Optimizing Large Join Queries in Mediation Systems

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Abstract

In data integration systems, queries posed to a mediator need to be translated into a sequence of queries to the underlying data sources. In a heterogeneous environment, with sources of diverse and limited query capabilities, not all the translations are feasible. In this paper, we study the problem of finding feasible and efficient query plans for mediator systems. We consider conjunctive queries on mediators and model the source capabilities through attribute-binding adornments. We use a simple cost model that focuses on the major costs in mediation systems, those involved with sending queries to sources and getting answers back. Under this metric, we develop two algorithms for source query sequencing – one based on a simple greedy strategy and another based on a partitioning scheme. The first algorithm produces optimal plans in some scenarios, and we show a linear bound on its worst case performance when it misses optimal plans. The second algorithm generates optimal plans in more scenarios, while having no bound on the margin by which it misses the optimal plans. We also report on the results of the experiments that study the performance of the two algorithms.

1 Introduction

Integration systems based on a *mediation* architecture [31] provide users with seamless access to data from many heterogeneous sources. Examples of such systems are TSIMMIS [3], Information Manifold [14], Garlic [8], and DISCO [26]. In these systems, mediators define integrated views based on the data provided by the sources. They translate user queries on integrated views into source queries and postprocessing operations on the source query results. The translation process can be quite challenging when integrating a large number of heterogeneous sources.

One of the important challenges for integration systems is to deal with the diverse capabilities of sources in answering queries [8,15,19]. This problem arises due to the heterogeneity in sources ranging from simple file systems to full-fledged relational databases. The problem we address in this paper is how to generate efficient mediator query plans that respect the limited and diverse capabilities of data sources. In particular, we focus our attention on the kind of queries that are the most expensive in mediation systems, *large join queries*. We propose efficient algorithms to find good plans for such queries.

1.1 Cost Model

In many applications, the cost of query processing in mediator systems is dominated by the cost of interacting with the sources. Hence, we focus on the costs associated with issuing queries to sources. Our results are first stated using a very simple cost model where we count the total number of source queries in a plan as its cost. In spite of the simplicity of the cost model, the optimization problem we are dealing with remains $\mathcal{NP}$-hard. Later in the paper, we show how to extend our main results to a more complex cost model that charges a fixed cost per query plus a variable cost that is proportional to the amount of data transferred.

1.2 Capabilities-Based Plan Generation

We consider mediator systems, where users pose conjunctive queries over integrated views provided by the mediator. These queries are translated into conjunctive queries over the source views to arrive at *logical query plans*. The logical plans deal only with the content descriptions of the sources. That is, they tell the mediator which sources provide the relevant data and what postprocessing operations need to be performed on this data. The logical plans are later translated into *physical plans* that specify details such as the order in which the sources are contacted and the exact queries to be sent. Our goal in this paper is to develop algorithms that will translate a mediator logical plan into an *efficient*, *feasible* (does not exceed the source capabilities) physical plan. We illustrate the process of translating a logical plan into a physical plan by an example.

EXAMPLE 1.1 Consider three sources that provide information about movies, and a mediator that provides an integrated view:

Source	Contents	Must Bind
S_1	`R(studio, title)`	either `studio` or `title`
S_2	`S(title, year)`	`title`
S_3	`T(title, stars)`	`title`

Mediator View:
`Movie(studio,title,year,stars) :- R(studio,title), S(title,year), T(title,stars)`

The "Must Bind" column indicates what attributes must be specified at a source. For instance, queries sent to S_1 must either provide the `title` or the `studio`. Suppose the user asks for the titles of all movies produced by Paramount in 1955 in which Gregory Peck starred. That is,

```
ans(title) :- Movie('Paramount', title, '1955', 'Gregory Peck')
```

The mediator would translate this query to the logical plan:

```
ans(title) :- R('Paramount', title), S(title, '1955'), T(title, 'Gregory Peck')
```

The logical plan states the information the mediator needs to obtain from the three sources and how it needs to postprocess this information. In this example, the mediator needs to join the results of the three source queries on the `title` attribute. There are many physical plans that correspond to this logical plan (based on various join orders and join methods). Some of these plans are feasible while others are not. Here are three physical plans for this logical plan:

- Plan P_1: Send query `R('Paramount', title)` to S_1; send query `S(title, '1955')` to S_2; and send query `T(title, 'Gregory Peck')` to S_3. Join the results of the three source queries on the `title` attribute and return the `title` values to the user.

- Plan P_2: First get the titles of movies produced by Paramount from source S_1. For each returned title t, send a query to S_2 to get its `year` and check if it is '1955.' If so, send a query to S_3 to get the `stars` of movie t. If the set of `stars` contains 'Gregory Peck,' return t to the user.

- Plan P_3: This plan is similar to P_2, except that we reverse the S_2 and S_3 queries. That is, after getting the titles of Paramount movies, we get their `stars` from S_3. If `stars` contains 'Gregory Peck,' then we send a query to S_2 to get the `year` of the movie. If the `year` is '1955,' we return this `title` to the user.

Among the three physical plans, the first one is not feasible because the queries to sources S_2 and S_3 do not provide a binding for `title`. The other two plans are feasible. It may be that plan P_2 is more efficient than plan P_3. In that case, the mediator may execute plan P_2. □

As illustrated by the example, we need to solve the following problems:

1. Given a logical plan and the description of the source capabilities, find feasible physical plans for the logical plan. The central problem is to determine the evaluation order for logical plan subgoals, so that attributes are appropriately bound.

2. Among all the feasible physical plans, pick the most efficient one.

1.3 Related Work

The problem of ordering subgoals to find the best feasible sequence can be viewed as the well known *join-order* problem. More precisely, we can assign *infinite* cost to infeasible sequences and then find the best join order.

The join-order problem has been extensively studied in the literature, and many solutions have been proposed. Some solutions perform a rather exhaustive enumeration of plans, and hence do not scale well [1,2,4,5,8,15,17,19,20,22,29]. In particular, we are interested in Internet scenarios with many sources and subgoals, so these schemes are too expensive. Some other solutions reduce the search space through techniques like *simulated annealing*, *random probes*, or other heuristics [6,11,12,16,18,23,24,25]. While these approaches may generate efficient plans in some cases, they do not have any performance guarantees in terms of the quality of plans generated (i.e., the plans generated by them can be arbitrarily far from the optimal one). Many of these techniques may even fail to generate a feasible plan, while the user query does have a feasible plan.

