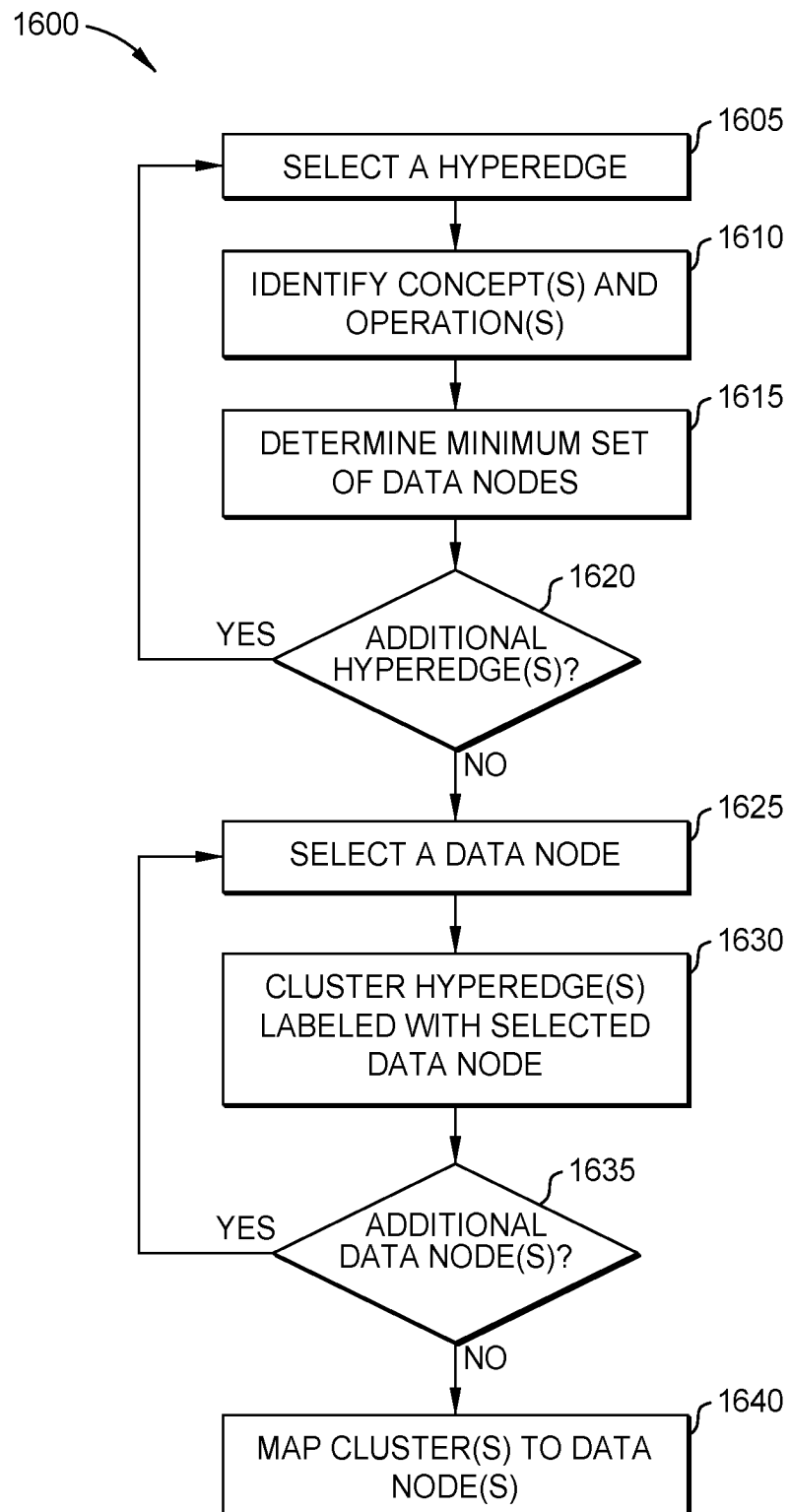


FIG. 16

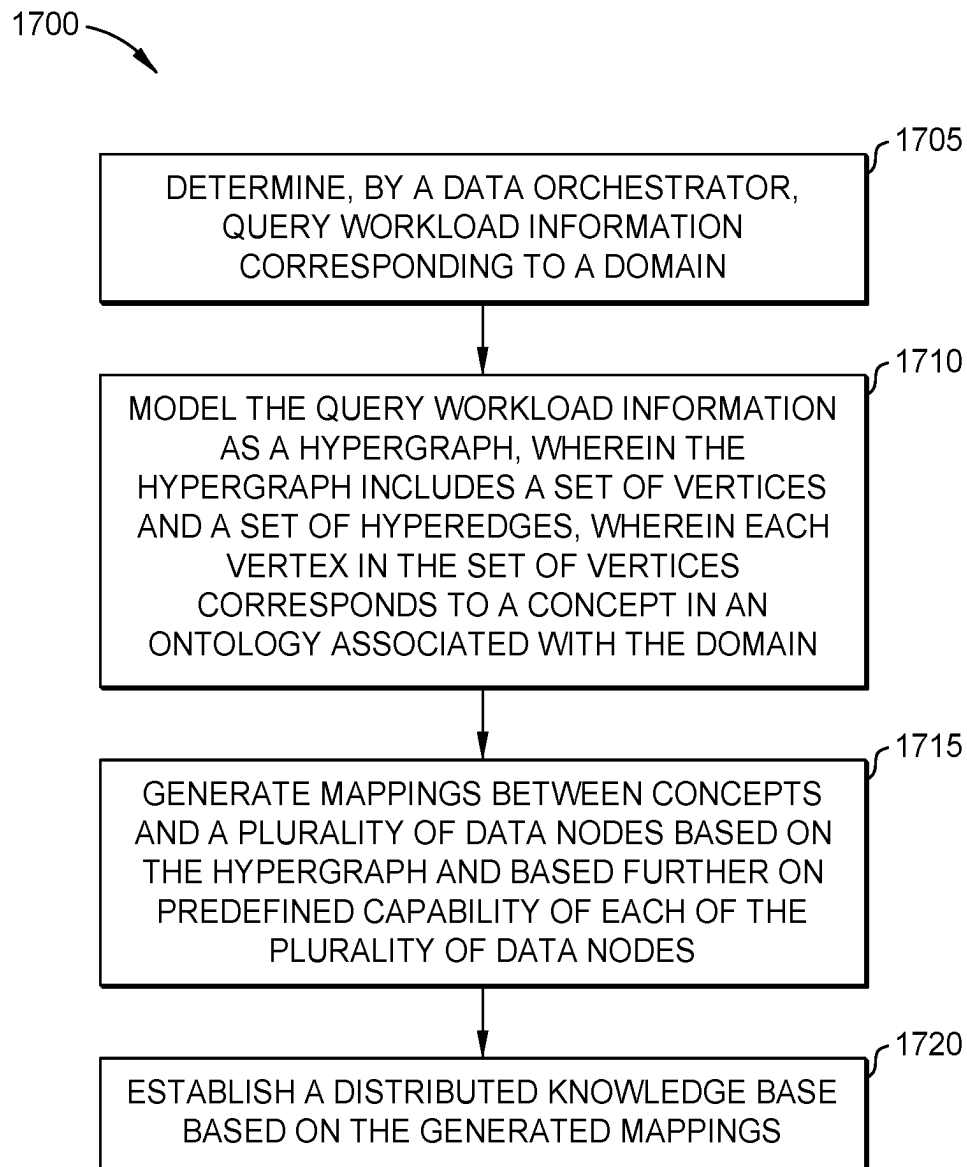


FIG. 17

ONTOLOGY-BASED DATA STORAGE FOR DISTRIBUTED KNOWLEDGE BASES

BACKGROUND

The present disclosure relates to knowledge bases, and more specifically, to using ontologies for effective data placement in distributed knowledge bases.

A growing number of enterprises are utilizing Knowledge Bases (KBs) to augment their analytics and improve decision-making, efficiency, and effectiveness of their systems. Often, the KBs are relatively specialized within the domain of the enterprise. For example, financial institutions rely on KBs with significant financial knowledge, such as data related to governmental regulations of financial markets. Conversely, healthcare enterprises may maintain KBs with a considerable amount of data collected from medical literature. There is substantial need for deep domain specialization, effective systems, and effective techniques to manage these KBs. Existing systems, which are not aware of the domain ontology that provides an entity-centric view of the domain schema, are unable to effectively manage and route queries for the KB.

Additionally, KBs may be distributed across a number of data sites with varying capabilities and costs, in order to improve operations. Existing architectures, such as federated databases, rely on a centralized mediator to aggregate data from each such source. This is inefficient and scales poorly. Additionally, existing systems do not understand the underlying ontology and capabilities of each data source, and thus cannot efficiently route queries. This reduces the efficiency of such systems, requiring significant computing resources to respond to typical queries.

SUMMARY

According to one embodiment of the present disclosure, a method is provided. The method includes determining, by a data orchestrator, query workload information corresponding to a domain. The method further includes modeling the query workload information as a hypergraph, where the hypergraph includes a set of vertices and a set of hyperedges, where each vertex in the set of vertices corresponds to a concept in an ontology associated with the domain. Additionally, the method includes generating mappings between concepts and a plurality of data nodes based on the hypergraph and based further on predefined capability of each of the plurality of data nodes, and establishing a distributed knowledge base based on the generated mappings. Advantageously, the method enables the data orchestrator to efficiently place and store data in a distributed environment based on an existing workload and the capabilities of each data node. This reduces computational expense required to store the data, and further improves system responsiveness by providing effective data maps.

According to another embodiment of the present disclosure, determining the query workload information includes receiving a set of prior ontological queries. A method according to this embodiment includes generating a first set of concepts accessed by a first query in the set of prior ontological queries, and generating a second set operations performed by the first query. A first summarized query is the generated by identifying a group of queries, from the set of prior ontological queries, with corresponding matching first sets, and determining, based on corresponding second sets for each query in the identified group of queries, an aggregate set of operations. The first summarized query is then

associated with the aggregate set of operations and concepts reflected in the corresponding matching first sets. In such an embodiment, the data orchestrator improves over existing systems by effectively summarizing prior queries to determine a good storage plan for the data, in order to meet expected needs. This again improves efficiency and reduces computational waste at runtime.

According to still another embodiment of the present disclosure, modeling the query workload information as a hypergraph includes creating a vertex for each concept in the ontology and creating a first hyperedge for the first summarized query, where the first hyperedge connects a first set of vertices in the hypergraph, where the first set of vertices corresponds to the concepts reflected in the matching first sets. In one such embodiment, the method further includes labeling the first hyperedge with the aggregate set of operations. Advantageously, such an embodiment enables the data orchestrator to effectively represent workloads in graph form, which allows the orchestrator to better and more efficiently evaluate the data to drive improved placement decisions. This dramatically improves runtime performance.

According to yet another embodiment of the present disclosure, generating the mappings comprises creating a first cluster for a first operation included in the hypergraph. The embodiment then includes identifying a first set of concepts connected by a first hyperedge in the hypergraph, and identifying a first set of operations indicated by the first hyperedge. Upon determining that the first set of operations includes the first operation, the method includes assigning the first set of concepts to the first cluster. One advantage of such an embodiment is that it enables the hypergraph to be efficiently evaluated, and leads to highly-reliable data placements that require minimal movement at runtime.

According to another embodiment of the present disclosure, generating the mappings further includes mapping the first set of concepts to one or more data nodes by identifying a set of data nodes capable of performing the first operation, and mapping each concept in the first set of concepts to each data node in the identified set of data nodes. Advantageously, this enables the system to generate data mappings based on capability of the nodes, while considering prior workloads. This improves the likelihood that the system will be adequately positioned to respond to future queries with minimal latency and resource consumption.

According to still another embodiment of the present disclosure, wherein generating the mappings includes identifying a first set of concepts connected by a first hyperedge in the hypergraph, identifying a first set of operations indicated by the first hyperedge, and determining a minimum set of data nodes capable of collectively performing the first set of operations. The method then includes generating a cluster including the first set of concepts, and labeling the cluster with the minimum set of data nodes. Such an embodiment improves over existing solutions by minimizing the replication of data in the system, which reduces storage costs, and additionally decreases latency and resource consumption caused by data movement in the system.

According to a further embodiment of the present disclosure, generating the mappings further comprises mapping each concept in the first set of concepts to each data node in the minimum set of data nodes. This similarly reduces storage costs and latency of the system.

According to yet another embodiment of the present disclosure, establishing the distributed knowledge base includes, for each respective concept in the ontology, identifying a respective data node indicated by the mappings,

identifying data corresponding to the respective concept, and facilitating storage of the identified data in the respective data node. Advantageously, such an embodiment enables the orchestrator to effectively generate mappings and place data in the appropriate nodes in an efficient manner, which reduces computation both before and during runtime.

According to a different embodiment of the present disclosure, any of the above-discussed embodiments can be implemented by a computer-readable storage medium. The computer-readable storage medium contains computer program code that, when executed by operation of one or more computer processors, performs an operation. In embodiments, the operation performed can correspond to any combination of the above methods and embodiments.

According to yet another different embodiment of the present disclosure, any of the above-discussed embodiments can be implemented by a system. The system includes one or more computer processors, and a memory containing a program which, when executed by the one or more computer processors, performs an operation. In embodiments, the operation performed can correspond to any combination of the above methods and embodiments.

BRIEF DESCRIPTION OF THE SEVERAL VIEWS OF THE DRAWINGS

FIG. 1 illustrates an architecture configured to place data for a knowledge base and route ontological queries, according to one embodiment disclosed herein.

FIG. 2 illustrates a workflow for processing and routing ontological queries, according to one embodiment disclosed herein.

FIGS. 3A and 3B depict an example ontology that can be used to evaluate and route queries, according to one embodiment disclosed herein.

FIGS. 4A and 4B illustrate a workflow for parsing and routing an example ontological query, according to one embodiment disclosed herein.

FIG. 5 is a block diagram illustrating a query processing orchestrator configured to route ontological queries, according to one embodiment disclosed herein.

