Query Processing in the SIMS Information Mediator

Yigal Arens, Chun-Nan Hsu, and Craig A. Knoblock
Information Sciences Institute and
Department of Computer Science
University of Southern California
4676 Admiralty Way
Marina del Rey, CA 90292, USA
{arens,chunnan,knoblock}@isi.edu

Abstract

A critical problem in building an information mediator is how to translate a domain-level query into an efficient query plan for accessing the required data. We have built a flexible and efficient information mediator, called SIMS. This system takes a domain-level query and dynamically selects the appropriate information sources based on their content and availability, generates a query access plan that specifies the operations and their order for processing the data, and then performs semantic query optimization to minimize the overall execution time. This paper describes these three basic components of the query processing in SIMS.

Introduction

SIMS (Arens et al. 1993; Knoblock, Arens, & Hsu 1994; Arens & Knoblock 1994; Ambite et al. 1995; Arens, Knoblock, & Shen 1996) is an information mediator that provides access and integration of multiple sources of information. Queries are expressed in a uniform language, independent of the distribution of information over sources, the various query languages, the location of sources, etc. SIMS determines which data sources to use, how to obtain the desired information, how and where to temporarily store and manipulate data, and how to efficiently retrieve information.

The core part of the mediator is the ability to intelligently retrieve and process data. Information sources are constantly changing, new information becomes available, old information may be eliminated or temporarily unavailable, and so on. Thus, SIMS dynamically selects an appropriate set of information sources, generates a plan for processing the data, and then optimizes the plan to minimize the execution cost. The basic SIMS architecture is shown in Figure 1 and the query processing components are shown by the shaded rectangles.

This paper focuses on the query processing in SIMS. Before describing the query processing, we first describe how the domain and information sources are modeled in SIMS. Second, we describe the process of selecting the information sources. Third, we present the approach to generating a query plan for execution. Fourth, we describe the semantic query optimization performed before execution. Fifth, we review the most closely related work. Finally, we conclude with a summary of the contributions and directions for future work.

Representing the Knowledge of a Mediator

A mediator contains a model of its domain of expertise, which provides the terminology for interacting with the mediator, as well as models of all information sources that are available to it. The domain model provides class descriptions, subclass and superclass relationships, roles for each class, and other domain-specific information. The information source models describe both the contents of the information sources and the mapping between those models and the domain model.

Modeling the Domain

The SIMS mediator is specialized to a single "application domain" and provides access to the available information sources within that domain. The largest application domain that we have to date is a transportation planning domain, with information about the movement of personnel and materiel from one location to another using aircraft, ships, trucks, etc.

The application domain models are defined using a hierarchical terminological knowledge base (Loom) (MacGregor 1988; 1990) with nodes representing each class of objects, and edges between nodes that define the relationships between the objects. For example, Figure 2 shows a fragment of the domain model in the transportation planning domain. In this figure, circles represent classes, the thick arrows represent subclass relationships, and the thin arrows represent relations between classes.

The classes defined in the domain model do not necessarily correspond directly to the objects described in any particular information source. The domain model is a high-level description of an application domain. Queries expressed in terms of this domain model are
 Queries to SIMS are expressed in terms of the general domain model, so there is no need to know or even be aware of the terms or language used in the underlying information sources. Instead the system translates the domain-level query into a set of queries to the underlying information sources. These information sources may be databases, knowledge bases, or other application programs.

Figure 3 illustrates a query expressed in the Loom language. This query requests all seaports and corresponding ships with a range greater than 10,000 that can be accommodated within each port. The first argument to the retrieve expression is the parameter list, which specifies which parameters of the query to return. The second argument is a description of the information to be retrieved. This description is expressed as a conjunction of concept and relation expressions, where the concepts describe classes of information, and the relations describe constraints on these classes. The first subclause of the query is an example of a concept expression and specifies that the variable ?port ranges over members of the class seaport. The second subclause is an example of a relation expression and states that the relation port_name holds between the value of ?port and the variable ?port_name. The query describes a class of seaports and a class of ships, and requests all seaport and ship pairs where the depth of the port exceeds the draft of the ship.