The remaining solutions [10,13,21] use specific cost models and clever techniques that exploit them to produce optimal join orders efficiently. While these solutions are very good for the join-order problem where those cost models are appropriate, they are hard to adopt in our context because of two difficulties. The first is that it is not clear how to model the feasibility of mediator query plans in their frameworks. A direct application of their algorithms to the problem we are studying may end up generating infeasible plans, when a feasible plan exists. The second difficulty is that when we use cost models that emphasize the main costs in mediator systems, the optimality guarantees of their algorithms may not hold.

1.4 Our Solution

In this paper, we use a simple cost model that focuses on the major costs in mediator query processing, that of getting the relevant data from the sources. In this cost model, we develop two algorithms that can find good feasible plans rapidly. The first algorithm runs in $O(n^2)$ time, where n is the number of subgoals in the logical plan. We also provide a linear bound on the margin by which this algorithm can miss the optimal plan. Our second algorithm can guarantee optimal plans in more scenarios than the first, although there is no bounded optimality for its plans. Both our algorithms are guaranteed to find a feasible plan, if the user query has a feasible plan. Furthermore, we show through experiments that our algorithms have excellent running time profiles in a variety of scenarios, and very often find optimal or close-to-optimal plans. This combination of efficient, scalable algorithms that generate provably good plans is not achieved by previously known approaches.

1.5 Paper Organization

The paper is organized as follows. In Section 2, we introduce the cost model and our notation. We present an efficient algorithm named CHAIN in Section 3, and prove its n-competitiveness (i.e., bounded optimality). In Section 4, we describe our second algorithm, called PARTITION, and discuss its ability to find optimal feasible plans. The results of our performance analysis of the two algorithms are reported in Section 5. Finally, in Section 6, we discuss how the main results of this paper can be extended to cost models other than the one introduced in Section 2.

2 Preliminaries

In this section, we introduce the notation we use throughout the paper. We also discuss the cost model used in our optimization algorithms.

2.1 Source Relations and Logical Plans

Let $S_1, \ldots, S_m$ be m sources in an integration system. To simplify the presentation, we assume that sources provide their data in the form of relations. If sources have other data models, one could use *wrappers* [9] to create the simple relational view of data. Each source is assumed to provide a single relation. If a source provides multiple relations, we can model it in our framework as a set of logical sources, all having the same physical source. Example 1.1 showed three sources S_1, S_2 and S_3 providing three relations R, S and T respectively.

A *query* to a source specifies atomic values to a subset of the source relation attributes and obtains the corresponding set of tuples. A source supports a set of access templates on its relation that specify binding adornment requirements for source queries.[1] In Example 1.1, source S_2 had one access template: $S^{bf}(\texttt{title}, \texttt{year})$, while source S_1 had two: $R^{bf}(\texttt{studio}, \texttt{title})$ and $R^{fb}(\texttt{studio}, \texttt{title})$.

[1]We consider source-capabilities described as *bf* adornment patterns that distinguish bound (b) and free (f) argument positions [27]. The techniques developed in this paper can also be employed to solve the problem of mediator query planning when other source capability description languages are used.

User queries to the mediator are conjunctive queries on the integrated views provided by the mediator. Each integrated view is defined as a set of conjunctive queries over the source relations. The user query is translated into a logical plan, which is a set of conjunctive queries on the source relations. The answer to the user query is the union of the results of this set of conjunctive queries. Example 1.1 showed a user query that was a conjunctive query over the *Movie* view, and it was translated into a conjunctive query over the source relations.

In order to find the best feasible plan for a user query, we assume that the mediator processes the logical plan one conjunctive query at a time (as in [3,8,14]). Thus, we reduce the problem of finding the best feasible plan for the user query to the problem of finding the best feasible plan for a conjunctive query in the logical plan. In a way, from now on, we assume without loss of generality that a logical plan has a single conjunctive query over the source relations.

Let the logical plan be $H :- C_1, C_2, \ldots, C_n$. We call each C_i a *subgoal*. Each subgoal specifies a query on one of the source relations by binding a subset of the attributes of the source relation. We refer to the attributes of subgoals in the logical plan as *variables*. In Example 1.1, the logical plan had three subgoals with four variables, three of which were bound.

2.2 Binding Relations and Source Queries

Given a sequence of n subgoals $C_1, C_2, \ldots, C_n$, we define a corresponding sequence of $n+1$ *binding relations* $I_0, I_1, \ldots, I_n$. I_0 has as its schema the set of variables bound in the logical plan, and it has a single tuple, denoting the bindings specified in the logical plan. The schema of I_1 is the union of the schema of I_0 and the schema of the source relation of C_1. Its instance is the join of I_0 and the source relation of C_1. Similarly, we define I_2 in terms of I_1 and the source relation of C_2, and so on. The answer to the conjunctive query is defined by a projection operation on I_n.

In order to compute a binding relation I_j, we need to evaluate $I_{j-1} \bowtie C_j$. There are two ways to do this evaluation:

1. Use I_0 to send a query to the source of C_j (by binding a subset of its attributes); perform the join of the result of this source query with I_{j-1} at the mediator to obtain I_j.
2. For $j \geq 2$, use I_{j-1} to send a set of queries to the source relation of C_j (by binding a subset of its attributes); union the results of these source queries; perform the join of this union relation with I_{j-1} to obtain I_j.

We call the first kind of source query a *block query* and the second kind a *parameterized query*. Obviously, answering C_j through the first method takes a single source query, while answering it by the second method can take many source queries. The main reason why we need to consider parameterized queries is that it may not be possible to answer some of the subgoals in the logical plan through block queries. This may be because the access templates for the corresponding source relations require bindings of variables that are not available in the logical plan. In order to answer these subgoals, we must use parameterized queries by executing other subgoals and collecting bindings for the required parameters of C_j.

2.3 The Plan Space

The space of all possible plans for a given user query is defined first by considering all sequences of subgoals in its logical plan. In a sequence, we must then decide on the choice of queries for each subgoal (among the set of block queries and parameterized queries available for the subgoal). We call a plan in this space *feasible* if all the queries in it are answerable by the sources. Note that the number of feasible physical plans, as well as the number of all plans, for a given logical plan can be exponential in the number of subgoals in the logical plan.

Note that the space of plans we consider is similar to the space of left-deep-tree executions of a join query. As stated in the following theorem, we do not miss feasible plans by not considering bushy-tree executions.

Theorem 2.1 *We do not miss feasible plans by considering only left-deep-tree executions of the subgoals.* □

Proof: Given any feasible execution of the logical plan based on a bushy tree of subgoals, we construct another feasible execution based on a left-deep tree of subgoals. The constructed left-deep tree will have the same leaf order as the given bushy tree.