FIG. 6 is a flow diagram illustrating a method for processing and routing ontological queries, according to one embodiment disclosed herein.

FIG. 7 is a flow diagram illustrating a method for processing ontological queries to efficiently route query blocks, according to one embodiment disclosed herein.

FIG. 8 is a flow diagram illustrating a method for evaluating potential query routing plans in order to efficiently route an ontological query, according to one embodiment disclosed herein.

FIG. 9 is a flow diagram illustrating a method for routing an ontological query, according to one embodiment disclosed herein.

FIG. 10 illustrates a workflow for evaluating workloads and storing knowledge base data, according to one embodiment disclosed herein.

FIG. 11 depicts an example hypergraph used to evaluate workloads and store knowledge base data, according to one embodiment disclosed herein.

FIG. 12 is a block diagram illustrating a data placement orchestrator configured to evaluate workloads and store data, according to one embodiment disclosed herein.

FIG. 13 is a flow diagram illustrating a method for evaluating and summarizing query workload to inform data placement decisions, according to one embodiment disclosed herein.

FIG. 14 is a flow diagram illustrating a method for modeling ontological workloads to inform data placement decisions, according to one embodiment disclosed herein.

FIG. 15 is a flow diagram illustrating a method for evaluating a hypergraph to drive data placement decisions, according to one embodiment disclosed herein.

FIG. 16 is a flow diagram illustrating a method for evaluating a hypergraph to drive data placement decisions, according to one embodiment disclosed herein.

FIG. 17 is a flow diagram illustrating a method for mapping ontological concepts to storage nodes, according to one embodiment disclosed herein.

DETAILED DESCRIPTION

Embodiments of the present disclosure provide an ontology-driven architecture that provides support for a variety of query types using multiple data stores or nodes, each of which may have differing capabilities. Advantageously, embodiments of the present disclosure enable queries to be processed and routed efficiently to the diverse data stores based on an existing ontology, which improves the latency of the system and reduces computing resources required to identify and return relevant data. In embodiments, the techniques described herein can be used to support a variety of querying applications, including natural language and conversational interfaces. The systems described herein can provide transparent access to the underlying backend stores via an abstract ontology query language (OQL) that allows users to express their information needs against the domain ontology.

In one embodiment, to provide improved performance for different query types, the system first optimizes the placement of the KB data into different stores by placing subsets of the data in appropriate backend stores according to their capabilities. In some embodiments, at runtime, the system parses and compiles the OQL query, and translates it into the query languages and/or APIs of the different backend data nodes. In one embodiment, the system described herein also employs a query orchestrator that routes the query to a single or multiple backend stores, according to the placement of the relevant data. This efficient routing reduces the latency required to generate and return results to the requesting entity.

In embodiments, the KB data to be queried can include any information, including structured, unstructured, and/or semi-structured data. To support deep domain specialization, embodiments disclosed herein leverage domain ontologies. Notably, in one embodiment, the domain ontology only defines the entities and their relationships at the meta-data level, without providing instance level information. That is, in one embodiment, the domain ontology provides the domain schema, while the instance level data is stored in various backend data stores (also referred to as data sites and data nodes). In embodiments, the data nodes can include any store architecture, including relational database(s), inverted index document store(s), JavaScript Object Notation (JSON) store(s), graph database(s), and the like.

In some embodiments, the system can move, store, and index the KB data in any backend that provides the needed capability for the query types to be supported. In other words, the system need not federate the data across existing operational data stores. This is distinctly different from

federated databases and mediator-based approaches. In some embodiments, the system performs a capability-based data placement step, where knowledge base data conforming to a given ontology is stored in the variety of backend resources. In at least one embodiment, the poly store architecture is configured to minimize data movement between different data stores, as data movement not only incurs data transfer costs, but also expensive data conversion costs. One solution to minimize data movement costs is to replicate the data in all backend nodes, ensuring that queries can be answered by a single store without any data movement. However, this also requires wasteful duplication, and defeats the purpose of using a poly store architecture to leverage the different capabilities of the multiple data stores. In embodiments of the present disclosure, the KB data may be stored in any number of backend resources, and the system intelligently routes queries to choose the most appropriate data store(s) and minimize data movement costs.

In some embodiments described herein, the system architecture provides appropriate abstractions to query the data without knowing how the data is stored and indexed in the multiple data stores. In one embodiment, to accomplish this purpose, an Ontology Query Language (OQL) is introduced. The OQL is expressed against the domain ontology for the enterprise. Users of the system need only know about the domain ontology which defines the entities and their relationships. In embodiments, the system understands the mappings of the various ontology concepts to the backend data stores, as well as their corresponding schemas, and provides query translators from OQL to the target query language of the underlying system.

In embodiments, for any given query, one or more data nodes may be involved. Embodiments of the present disclosure provide techniques to identify the stores that are involved and generate the appropriate sub-queries to compute the final query result. In some embodiments, the system does not use a mediator approach, where a global query is divided into multiple sub-queries and the final results are assembled in the mediator. Instead, one or more of the data stores are used as the mediator, and the backend data store(s) finalize the query answers. For example, in one embodiment, the relational database is used to finalize the query response, as the relational store is likely to be able to quickly complete join operations.

FIG. 1 illustrates an Architecture 100 configured to route ontological queries, according to one embodiment disclosed herein. In the illustrated embodiment, a Query Processing Orchestrator 115 receives Ontological Queries 105 constructed using an OQL, which has a corresponding Ontology Schema 110. The Ontological Queries 105 are processed by the Query Processing Orchestrator 115 to identify and return relevant data. In embodiments, the Query Processing Orchestrator 115 routes the queries to a Backend 125 comprising a variety of Data Nodes 130A-N. In the illustrated embodiment, this routing is performed based at least in part on a set of Concept Mappings 140 and Capabilities 135.

In the illustrated embodiment, the Ontological Queries 105 are formatted based on an OQL that is used to represent queries that operate on the set of concepts and relationships in the Ontology Schema 110. In an embodiment, the OQL can express queries including aggregations, unions, nested subqueries, and the like. In some embodiments, OQL can also express full-text and fielded search predicates, as well as path queries. An OQL query generally consists of a single query block or a union of multiple OQL query blocks, where each OQL query block consists of a SELECT clause and a

FROM clause. In some embodiments, an OQL block can also contain a WHERE clause, a GROUP BY clause, an ORDER BY clause, A FETCH FIRST clause, and/or a HAVING clause. In embodiments, the OQL query operates on the set of tuples constructed by the Cartesian product of the concepts referred to in the FROM clause.

In an embodiment, the Ontology Schema 110 describes the entities and their relationships in a KB at a semantic level, irrespective of how the data is actually stored in backend resources. In one embodiment, the Ontology Schema 110 describes the entities relevant to the domain, the properties potentially associated with the various entities, and the potential relationships among different entities. The Ontology Schema 110 can provide a rich and expressive data model capturing a variety of real-world relationships between entities, such as functional, inheritance, unions, and the like. In some embodiments, the Ontology Schema 110 does not include instance data. That is, the Ontology Schema 110 defines the entities and relationships, but does not include data relating to particular entities or relationships in the KB. For example, the Ontology Schema 110 may define that a “company” entity can have several properties such as “name” and “address,” but the Ontology Schema 110 does not include data for particular instances, such as a company with the name “Main Street Grocer” and address “123 Main Street.” Instead, this instance data is maintained separately in the Backend 125.

In an embodiment, the Concept Mappings 140 indicate the correspondence between the logical schema represented by the Ontology Schema 110 and the physical schema of the underlying Data Nodes 130 in the Backend 125. For example, suppose the Ontology Schema 110 is defined as $O(C, R, P)$ where $C = \{c_n | 1 \leq n \leq N\}$ denotes a set of concepts (also referred to as entities), $R = \{r_k | 1 \leq k \leq K\}$ denotes a set of relationships between the concepts/entities, and $P = \{p_m | 1 \leq m \leq M\}$ is a set of data properties. In one embodiment, each relationship is between two or more concepts, while each data property corresponds to a characteristic of a concept. In the illustrated embodiment, the Concept Mappings 140 indicate the mapping between concepts, relationships, and properties (defined in the Ontology Schema 110) and the underlying Data Nodes 130. That is, in one such embodiment, the Concept Mappings 140 indicate each Data Node 130 that stores a given concept (e.g., entity), relationship, and/or property. For example, the Concept Mappings 140 may indicate that instances of the “company” entity are stored in the Data Nodes 130A and 130M, while data relating to a particular type of relationship between “company” entities is stored in Data Node 130B.

In one embodiment, the Capabilities 135 indicate the operations and capabilities provided by each Data Node 130. In some embodiments, the capabilities of a Data Node 130 is expressed as views that enumerate all possible queries (view definitions) that can be handled/answered by the data store. This approach, although flexible, is not scalable as the number of view definitions can be very large, potentially leading to the problem of query rewriting using infinite number of views. To improve scalability, some embodiments of the present disclosure describe the capabilities of the backend Data Nodes 130 in terms of the operations that they support (e.g., join, group by, aggregation, fuzzy-text matching, path expressions, and the like) rather than enumerating all possible queries that can be answered by the data stores. Additionally, at least one embodiment of the present disclosure provides a finer grained description of each supported operation by utilizing a mechanism to express any associated limitations. For example, in one such

embodiment, an aggregation function of type MAX might only be supported over numeric types.

Thus, in one embodiment, the Capabilities **135** indicate, for each given Data Node **130**, the set of operations the node can complete (as well as relevant limitations on that capability, in some embodiments). In an embodiment, the Query Processing Orchestrator **115** evaluates the Capabilities **135** and Concept Mappings **140** to select one or more Data Nodes **130** to which the received Ontological Query **105** should be routed. To do so, in one embodiment, the Query Processing Orchestrator **115** identifies Data Nodes **130** which either contain the needed data (e.g., based on the Concept Mappings **140**), are able to complete the needed operation(s) (e.g., based on the Capabilities **135**), or both. The Query Processing Orchestrator **115** can then generate sub-queries for each selected Data Node **130**.

In embodiments, the Query Processing Orchestrator **115** uses a set of Translators **120A-N** to translate the subqueries as needed. In the illustrated embodiment, each type of Data Node **130** has a corresponding Translator **120**. In some embodiments, each Translator **120A-N** receives all or a portion of an OQL query and generates an equivalent query in the language and/or syntax of the corresponding Data Node **130A-N**. For example, the Translator **120A** may generate SQL queries for a relational database contained in Data Node **130A**, while the Translator **120B** outputs graph queries for a graph store contained in Data Node **130B**.

In an embodiment, the Translators **120** rely on schema mappings that map concepts and relations represented in the domain ontology to appropriate schema objects in the target physical schema. For example, for a relational backend Data Node **130**, the schema mappings can provide a correspondence between (1) the concepts in the ontology and the tables in the relational schema; (2) data properties or attributes of concepts in the ontology and the table columns in the physical schema; and/or (3) the relations between the concepts in the ontology and the primary key-foreign key constraints between the tables that correspond to the concepts in the database. Similarly, for a JSON document store, the schema mappings may map the concepts, data properties, and relations represented in the ontology to appropriate field paths in the JSON document.

In some embodiments, the Translators **120** also handle special concepts and relations that can be represented in an ontology, such as union, inheritance, and traversals between concepts that typically represent join conditions between the ontology concepts. Depending on the physical data layout, these are translated to appropriate operations supported by the Backend **125** Data Nodes **130**.

In embodiments, each Data Node **130** receives subqueries and generates a response for the Query Processing Orchestrator **115**. If the Data Node **130** has all of the necessary data locally and is able to complete the indicated operation(s), the node executes the query and returns results. In some embodiments, the subquery can indicate that the Data Node **130** should transmit a query to one or more other Data Nodes **130** to retrieve data needed to complete the query. For example, in some embodiments, it is preferred that join operations be performed by a relational data node, as relational systems tend to have low latency for join operations. Additionally, some operations are only possible on certain nodes. For example, suppose the Data Node **130A** is the only node which can complete join operations, but the data to be joined exists only on the Data Node **130B**. In one embodiment, the Data Node **130A** receives a subquery instructing

it to join the relevant data, as well as one or more other subqueries to be forwarded to the Data Node **130B** to retrieve the data.

That is, in one such embodiment, the Query Processing Orchestrator **115** prepares translated subqueries for the Data Node **130B**, and transmits them to the Data Node **130A**. This allows the Data Node **130A** to simply forward them to the Data Node **130B**. The data is then returned by Data Node **130B** to the Data Node **130A**, which completes the operation and returns the results to the Query Processing Orchestrator **115**. In another embodiment, the Query Processing Orchestrator **115** may transmit the subqueries to the Data Node **130B**, and forward the resulting data to the Data Node **130A** for processing. In still another embodiment, the Query Processing Orchestrator **115** performs the join locally.

In the illustrated embodiment, the architecture **100** further includes a Data Placement Orchestrator **150**, which determines which Data Node(s) **130A-N** should be used to store the data in the knowledge base. As illustrated, the Data Placement Orchestrator **150** receives a similar indication of the Capabilities **155** of the Data Nodes **130**, as well as an indication of the Query Workload **160**. In one embodiment, the Query Workload **160** indicates the average or expected set of queries for the knowledge base. For example, in one embodiment, the Query Workload **160** is generated by observing user interactions with the knowledge base over time. The system can then aggregate these interactions to determine the average, expected, or typical workload for the system. In some embodiments, the Query Workload **160** includes an indication of which concept(s) are queried together, which operation(s) are applied to each concept, and the like.

In embodiments, based on the node Capabilities **155** and the known Query Workload **160**, the Data Placement Orchestrator **150** determines, for each concept/entity in the Ontology Schema **110**, which Data Node(s) **130** should store instance-level data for the concept. For example, based on the operations a given Data Node **130A** can perform and further based on the Query Workload **160**, the Data Placement Orchestrator **150** may determine that the Data Node **130A** should store all data for a “company” entity and “public metric” entity, because they are often queried together. Similarly, the Data Placement Orchestrator **150** may determine to place instances of a “document” concept in the Data Node **130B**, based on determining that the queries frequently include performing fuzzy match operations on the “document” data, and the Data Node **130B** supports fuzzy match.