(retrieve (?port_name ?depth ?ship_type ?draft)
  (and (seaport ?port)
    (channel_depth ?depth ?port)
    (ship ?ship)
    (vehicle_type ?ship ?ship_type)
    (range ?ship_range)
    (> ?ship_range 10000)
    (max_draft ?ship ?draft)
    (> ?depth ?draft)))

Figure 3: Example Loom query

Modeling Information Sources

The critical part of the information source models is the description of the contents of the information sources. This consists of both a description of the objects contained in the information source as well as the relationship between these objects and the objects in the domain model. The mappings between the domain model and the information source model are used for transforming a domain-level query into a set of queries into actual information sources.

Figures 4 illustrates how an information source is modeled in Loom and how it is related to the domain model. In the picture, the shaded circle represents the Seaports table in the GEO database. All of the con-
cepts and relations in the information source model are mapped to concepts and relations in the domain model. A mapping link between two concepts indicates that they represent the same class of information. Thus, if the user requests all seaports, that information can be retrieved from the GEO database, which has information about seaports.

Figure 4: Relating an Information Source Model to a Domain Model

**Information Source Selection**

The first step in answering a query expressed in the terms of the domain model is to select the appropriate information sources (Arens, Knoblock, & Shen 1996). This is done by transforming a query expressed in terms of the concepts in the domain model into a query expressed in terms of the concepts in the information source models. If the user requests information about ports and there is an information source-level concept that contains ports, then the mapping is straightforward. However, in many cases there will not be a direct mapping. Instead, the original domain-model query must be reformulated in terms of concepts that do correspond to information sources.

Consider the fragment of the knowledge base shown in Figure 5, which covers the knowledge relevant to the example query in Figure 3. The concepts Seaport, Channel, and Ship have subconcepts shown by the shaded circles that correspond to concepts whose instances can be retrieved directly from some information source. Thus, the GEO information source contains information about both seaports and channels and the PORT information source contains information about only seaports. Thus, if the user asks for seaports, then it must be translated into one of the information source concepts —— Seaports in GEO or Ports in PORT.

In order to select the information sources for answering a query, the system applies a set of reformulation operators to transform the domain-level concepts into concepts that can be retrieved directly from an information source. The system has a number of truth-preserving reformulation operations that can be used for this task. The operations include Select-Information-Source, Generalize-Concept, Specialize-Concept, and Decompose-Relation. These operations are described briefly below.

**Select-Information-Source** maps a domain-level concept directly to an information-source-level concept. In many cases this will simply be a direct mapping from a concept such as Seaport to a concept that corresponds to the seaports in some information source. There may be multiple information sources that contain the same information. In that case the domain-level query can be reformulated in terms of any one of the information source concepts. In general, the choice is made so as to minimize the overall cost of the retrieval. For example, the cost can be minimized by using as few information sources as possible.

**Generalize-Concept** uses knowledge about the relationship between a class and a superclass to reformulate a query in terms of the more general concept. In order to preserve the semantics of the original request, one or more additional constraints may need to be added to the query in order to avoid retrieving extraneous data. For example, if a query requires some information about airports, but the information sources that correspond to the airport concept do not contain the requested information, then it may be possible to generalize airport to port and retrieve the information from some information source that contains port information. In order to ensure that no extraneous data is returned, the reformulation will include a join between airport and port.

**Specialize-Concept** replaces a concept with a more specific concept by checking the constraints on the query to see if there is an appropriate specialization of the requested concept. For example, if a query requests all ports with an elevation greater than 1000 feet, it may be possible to reformulate this in terms of all airports with an elevation greater than 1000 feet since there are no seaports with an elevation greater than 1000 feet.
this high. Even if there was an information source corresponding to the port concept, this may be a more efficient way to retrieve the data. Range information such as this is naturally represented and stored as part of the domain model.

Decompose-Relation replaces a relation defined between concepts in the domain model with equivalent terms that are available in the information source models. For example, channel_of is a property of the domain model, but it is not defined in any information source. Instead, it can be replaced by joining over a key, geoloc-code, that in this case happens to occur in both seaport and channel.

Reformulation is performed by treating the reformulation operators as a set of transformation operators and then using a planning system to search for a reformulation of the given query description. The planner searches for a way to map each of the concepts and relations into concepts and relations for which data is available.