Consider a feasible plan P based on the bushy tree of subgoals. We will derive a feasible plan P' from the left-deep tree constructed above. If a subgoal is answered by a block query in P, it is also answered by a block query in P'. If it is answered by parameterized queries in P, it can also be answered by parameterized queries in P'. Note that this is always possible because the left-deep-tree execution keeps the cumulative bindings of all the variables of all the subgoals to the left of the subgoal under consideration. This observation is similar to the *bound-is-easier* assumption of [28].

Thus, we conclude that if a bushy tree of subgoals has a feasible plan, we are guaranteed to find a feasible plan by considering only left-deep-tree executions. ∎

2.4 The Formal Cost Model

Our cost model is defined as follows:

1. The cost of a subgoal in a feasible plan is the number of source queries needed to answer the subgoal.
2. The cost of a feasible plan is the sum of the costs of all the subgoals in the plan.

We develop the main results of the paper in the simple cost model presented above. Later, in Section 6, we will show how to extend these results to more complex cost models. Here, we note that even in the simple cost model that counts only the number of source queries, the problem of finding the optimal feasible plan is quite hard.

Theorem 2.2 *The problem of finding the feasible plan with the minimum number of source queries is $\mathcal{NP}$-hard.* □

Proof: We reduce the Vertex Cover problem ([7]) to our problem. Since the Vertex Cover problem is $\mathcal{NP}$-complete, our problem is $\mathcal{NP}$-hard.

Given a graph G with n vertices $V_1, \ldots, V_n$, we construct a database and a logical plan as follows. Corresponding to each vertex V_i we define a relation R_i. For all $1 \leq i \leq j \leq n$, if V_i and V_j are connected by an edge in G, R_i and R_j include the attribute A_{ij}. In addition, we define a special attribute X and two special relations R_0 and R_{n+1}. In all, we have a total of $m+1$ attributes, where m is the number of edges in G. The special attribute X is in the schema of all the relations. The special relation R_{n+1} also has all the attributes A_{ij}. That is, R_0 has only one attribute and R_{n+1} has $m+1$ attributes. Each relation has a tuple with a value of 1 for each of its attributes. In addition, all relations except R_{n+1} include a second tuple with a value of 2 for all their attributes. Each relation has a single access template: R_0 has no binding requirements, R_1 through R_n require the attribute X to be bound, and R_{n+1} requires all of the attributes to be bound. Finally, the logical plan consists of all the $n+2$ relations, with no variables bound.

It is obvious that the above construction of the database and the logical plan takes time that is polynomial in the size of G. Now, we show that G has a vertex cover of size k if and only if the logical plan has a feasible physical plan that requires $(n+k+3)$ source queries.

Suppose G has a vertex cover of size k. Without loss of generality, let it be $V_1, \ldots, V_k$. Consider the physical plan P that first answers the subgoal R_0 with a block query, then answers $R_1, \ldots, R_k, R_{n+1}, R_{k+1}, \ldots, R_n$ using parameterized queries. P is a feasible plan because R_0 has no binding requirements, $R_1, \ldots, R_k$ need X to be bound and X is available from R_0, and $R_1, \ldots, R_k$ will bind all the variables (since $V_1, \ldots, V_k$ is a vertex cover). In P, R_0 is answered by a single source query, $R_1, \ldots, R_k$ and R_{n+1} are answered by two source queries each, and $R_{k+1}, \ldots, R_n$ are answered by one source query each. This gives a total of $(n+k+3)$ source queries for this plan. Thus, we see that if G has a vertex cover of size k, we have a feasible plan with $(n+k+3)$ source queries.

Suppose, there is a feasible plan P' with f source queries. In P', the first relation must be R_0, and this subgoal must be answered by a block query (because the logical plan does not bind any variables). All the other subgoals must be answered by parameterized queries. Consider the set of subgoals in P' that are answered before R_{n+1} is answered. Let j be the size of this set of subgoals (excluding R_0). Since R_{n+1} needs all attributes to be bound, the union of the schemas of these j subgoals must be the entire attribute set. That is, the vertices corresponding to these j subgoals form a vertex cover in G. In P', each of these j subgoals takes two source queries, along with R_{n+1}, while the rest of $(n-j)$ subgoals in $R_1, \ldots, R_n$ take one source query each. That is, $f = 1 + 2 * j + 2 + (n-j)$. From this, we see that we can find a vertex cover for G of size $(f-n-3)$.

Hence, G has a vertex cover of size k if and only if there is a feasible plan with $(n+k+3)$ source queries. That is, we have reduced the problem of finding the minimum vertex cover in a graph to our problem of finding a feasible plan with minimum source queries. ∎

Recall that the space of plans we consider does not include bushy-tree executions of the set of subgoals. It turns out that in our cost model, we can safely (without missing the optimal plan) restrict our attention to plans based on left-deep-tree executions of the set of subgoals.

Theorem 2.3 *We do not miss the optimal plan by not considering the executions of the logical plan based on bushy trees of subgoals.* □

Proof: The proof is similar to that of Theorem 2.1. Once again, given any physical plan based on a bushy tree of subgoals, we can construct an physical plan based on a left-deep tree of subgoals (with the same leaf order) that is at least as good.

If a subgoal is answered by a block query in the bushy-tree plan, it will also be answered by a block query in the left-deep-tree plan. This subgoal will have the same cost (of 1) in both the plans. If a subgoal is answered by parameterized queries in the bushy-tree plan, it is also answered by parameterized queries in the left-deep-tree plan. Note that by using cumulative binding relations in the left-deep-tree plan, we can only reduce the number of distinct values for the parameters (to the queries) of the subgoal. Thus, the cost of the subgoal in the left-deep-tree plan can be at most equal to that in the bushy-tree plan. So, the plan based on the constructed left-deep tree is at least as cheap as the plan based on the bushy tree.

Hence, by considering only left-deep trees of subgoals, we do not miss the optimal plan. ∎

2.5 Subgoal Sequences and Physical Plans

We extend the notion of cost and feasibility of physical plans to sequences of subgoals in the logical plan. For each sequence of subgoals, we associate a set of physical plans with it by making the choices of source queries (block queries and parameterized queries) for the subgoals. A given sequence of subgoals is *feasible* if there is a feasible plan in the set of physical plans associated with that sequence. The cost of a given sequence of subgoals is the cost of the cheapest physical plan associated with that sequence. The cost of a subgoal in a sequence is the cost of the subgoal in the best physical plan for the sequence.

Sequences of subgoals satisfy some interesting properties stated by the following lemmas.