This intelligent data placement can reduce subsequent data transfers during runtime. In embodiments, the Data Placement Orchestrator **150** may be utilized at the outset (e.g., to provide the initial placements), and/or periodically during runtime (e.g., to reform the placement decisions based on how the Query Workload **160** has evolved over time). Although depicted as discrete components for conceptual clarity, in embodiments, the operations of the Query Processing Orchestrator **115** and Data Placement Orchestrator **150** may be combined or distributed across any number of components.

As illustrated, the Data Placement Orchestrator **150** outputs a set of Placement Decisions **165** to the Backend **125**, and/or to one or more intermediate services such as an extract, transform, and load (ETL) service. The instance-level data in the knowledge base is then stored in the appropriate Data Nodes **130** based on these selections. The Concept Mappings **140** reflect the current placement of data. In an embodiment, if the Data Placement Orchestrator **150**

is used to revise the data placement based on updated Query Workloads **160**, the Concept Mappings **140** are similarly updated. In the following, FIG. 2 through FIG. 9 discuss the Query Processing Orchestrator **115** in more detail, and presume that the data has already been placed. The Data Placement Orchestrator **150** and various techniques to ensure efficient data placement are discussed in more detail with reference to FIGS. 10 through 17.

FIG. 2 illustrates a workflow **200** for processing and routing ontological queries, according to one embodiment disclosed herein. As illustrated, the workflow **200** begins when an OQL Query **205** is received. The OQL Query **205** is provided to an OQL Parser **210**, which parses the query to determine the meaning of the query. As illustrated by arrow **215**, this parsed OQL query is then provided to a Query Graph Model (QGM) Constructor **220**. In an embodiment, the QGM Constructor **200** generates a logical representation of the query in the form of a query graph model. This reduces the complexity of query compilation and optimization. An example query graph model is discussed in more detail below with regards to FIGS. 4A and 4B. In an embodiment, the QGM captures the data flow and dependencies in a query using operator boxes, such as SELECT, GROUP BY, SETOP, and the like. In embodiments, the operations within a box can be freely reordered among themselves, but the box boundaries are respected when generating the query execution plans. That is, the query execution plans must follow the order of the query boxes.

In one embodiment, data flow between the query boxes is represented using quantifiers. This format allows the system to reason about query equivalences, and apply rewrite optimizations. In an embodiment, the QGM representation of the query enables the system to focus on optimizing the data flow between the different data stores during query execution, while the choice of the actual physical execution plan is deferred to the underlying Data Node **130** that is responsible for the execution of the query box or fragment. In embodiments, the QGM **225** is used to produce an optimized multi-store execution plan that minimizes data movement and transformation across different back-ends.

In some embodiments, the QGM **225** includes a set of quantifiers at the bottom which provide the input concept sets to the query, and each query block in the QGM has a head and body. The body of each block includes a set of predicates describing the set operations that are to be performed on the input concept sets (such as joins), and the head expressions describe how the output properties of the result concept should be computed. Stated differently, in an embodiment, the body of each box contains a set of predicates (also referred to as operations), each of which are to be applied to the input quantifiers for the box. In some embodiments, a predicate/operation referring to a single quantifier is classified as a local predicate, while a predicate/operation that refers to multiple quantifiers expresses a join predicate.

In the illustrated workflow **200**, the QGM **225** is passed to an Operator Placement Component **230** which continues the query routing process. As illustrated, the Operator Placement Component **230** further receives the set of Concept Mappings **235** and Node Capabilities **240**, and annotates the query blocks in the QGM **225** based on the capabilities and concept mappings. In one embodiment, the Operator Placement Component **230** walks the QGM from the bottom to the top, and annotates each operation in the query with the set of possible stores where the operation can be performed. In some embodiments, annotations are generated differently for local and join predicates. Recall that in some embodi-

ments, all head expressions that are associated with a single quantifier are treated in the same way as local predicates.

In one embodiment, if the query block includes a local predicate/operation (e.g., a single quantifier), the Operator Placement Component **230** determines whether the quantifier is a base concept. If so, the predicate is annotated with an indication of the Data Node(s) **130** that both (i) contain the concept and (ii) have the capability to execute the predicate. In an embodiment, if the quantifier is coming from another QGM block (i.e., it is computed by another block), the Operator Placement Component **230** annotates the predicate with the set of data stores that (i) complete the QGM box of this quantifier, and (ii) are capable of executing the predicate. In some embodiments, if none of the Data Nodes **130** that contain the input to this predicate also have the capability to execute the predicate, the Operator Placement Component **230** annotates it with the set of stores that are able to execute the predicate.

For example, if the predicate contains fuzzy search but the data is only stored in the relational backend Data Node **130**, the Operator Placement Component **230** can annotate the predicate with a document store that is able to compute that fuzzy search, even though the data is not stored there. Note that the data will need to be moved in such cases during query execution.

In some embodiments, if the query block includes a join predicate/operation, the Operator Placement Component **230** examines the join type and the join predicate. In an embodiment, each join predicate is associated with two or more quantifiers: one for each of the join inputs. In embodiments, the Operator Placement Component **230** identifies these quantifiers proceeds based on whether the identified quantifiers are computed inputs or base concepts, as well as where the quantifier comes from (e.g., whether it is computed and/or stored locally, or will be received from another node).

In the event that all of the quantifiers range over base concepts, the Operator Placement Component **230** evaluates the set of Data Nodes **130** where any of the base concepts reside, and determines, for each such store, whether the store supports join operations. The Operator Placement Component **230** then annotates the join operation with an indication of the stores that contain one or more of the needed concepts, and support the type of join operation. In some embodiments, if one of the stores is a relational node, the Operator Placement Component **230** annotates the operation with an indication of this relational Data Node **130** rather than the remaining nodes.

In some embodiments, if both the quantifiers are produced by other QGM query blocks, the Operator Placement Component **230** annotates the join operation with the Data Nodes **130** that support the join operation type (in some embodiments, including only relational stores). In an embodiment, the Operator Placement Component **230** further annotates the operation with an indication of the data stores that produce the quantifiers, if they are capable of executing the JOIN.

In a further embodiment, if one of the quantifiers is a base concept and another is computed from another QGM query block, the join operation placement decision is similar to the above discussion when the quantifiers are both computed by other QGM blocks. In an embodiment, the Operator Placement Component **230** annotates the join operation with the set of data stores that support the join type and are local to at least one of the join inputs.

As illustrated, this Annotated QGM **245** is then passed to the Block Placement Component **250**. In an embodiment,

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the Block Placement Component 250 utilizes the annotations generated by the Operator Placement Component 230 to determine the possible placement options for the query boxes in the query.

In one embodiment, determining the placement options for “select” query boxes is modeled as a problem of determining the minimum set cover. That is, the Block Placement Component 250 determines the minimum number of Data Nodes 130 that are required to satisfy the placement of all the operators within the given select box. In some embodiments, the Block Placement Component 250 utilizes a greedy heuristic for performing the predicate-store grouping which guarantees that each predicate is placed in a single store, and the total number of stores spanned by the query box is minimized. Once each predicate is annotated with the appropriate store where it will be placed, the Block Placement Component 250 determines whether the query block needs to be split.

In an embodiment, if all the predicates in the select query box are placed in the same Data Node 130, the query box is annotated to be placed in that store. In contrast, if the predicates in the select query box are placed in more than one Data Node 130 (indicating that the query box needs to be processed by multiple stores), the Block Placement Component 250 determines that the block must be split into multiple query boxes. In that case, the Block Placement Component 250 then divides the block such that each resulting (sub-)block includes predicates assigned to a single data node.

In some embodiments, for “group by” query boxes, the Block Placement Component 250 determines the placement based on the stores that support the type of aggregation operation, and the store processing the preceding query box that feeds the group by box. In an embodiment, if the store feeding these inputs also supports the group by and aggregation functions, then the Block Placement Component 250 places the selected “group by” box in the same store. However, if that store does not support these operations, the Block Placement Component 250 annotates the box with a list of the Data Nodes 130 that can execute the group by operation. Note that such a placement would necessitate data movement from the feeding store to the store that can process the box.

Once the Block Placement Component 250 has annotated each query block with all possible placement(s) of each (e.g., all Data Nodes 130 which can execute the block), the Cost Component 255 determines the cost of each combination of placements. In one embodiment, the cost model for query routing focuses only on data transfer and data conversion costs in order to choose between alternative query execution plans, as the cost of data movement and transformation is likely to dominate the overall cost of any execution plan in the poly store environment. In at least some embodiments, therefore, the cost of a given execution plan execution is determined by aggregating the cost of data movement for each source and target data store pair in the query execution plan. Note that in some embodiments, different operations such as joins and graph operations may be executed with very different performance on different Data nodes 130. For example, although join operations might be supported by a variety of data stores (such as JSON stores), relational databases typically provide the best performance for join operations.

In some embodiments, the cost model further considers this variance in the execution costs of the operations for different stores. In other embodiments, the cost model does not include these factors. In one such embodiment, such

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cases are handled using a declarative mechanism of expressing the capabilities of the underlying stores. For example, to avoid the execution of a join operation on a JSON store, the system can mask the join capability of JSON stores completely in the capability description, or add limitations to restrict its applicability for certain data types.

In an embodiment, the Cost Component 255 enumerates over all possible placement combinations across all query blocks, and generates an execution plan for each such combination by grouping together certain query boxes into groups. In one embodiment, each group in the query plan includes query boxes that are both (i) consequent in the QGM (e.g., separated by a single hop) and (ii) can be processed by the same Data Node 130. The Cost Component 255 then connects these groups of blocks based on the QGM flow, defining edges representing the data flow between Data Nodes 130. In an embodiment, the Cost Component 255 further generates a set of data movement descriptors for each execution plan, based on the edges between groups in the generated plan.

In some embodiments, using these movement descriptors for each plan, the Cost Component 255 utilizes the data movement cost model described above to find a cost for each execution plan, and picks the one with the minimum cost. For example, in one embodiment, the Cost Component 255 determines, for each possible execution plan, a cost of each of the corresponding movement descriptors. This may include latency, computing costs, and the like. The values can then be aggregated within each execution plan, in order to determine which execution plan(s) have the lowest cost. As illustrated, this minimum cost plan is then selected and used to generate one or more Translated Queries 260 for the Data Nodes 130.

FIGS. 3A and 3B depict an example Ontology 300 that can be used to evaluate and route queries, according to one embodiment disclosed herein. In the illustrated embodiment, each Concept 305A-I is depicted using an ellipse, while each Property 310A-N is depicted using a rounded rectangle. Further, arrows are used to depict the associations between Concepts 305 and Properties 310, while bolded arrows depict the relationships between Concepts 305. Additionally, each relationship arrow is labeled based on the type of the relationship. For example, as illustrated, the “Company” Concept 305B is a subclass of the “PublicCompany” Concept 305D. Further, the Company Concept 305B is associated with several Properties 310, including a “name” Property 310E and an identifier Property 310D, both of which are strings.

As discussed above, in an embodiment, the data in the knowledge base conforms to the Ontology 300. Stated differently, the Ontology 300 defines the concepts and entities in the knowledge base, as well as the relationships between the entities and the properties associated with each concept. Notably, the Ontology 300 does not include any instance data (e.g., data about a specific company), but instead defines the structure of the data. In some embodiments, the Concepts 305, Properties 310, and/or relationships may be distributed across any number of Data Nodes 130. In one embodiment, the data is placed in the Data Nodes 130 based at least in part on the type of the data.

In one such embodiment, if the concept mappings indicate that a given Concept 305 is stored in a given Data Node 130, all instance data that corresponds to that Concept 305 is stored in the Data Node 130. For example, if the mapping indicates that a Data Node 130A includes the “PublicMetric” Concept 305F, the Query Processing Orchestrator 115 can retrieve data about any instance of the “PublicMetric” (e.g.,

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any metric, for any company) from the Data Node 130A. Thus, if a received query will require accessing “PublicMetric” data, the Query Processing Orchestrator 115 will route at least a portion of the query to the Data Node 130A (or to another node that also serves the Concept 305F).

FIGS. 4A and 4B illustrate a workflow 400 for parsing and routing an example ontological query, according to one embodiment disclosed herein. In the illustrated embodiment, Input 405 is received and evaluated to retrieve relevant data from the Data Nodes 130. In the illustrated embodiment, the Input 405 is natural language text (e.g., from a user). In various embodiments, however, the Input 405 may include a query or other data. Further, the Input 405 may be received from any number of sources, including automated applications, user-facing applications, directly from a user, and the like. In some embodiments, the Input 405 is received as part of a chat bot or other interactive application that allows the user to search and explore the knowledge base.

In the illustrated example, the Input 405 is a phrase “Show me the total revenue of all companies that filed technology patents in the last 5 years.” In the illustrated workflow 400, the Input 405 is parsed and evaluated using one or more natural language processing (NLP) techniques such as semantic analysis, keyword searching, sentiment analysis, intent analysis, and the like. This enables the system to generate an OQL Query 410 based on the Input 405. Of course, in some embodiments, the Input 405 itself is an OQL query.

As illustrated, the corresponding OQL Query 410 for the Input 405 includes a “select” operation and a “group by” operation, as well as an indication as to the tables or concepts that are relevant, and a “where” clause indicating the limitations on the query. This OQL Query 410 is then parsed by the Query Processing Orchestrator 115 to generate an OGM 435A, which is a logical representation of the query, and includes a number of query blocks. In the illustrated embodiment, the OGM includes a “select” Query Block 415B, and a “group by” Query Block 415A.