For example, consider the query shown in Figure 3. There are two concept expressions — one about ships and the other about seaports. In the reformulation that is found, the first step translates the seaport expression into a information-source-level expression. Unfortunately, none of the information sources contain information that corresponds to channel_of. Thus, the system must reformulate channel_of, using the decompose operator. This expresses the fact that channel_of is equivalent to performing a join over the keys for the seaport and channel concepts. The resulting reformulation is shown in Figure 6.

The next step reformulates the seaport portion of the query into a corresponding information source query. This can be done using the select-information-source operator, which selects between the GEO and PORT databases. In this case GEO is selected because the information on channels is only available in the GEO database. The resulting query is shown in Figure 7.

The channel and ship portions of the query are then similarly reformulated. The final query, which is the result of reformulating the entire query is shown in Figure 8.

Query Access Planning

Once the system has reformulated the query so that it uses only terms from the information source models, the next step is to generate a query plan for retrieving and processing the data. The query plan specifies the precise operations that need to be performed, as well as the order in which they are to be performed.

There may be a significant difference in efficiency between different plans for a query. Therefore, the planner searches for a plan that can be implemented as efficiently as possible. To do this the planner must take into account the cost of accessing the different information sources, the cost of retrieving intermediate results, and the cost of combining these intermediate results to produce the final results. In addition, since the information sources are distributed over different machines or even different sites, the planner takes advantage of potential parallelism and generates subqueries that can be issued concurrently.

There are three basic operators that are used to plan out the processing of a query:
Move-Data — Moves a set of data from one information source to another information source.

Join — Combines two sets of data into a combined set of data using the given join relations.

Retrieve-Data — Specifies the data that is to be retrieved from a particular information source.

Each of these operations manipulates one or more sets of data, where the data is specified in the same terms that are used for communicating with SIMS. This simplifies the input/output since there is no conversion between languages.

The planner (Knoblock 1994; 1995; 1996) is implemented in a version of UCPOP (Penberthy & Weld 1992; Barrett et al. 1993) that has been modified to generate parallel execution plans. The system searches through the space of possible plans using a branch-and-bound search until a complete plan is found.

The plan generated for the example query in Figure 8 is shown in Figure 9. In this example, the system partitions the given query such that the ship information is retrieved in a single query to the ASSETS database and the seaport and channel information is retrieved in a single query to the GEO database. All of the information is brought into the local system (Loom) where the draft of the ships can be compared against the depth of the seaports. Once the final set of data has been generated, it is output for the user.

The system attempts to minimize the overall execution time by searching for a query that can be implemented as efficiently as possible. It does this by using a simple estimation function to calculate the expected cost of the various operations and then selecting a plan that has the lowest overall parallel execution cost. In the example, the system performs the join between the seaport and channel tables in the remote database since this will be cheaper than moving the tables into the local system. If the system could perform all of the work in one remote system, then it would completely bypass the local system and return the data directly to the user. Once an execution plan has been produced, it is sent to the optimization system for global optimization, as described in the next section.

Semantic Query Optimization

This section first describes how the system optimizes a single subquery and then describes how the system optimizes the entire query plan.

Subquery Optimization

The goal of the semantic query optimization is to search for the least expensive query in the space of semantically equivalent queries. The transformation from one query to another is done through logical inference using semantic rules, the abstracted knowledge of the contents of relevant databases. See (Hsu & Knoblock 1994; 1995; 1996) for an explanation of how rules like these are automatically learned. The semantic rules describe the databases in terms of the set of closed formulas of first-order logic. These formulas describe the database in the sense that they are true with regard to all instances in the database.

Consider the example shown in Figure 10. The input query retrieves ship types whose ranges are greater than 10,000 miles. This query could be expensive to evaluate because there is no index placed on the range attribute. The system must scan the entire database table notional_ship and check the values of range to retrieve the answer.

A set of applicable rules for this query is shown in Figure 11. These rules would either be learned by the system or provided as semantic integrity constraints. Rule R1 states that for all ships with maximum drafts greater than 10 feet, their range is greater than 12,000 miles. Rule R2 states that all ships with range greater
Input Query:

$$\text{db-retrieve (?sht-type ?ship ?draft)}$$

$$(:\text{and} (\text{notional\_ship ?ship})$$

$$\text{(notional\_ship.sht\_nm ?ship ?ship-type)}$$

$$\text{(notional\_ship.max\_draft ?ship ?draft)}$$

$$\text{(notional\_ship.range ?ship ?range)}$$

$$\text{(}> ?range 10000))$$


Figure 10: Example Subquery

than 10,000 miles have fuel capacities greater than 5,000 gallons. The last rule R3 simply states that the drafts of ships are greater than 12 feet when their fuel capacity is more than 4,500 gallons.