Lemma 2.1 *Given a sequence of subgoals, one can ascertain its feasibility in $O(n)$ time, where n is the number of subgoals.* □

Lemma 2.2 *Given a sequence of subgoals, one can find its cost in $O(n)$ time, where n is the number of subgoals.* □

Lemma 2.3 *Given a sequence of subgoals, one can find the best physical plan for the sequence in $O(n)$ time, where n is the number of subgoals.* □

Lemma 2.4 *Postponing the processing of an answerable subgoal in a sequence can not make it unanswerable.* □

Lemma 2.5 *Postponing the processing of an answerable subgoal in a sequence can not increase its cost.* □

2.6 Problem Statement

The problem we are addressing in this paper is how to find efficient, feasible physical plans for given logical plans. As noted above, given a sequence of subgoals, one can easily compute the best plan for that sequence. Because it is easy to go from a sequence of subgoals to its best plan, we sometimes refer to our problem as finding the best sequence of subgoals. In particular, the algorithms of Section 3 and Section 4 actually find the best sequence of subgoals and then translate it into the best physical plan.

3 The CHAIN Algorithm

In this section, we present the CHAIN algorithm for finding the best feasible query plan. This algorithm is based on a greedy strategy of building a single sequence of subgoals that is feasible and efficient. First, we describe the algorithm formally. Then we analyze its complexity as well as its ability to generate efficient, feasible plans.

The CHAIN Algorithm
Input: Logical plan – subgoals and bound variables.
Output: Feasible physical plan.

- Initialize:

    $S \leftarrow \{C_1, C_2, \ldots, C_n\}$ /*set of subgoals in the logical plan*/

    $B \leftarrow$ set of bound variables in the logical plan

    $L \leftarrow \phi$ /* start with an empty sequence */

- Construct the sequence of subgoals:

```
while (S ≠ φ ) do
  M ← infinity;
  N ← null;
  for each subgoal C_i in S do    /* find the cheapest subgoal */
    if (C_i is answerable with B) then
      c ← Cost_L(C_i);        /* get the cost of this subgoal in sequence L */
      if ( c < M ) then
        M ← c;
        N ← C_i;
  If no next answerable subgoal, declare no feasible plan ...
  if (N = null)                 /* no feasible plan */
    return(φ);
  Add next subgoal to plan ....
  L ← L + N;
  S ← S − {N};
  B ← B ∪ {variables of N};
```

- Return the feasible plan:

    return($Plan(L)$); /* construct plan from sequence L */

Figure 1: Algorithm CHAIN

The algorithm is shown in Figure 1. The essential idea behind CHAIN is as follows. CHAIN finds all subgoals that are answerable with the initial bindings in the logical plan, and picks the one with the least cost. It computes the additional variables that are now bound due to the chosen subgoal. It repeats the process of finding answerable subgoals, picking the cheapest among them and updating the set of bound variables, until no more subgoals are left or some subgoals are left but none of them is answerable. If there are subgoals left over, CHAIN declares that there is no feasible plan. Otherwise it outputs the plan it has constructed.

3.1 Feasible Plan Generation

Lemma 3.1 *If a logical plan has feasible physical plans, CHAIN will not fail to generate a feasible plan.* □

Proof: If CHAIN fails to generate a feasible plan, there are some left over subgoals in the logical plan for which the initial bindings along with the variables of the other subgoals are not sufficient. This can only

$R^{bff}(A, B, D)$	$S^{bf}(B, E)$	$T^{bf}(D, F)$
(1, 1, 1)	(1, 1)	(4, 1)
(1, 2, 2)	(2, 1)	(5, 1)
(1, 3, 3)	(3, 1)	(6, 1)
(1, 1, 4)	(4, 1)	(7, 1)

Table 1: Proof of Lemma 3.4: Data of 3 Sources

be possible if there is no feasible physical plan for the logical plan. Otherwise, consider the first subgoal in a feasible physical plan that is one of the left over subgoals in CHAIN. Since all the subgoals preceding this subgoal in the feasible plan are accumulated in the sequence built by CHAIN (before it gave up), this subgoal will also be deemed answerable by CHAIN. So, it cannot be one of the left over subgoals. Hence, it is not possible for the feasible physical plan to exist. ∎

3.2 Complexity of CHAIN

Lemma 3.2 *CHAIN runs in $O(n^2)$ time where n is the number of subgoals in the logical plan.*[2] □

Proof: There can be at most n iterations in CHAIN as in each iteration it adds a subgoal to the plan it constructs. Each iteration takes $O(n)$ time as it examines at most n subgoals to find the next cheapest answerable subgoal. Thus, CHAIN takes a total of $O(n^2)$ time. ∎

3.3 Optimality of Plans Generated by CHAIN

Lemma 3.3 *If the result of the user query is nonempty, and the number of subgoals in the logical plan is less than 3, CHAIN is guaranteed to find the optimal plan.* □

Proof: If there is only one subgoal, CHAIN will obviously find the optimal plan consisting of the lone subgoal. If there are two subgoals, we have two cases: (i) both can be executed using block queries, (ii) only one of them can be executed using a block query (the other one needs parameterized queries). In the first case, the cost of the plan chosen by CHAIN is 2, and this is same as the cost of the optimal plan. In the second case, there is only one feasible sequence of subgoals, and so CHAIN will end up with the optimal plan. ∎

Lemma 3.4 *CHAIN can miss the optimal plan if the number of subgoals in the logical plan is greater than 2.* □

Proof: We construct a logical plan with 3 subgoals and a database instance that result in CHAIN generating a suboptimal plan.

Consider a logical plan $H :- R(1, B, D),\ S(B, E),\ T(D, F)$ and the database instance shown in Table 1. For this logical plan and database, CHAIN will generate the plan: $R \rightarrow S \rightarrow T$, with a total cost of

[2] We are assuming here that finding the cost of a subgoal following a partial sequence takes $O(1)$ time.

$1 + 3 + 4 = 8$. We observe that a cheaper feasible plan is: $R \rightarrow T \rightarrow S$, with a total cost of $1 + 4 + 1 = 6$. Thus, CHAIN misses the optimal plan in this case. ∎

It is not difficult to find situations in which CHAIN misses the optimal plan. However, surprisingly, there is a linear upper bound on how far its plan can be from the optimal. In fact, we prove a stronger result in Lemma 3.5.