As illustrated, the QGM 435A includes a set of Quantifiers 430A-E at the bottom, which provide the input concept sets to the query. In the illustrated embodiment, these include “PublicMetricData,” “PublicMetric,” “PublicCompany,” “Document,” and “CompanyInfo.” In an embodiment, each Query Block 415 in the QGM 435A includes has a Head 420 and Body 425. The Body 425 generally describes the set operations that are to be performed on the input concept sets (such as joins), while the Head 420 expressions describe how the output properties of the result concept should be computed. For example, in the illustrated embodiment, the Head 420B of the “select” Query Block 415B specifies output properties “oPMD.value,” “oPMD.year_calendar,” and “oCI.id.” The Body 425B contains a set of predicates to be applied on the input Quantifiers 430A-E. As discussed above, in embodiments, a predicate referring to a single quantifier is a local predicate, while a predicate that refers to multiple quantifiers expresses a join predicate.

As illustrated in FIG. 4B, because the Query Processing Orchestrator 115 recognizes that the “select” Query Block 415B includes predicates that must be executed by differing Data Nodes 130. Specifically, although most of the predicates in the Query Block 415B can be executed by a relational data store, the Query Processing Orchestrator 115 has determined that the predicates “oD->companyInfo=oCI” and “oD.selfMATCH(‘Tech Patent Filed’)” correspond to operations that are performed using an elastic search, which the relational database node does not support. Thus, the Query Processing Orchestrator 115

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has split the Query Block 415B by separating out these predicates into a new Query Block 415C. As illustrated, this Query Block 415C acts as input to the Query Block 415B.

In the illustrated embodiment, by splitting the Query Block 415B, the Query Processing Orchestrator 115 has ensured that each block can be executed entirely within a single Data Node 130. For example, both the Query Block 415A and 415B can be executed in a relational Data Node 130, while the Query Block 415C is to be executed by a Data Node 130 supporting elastic search. In an embodiment, therefore, the Query Processing Orchestrator 115 identifies or generates a subquery corresponding to Query Blocks 415A and 415B, translates the subquery to the appropriate language and/or format of the relational node, and transmits the translated subquery to the relational node.

In the illustrated embodiment, the Query Processing Orchestrator 115 will further identify or generate a subquery to accomplish the Query Block 415C, and translate it to a language and/or format supported by the elastic search node. In one embodiment, the Query Processing Orchestrator 115 additionally transmits this subquery to the relational data store, which is to act as the aggregator. The relational node can then forward the subquery to the elastic node, and complete its own subquery using the results returned by the elastic node.

FIG. 5 is a block diagram illustrating a Query Processing Orchestrator 115 configured to route ontological queries, according to one embodiment disclosed herein. Although depicted as a physical device, in embodiments, the Query Processing Orchestrator 115 may be implemented using virtual device(s), and/or across a number of devices (e.g., in a cloud environment). As illustrated, the Query Processing Orchestrator 115 includes a Processor 510, Memory 515, Storage 520, a Network Interface 525, and one or more I/O Interfaces 530. In the illustrated embodiment, the Processor 510 retrieves and executes programming instructions stored in Memory 515, as well as stores and retrieves application data residing in Storage 520. The Processor 510 is generally representative of a single CPU and/or GPU, multiple CPUs and/or GPUs, a single CPU and/or GPU having multiple processing cores, and the like. The Memory 515 is generally included to be representative of a random access memory. Storage 520 may be any combination of disk drives, flash-based storage devices, and the like, and may include fixed and/or removable storage devices, such as fixed disk drives, removable memory cards, caches, optical storage, network attached storage (NAS), or storage area networks (SAN).

In some embodiments, input and output devices (such as keyboards, monitors, etc.) are connected via the I/O Interface(s) 530. Further, via the Network Interface 525, the Query Processing Orchestrator 115 can be communicatively coupled with one or more other devices and components (e.g., via the Network 580, which may include the Internet, local network(s), and the like). As illustrated, the Processor 510, Memory 515, Storage 520, Network Interface(s) 525, and I/O Interface(s) 530 are communicatively coupled by one or more Buses 575. Additionally, the Query Processing Orchestrator 115 is communicatively coupled to a number of Data Nodes 130A-N via the Network 580. Of course, in embodiments, the Data Nodes 130A-N may be directly connected to the Query Processing Orchestrator 115, accessible via a local network, integrated into the Query Processing Orchestrator 115, and the like. Although not included in the illustrated embodiment, in some embodiments, the Query Processing Orchestrator 115 is further communicatively coupled with the Data Placement Orchestrator 150.

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In the illustrated embodiment, the Storage **520** includes the Ontology **560**, Capability Data **565**, and Data Mappings **570**. Although depicted as residing in Storage **520**, in embodiments, the Ontology **560**, Capability Data **565**, and Data Mappings **570** may be stored in any suitable location and manner. In an embodiment, as discussed above, the Ontology **560** indicates the entities or concepts that are relevant for the domain in which the Query Processing Orchestrator **115** operates, as well as the potential properties of each concept/entity and the relationships between and among the entities/concepts. In at least one embodiment, the Ontology **560** does not include instance-level data. Instead, the actual data in the KB is stored in the Data Nodes **130A-N**.

In an embodiment, as discussed above, the Capability Data **565** indicates the capabilities of each Data node **130A-N**. This may include, for example, an indication as to which operation(s) each Data Node **130A-N** supports, as well as any corresponding limitation(s) on that support. For example, the Capability Data **565** may indicate that the Data Node **130A** supports “join” operations, but only for integer data types. In embodiments, as discussed above, the Data Mappings **570** indicate the Data Node(s) **130** where instance data for each entity/concept defined in the Ontology **560** is stored. For example, the Data Mappings **570** may indicate that all instances of a “Company” concept are stored in Data Nodes **130A** and **130B**, while all instances of a “Document” concept are stored in Data Nodes **130B** and **130N**.

In the illustrated embodiment, the Memory **515** includes a Query Application **535**. Although depicted as software residing in Memory **515**, in embodiments, the Query Application **535** may be implemented using hardware, software, or a combination of hardware and software. As illustrated, the Query Application **535** includes a Parsing Component **540**, a Routing Component **545**, and a set of Translator(s) **120**. Although depicted as discrete components for conceptual clarity, in embodiments, the operations of the Parsing Component **540**, Routing Component **545**, and Translator(s) **120** can be combined or distributed across any number of components.

In an embodiment, the Parsing Component **540** receives OQL queries and parses them to determine their meaning and generate a logical representation of the query (such as a QGM). As discussed above, in some embodiments, the logical representation includes a set of query blocks, where each query block specifies one or more predicates defining the operations to be performed on the block’s input quantifiers. In embodiments, these quantifiers may be base concept(s) stored in one or more Data Nodes **130**, and/or data that is computed by another query block. In an embodiment, this logical representation enables the Query Application **535** to understand and reason about the structure of the query and how data flows between blocks. This enables the Routing Component **545** to efficiently route the query (or subqueries therefrom).

In the illustrated embodiment, the Routing Component **545** receives the logical representation (e.g., the query graph model) from the Parsing Component **540** and evaluates it to identify one or more Data Nodes **130** to which the query should be routed. In some embodiments, this includes analyzing the predicates included in each query block in the logical representation. In one embodiment, the Routing Component **545** labels or annotates each predicate in a given query block based on the Data Node(s) **130** that can complete the predicate. In some embodiments, this includes the Data Node(s) **130** that contain the relevant quantifier(s) and/or are capable of performing the indicated operation(s).

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Further, in at least one embodiment, once each predicate in a block has been processed, the Routing Component **545** can evaluate the annotations to determine a placement location for the block. That is, the Routing Component **545** determines whether the query block can be placed in a single Data Node **130**. If so, in one embodiment, the Routing Component **545** assigns the block to that store. Further, in an embodiment, if the block cannot be processed by a single Data Node **130**, the Routing Component **545** splits the block into two or more query blocks, and repeats the routing process for each.

In an embodiment, once each query block has been assigned to a single Data Node **130**, the Translator(s) **120** generate one or more corresponding translated queries. In an embodiment, each Translator **120** corresponds to a particular Data Node **130** architecture, and is configured to translate OQL queries (or subqueries) to an appropriate query for the corresponding data store architecture. For example, in one such embodiment, the system may include a first Translator **120** to translate OQL to a query for a relational store (e.g., SQL), a second Translator **120** to translate OQL to a JSON query, a third Translator **120** to translate to a query for a document search, and a fourth Translator **120** to translate the OQL to a graph query.

In embodiments, the query (or subqueries) is routed to the appropriate Translator **120** based on the Data Node **130** that will execute the query or subquery. In some embodiments, each query (or subquery) is then transmitted directly to that Data Node **130** (e.g., via an application programming interface or API). In some embodiments, if the completing the query will require moving data between the Data Nodes **130** (e.g., to join data from two or more stores), the Query Application **535** can determine the flow of data based on the generated logical representation, and transmit the queries appropriately. That is, the Query Application **535** uses the QGM to determine which store(s) will need to receive data from other store(s), and transmit the needed queries to these joining stores. For example, if a Data Node **130A** is to receive data from Data Node **130N** and complete one or more operations on it, the Query Application **535** can transmit a first query to the Data Node **130A** to retrieve data from that node, as well as a second query that is configured for the Data Node **130N**. The Data Node **130A** can then itself query the Data Node **130N**, using the provided query.

FIG. 6 is a flow diagram illustrating a method **600** for processing and routing ontological queries, according to one embodiment disclosed herein. The method **600** begins at block **605**, where a Query Processing Orchestrator **115** receives an ontological query for execution against a knowledge base. In an embodiment, the ontological query is expressed relative to a predefined domain ontology, where the ontology specifies the concepts, properties, and relationships that are relevant for the domain. At block **610**, the Query Processing Orchestrator **115** parses the received query and generates a logical representation of it. In some embodiments, the Query Processing Orchestrator **115** generates a query graph mode representation of the query. In embodiments, the logical representation includes one or more query blocks denoting the underlying concept(s) that are implicated by the query, the operation(s) that are to be performed on the data, as well as the data flow.

The method **600** then continues to block **615**, where the Query Processing Orchestrator **115** maps each query block in the logical representation to one or more data stores, based on a predefined concept mapping, and/or data store capabilities. For example, in one embodiment, the Query Processing Orchestrator **115** determines, for each query

block, what concept(s) are relevant (e.g., what data the query block will access). Using the concept mappings, the Query Processing Orchestrator 115 can then identify the data store(s) that are capable of providing the needed data. Additionally, in one embodiment, the Query Processing Orchestrator 115 determines, for each query block, what operation(s) will be required. Using the predefined store capabilities, the Query Processing Orchestrator 115 can then identify which data node(s) are capable of performing the needed operation(s). The Query Processing Orchestrator 115 then maps the query block(s) to data node(s), taking effort to minimize data movement between stores.

At block 620, the Query Processing Orchestrator 115 selects one of the mapped query blocks. The method 600 then proceeds to block 625, where the Query Processing Orchestrator 115 generates a corresponding translated query for the query block, based on the mapped data store. In one embodiment, this includes identifying or generating a sub-query, from the received query, to carry out the selected query block. The Query Processing Orchestrator 115 then determines the configuration of the data node that will execute the query block. That is, in one embodiment, the Query Processing Orchestrator 115 determines the language and/or format of query that the node is configured to process. In another embodiment, the Query Processing Orchestrator 115 identifies the translator that corresponds to the mapped data store. The Query Processing Orchestrator 115 then uses this translator to generate an appropriate query for the store.

The method 600 then continues to block 630, where the Query Processing Orchestrator 115 determines whether there is at least one additional query block that has not yet been processed. If so, the method 600 returns to block 620. Otherwise, the method 600 continues to block 635, where the Query Processing Orchestrator 115 transmits the translated query or queries to one or more data nodes. In one embodiment, the Query Processing Orchestrator 115 transmits each query to the corresponding node. In another embodiment, the Query Processing Orchestrator 115 transmits the queries based on the flow of data in the logical representation. For example, the Query Processing Orchestrator 115 may transmit multiple queries to a single node, such that the node can forward the queries to the appropriate store(s) to retrieve the data. The node can then act as a mediator to finalize the results.

Advantageously, by employing one of the data nodes as mediator, the Query Processing Orchestrator 115 can reduce its computational expenses and expand scalability of the system. At block 640, the Query Processing Orchestrator 115 receives the finalized query results from the data store acting as mediator (or from the only data store to which queries were transmitted, if the received query can be executed in a single backend resource). The Query Processing Orchestrator 115 then returns the results to the requesting entity.

FIG. 7 is a flow diagram illustrating a method 700 for processing ontological queries to efficiently route query blocks, according to one embodiment disclosed herein. The method 700 provides additional detail for the routing of query blocks, in some embodiments. The method 700 begins at block 705, where the Query Processing Orchestrator 115 generates one or more query blocks to represent the received query, as discussed above. In one embodiment, each query block specifies one or more quantifiers indicating the input data for the block. These quantifiers may correspond to base concepts (e.g., instance data in the knowledge base) and/or interim computed data (e.g., data which was retrieved from a store and processed and/or transformed in some way).

Additionally, in an embodiment, each query block specifies the operation(s) to be performed on the quantifiers.

At block 710, the Query Processing Orchestrator 115 selects one of the generated blocks. Further, at block 715, the Query Processing Orchestrator 115 identifies the set of data nodes that are capable of satisfying the operation(s) defined by the selected block. In one embodiment, the Query Processing Orchestrator 115 does so by accessing predefined capability definitions that define the set of operation(s) each data store can complete, as well as any corresponding limitation(s) on this capability. The method 700 then proceeds to block 720, where the Query Processing Orchestrator 115 identifies the set of nodes that are capable of satisfying the quantifier(s) listed in the query block. That is, for each quantifier corresponding to a base concept, the Query Processing Orchestrator 115 identifies nodes that store the base concept.

In one embodiment, for each quantifier that is computed by another query block, the Query Processing Orchestrator 115 identifies the data node(s) that have been assigned to that query block. Recall that in embodiments, the Query Processing Orchestrator 115 maps query blocks to nodes by walking up from the bottom of the QGM. Thus, if a first block depends on data computed in a second block, the second block will necessarily have been evaluated and assigned one or more data nodes, prior to the Query Processing Orchestrator 115 beginning evaluation of the first query block.