Semantic Rules:

R1:$$
(:\text{if}$$

$$\text{(}> ?draft 10))$$

$$\text{(}> ?range 12000))$$

$$\text{(}> ?fuel\_cap 5000))$$

R2:$$
(:\text{if}$$

$$\text{(}> ?fuel\_cap 4500))$$

$$\text{(}> ?draft 12))$$

Figure 11: Applicable Semantic Rules

Optimized Query:

$$\text{db-retrieve (?sht-type ?ship ?draft)}$$

$$(:\text{and} (\text{notional\_ship ?ship})$$

$$\text{(notional\_ship.sht\_nm ?ship ?ship-type)}$$

$$\text{(notional\_ship.max\_draft ?ship ?draft)}$$

$$\text{(notional\_ship.range ?ship ?range)}$$

$$\text{(}> ?range 10000))$$

$$\text{(}> ?fuel\_cap 5000))$$

$$\text{(}> \text{?draft 12}))$$

Figure 12: Optimized Query

be useful information for extending the algorithm to optimize an entire query plan. Previous work only optimizes single database queries. In addition, our algorithm is polynomial in terms of the number of semantic rules and the syntactic length of the input query (Hsu & Knoblock 1993). A large number of rules may slow down the optimization. In this case, we can adopt sophisticated indexing and hashing techniques in rule matching, or constrain the size of the semantic rules by removing rules with low utility.

Query Plan Optimization

We can optimize each subquery in the query plan with the subquery optimization algorithm and improve their efficiency. However, the most expensive aspect of the multidatabase query is often processing intermediate data. In the example query plan in Figure 9, the constraint on the final subquery involves the variables ?draft and ?depth that are bound in the preceding subqueries. If we can optimize these preceding subqueries so that they retrieve only the data instances possibly satisfying the constraint $$\text{(}< ?\text{draft } \text{?depth})$$ in the final subquery, the intermediate data will be reduced. This requires the query plan optimization algorithm to be able to propagate the constraints along the data flow paths in the query plan. We developed a query plan optimization algorithm that achieves this by inferring the ranges of intermediate data and rearranging constraints. We explain the algorithm using the query plan in Figure 9.

The algorithm first optimizes each subquery in the partial order (i.e., the data flow order) specified in the plan. The two subqueries to databases are optimized first. The constraints inferred from the semantic rules are saved in $\text{Inferred-Set}$, which is returned from the subquery optimization to propagate the constraints to later subqueries. For example, when optimizing the subquery to $\text{ASSETS}$, $$\text{(}> \text{?draft 12})$$ is inferred and saved in the inferred set. In addition, the constraint $$\text{(}> \text{?fuel\_cap 5000})$$
?range 10000) in the original subquery is propagated along the data flow path to its succeeding subquery. Similarly, the system can infer the range of ?depth in this manner. In this case, the range of ?depth is 41 ≤ ?depth ≤ 60.

Now that the updated ranges for ?draft and ?depth are available, the subquery optimization algorithm can infer from the constraint (< ?draft ?depth) a new constraints (< ?depth 60) and add it to the subquery for the join. However, this constraint should be placed on the remote subquery instead of the local query because it only depends on the data in the remote database. In this case, when updating the query plan with the optimized subquery, the algorithm locates where the constrained variable of each new constraint is bound, and inserts the new constraint in the corresponding subqueries. In our example, the variable is bound by (max_draft ?ship ?draft) in the subquery to ASSETS in Figure 9. The algorithm will insert the new constraint on ?draft in that subquery.

The semantics of the modified subqueries, such as the subquery to ASSETS in this example, are changed because of the newly inserted constraints. However, the semantics of the overall query plan remain the same. After all the subqueries in the plan have been optimized, the system optimizes these modified subqueries again to improve their efficiency. In our example, the subquery optimization algorithm is applied again to the subquery to ASSETS. This time, no optimization is found. The final optimized query plan is returned and shown in Figure 13.