Lemma 3.5 *Suppose P^c is the plan generated by CHAIN for a logical plan with n subgoals; P^o is the optimal plan, and E_{max} is the cost of the most expensive subgoal in P^o. Then,*

$$Cost(P^c) \leq n \times E_{max}$$

□

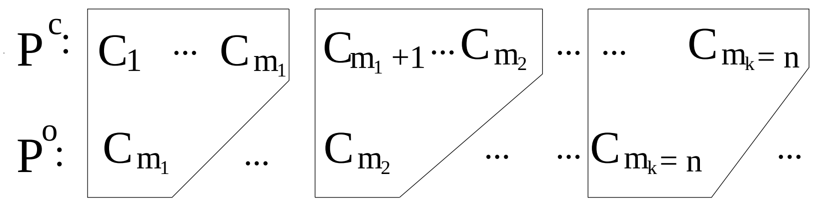


Figure 2: Proof for Lemma 3.5

Proof: Without loss of generality, suppose the sequence of subgoals in P^c is $C_1, C_2, \ldots, C_n$. As shown in Figure 2, let the first subgoal in P^o be C_{m_1}. Let G_1 be the prefix of P^c, such that $G_1 = C_1 \ldots C_{m_1}$. When CHAIN chooses C_1, the subgoal C_{m_1} is also answerable. This implies that the cost of C_1 in P^c is less than or equal to the cost of C_{m_1} in P^o. After processing C_1 in P^c, the subgoal C_{m_1} remains answerable (see Lemma 2.4) and its cost of processing cannot increase (see Lemma 2.5). So, if CHAIN has chosen another subgoal C_2 instead of C_{m_1}, once again we can conclude that the cost of C_2 in P^c is not greater than the cost of C_{m_1} in P^o. Finally, at the end of G_1, when C_{m_1} is processed in P^c, we note that the cost of C_{m_1} in P^c is no more than the cost of C_{m_1} in P^o. Thus, the cost of each subgoal of G_1 is less than or equal to the cost of C_{m_1} in P^o.

We call C_{m_1} the first *pivot* in P^o. We define the next pivot C_{m_2} in P^o as follows. C_{m_2} is the first subgoal after C_{m_1} in P^o such that C_{m_2} is not in G_1. Now, we can define the next subsequence G_2 of P^c such that the last subgoal of G_2 is C_{m_2}. The cost of each subgoal in G_2 is less than or equal to the cost of C_{m_2}.

We continue finding the rest of the pivots $C_{m_3}, \ldots C_{m_k}$ in P^o and the corresponding subsequences $G_3, \ldots, G_k$ in P^c. Based on the above argument, we have:

$$\forall C_i \in G_j : (\text{cost of } C_i \text{ in } P^c) \leq (\text{cost of } C_{m_j} \text{ in } P^o)$$

From this, it follows that

$$Cost(P^c) = \sum_{j=1}^{k} \sum_{C_i \in G_j} (\text{cost of } C_i \text{ in } P^c) \leq \sum_{j=1}^{k} |G_j| \ \times \ (\text{cost of } C_{m_j} \text{ in } P^o) \leq n \times E_{max}$$

∎

Theorem 3.1 *CHAIN is n-competitive. That is, the plan generated by CHAIN can be at most n times as expensive as the optimal plan, where n is the number of subgoals.* □

Proof: Follows from Lemma 3.5, by observing that $E_{max} \leq$ cost of P^o. ∎

The cost of the plan generated by CHAIN can be arbitrarily close to the cost of the optimal plan multiplied by the number of subgoals. In this sense, the linear bound on optimality for CHAIN is tight. However, in many situations CHAIN yields optimal plans or plans whose cost is very close to that of the optimal plan. In Section 5, we study the quality of plans generated by CHAIN in a wide range of scenarios.

4 The PARTITION Algorithm

We present another algorithm called PARTITION for finding efficient, feasible plans. PARTITION takes a very different approach to solve the plan generation problem. It is guaranteed to generate optimal plans in more scenarios than CHAIN but has a worse running time. First, we formally present the PARTITION algorithm and discuss its ability to generate efficient, feasible plans. Towards the end of the section, we describe two variations of PARTITION that specifically target the generation of optimal plans and the efficiency of the plan generation process respectively.

4.1 PARTITION

PARTITION organizes the subgoals into *clusters* based on the capabilities of the sources. Then it performs local optimization within each cluster, and builds the feasible plan by merging the subplans from all the clusters.

As shown in Figure 3, PARTITION has two phases. The first phase organizes the set of subgoals in the logical plan into a list of clusters. The property satisfied by the clusters is as follows. All the subgoals in the first cluster are answerable by block queries; all the subgoals in each subsequent cluster are answerable by parameterized queries that use attribute bindings from the subgoals of the earlier clusters. In the second phase, PARTITION finds the best subplan for each cluster of subgoals. It then combines all these subplans to arrive at the best feasible plan for the user query.

Now, let us describe the algorithm in more detail. Let Ψ and S denote the list of clusters and the set of subgoals respectively. Initially, Ψ is empty and S contains all the subgoals in the logical plan. S will become smaller as more subgoals are removed from it. Let Γ denote the new cluster that would be generated in each round by adding more feasible subgoals.

Let B denote the cumulative set of bound variables in the process of finding clusters. Initially, B contains the set of variables that are bound in the logical plan. Using this B, PARTITION finds the set of subgoals that are answerable and collects them into Γ. When all the subgoals that are answerable at this stage have been added to Γ, this cluster is added to Ψ, and the bound variables of these subgoals are added to B. Given the new B, some new subgoals will become feasible in the second round, and they are put into the second cluster. This process is repeated until one of two cases happens:

1. No subgoals are left (S is empty), and we end up with a complete list of clusters.
2. Some subgoals are left in S, and no more new clusters can be formed.

In case 2, PARTITION declares that there is no feasible sequence for this logical plan. In case

The PARTITOIN Algorithm
Input: Logical plan – subgoals and bound variables.
Output: Feasible physical plan.

- Initialize:
  $S \leftarrow \{C_1, C_2, \ldots, C_n\}$ /* set of subgoals in the logical plan */
  $B \leftarrow$ set of bound variables in the logical plan
  $\Psi \leftarrow \phi$ /* start with the empty list of clusers */
- Phase 1: Construct the list of clusters ...
  while ($S \neq \phi$) do
    $\Gamma \leftarrow null$;
    for each subgoal C_i in S do
      if (C_i is answerable with B) then
        $\Gamma \leftarrow \Gamma \cup \{C_i\}$;
        $S \leftarrow S - \{C_i\}$
    If no next cluster, declare no feasible plan ...
    if ($\Gamma = null$) then
      return(ϕ);
    Add new cluster to the list of clusters ...
    $\Psi \leftarrow \Psi + \Gamma$;
    $B \leftarrow B \cup \{$ variables in subgoals of $\Gamma\}$;
- Phase 2: Construct the sequence of subgoals ...
  $L \leftarrow \phi$ /* start with an empty sequence */
  for each cluster Γ in Ψ do
    $L' \leftarrow$ the best subsequence of subgoals in Γ;
    $L \leftarrow L \mid\mid L'$;
- Return the feasible plan:
  return($Plan(L)$); /* construct plan from sequence L */

Figure 3: Algorithm PARTITION

1, PARTITION will perform its second phase to generate the best feasible plan. For each cluster of subgoals, the algorithm performs local optimization by trying all the possible permutations of these subgoals. Then it will combine all the local subplans and create the global plan for the user query.