The method 700 then continues to block 725, where the Query Processing Orchestrator 115 determines whether there is at least one data node capable of both providing the quantifiers and executing the operations. In one embodiment, this includes determining whether there is overlap between the identified sets. For example, if the quantifiers are all base concepts, the overlap between the two sets indicates the set of nodes that are capable of executing all of the needed operations, and store all of the concepts. If the quantifiers include items computed by other query blocks, the overlapping set indicates nodes that can perform the operations, and that will (potentially) execute the other block(s).

In an embodiment, if there is overlap between the sets, the method 700 continues to block 730, where the Query Processing Orchestrator 115 annotates the selected query block with the identified nodes in the overlap. This annotation indicates that the specified nodes have the potential to execute the query block, but does not amount to a final assignment of the block to the node(s). In an embodiment, if any query block has multiple nodes included in the annotations, the Query Processing Orchestrator 115 performs cost analysis to evaluate each alternative in an effort to minimize data transfers among the stores, as discussed in more detail below. The method 700 then proceeds to block 740.

In the illustrated embodiment, if there is no overlap between the sets, the Query Processing Orchestrator 115 determines that there is no single data node that can complete the query block. In some embodiments, if all of the operations can be performed by a single store, the Query Processing Orchestrator 115 annotates the block with the store(s) that can perform the operations of the block. One or more other store(s) can then be assigned to provide the quantifiers. In the illustrated embodiment, the method 700 then continues to block 735, where the Query Processing Orchestrator 115 splits the selected query block into two or more blocks in an effort to create query blocks capable of being executed entirely within a single node. In one embodi-

ment, splitting the selected query block includes identifying subset(s) of the quantifier(s) and/or operation(s) that can be executed by a single store. For example, the Query Processing Orchestrator 115 may identify subsets of the specified predicates that share annotations (e.g., predicates that could be executed by the same store). The query block can then be split by separating the predicates into corresponding boxes based on the subset to which they belong. For example, if a query block requires traditional relational database operations as well as a fuzzy match operation, the Query Processing Orchestrator 115 may determine that the fuzzy match(es) should be split into a separate box. This may enable the Query Processing Orchestrator 115 to assign each split block into a single data store (e.g., the relational operations can be assigned to a relational store, and the fuzzy match operations can be assigned to a different backend capable of performing it).

In the illustrated embodiment, these newly generated query blocks are placed in the queue to be evaluated, as with the existing blocks. The method 700 then continues to block 740. At block 740, the Query Processing Orchestrator 115 determines whether there is at least one additional query block that has not been evaluated. If so, the method 700 returns to block 710 to iterate through the blocks. That is, the Query Processing Orchestrator 115 continues to iterate through the query blocks, splitting the boxes if necessary, until all of the query blocks are annotated with at least one data node.

If all query blocks have been annotated, the method 700 continues to block 745, where the Query Processing Orchestrator 115 executes the query. In some embodiments, this includes evaluating the alternative combinations of assignments in order to minimize data transfer, as discussed below in more detail. In some embodiments, if the annotations of one or more of the query blocks indicate a single data node, the Query Processing Orchestrator 115 simply assigns the block to that indicated node, as there are no alternatives that can be considered.

FIG. 8 is a flow diagram illustrating a method 800 for evaluating potential query routing plans in order to efficiently route an ontological query, according to one embodiment disclosed herein. In the illustrated embodiment, the method 800 begins after the query blocks have been annotated with their potential assignments (e.g., with nodes that are capable of executing the entire block and providing all needed quantifiers). The method 800 begins at block 805, where the Query Processing Orchestrator 115 selects one of the possible combinations of node assignments. That is, in an embodiment, the Query Processing Orchestrator 115 generates all possible combinations of stores for the blocks, based on the corresponding annotations. To do so, the Query Processing Orchestrator 115 can iteratively select a different option for each block, until all possible selections have been generated.

For example, suppose a first block is annotated with “node A” and “node B,” while a second block is annotated with “node A.” In an embodiment, the Query Processing Orchestrator 115 will determine that the possible routing plans include assigning the first block and the second block to “node A,” or assigning the first block to “node B” and the second block to “node A.” At block 805, the Query Processing Orchestrator 115 selects one of the identified combinations for evaluation. The method 800 then continues to block 810.

At block 810, the Query Processing Orchestrator 115 identifies the data movement(s) that will be required under the selected plan. In embodiments, the movements are

determined based on the store selections in the plan, and/or the query graph model. Continuing the above example, if the Query Processing Orchestrator 115 may determine that the plan that assigns both blocks to “node A” will require no movement, because both of the query blocks can be grouped into a single node. That is, because the blocks are consequent in the model (e.g., directly connected/separated by a single hop, with no other blocks in between) and assigned the same node, they are grouped together and no data movement is needed. In contrast, assigning the first block to “node B” will require transfer of data between “node A” and “node B” because the QGM indicates that data flows from the second block to the first block, and the blocks are assigned to different stores.

The method 800 then continues to block 815, where the Query Processing Orchestrator 115 selects one of the identified data transfers that are required by the selected query plan. At block 820, the Query Processing Orchestrator 115 determines the computational cost of the selected movement. In an embodiment, this determination is made based on a predefined cost model. In some embodiments, the model may indicate, for each ordered pair of data nodes, the computational costs of transferring data from the first to the second. The cost may include, for example, latency introduced to actually transfer the data and/or to transform the data as needed to allow the destination node to operate on it, processing time and/or memory requirements for the transfer/transformation, and the like.

At block 825, the Query Processing Orchestrator 115 determines whether the selected combination requires any additional data transfers. If so, the method 800 returns to block 815. Otherwise, the method 800 continues to block 830, where the Query Processing Orchestrator 115 computes the total cost of the selected plan by aggregating the individual costs of each movement. At block 835, the Query Processing Orchestrator 115 determines whether there is at least one alternative plan that has not been evaluated. If so, the method 800 returns to block 805. Otherwise, the method 800 proceeds to block 840, where the Query Processing Orchestrator 115 ranks the plans based on their aggregate costs. In an embodiment, the Query Processing Orchestrator 115 selects the plan that has the lowest determined cost. The Query Processing Orchestrator 115 then executes the plan by translating and routing the subqueries based on the node assignments for the minimal cost plan.

FIG. 9 is a flow diagram illustrating a method 900 for routing an ontological query, according to one embodiment disclosed herein. The method 900 begins at block 905, where a Query Processing Orchestrator 115 receives an ontological query. At block 910, the Query Processing Orchestrator 115 generates, based on the ontological query, one or more query blocks, each indicating one or more operations and one or more quantifiers representing data flow between query blocks. The method 900 then proceeds to block 915, where the Query Processing Orchestrator 115 identifies, for each of the one or more query blocks, at least one data node based on the one or more quantifiers and the one or more operations. Further, at block 920, the Query Processing Orchestrator 115 selects one or more of the identified data nodes based on predefined cost criteria. Additionally, the Query Processing Orchestrator 115 then transmits one or more subqueries to the selected one or more data nodes at block 925.

FIG. 10 illustrates a workflow 1000 for evaluating workloads and storing knowledge base data, according to one embodiment disclosed herein. As discussed above, enterprise applications often need support for different query

types, depending on their query workload. To support these different query types, embodiments of the present disclosure utilize multiple backend stores, such as relational databases, document stores, graph stores, and the like. In embodiments of the present disclosure, the system has the ability to move, store, and index the knowledge base data in any backend that provides the required capability for the query types that are supported. With this flexibility to organize the data, the initial data placement across multiple backend stores can play a critical role in efficient query execution.

To achieve efficient runtime execution with minimal replication overhead, some embodiments of the present disclosure provide an off-line data preparation and loading phase, which includes intelligent data placement. Generally, data ingestion, placement, and loading into the multiple back end stores involves a series of operations. Initially, data for the domain specific knowledge base is ingested from a variety of different sources, including structured, semi-structured and unstructured data. In some embodiments, the first phase of data ingestion from these data sources is a data enrichment/curation process which includes information extraction, entity resolution, data integration and transformation. The output data produced by this step, which conforms to the domain ontology, is then fed to the Data Placement Orchestrator 150 to generate an appropriate data placement for the multiple backend data stores. In some embodiments, the data has already been curated, and may have already been in use in responding to queries prior to the Data Placement Orchestrator 150 being applied. Once a satisfactory data placement has been determined, a data load module places the instance data in appropriate data stores according to the data placement plan.

In some embodiments, data movement can be avoided during query execution by replicating the entire set of data across all the data nodes. However, this solution leads to tremendous replication overhead and dramatically increases storage space requirements. Moreover, in many embodiments, not all stores provide all the necessary capabilities needed by the queries, and even full replication cannot eliminate data movement completely. To minimize unnecessary storage costs and data movement, some embodiments of the present disclosure provide capability-based data placement techniques that assign data to data stores while taking into consideration both the expected workload and the capabilities of the backend data stores (e.g., in terms of the operations that they can perform on the stored data).

In embodiments, the Data Placement Orchestrator 150 reasons about the data placement at the level of query operations over the concepts of the domain ontology representing the schema of the data stored in the knowledge base. In some embodiments, the orchestrator identifies different and potentially overlapping subsets of the ontology based on a given workload against the knowledge base, as well as the capabilities of the underlying stores, and outputs a mapping between the identified subsets of the data and the target data stores in which the data should be stored.

In the illustrated embodiment, the workflow 1000 begins when a set of OQL Queries 1005 is received. In some embodiments, the OQL Queries 1005 are previously-submitted queries for the knowledge base. For example, in some embodiment, the knowledge base is a pre-existing corpus of data which users and applications can query and explore. In such an embodiment, the OQL Queries 1005 can correspond to queries that users, applications, and other entities previously submitted while interacting with the knowledge base.

In embodiments, the OQL Queries 1005 generally represent the average, typical, expected, and/or historical work-

load of the knowledge base. Stated differently, the OQL Queries 1005 are generally representative of the queries that the knowledge base receives (or is expected to receive) during runtime operations, and can be used to identify the sets of concepts that are often queried together, operations that are typically performed on each concept, and the like. As illustrated, these representative OQL Queries 1005 are provided to the OQL Query Analyzer 1010, which analyzes and evaluates them to generate a Summarized Workload 1015.

In an embodiment, the OQL Query Analyzer 1010 expresses the OQL Queries 1005 as a set of concepts and relations with the corresponding operations that are executed against them. Based on this, the analyzer generates the Summarized Workload 1015. Stated differently, the Summarized Workload 1015 reflects a summary of the provided OQL Queries 1005, which enables deeper analysis to identify patterns in the data. In one embodiment, the Summarized Workload 1015 includes a set of summarized queries generated based on the OQL Queries 1005. Notably, in some embodiments, the summarized queries are not fully formatted queries that could be executed against the knowledge base. Instead, the summarized queries indicate clusters of concepts that are likely to be queried together during runtime, along with sets of operations that are likely to be applied to each cluster of concepts.

In some embodiments, the OQL Query Analyzer 1010 takes the set of OQL Queries 1005 expressed against the domain ontology as the input, and, for each query, creates two sets. In one such embodiment, the first is a set of concepts that the query accesses, while the second is a set of operations (e.g., join, aggregation, etc.) that the query performs over those concepts. In at least one embodiment, to generate the Summarized Workload 1015 representation of the given OQL Queries 1005, the OQL Query Analyzer 1010 groups the queries that access the same set of concepts into a group, and then creates a set which combines the associated operations of each query in the group. This is discussed below in more detail.

In the illustrated embodiment, the Summarized Workload 1015 is then provided to a Hypergraph Modeler 1020, which evaluates the provided summarized queries to generate a Hypergraph 1025. In an embodiment, the Hypergraph 1025 is a graph including a set of vertices and a set of edges (also referred to as hyperedges), where each edge can connect to any number of vertices. In some embodiments, each vertex in the Hypergraph 1025 corresponds to a concept from the domain ontology, and each hyperedge corresponds to a summarized query from the Summarized Workload 1015. For example, each hyperedge spans over the set of concepts indicated by the corresponding summarized query. In one embodiment, each hyperedge is further annotated or labeled with an indication of the set of operations that are indicated by the corresponding summarized query.

As illustrated, the Hypergraph 1025 is evaluated by the Data Placement Component 1030, along with the Ontology Schema 110 and Node Capabilities 155. In one embodiment, the Data Placement Component 1030 groups the concepts and relations in the Hypergraph 1025 into potentially overlapping subsets based on the query operations. The data corresponding to these subsets can then be placed on individual backend data nodes based on their supported operations. In some embodiments, the data placement decisions are made at the granularity of the identified ontology subsets, placing all the data of any ontology concept in its entirety. In other words, the Placement Decisions 165 do not horizontally partition concepts across different stores. For

example, if the Data Placement Component **1030** places the “company” concept in a first data node, all instance-level data that corresponds to the “company” concept are placed in the first data node.

In some embodiments, the ontology-based Data Placement Component **1030** follows a two-step approach for data placement. First, the Data Placement Component **1030** runs graph analysis algorithms over the Hypergraph **1025** representing the Summarized Workload **1015** in order to group the concepts in the domain Ontology Schema **110** based on the similarity of the operations that are performed on these concepts. Next, the data corresponding to these identified groups or subsets of the ontology is mapped to underlying data stores based on their respective capabilities, while minimizing the amount of replication required. In embodiments, the resulting capability based data placement minimizes data movement (and data transformation) for a given workload at query processing time, greatly enhancing the efficiency of query processing in a poly store environment. As illustrated, the final output of the Data Placement Component **1030** is a concept-to-store mapping (e.g., Placement Decisions **165**) that maps the ontology concepts to the appropriate data nodes.

Although not depicted in the illustrated workflow **1000**, in embodiments, the system then utilizes the Placement Decisions **165** to store the data in the various backend resources. In one embodiment, the system does so by invoking an extract, transform, and load (ETL) service that performs any transformations or conversions necessary to allow the data to be stored in the relevant Data Node(s) **130**.