This query plan is more efficient and returns the same answer as the original one. In our example, the subquery to ASSETS is more efficient because the constraint on the attribute range is replaced with another constraint that can be evaluated more efficiently. The intermediate data are reduced because of the new constraint on the attribute ?draft. The logical rationale of this new constraint is derived from the constraints in the other two subqueries: (> ?range 10000) and (< ?draft ?depth), and the semantic rules. The entire algorithm for query plan optimization is still polynomial. Our experiments show that the overhead of optimization is very small compared to the overall query processing cost. On a set of 32 example queries, the query optimization yielded significant performance improvements with an average reduction in execution time of 43%.

**Related Work**

In the database community, there are a variety of approaches to handling distributed, heterogeneous, and autonomous databases (Reddy, Prasad, & Reddy 1989; Sheth & Larson 1990). Of these approaches, the tightly-coupled federated systems (e.g., Multibase (Landers & Rosenberg 1982)) are the most closely related to SIMS in that they attempt to support total integration of all information sources in the sense that SIMS provides. However, building tightly-coupled federated systems requires constructing a global schema for the databases to be combined and then hard-wiring the mapping between the global schema and the local schemas.

The information source selection in SIMS is used instead of the standard schema integration used in database systems (Batini & Lenzerini 1986). Our approach requires constructing a general domain model that encompasses the relevant parts of the database schemas. Then each of the database models is related to this general domain model. The integration problem is shifted from how to build a single integrated model to how to map between the domain and the information source models. After defining this mapping, the remaining integration process is performed automatically by the reformulation system using operators that transform the high-level query into an information
source-level query. An important advantage of this approach is that it is easier and simpler to map one model to another model than it is to provide a completely integrated view of a number of models with different structures, types, and dependencies.

The query planning in SIMS is similar to the query access planning performed in many database systems. The primary difference between the planning in SIMS and query access planning in other systems is that the planning in SIMS is performed by an AI planner, which provides a level of flexibility that goes well beyond what standard database systems can provide. Currently, it allows the system to construct a plan that takes into account the availability of the various databases. In addition, we have integrated the planning with the execution system (Knoblock 1993), which allows the system to dynamically replan parts of a query that fail while continuing to execute the other subqueries of the overall plan.

The semantic approach to query optimization was first developed by King (1981) and has since been extended in a number of systems (Adam, Gangopadhyay, & Geller 1993; Shekhar, Srivastava, & Dutta 1988; Shenoy & Ozsoyoglu 1989; Siegel, Sciore, & Salveter 1993). Our approach to this problem differs from other related work in that we do not rely on explicit heuristics of the database implementation to guide search for optimized queries in the combinatorially large space of potential optimizations. Instead, our algorithm considers all possible optimizations by firing all applicable rules and collecting candidate constraints in an inferred set. Then the system selects the most efficient set of the constraints from the inferred set to form the optimized subqueries.

The Carnot project (Collet, Huhns, & Shen 1991) is similar to SIMS in that it uses a knowledge base to integrate a variety of information sources. Carnot integrates heterogeneous databases using a set of articulation axioms that describe how to map between SQL queries and domain concepts. Carnot uses the Cyc knowledge base (Lenat & Guha 1990) to build the articulation axioms, but after the axioms are built the domain model is no longer used or needed. In contrast, the domain model in SIMS is an integral part of the system, and allows SIMS to both combine information stored in the knowledge base and to optimize queries.

Conclusion

SIMS provides a flexible system for processing queries to multiple information sources. In this paper we described the process of transforming a domain-level query into an efficient and executable query plan. This process consists of three steps. First, the information sources are selected in the process of transforming the domain-level query into an information source-level query. Second, the system generates a query plan, which specifies all the operations to be performed on the data as well as the order of these operations. Third, the system performs global optimization through the use of semantic rules to optimize the query plans.

Future work will focus on extending the selection, planning, and optimization capabilities described in this paper. An important issue that we have not yet addressed is how to handle the various forms of incompleteness and inconsistency that will inevitably arise from using autonomous information sources. We plan to address these issues by exploiting available domain knowledge and employing more sophisticated planning and reasoning capabilities to both detect and recover from these problems.

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