EXAMPLE 4.1 Consider a logical plan with four subgoals:

$$H\ :-\ R(A,B),\ S(A,D),\ T(B,E),\ U(D,B)$$

Initially, assume no attribute in the query has been bound. Let there be four source relations to answer these subgoals:

$$R^{ff}(A,B), S^{bf}(A,D), T^{bf}(B,E), U^{bf}(D,B)$$

Since, each subgoal has a different predicate, we refer to the predicates (R, S, etc.) as subgoals. Let us consider the first phase of PARTITION. Initially, only one subgoal, R, is answerable. Therefore, the first cluster contains only subgoal R. After R is answered, variables A and B are bound. Then, subgoals S and T will both become feasible, and they are put into the second cluster. After S and T have been answered, variables D and E are also bound, and subgoal U becomes feasible. It is the only subgoal in the third cluster. So the clusters generated by PARTITION are: $< \{R\}, \{S,\ T\}, \{U\} >$.

In the second phase, PARTITION considers the two feasible subsequences in Γ_2, and picks the one with the lower cost, say $S \rightarrow T$. The plan output by PARTITION would be $R \rightarrow S \rightarrow T \rightarrow U$. Essentially, PARTITION considers two possible sequences: $R \rightarrow S \rightarrow T \rightarrow U$ and $R \rightarrow T \rightarrow S \rightarrow U$. □

4.2 Feasible Plan Generation

Lemma 4.1 *If feasible physical plans exist for a given logical plan, PARTITION is guaranteed to find a feasible plan.* □

Proof: If PARTITION fails to find a feasible plan, there must be some subgoals in the logical plan that are not answerable with respect to the set of variables that are initially bound or that occur in the other subgoals. If there is a feasible physical plan, it is not possible to have such unanswerable subgoals in the logical plan. Hence, PARTITION will not fail to find a feasible plan when feasible plans exist. ∎

Lemma 4.2 *If the number of clusters generated is less than 3, and the result of the query is not empty, then PARTITION will find the optimal plan.* □

Proof: We proceed by a simple case analysis. There are two cases to consider.

The first case is when there is only one cluster Γ_1. PARTITION finds the best sequence among all the permutations of the subgoals in Γ_1. Since Γ_1 contains all the subgoals of the logical plan, PARTITION will find the best possible sequence.

The second case is when there are two clusters Γ_1 and Γ_2. Let P be the optimal feasible plan. We will show how we can transform P into a plan in the plan space of PARTITION that is at least as good as P.

Let C_i be a subgoal in Γ_1. There are two possibilities:

1. C_i is answered in P by using a block query;

2. C_i is answered in P by using parameterized queries.

If C_i is answered by a block query, we make no change to P. Otherwise, we modify P as follows. As the result of the query is not empty, the cost of subgoal C_i (using parameterized queries) in P must be at least 1. Since C_i is in the first cluster, it can be answered by using a block query. So we can modify P by replacing the parameterized queries for C_i with the block query for C_i. Since the cost of a block query can be at most 1, this modification cannot increase the cost of the plan. For all subgoals in Γ_1, we repeat the above transformation until we get a plan P', in which all the subgoals in Γ_1 are answered by using block queries.

We apply a second transformation to P' with respect to the subgoals in Γ_1. Since all these subgoals are answered by block queries in P', we can move them to the beginning of P' to arrive at a new plan P''. Moving these subgoals ahead of the other subgoals will preserve the feasibility of the plan (see Lemma 2.4). It is also true that this transformation cannot increase the cost of the plan. This is because it does not change the cost of these subgoals, and it cannot increase the cost of the other subgoals in the sequence (see Lemma 2.5). Hence, P'' cannot be more expensive than P'.

After the two-step transformation, we get a plan P'' that is as good as the optimal plan. Finally, we note that P'' is in the plan space of PARTITION, and so the plan generated by PARTITION cannot be worse than P''. Thus, the plan found by PARTITION must be as good as the optimal plan. ∎

Lemma 4.3 *If the number of subgoals in the logical plan does not exceed 3, and the result of the query is not empty, then PARTITION will always find the optimal plan.* □

Proof: If the number of subgoals in the logical plan does not exceed 3, the number of clusters generated is at most 3. In Lemma 4.2, we proved that if the number of clusters is 1 or 2, PARTITION finds the optimal plan. Now, we show that in the case where there are three clusters with 1 subgoal each, PARTITION will find the optimal plan.

Without loss of generality, let the clusters generated be $\Gamma_1 = \{C_1\}$, $\Gamma_2 = \{C_2\}$, $\Gamma_3 = \{C_3\}$. Then the only feasible sequence of subgoals is (C_1, C_2, C_3), and this precisely is what PARTITION will output. ∎

It is not true that PARTITION can generate the optimal plan in all the cases. One can construct logical plans with as few as 4 subgoals that lead the algorithm to generate suboptimal plans. We also note that PARTITION can miss the optimal plan by a margin that is unbounded by the query parameters.

Lemma 4.4 *For any $k > 0$, there exists a logical plan and a database for which PARTITION generates a plan that is at least k times as expensive as the optimal plan.* □

Proof: Consider Example 4.1. Suppose the tables of the four sources are as shown in Table 2. PARTITION essentially considers two plans: $R \rightarrow S \rightarrow T \rightarrow U$, $R \rightarrow T \rightarrow S \rightarrow U$. In the first sequence: cost of R is 1, cost of S is 1, cost of T is 10000, cost of U is 1. So the cost of the first plan is 10003. For the second sequence: cost of R is 1, cost of T is 10000, cost of S is 1, cost of U is 1. So the cost of the second plan is 10003. PARTITION picks one of these two plans as the final physical plan with a cost of 10003.