In some embodiments, the workflow **1000** is used to periodically re-evaluate and refine the data placement in order to maintain efficiency of the system. For example, during off-peak times (e.g., during non-business hours) the system may invoke the workflow **1000** based on an updated set of OQL Queries **1005** (e.g., including queries received after the last data placement decision) in order to determine whether the placements should be updated to reflect the evolving workload. This can improve the efficacy of the system by preventing data locations from becoming stale.

FIG. **11** depicts an example Hypergraph **1100** used to evaluate workloads and store knowledge base data, according to one embodiment disclosed herein. In the depicted embodiment, each Concept **1105A-G** is depicted as an ellipse, and each Hyperedge **1110A-D** is depicted as a dashed line encircling the Concepts **1105** to which it corresponds. For example, the Hyperedge **1110A** joins Concepts **1105A** (“Company”), **1105B** (“PublicCompany”), **1105C** (“PublicMetric”), and **1105D** (“PublicMetricData”). As illustrated, each Hyperedge **1110** can include both disjointed subsets of the Concepts **1105** (e.g., Hyperedge **1110A** and **1110C** do not overlap), as well as overlapping subsets (e.g., Hyperedge **1110A** and **1110B** overlap with respect to the “Company” Concept **1105A**).

Additionally, as illustrated, each Hyperedge **1110** is labeled with the relevant Operations **1115A-C** for the edge. As discussed above, in one embodiment, the labels indicate the set of operations that may be or have been applied to the Concepts **1105** connected by the Hyperedge **1110**. For example, in the depicted example, the Hyperedge **1110A** is associated with Operations **1115A** (“Join”), **1115B** (“Aggregation”), and **1115C** (“Fuzzy” matching). Notably, each Operation **1115** can be associated with any number of Hyperedges **1110** and/or Concepts **1105**. In the depicted embodiment, the “Join” Operation **1115A** is associated with Hyperedges **1110A** and **1110B**, the “Aggregation” Operation

1115B is associated with Hyperedges **1110A** and **1110D**, and the “Fuzzy” Operation **1115C** is associated with Hyperedges **1110A**, **1110D**, and **1110C**.

FIG. **12** is a block diagram illustrating a Data Placement Orchestrator **150** configured to evaluate workloads and store data, according to one embodiment disclosed herein. Although depicted as a physical device, in embodiments, the Data Placement Orchestrator **150** may be implemented using virtual device(s), and/or across a number of devices (e.g., in a cloud environment). As illustrated, the Data Placement Orchestrator **150** includes a Processor **1210**, Memory **1215**, Storage **1220**, a Network Interface **1225**, and one or more I/O Interfaces **1230**. In the illustrated embodiment, the Processor **1210** retrieves and executes programming instructions stored in Memory **1215**, as well as stores and retrieves application data residing in Storage **1220**. The Processor **1210** is generally representative of a single CPU and/or GPU, multiple CPUs and/or GPUs, a single CPU and/or GPU having multiple processing cores, and the like. The Memory **1215** is generally included to be representative of a random access memory. Storage **1220** may be any combination of disk drives, flash-based storage devices, and the like, and may include fixed and/or removable storage devices, such as fixed disk drives, removable memory cards, caches, optical storage, network attached storage (NAS), or storage area networks (SAN).

In some embodiments, input and output devices (such as keyboards, monitors, etc.) are connected via the I/O Interface(s) **1230**. Further, via the Network Interface **1225**, the Data Placement Orchestrator **150** can be communicatively coupled with one or more other devices and components (e.g., via the Network **1280**, which may include the Internet, local network(s), and the like). As illustrated, the Processor **1210**, Memory **1215**, Storage **1220**, Network Interface(s) **1225**, and I/O Interface(s) **1230** are communicatively coupled by one or more Buses **1275**. Additionally, the Data Placement Orchestrator **150** is communicatively coupled to the Data Nodes **130A-N** via the Network **1280**. Of course, in embodiments, the Data Nodes **130A-N** may be directly connected to the Data Placement Orchestrator **150**, accessible via a local network, integrated into the Data Placement Orchestrator **150**, and the like. Although not included in the illustrated embodiment, in some embodiments, the Data Placement Orchestrator **150** is further communicatively coupled with the Query Processing Orchestrator **115**.

In the illustrated embodiment, the Storage **1220** includes a copy of the domain Ontology **1260**, Capability Data **1265**, and Data Mappings **1270**. Although depicted as residing in Storage **1220**, in embodiments, the Ontology **1260**, Capability Data **1265**, and Data Mappings **1270** may be stored in any suitable location and manner. In one embodiment, the Ontology **1260**, Capability Data **1265**, and Data Mappings **1270** correspond to the Ontology **560**, Capability Data **565**, and Data Mappings **570** discussed above with reference to the Query Processing Orchestrator **115**.

For example, as discussed above, the Ontology **1260** can indicate the entities or concepts that are relevant for the domain, as well as the potential properties of each concept/entity and the relationships between and among the entities/concepts, without including instance-level data. Similarly, as discussed above, the Capability Data **1265** indicates the capabilities of each Data node **130A-N**. This may include, for example, an indication as to which operation(s) each Data Node **130A-N** supports, as well as any corresponding limitation(s) on that support.

In embodiments, the Data Mappings **1270** are generated by the Placement Application **1235**, and indicate the Data

Node(s) **130** that store instance data for each entity/concept defined in the Ontology **1260**. For example, the Data Mappings **1270** may indicate that all instances of a “Company” concept are stored in Data Nodes **130A** and **130B**, while all instances of a “Document” concept are stored in Data Nodes **130B** and **130N**.

In the illustrated embodiment, the Memory **1215** includes a Placement Application **1235**. Although depicted as software residing in Memory **1215**, in embodiments, the Placement Application **1235** may be implemented using hardware, software, or a combination of hardware and software. As illustrated, the Placement Application **1235** includes a Summary Component **1240**, a Hypergraph Component **1245**, and a Placement Component **1250**. Although depicted as discrete components for conceptual clarity, in embodiments, the operations of the Summary Component **1240**, Hypergraph Component **1245**, and Placement Component **1250** can be combined or distributed across any number of components.

In an embodiment, the Summary Component **1240** receives previous OQL queries (or sample queries) that reflect the prior, current, expected, typical, average, anticipated, and/or general workload on the system. The Summary Component **1240** then evaluates the provided queries to summarize the workload in the form of summarized queries. In embodiments, the summarized queries generally indicate sets of concepts that are queried together, along with the operations performed on the concepts, but do not correspond to an actual query that could be executed. The functionality of the Summary Component **1240** is discussed in more detail below with reference to FIG. **13**.

In embodiments, the Hypergraph Component **1245** receives the summarized workload information from the Summary Component **1240** and parses it to generate a hypergraph representing the query workload. As discussed above, in some embodiments, the hypergraph includes a vertex for each concept in the Ontology **1260**. Additionally, in embodiments, the concept vertices are connected by hyperedges representing the summarized query workload. The operations of the Hypergraph Component **1245** are discussed in more detail below with reference to FIG. **14**.

In one embodiment, the Placement Component **1250** evaluates the hypergraph in order to generate data placement decisions (e.g., Data Mappings **1270**). These decisions can then be used to route data to the appropriate nodes. For example, in one embodiment, the system iterates through the knowledge base to place the data. For each data item, the system can determine the concept(s) to which it corresponds, look up the corresponding Data Node(s) **130**, and store the data in the indicated node(s). In some embodiments, the system also performs any transformations or conversions that are appropriate for the destination store. The functionality of the Placement Component **1250** is discussed in more detail below with reference to FIGS. **15** and **16**.

FIG. **13** is a flow diagram illustrating a method **1300** for evaluating and summarizing query workload to inform data placement decisions, according to one embodiment disclosed herein. The method **1300** begins at block **1305**, where a Data Placement Orchestrator **150** receives one or more queries representative of the knowledge base workload. At block **1310**, the Data Placement Orchestrator **150** selects one of the received queries for evaluation. The method **1300** then proceeds to block **1315**, where the Data Placement Orchestrator **150** identifies the concept(s) that are involved by the

selected query. Similarly, at block **1320**, the Data Placement Orchestrator **150** identifies the operation(s) invoked by the query.

In one embodiment, the Data Placement Orchestrator **150** associates the determined set of concept(s) specified by the query with the set of operation(s) invoked by the query. In some embodiments, the operation-concept pairings are determined on a granular concept/operation-level basis. In some other embodiments, the Data Placement Orchestrator **150** does not determine which operations are linked to which concepts, but rather links the set of operations, as a whole, to the set of concepts, as a whole. That is, the Data Placement Orchestrator **150** ignores the actual execution details/desired outcome of the query, and defines the sets of relevant concepts and operations based on the data/operations involved, rather than the particular application of the transformations.

The method **1300** then proceeds to block **1325**, where the Data Placement Orchestrator **150** determines whether there is at least one additional query yet to be evaluated. If so, the method **1300** returns to block **1310**. Otherwise, the method **1300** proceeds to block **1330**. At group **1330**, the Data Placement Orchestrator **150** groups the received queries based on the corresponding set of concept(s) for each. In one embodiment, this includes grouping or clustering all queries that specify a matching set of concepts. For example, the Data Placement Orchestrator **150** can group all queries that specify both a “Company” concept and a “PublicMetric” concept into a first group. Notably, in such an embodiment, queries specifying only the “Company” concept or the “PublicMetric” concept alone would be placed in differing groups. Similarly, a query that specifies “Company” and “PublicMetric,” but also includes a “Document” concept would not be placed in the first group.

That is, in an embodiment, the Data Placement Orchestrator **150** groups queries that specify an exactly-matched set of concepts. Queries that specify additional concepts or fewer concepts are placed in other groups. In one embodiment, the set of concepts corresponding to each respective group are used to form a respective summarized query. That is, in the illustrated embodiment, the Data Placement Orchestrator **150** aggregates the received prior queries by grouping the queries that access identical concepts into a cluster, regardless of the operations each query performs.

The method **1300** then proceeds to block **1335**, where the Data Placement Orchestrator **150** selects one of these defined query groups. At block **1340**, the Data Placement Orchestrator **150** selects one of the queries associated with the selected group. Additionally, at block **1345**, the Data Placement Orchestrator **150** associates the corresponding operations specified by the selected query with the summarized query representing the selected query group. In one embodiment, if an operation is already reflected in the summarized query, the Data Placement Orchestrator **150** does not add it again. That is, in an embodiment, the set of operations associated with the summarized query are binary values, indicating either the presence or absence of a given operation.

In embodiments, the operations associated with the summarized query can be any level of granularity. For example, in some embodiments, the Data Placement Orchestrator **150** defines the summarized query at the operation level (e.g., “join”), without regards to the specific type of operation (e.g., an inner join), limitations on the operation, or specifics of the operation (e.g., the type of data, such as a string join or an integer join). In other embodiments, these details are

included in the summarized query description, in order to provide richer detail for subsequent processing.

The method **1300** then continues to block **1350**, where the Data Placement Orchestrator **150** determines whether there is at least one additional query in the selected group. If so, the method **1300** returns to block **1340**. If not, at block **1355**, the Data Placement Orchestrator **150** determines whether there is at least one additional group of queries yet to be evaluated. If so, the method **1300** returns to block **1335**. Otherwise, the method **1300** continues to block **1360**. At block **1360**, the Data Placement Orchestrator **150** stores the summarized workload such that it can be used and evaluated to generate a hypergraph.

FIG. **14** is a flow diagram illustrating a method **1400** for modeling ontological workloads to inform data placement decisions, according to one embodiment disclosed herein. The method **1400** begins at block **1405**, where the Data Placement Orchestrator **150** selects one of the concepts of the ontology. At block **1410**, the Data Placement Orchestrator **150** generates a hypergraph vertex for this selected concept. The method **1400** then continues to block **1415**, where the Data Placement Orchestrator **150** determines whether there are any additional concepts remaining in the ontology which do not yet have a vertex in the hypergraph. If so, the method **1400** returns to block **1405**. Otherwise, the method **1400** proceeds to block **1420**.

At block **1420**, the Data Placement Orchestrator **150** selects one of the summarized queries. As discussed above, in an embodiment, each summarized query indicates a set of concepts and a corresponding set of operations that have been applied to the concepts in the prior workload. At block **1425**, the Data Placement Orchestrator **150** generates a hyperedge linking each of the concept(s) indicated by the selected summarized query. The method **1400** then proceeds to block **1430**, where the Data Placement Orchestrator **150** labels the newly-generated hyperedge with an indication of the operations indicated by the selected summarized query. In this way, the Data Placement Orchestrator **150** can subsequently evaluate the hypergraph to identify relationships and patterns of usage for the knowledge base.

The method **1400** then continues to block **1435**, where the Data Placement Orchestrator **150** determines whether there is at least one additional summarized query to be evaluated and incorporated into the hypergraph. If so, the method **1400** returns to block **1420**. Otherwise, the method **1400** continues to block **1440**, where the Data Placement Orchestrator **150** stores the generated hypergraph for subsequent use.

FIGS. **15** and **16** depict flow diagrams illustrating methods for evaluating a hypergraph to drive data placement decisions, according to one embodiment disclosed herein. The method **1500**, discussed in reference to FIG. **15**, illustrates one embodiment of an operation-based clustering technique for generating concept mappings, while the method **1600**, discussed below with reference to FIG. **16**, illustrates one embodiment of a minimum-cover technique.

In one embodiment, the operation-based clustering technique groups concepts based on the operations that they are subject to. In one such embodiment, for each operation description in the hypergraph, the Data Placement Orchestrator **150** creates a respective cluster. The Data Placement Orchestrator **150** then iterates over the set of operation descriptions associated with each hyperedge, and for each such operation description, assigns all the concepts spanned by the hyperedge to the cluster of the corresponding operation. In an embodiment, once the concepts have been clustered together, the Data Placement Orchestrator **150** assigns each concept cluster to a set of data nodes such that

each node has a capability description that matches the operation description of the cluster (e.g., is capable of performing the corresponding operation of the cluster). Finally, in an operation-based system, the Data

Placement Orchestrator **150** generates a mapping that maps each concept in each cluster to the corresponding set of identified data stores.