Notice that after S has been answered, subgoal U becomes feasible. By answering U before T, all the tuples whose B value is not 2 will be filtered, so they don't need to be parameterized to answer subgoal T. Based on this, we can define the following plan: $R \rightarrow S \rightarrow U \rightarrow T$, in which cost of R is 1, cost of S is 1, cost of U is 1 and cost of T is 1, for a total cost of 4. But PARTITION misses this plan. Thus, the ratio of the cost of the PARTITION plan to the optimal cost is at least 10003/4. We can make this ratio arbitrarily large by having the appropriate number of tuples in R. Thus, PARTITION can generate plans that are k times as expensive as optimal plans, for any $k > 0$. ∎

$R^{ff}(A,B)$	$S^{bf}(A,D)$	$T^{bf}(B,E)$	$U^{bf}(D,B)$
(1, 1)	(1, 1)	(1, 1)	(1, 2)
(1, 2)			
(1, 3)			
...			
(1, 10000)			

Table 2: Proof of Lemma 4.4: Data of 4 Sources

Lemma 4.5 *The PARTITION algorithm runs in $O(n^2 + (k_1! + k_2! + \ldots + k_p!))$, where n is the number of subgoals in the logical plan, p is the number of clusters found by PARTITION and k_i is the number of subgoals in the i^{th} cluster.* [3] □

Proof: The first phase of PARTITION takes $O(n^2)$ time to generate the clusters. This is because there can be at most n rounds in the first phase and each round takes $O(n)$ time. In the second phase, for each cluster Γ_i, PARTITION tries all the permutations of the subgoals in the cluster, which takes $O(k_i!)$ time. Therefore, the total running time of PARTITION is $O(n^2 + (k_1! + k_2! + \ldots + k_p!))$. ∎

4.3 Variations of PARTITION

We have seen that the PARTITION algorithm can miss the optimal plan in many scenarios, and in the worst case it has a running time that is exponential in the number of subgoals in the logical plan. In a way, it attempts to strike a balance between running time and the ability to find optimal plans. A naive algorithm that enumerates all sequences of subgoals will always find the optimal plan, but it may take much longer than PARTITION. PARTITION tries to cut down on the running time, and gives up the ability to find optimal plans to a certain extent. Here, we consider two variations of PARTITION that highlight this trade-off.

We call the first variation FILTER. This variation is based on the observation of Lemma 4.2. FILTER is guaranteed to find the optimal plan (as long as the query result is nonempty), but its running time is much worse than PARTITION. Yet, it is more efficient than the naive algorithm that enumerates all plans.

FILTER also has two phases like PARTITION. In its first phase, it mimics PARTITION to arrive at the clusters $\Gamma_1, \Gamma_2, \ldots, \Gamma_p$. At the end of the first phase, it keeps the first cluster as is, and collapses all the other clusters into a new second cluster Γ'. That is, it ends up with Γ_1 and Γ'. The second phase of FILTER is identical to that of PARTITION.

Lemma 4.6 *If the user query has nonempty result, FILTER will generate the optimal plan.* □

Proof: We can prove this lemma in the same way we proved Lemma 4.2. ∎

Lemma 4.7 *The running time of FILTER is $O(n^2 + (k_1! + (n - k_1)!)$.* [4] □

[3] If the query result in nonempty, PARTITION can consider just one sequence (instead of $k_1!$) for the first cluster.

[4] If the query result in nonempty, FILTER can consider just one sequence (instead of $k_1!$) for the first cluster.

Proof: FILTER takes $O(n^2)$ time to generate all the clusters. It then takes an additional $O(n)$ time to merge clusters $\Gamma_2, \ldots, \Gamma_p$ into Γ'. Now, it will have two clusters Γ_1 with k_1 subgoals and Γ' with $(n-k_1)$ subgoals. In the second phase, FILTER tries all permutations of subgoals in Γ_1 and all permutations of subgoals in Γ'. This takes $O(k_1!)$ and $O((n-k_1)!)$ time, respectively. So the total running time of FILTER is $O(n^2 + k_1\,! + (n-k_1)!)$. ∎

The second variation of PARTITION is called SCAN. This variation focuses on efficient plan generation. The main idea here is to simplify the second phase of PARTITION so that it can run efficiently. The penalty is that SCAN may not generate optimal plans in many cases where PARTITION does.

SCAN also has two phases of processing. The first phase is identical to that of PARTITION. In the second phase, SCAN picks an order for each cluster without searching over all the possible orders. This leads to a second phase that runs in $O(n)$ time. Note that since it does not search over the space of subsequences for each cluster, SCAN tends to generate plans that are inferior to those of PARTITION.

Lemma 4.8 *SCAN runs in $O(n^2)$ time, where n is the number of subgoals in the logical plan.* □

Proof: The first phase of SCAN takes $O(n^2)$ like the first phase of PARTITION. The second phase takes $O(n)$ time. So the running time complexity of SCAN is $O(n^2)$. ∎

5 Performance Analysis

In this section, we address the following questions regarding the performance of CHAIN and PARTITION: How often do CHAIN and PARTITION find the optimal plan? When they miss the optimal plan, what is the expected margin by which they miss? We attempt to answer these questions by way of performance analysis of the algorithms in a simulated environment.

5.1 Simulation Parameters

In our experiments, we had a test bed of 15 sources, which participated in the integrated views on which user queries could be posed. The source size distribution was 30% small, 60% medium and 10% large. Each source in our test bed had two access templates, each requiring that a different attribute be bound.

We employed randomly generated user queries that created logical plans over a subset of the 15 sources in the test bed. We varied the subset size from 1 to 10. For each query, we computed the plans generated by the CHAIN algorithm and the PARTITION algorithm. We also exhaustively searched for the optimal plan for the query. The cost of the three plans was computed based on the model of Section 2.

5.2 Results of the Experiments

For each number of subgoals in the logical plan n, we generated 100 user queries, and studied the performance of the algorithms on these queries. Figure 4 plots the number of query subgoals (on