As an example of one embodiment of the operation-based clustering technique, consider the Hypergraph **1100** provided in FIG. **11**. Initially, the Data Placement Orchestrator **150** generates a cluster **C** for each Operation **1115A-C** (e.g., a C_{Join} , a C_{Agg} , and a C_{Fuzzy}). The system then determines, for each hyperedge, the set of operations associated with it. For each indicated operation, the system assigns the concepts specified by the Hyperedge **1110** to the corresponding cluster. Continuing the above example, C_{Join} will contain Concepts **1105A**, **1105B**, **1105C**, and **1105D** from Hyperedge **1110A**, as well as Concepts **1105E** and **1105F** from Hyperedge **1110B**. Further, C_{Agg} will contain Concepts **1105A**, **1105B**, **1105C**, and **1105D** from Hyperedge **1110A**, as well as Concept **1105G** from Hyperedge **1110D**. Finally, C_{Fuzzy} will contain Concepts **1105A**, **1105B**, **1105C**, and **1105D** from Hyperedge **1110A**, as well as Concept **1105H** from Hyperedge **1110C**.

In many embodiments, these operation-based clusters have significant overlap. For example, note that the Concepts **1105A**, **1105B**, **1105C**, and **1105D** are included in every cluster. To finalize the mappings, in one embodiment, the Data Placement Orchestrator **150** identifies, for each cluster, all Data Nodes **130** capable of performing the corresponding operation. The Data Placement Orchestrator **150** then maps all Concepts **1105** in the cluster to all of the identified Data Nodes **130**. In some embodiments, although the operation-based technique can minimize or reduce data movement at query processing time by placing data into all stores supporting the corresponding operations, it does introduce some replication overheads, as the same cluster of concepts can be placed at multiple stores if they have the capability to satisfy the cluster's operation.

In some implementations, to further reduce the replication overhead, embodiments of the minimum-cover technique are utilized. In one embodiment, minimum-cover embodiments improve over the operation-based techniques by further minimizing the amount of data replication, while still minimizing the data movement at query processing time. In an embodiment, this technique leverages a minimum set-cover algorithm to find the minimum number of data stores needed to support the complete set of operations required by each hyperedge in the query workload hypergraph. In some embodiments, the minimum-cover technique minimizes the span of each hyperedge across the set of data stores that satisfy the set of operations required by the hyperedge.

In one example embodiment of the minimum-cover technique, the Data Placement Orchestrator **150**, for each hyperedge in the hypergraph, finds the minimum number of data nodes that cover all of the indicated operations. For example, if all of the operations can be completed by a single Data Node **130A**, the minimum set includes only this node. If one or more of the operations cannot be completed by the Data Node **130A**, one or more other Data Nodes **130B-N** are added to the minimum set until all operations are satisfied. Once the minimum set is determined for a hyperedge, each concept in the hyperedge is mapped to each of the nodes in the corresponding minimum set.

As an example of one embodiment of the minimum-cover clustering technique, consider the Hypergraph **1100** provided in FIG. **11**. Suppose the Data Nodes **130** include a first

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Data Node **130A** configured to support Operations **1115A** and **1115B**, a second Data Node **130B** configured to support Operations **1115B** and **1115C**, and a third Data Node **130C** supports only Operation **1115B**. For the Hyperedge **1110A**, the Data Placement Orchestrator **150** can determine that no node alone can support all three of the indicated operations, but that the set of Data Nodes **130A** and **130B** can. Because these two nodes can support the entire hyperedge, there is no need to add Data Node **130C** to the set.

Similarly, Hyperedge **1110B** will be assigned to Data Node **130A** (the only node configured to provide join operations), while Hyperedge **1110C** will be assigned to Data Node **130B** (the only node configured to provide fuzzy matching). Finally, the Hyperedge **1110D** can either be assigned to Data Nodes **130A** and **130B**, or Data Nodes **130B** and **130C**. In some embodiments, the Data Placement Orchestrator **150** selects between these otherwise-equivalent alternatives based on other criteria, such as the latency or compute resources of each, predefined preferences, and the like. The Data Placement Orchestrator **150** then maps the Concepts **1105** of each Hyperedge **1110** to the assigned Data Node(s) **130**.

FIG. **15** is a flow diagram illustrating an operator-based method **1500** for evaluating a hypergraph to drive data placement decisions, according to one embodiment disclosed herein. The method **1500** begins at block **1505**, where the Data Placement Orchestrator **150** selects one of the operations indicated by the hypergraph. At block **1510**, the Data Placement Orchestrator **150** generates a cluster for the selected operation. The method **1500** then proceeds to block **1515**, where the Data Placement Orchestrator **150** determines whether there is at least one additional operation reflected in the hypergraph, which does not yet have a cluster associated with it. If so, the method **1500** returns to block **1505**. Otherwise, the method **1500** continues to block **1520**.

At block **1520**, the Data Placement Orchestrator **150** selects for analysis one of the hyperedges in the hypergraph. At block **1525**, the Data Placement Orchestrator **150** identifies the concept(s) and operation(s) that are associated with the selected edge. The method **1500** then continues to block **1530**, where the Data Placement Orchestrator **150** selects one of these indicated operations. Additionally, at block **1535**, the Data Placement Orchestrator **150** identifies the corresponding cluster for the selected operation, and adds all of the concepts indicated by the selected hyperedge to this cluster. The method **1500** continues to block **1540**, where the Data Placement Orchestrator **150** determines whether the selected edge indicates at least one additional operation yet-to-be processed. If so, they method **1500** returns to block **1530**.

If no additional operations are associated with the selected hyperedge, the method **1500** continues to block **1545**, where the Data Placement Orchestrator **150** determines whether the hypergraph includes at least one additional edge that has not yet been evaluated. If so, they method **1500** returns to block **1520**. Otherwise, the method **1500** proceeds to block **1550**, where the Data Placement Orchestrator **150** maps the operation cluster(s) to corresponding data node(s) configured to handle each operation. For example, in one embodiment, the Data Placement Orchestrator **150** identifies, for each cluster, the set of data nodes that are capable of performing the corresponding operation. In an embodiment, the Data Placement Orchestrator **150** then maps every concept in the cluster to each node in the identified set of data node(s). The Data Placement Orchestrator **150** can use these mappings to distribute the data in the knowledge base across the variety of data nodes.

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FIG. **16** is a flow diagram illustrating a minimum-cover based method **1600** for evaluating a hypergraph to drive data placement decisions, according to one embodiment disclosed herein. The method **1600** begins at block **1605**, where the Data Placement Orchestrator **150** selects one of the hyperedges in the hypergraph. At block **1610**, the Data Placement Orchestrator **150** identifies the corresponding concepts and operations associated with the selected edge. Further, at block **1615**, the Data Placement Orchestrator **150** determines the minimum set of data nodes capable of collectively satisfying all of the indicated operations.

In one embodiment, the Data Placement Orchestrator **150** does so by iteratively evaluating each combination of data nodes to determine whether the combination satisfies the indicated operations. That is, whether every operation indicated by the selected edge can be performed by at least one data node in the combination. If not, the combination can be discarded and another node or combination can be selected for testing (or another node can be added to the current combination). The Data Placement Orchestrator **150** may determine whether each combination is complete and satisfactory, in that it can perform all required operations, and identify the combination(s) with the minimum number of data nodes, as these combinations will likely lead to the minimum data movement during runtime. In one embodiment, if two or more combinations are equally small, the Data Placement Orchestrator **150** can utilize predefined criteria or preferences to select the best combination. For example, predefined rules may indicate that combinations including at least one relational data store are prioritized over combinations with no relational data stores. As another example, a rule may indicate weights or priorities for particular type(s) of store and/or particular Data Node(s) **130**. In such an embodiment, the Data Placement Orchestrator **150** may aggregate or otherwise these weights for each combination to determine which stores to use. The selected edge is then labeled with an indication of the determined set of data nodes.

Once the minimum set of data nodes has been determined, the method **1600** proceeds to block **1620**, where the Data Placement Orchestrator **150** determines whether there is at least one additional hyperedge in the hypergraph. If so, the method **1600** returns to block **1605**. Otherwise, the method **1600** proceeds to block **1625**. At block **1625**, the Data Placement Orchestrator **150** selects one of the available data nodes in the system. At block **1630**, the Data Placement Orchestrator **150** identifies all hyperedges in the hypergraph having a label that includes the selected data node. The Data Placement Orchestrator **150** then groups or clusters these hyperedges (or the concepts each include) together to form a group/cluster of concepts that will be stored in the selected node. The method **1600** then proceeds to block **1635**, where the Data Placement Orchestrator **150** determines whether there is at least one additional data node in the system that has not yet been assigned a group/cluster. If so, the method **1600** returns to block **1625**.

Otherwise, the method **1600** proceeds to block **1640**, where the Data Placement Orchestrator **150**, for each data node, maps all of the concepts included in the corresponding cluster to the store. The Data Placement Orchestrator **150** can subsequently use these mappings to distribute the data in the knowledge base across the variety of data nodes.

FIG. **17** is a flow diagram illustrating a method **1700** for mapping ontological concepts to storage nodes, according to one embodiment disclosed herein. The method **1700** begins at block **1705**, where a Data Placement Orchestrator **150** determines query workload information corresponding to a

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domain. At block 1710, the Data Placement Orchestrator 150 models the query workload information as a hypergraph, wherein the hypergraph includes a set of vertices and a set of hyperedges, wherein each vertex in the set of vertices corresponds to a concept in an ontology associated with the domain. The method 1700 then proceeds to block 1715, where the Data Placement Orchestrator 150 generates mappings between concepts and a plurality of data nodes based on the hypergraph and based further on predefined capability of each of the plurality of data nodes. Additionally, at block 1720, the Data Placement Orchestrator 150 establishes a distributed knowledge base based on the generated mappings.

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

In the preceding and/or following, reference is made to embodiments presented in this disclosure. However, the scope of the present disclosure is not limited to specific described embodiments. Instead, any combination of the preceding and/or following features and elements, whether related to different embodiments or not, is contemplated to implement and practice contemplated embodiments. Furthermore, although embodiments disclosed herein may achieve advantages over other possible solutions or over the prior art, whether or not a particular advantage is achieved by a given embodiment is not limiting of the scope of the present disclosure. Thus, the preceding and/or following aspects, features, embodiments and advantages are merely illustrative and are not considered elements or limitations of the appended claims except where explicitly recited in a claim(s). Likewise, reference to "the invention" shall not be construed as a generalization of any inventive subject matter disclosed herein and shall not be considered to be an element or limitation of the appended claims except where explicitly recited in a claim(s).

Aspects of the present disclosure may take the form of an entirely hardware embodiment, an entirely software embodiment (including firmware, resident software, micro-code, etc.) or an embodiment combining software and hardware aspects that may all generally be referred to herein as a "circuit," "module" or "system."

The present invention may be a system, a method, and/or a computer program product. The computer program product may include a computer readable storage medium (or media) having computer readable program instructions thereon for causing a processor to carry out aspects of the present invention.

The computer readable storage medium can be a tangible device that can retain and store instructions for use by an instruction execution device. The computer readable storage medium may be, for example, but is not limited to, an electronic storage device, a magnetic storage device, an optical storage device, an electromagnetic storage device, a semiconductor storage device, or any suitable combination of the foregoing. A non-exhaustive list of more specific examples of the computer readable storage medium includes the following: a portable computer diskette, a hard disk, a

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random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), a static random access memory (SRAM), a portable compact disc read-only memory (CD-ROM), a digital versatile disk (DVD), a memory stick, a floppy disk, a mechanically encoded device such as punch-cards or raised structures in a groove having instructions recorded thereon, and any suitable combination of the foregoing. A computer readable storage medium, as used herein, is not to be construed as being transitory signals per se, such as radio waves or other freely propagating electromagnetic waves, electromagnetic waves propagating through a waveguide or other transmission media (e.g., light pulses passing through a fiber-optic cable), or electrical signals transmitted through a wire.

Computer readable program instructions described herein can be downloaded to respective computing/processing devices from a computer readable storage medium or to an external computer or external storage device via a network, for example, the Internet, a local area network, a wide area network and/or a wireless network. The network may comprise copper transmission cables, optical transmission fibers, wireless transmission, routers, firewalls, switches, gateway computers and/or edge servers. A network adapter card or network interface in each computing/processing device receives computer readable program instructions from the network and forwards the computer readable program instructions for storage in a computer readable storage medium within the respective computing/processing device.

Computer readable program instructions for carrying out operations of the present invention may be assembler instructions, instruction-set-architecture (ISA) instructions, machine instructions, machine dependent instructions, microcode, firmware instructions, state-setting data, or either source code or object code written in any combination of one or more programming languages, including an object oriented programming language such as Smalltalk, C++ or the like, and conventional procedural programming languages, such as the "C" programming language or similar programming languages. The computer readable program instructions may execute entirely on the user's computer, partly on the user's computer, as a stand-alone software package, partly on the user's computer and partly on a remote computer or entirely on the remote computer or server. In the latter scenario, the remote computer may be connected to the user's computer through any type of network, including a local area network (LAN) or a wide area network (WAN), or the connection may be made to an external computer (for example, through the Internet using an Internet Service Provider). In some embodiments, electronic circuitry including, for example, programmable logic circuitry, field-programmable gate arrays (FPGA), or programmable logic arrays (PLA) may execute the computer readable program instructions by utilizing state information of the computer readable program instructions to personalize the electronic circuitry, in order to perform aspects of the present invention.

Aspects of the present invention are described herein with reference to flowchart illustrations and/or block diagrams of methods, apparatus (systems), and computer program products according to embodiments of the invention. It will be understood that each block of the flowchart illustrations and/or block diagrams, and combinations of blocks in the flowchart illustrations and/or block diagrams, can be implemented by computer readable program instructions.

These computer readable program instructions may be provided to a processor of a general purpose computer,

special purpose computer, or other programmable data processing apparatus to produce a machine, such that the instructions, which execute via the processor of the computer or other programmable data processing apparatus, create means for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks. These computer readable program instructions may also be stored in a computer readable storage medium that can direct a computer, a programmable data processing apparatus, and/or other devices to function in a particular manner, such that the computer readable storage medium having instructions stored therein comprises an article of manufacture including instructions which implement aspects of the function/act specified in the flowchart and/or block diagram block or blocks.

The computer readable program instructions may also be loaded onto a computer, other programmable data processing apparatus, or other device to cause a series of operational steps to be performed on the computer, other programmable apparatus or other device to produce a computer implemented process, such that the instructions which execute on the computer, other programmable apparatus, or other device implement the functions/acts specified in the flowchart and/or block diagram block or blocks.

The flowchart and block diagrams in the Figures illustrate the architecture, functionality, and operation of possible implementations of systems, methods, and computer program products according to various embodiments of the present invention. In this regard, each block in the flowchart or block diagrams may represent a module, segment, or portion of instructions, which comprises one or more executable instructions for implementing the specified logical function(s). In some alternative implementations, the functions noted in the block may occur out of the order noted in the figures. For example, two blocks shown in succession may, in fact, be executed substantially concurrently, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved. It will also be noted that each block of the block diagrams and/or flowchart illustration, and combinations of blocks in the block diagrams and/or flowchart illustration, can be implemented by special purpose hardware-based systems that perform the specified functions or acts or carry out combinations of special purpose hardware and computer instructions.

Embodiments of the invention may be provided to end users through a cloud computing infrastructure. Cloud computing generally refers to the provision of scalable computing resources as a service over a network. More formally, cloud computing may be defined as a computing capability that provides an abstraction between the computing resource and its underlying technical architecture (e.g., servers, storage, networks), enabling convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction. Thus, cloud computing allows a user to access virtual computing resources (e.g., storage, data, applications, and even complete virtualized computing systems) in "the cloud," without regard for the underlying physical systems (or locations of those systems) used to provide the computing resources.

Typically, cloud computing resources are provided to a user on a pay-per-use basis, where users are charged only for the computing resources actually used (e.g. an amount of storage space consumed by a user or a number of virtualized systems instantiated by the user). A user can access any of the resources that reside in the cloud at any time, and from anywhere across the Internet. In context of the present

invention, a user may access applications (e.g., the Query Processing Orchestrator 115) or related data available in the cloud. For example, the Query Processing Orchestrator 115 could execute on a computing system in the cloud and evaluate queries and backend resources. In such a case, the Query Processing Orchestrator 115 could route queries and store backend resources and/or capability configurations at a storage location in the cloud. Doing so allows a user to access this information from any computing system attached to a network connected to the cloud (e.g., the Internet).

While the foregoing is directed to embodiments of the present invention, other and further embodiments of the invention may be devised without departing from the basic scope thereof, and the scope thereof is determined by the claims that follow.

What is claimed is:

1. A method, comprising:

determining, by a data orchestrator, query workload information corresponding to a domain, the query workload information comprising ontological queries specifying respective concepts in an ontology associated with the domain and respective operations performed by the ontological queries, the ontological queries comprising a first group with corresponding matching concepts that are accessed, the first group performing an aggregate set of operations;

modeling the query workload information as a hypergraph, wherein the hypergraph includes a plurality of vertices and a plurality of hyperedges, wherein each respective vertex in the plurality of vertices corresponds to a respective concept in the ontology and each respective hyperedge in the plurality of hyperedges indicates a respective set of operations applied to concepts associated with the respective hyperedge, wherein a first hyperedge of the plurality of hyperedges is labelled with the aggregate set of operations and connects first vertices representing the matching concepts;

generating mappings between concepts in the ontology and a plurality of data stores based on the hypergraph, wherein:

the plurality of data stores are distributed over multiple data sites and communicate with each other via data transmissions sent over a network, and

the mappings indicate, for each respective concept in the ontology, a respective subset of the plurality of data stores on which the respective concept is to be stored; and

establishing a distributed knowledge base based on the generated mappings, comprising:

storing data associated with concepts of the ontology among the plurality of data stores based on the generated mappings;

storing data associated with a first concept on a first data store of the plurality of data stores; and

storing data associated with a second concept in the ontology on a second data store of the plurality of data stores, wherein the first data store does not store the data associated with the second concept and the second data store does not store the data associated with the first concept.

2. The method of claim 1, wherein determining the query workload information comprises:

receiving a set of prior ontological queries;

generating a first set of concepts accessed by a first query in the set of prior ontological queries;

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generating a first set of operations performed by the first query; and
 generating a first summarized query by:
 identifying the first group of queries, from the set of prior ontological queries, with corresponding matching first sets;
 determining, based on corresponding sets of operations for each query in the first group of queries, the aggregate set of operations; and
 associating the first summarized query with the aggregate set of operations and concepts reflected in the corresponding matching first sets.

3. The method of claim 2, wherein modeling the query workload information as a hypergraph comprises:
 creating a vertex for each concept in the ontology;
 creating the first hyperedge for the first summarized query, wherein the first hyperedge connects a first set of vertices in the hypergraph, wherein the first set of vertices corresponds to the concepts reflected in the matching first sets; and
 labeling the first hyperedge with the aggregate set of operations.

4. The method of claim 1, wherein generating the mappings comprises:
 creating a first cluster for a first operation included in the hypergraph;
 identifying a first set of concepts connected by a first hyperedge in the hypergraph;
 identifying a first set of operations indicated by the first hyperedge; and
 upon determining that the first set of operations includes the first operation, assigning the first set of concepts to the first cluster.

5. The method of claim 4, wherein generating the mappings further comprises mapping the first set of concepts to one or more data stores by:
 identifying a set of data stores capable of performing the first operation; and
 mapping each concept in the first set of concepts to each data store in the identified set of data stores.

6. The method of claim 1, wherein generating the mappings comprises:
 identifying a first set of concepts connected by a first hyperedge in the hypergraph;
 identifying a first set of operations indicated by the first hyperedge;
 determining a minimum set of data stores capable of collectively performing the first set of operations;
 generating a cluster including the first set of concepts; and
 labeling the cluster with the minimum set of data stores.

7. The method of claim 6, wherein generating the mappings further comprises mapping each concept in the first set of concepts to each data store in the minimum set of data stores.

8. The method of claim 1, wherein establishing the distributed knowledge base comprises, for each respective concept in the ontology:
 identifying a respective data store indicated by the mappings;
 identifying data corresponding to the respective concept; and
 facilitating storage of the identified data in the respective data store.

9. A computer-readable storage medium containing computer program code that, when executed by operation of one or more computer processors, performs an operation comprising:

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determining, by a data orchestrator, query workload information corresponding to a domain, the query workload information comprising at least a first query specifying a first concept in an ontology associated with the domain and a first operation performed on the first concept based on the first query;
 modeling the query workload information as a hypergraph, wherein the hypergraph includes a plurality of vertices and a plurality of hyperedges, wherein each respective vertex in the plurality of vertices corresponds to a respective concept in the ontology and each respective hyperedge in the plurality of hyperedges indicates a respective set of operations applied to concepts associated with the respective hyperedge;
 generating mappings between concepts in the ontology and a plurality of data stores based on the hypergraph, wherein:
 the plurality of data stores are distributed over multiple data sites and communicate with each other via data transmissions sent over a network, and
 the mappings indicate, for each respective concept in the ontology, a respective subset of the plurality of data stores on which the respective concept is to be stored; and
 establishing a distributed knowledge base based on the generated mappings, comprising:
 storing data associated with concepts of the ontology among the plurality of data stores based on the generated mappings;
 storing data associated with the first concept on a first data store of the plurality of data stores;
 storing data associated with a second concept in the ontology on a second data store of the plurality of data stores, wherein the first data store does not store the data associated with the second concept and the second data store does not store the data associated with the first concept;
 identifying a first set of concepts connected by a first hyperedge in the hypergraph;
 identifying a first set of operations indicated by the first hyperedge, the first set of operations comprising a first operation;
 identifying a set of the data stores capable of performing the first operation; and
 mapping each concept in the first set of concepts to data stores in the identified set of data stores.

10. The computer-readable storage medium of claim 9, wherein determining the query workload information comprises:
 receiving a set of prior ontological queries;
 generating a first set of concepts accessed by a first query in the set of prior ontological queries;
 generating a first set of operations performed by the first query; and
 generating a first summarized query by:
 identifying a group of queries, from the set of prior ontological queries, with corresponding matching first sets;
 determining, based on corresponding sets of operations for each query in the identified group of queries, an aggregate set of operations; and
 associating the first summarized query with the aggregate set of operations and concepts reflected in the corresponding matching first sets.

11. The computer-readable storage medium of claim 10, wherein modeling the query workload information as a hypergraph comprises:

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creating a vertex for each concept in the ontology;
 creating a first hyperedge for the first summarized query,
 wherein the first hyperedge connects a first set of
 vertices in the hypergraph, wherein the first set of
 vertices corresponds to the concepts reflected in the
 matching first sets; and
 labeling the first hyperedge with the aggregate set of
 operations.

12. The computer-readable storage medium of claim 9,
 wherein generating the mappings comprises:

creating a first cluster for the first operation included in
 the hypergraph; and
 upon determining that the first set of operations includes
 the first operation, assigning the first set of concepts to
 the first cluster.

13. The computer-readable storage medium of claim 9,
 wherein generating the mappings comprises:

identifying a first set of concepts connected by a first
 hyperedge in the hypergraph;
 identifying a first set of operations indicated by the first
 hyperedge;
 determining a minimum set of data stores capable of
 collectively performing the first set of operations;
 generating a cluster including the first set of concepts; and
 labeling the cluster with the minimum set of data stores.

14. The computer-readable storage medium of claim 9,
 wherein establishing the distributed knowledge base com-
 prises, for each respective concept in the ontology:

identifying a respective data store indicated by the map-
 pings;
 identifying data corresponding to the respective concept;
 and
 facilitating storage of the identified data in the respective
 data store.

15. A system comprising:

one or more computer processors; and
 a memory containing a program which when executed by
 the one or more computer processors performs an
 operation, the operation comprising:

determining, by a data orchestrator, query workload infor-
 mation corresponding to a domain, the query workload
 information comprising at least a first query specifying
 a first concept in an ontology associated with the
 domain and a first operation performed on the first
 concept based on the first query;

modeling the query workload information as a hyper-
 graph, wherein the hypergraph includes a plurality of
 vertices and a plurality of hyperedges, wherein each
 respective vertex in the plurality of vertices corre-
 sponds to a respective concept in the ontology and each
 respective hyperedge in the plurality of hyperedges
 indicates a respective set of operations applied to
 concepts associated with the respective hyperedge;

generating mappings between concepts in the ontology
 and a plurality of data stores based on the hypergraph,
 wherein:

the plurality of data stores are distributed over multiple
 data sites and communicate with each other via data
 transmissions sent over a network, and

the mappings indicate, for each respective concept in the
 ontology, a respective subset of the plurality of data
 stores on which the respective concept is to be stored;
 and

establishing a distributed knowledge base based on the
 generated mappings, comprising:

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storing data associated with concepts of the ontology
 among the plurality of data stores based on the gener-
 ated mappings;

storing data associated with the first concept on a first data
 store of the plurality of data stores;

storing data associated with a second concept in the
 ontology on a second data store of the plurality of data
 stores, wherein the first data store does not store the
 data associated with the second concept and the second
 data store does not store the data associated with the
 first concept;

identifying a first set of concepts connected by a first
 hyperedge in the hypergraph;

identifying a first set of operations indicated by the first
 hyperedge, the first set of operations comprising a first
 operation;

identifying a set of the data stores capable of performing
 the first operation; and

mapping each concept in the first set of concepts to data
 stores in the identified set of data stores.

16. The system of claim 15, wherein determining the
 query workload information comprises:

receiving a set of prior ontological queries;
 generating a first set of concepts accessed by a first query
 in the set of prior ontological queries;

generating a first set of operations performed by the first
 query; and

generating a first summarized query by:

identifying a group of queries, from the set of prior
 ontological queries, with corresponding matching first
 sets;

determining, based on corresponding sets of operations
 for each query in the identified group of queries, an
 aggregate set of operations; and

associating the first summarized query with the aggregate
 set of operations and concepts reflected in the corre-
 sponding matching first sets.

17. The system of claim 16, wherein modeling the query
 workload information as a hypergraph comprises:

creating a vertex for each concept in the ontology;
 creating a first hyperedge for the first summarized query,

wherein the first hyperedge connects a first set of
 vertices in the hypergraph, wherein the first set of
 vertices corresponds to the concepts reflected in the
 matching first sets; and

labeling the first hyperedge with the aggregate set of
 operations.

18. The system of claim 15, wherein generating the
 mappings comprises:

creating a first cluster for the first operation included in
 the hypergraph; and

upon determining that the first set of operations includes
 the first operation, assigning the first set of concepts to
 the first cluster.

19. The system of claim 15, wherein generating the
 mappings comprises:

identifying a first set of concepts connected by a first
 hyperedge in the hypergraph;

identifying a first set of operations indicated by the first
 hyperedge;

determining a minimum set of data stores capable of
 collectively performing the first set of operations;

generating a cluster including the first set of concepts; and
 labeling the cluster with the minimum set of data stores.

20. The method of claim 1, wherein the mappings between concepts and the plurality of data stores are generated based further on predefined capabilities of each of the plurality of data stores.

21. The computer-readable storage medium of claim 9, 5 wherein the mappings between concepts and the plurality of data stores are generated based further on predefined capabilities of each of the plurality of data stores.

22. The system of claim 15, wherein the mappings between concepts and the plurality of data stores are gen- 10 erated based further on predefined capabilities of each of the plurality of data stores.

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