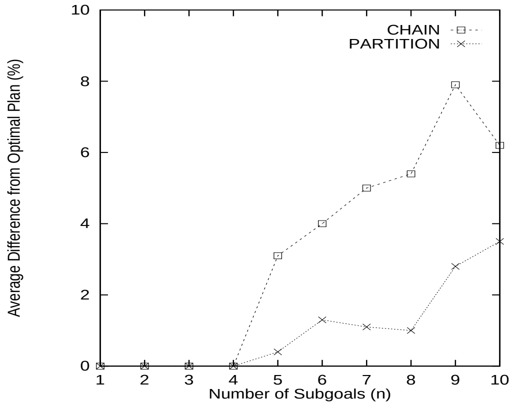
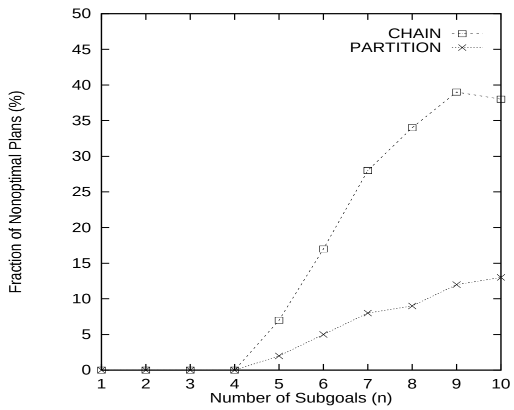
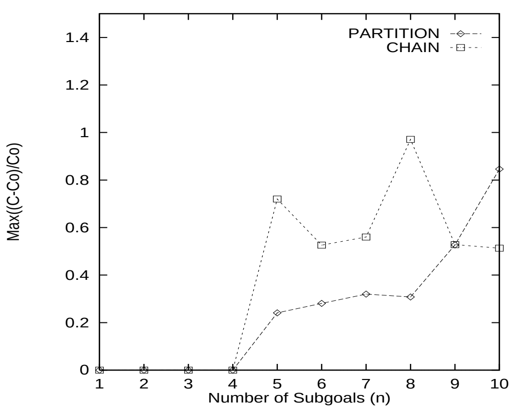


Figure 4: Average Cost



(a) Fraction of non-optimal plan



(b) Worst case miss

Figure 5: Optimality of Each Algorithm

the horizontal axis) vs. the average margin by which generated plans miss the optimal plan (on the vertical axis). Both CHAIN and PARTITION found near-optimal plans in the entire range of inputs (a total of 1000 randomly generated queries) and, on the average, missed the optimal plan by less than 10%.

Figure 4 also shows that as n increased, the average cost of the plan didn't necessarily increase. Even though this is a bit surprising, we realize that it is because more subgoals in a logical plan means more chances to choose some subgoals that have low cost, and thereby decrease the cost of other expensive subgoals.

We also conducted experiments that measured the fraction of the queries for which the algorithms found optimal plans, and the maximum margin by which the algorithms missed the optimal plans. The results of these experiments are shown in Figure 5.

Figure 5(a) shows how often CHAIN and PARTITION found optimal plans. Over the entire set of 1000 queries with n ranging from 1 to 10, CHAIN found the optimal plans more than 80% of the time, while PARTITION found the optimal plans more than 95% of the time. This result is surprising because we had proved in Section 3 that logical plans with as few as 3 subgoals can lead

CHAIN to miss the optimal plans, and logical plans with as few as 4 subgoals can lead PARTITION to suboptimal plans.

Figure 5(b) shows the largest margin by which CHAIN and PARTITION miss the optimal plans. In the worst case, over the 1000 queries, CHAIN generated a plan that was 1.95 times as expensive as the optimal plan; the worst case miss for PARTITION was a plan that was 1.5 times as expensive as the optimal plan. Once again, these results are surprising in that our theoretical results predicted that CHAIN can generate plans that cost as much as 10 times the optimal plan. We also proved that PARTITION can miss the optimal plan by an "unbounded" margin.

In summary, our experiments show that the PARTITION algorithm can have excellent practical performance, even though it gives very few theoretical guarantees. The CHAIN algorithm also has very good performance, well beyond the theoretical guarantees we proved in Section 3. Finally, comparing the two algorithms, we observe that PARTITION consistently outperforms CHAIN in finding near-optimal plans.

6 Other Cost Models

So far, we discussed algorithms that minimize the number of source queries. Now, we consider more complex cost models where different source queries can have different costs.

First, we consider a simple extension (say M_1) where the cost of a query to source S_i is e_i. That is, queries to different sources cost different amounts. Note that in M_1, we still do not charge for the amount of data transferred. Nevertheless, it is strictly more general than the model we discussed in Section 2. All of our results presented so far hold in this new model.

Theorem 6.1 *In the cost model M_1, Theorem 3.1 holds. That is, the CHAIN algorithm is n-competitive, where n is the number of subgoals.* □

Theorem 6.2 *In the cost model M_1, Lemma 4.2 holds. That is, the PARTITION algorithm will find the optimal plan, if there are at most two clusters and the user query has nonempty result.* □

Next, we consider a more complex cost model (say M_2) where the data transfer costs are factored in. That is, the cost of a query to source S_i is $e_i + f_i \times$ (size of query result). Note that this cost model is strictly more general than M_1.

Theorem 6.3 *In the cost model M_2, Theorem 3.1 holds. That is, the CHAIN algorithm is n-competitive, where n is the number of subgoals.* □

Theorem 6.4 *In the cost model M_2, Lemma 4.2 does not hold. That is, the PARTITION algorithm cannot guarantee the optimal plan, even when there are at most two clusters.* □

When considering other cost models that are more complex than the one presented in Section 2, we note that the problem of finding the optimal feasible plan remains $\mathcal{NP}$-hard. It is also clear that both CHAIN and PARTITION guarantee the generation of feasible plans (if they exist), irrespective of the cost model being considered. The only issue at hand is the ability of these algorithms to generate near optimal plans.

We observe that the n-competitiveness of CHAIN holds in any cost model with the following property: the cost of a subgoal in a plan does not increase by postponing its processing to a later time in the plan. Both M_1 and M_2 have this property and so CHAIN is n-competitive in those models. We also note that the PARTITION algorithm with two clusters will always find the optimal plan (assuming the query has nonempty result) if block queries cannot cost more than the corresponding parameterized queries. This property holds, for instance, in model M_1 and not in model M_2.

When one considers cost models other than those discussed here, the properties noted above may hold in those models and consequently CHAIN and PARTITION may yield very good results. Even when the properties do not hold, the strategies employed by the two algorithms may act as good heuristics and help them generate efficient plans. For instance, in the cost model M_2, PARTITION cannot guarantee the generation of optimal plans even when there are only two clusters. In our simulation experiments we studied the performance of PARTITION in this cost model and found that it continues to find plans that are very close to optimal.

7 Conclusion

In this paper, we considered the problem of query planning in heterogeneous data integration systems based on the mediation approach. We employed a cost model that focuses on the main costs in mediation systems. In this cost model, we developed two algorithms that guarantee the generation of feasible plans (when they exist). We showed that the problem at hand is $\mathcal{NP}$-hard. One of our algorithms runs in polynomial time. It generates optimal plans in many cases and in other cases it has a linear bound on the worst case margin by which it misses the optimal plans. The second algorithm finds optimal plans in more scenarios, but has no bound on the margin of missing the optimal plans in the bad scenarios. We analyzed the performance of our algorithms using simulation experiments and extended our results to more complex cost models.

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