Distributed Query Optimization by Query Trading

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Abstract. Large-scale distributed environments, where each node is completely autonomous and offers services to its peers through external communication, pose significant challenges to query processing and optimization. Autonomy is the main source of the problem, as it results in lack of knowledge about any particular node with respect to the information it can produce and its characteristics. Inter-node competition is another source of the problem, as it results in potentially inconsistent behavior of the nodes at different times. In this paper, inspired by e-commerce technology, we recognize queries (and query answers) as commodities and model query optimization as a trading negotiation process. Query parts (and their answers) are traded between nodes until deals are struck with some nodes for all of them. We identify the key parameters of this framework and suggest several potential alternatives for each one. Finally, we conclude with some experiments that demonstrate the scalability and performance characteristics of our approach compared to those of traditional query optimization.

1 Introduction

The database research community has always been very interested in large (intranet- and internet-scale) federations of autonomous databases as these seem to satisfy the scalability requirements of existing and future data management applications. These systems, find the answer of a query by splitting it into parts (sub-queries), retrieving the answers of these parts from remote "black-box" database nodes, and merging the results together to calculate the answer of the initial query [1]. Traditional query optimization techniques are inappropriate [2,3,4] for such systems as node autonomy and diversity result in lack of knowledge about any particular node with respect to the information it can produce and its characteristics, e.g., query capabilities, cost of production, or quality of produced results. Furthermore, if inter-node competition exists (e.g., commercial environments), it results in potentially inconsistent node behavior at different times.

In this paper, we consider a new scalable approach to distributed query optimization in large federations of autonomous DBMSs. Inspired from microeconomics, we adapt e-commerce trading negotiation methods to the problem. The result is a query-answers trading mechanism, where instead of trading goods, nodes trade answers of (parts of) queries in order to find the best possible query execution plan.

Motivating example: Consider the case of a telecommunications company with thousands of regional offices. Each of them has a local DBMS, holding customer-care (CC) data of millions of customers. The schema includes the relations `customer(`*`custid,`*` custname, office)`, holding customer information such as the regional office responsible for them, and `invoiceline(`*`invid,`*` linenum, custid, charge)`, holding the details (charged amounts) of customers' past invoices. For performance and robustness reasons, each relation may be horizontally partitioned and/or replicated across the regional offices. Consider now a manager at the Athens office asking for the total amount of issued bills in the offices in the islands of Corfu and Myconos:

```
SELECT SUM(charge) FROM invoiceline i, customer c
WHERE i.custid=c.custid AND office in ('Corfu','Myconos');
```

The Athens node will ask the rest of the company's nodes whether or not they can evaluate (some part of) the query. Assume that the Myconos and Corfu nodes reply positively about the part of the query dealing with their own customers with a cost of 30 and 40 seconds, respectively. These offers could be based on the nodes actually processing the query, or having the offered result pre-computed already, or even receiving it from yet another node; whatever the case, it is no concern of Athens. It only has to compare these offers against any other it may have, and whatever has the least cost wins.

In this example, Athens effectively *purchases* the two answers from the Corfu and Myconos nodes at a cost of 30 and 40 seconds, respectively. That is, queries and query-answers are commodities and query optimization is a common trading negotiation process. The buyer is Athens and the potential sellers are Corfu and Myconos. The cost of each query-answer is the time to deliver it. In the general case, the cost may involve many other properties of the query-answers, e.g., freshness and accuracy, or may even be monetary. Moreover, the participating nodes may not be in a cooperative relationship (parts of a company's distributed database) but in a competitive one (nodes in the internet offering data products). In that case, the goal of each node would be to maximize its private benefits (according to the chosen cost model) instead of the joint benefit of all nodes.

In this paper, we present a complete query and query-answers trading negotiation framework and propose it as a query optimization mechanism that is appropriate for a large-scale distributed environment of (cooperative or competitive) *autonomous* information providers. It is inspired by traditional e-commerce trading negotiation solutions, whose properties have been studied extensively within B2B and B2C systems [5,6,7,8, 9], but also for distributing tasks over several agents in order to achieve a common goal (e.g., Contract Net [10]). Its major differences from these traditional frameworks stem primarily from two facts:

– A query is a complex structure that can be cut into smaller pieces that can be traded separately. Traditionally, only atomic commodities are traded, e.g., a car; hence, buyers do not know *a priori* what commodities (query answers) they should buy.
– The *value* of a query answer is in general multidimensional, e.g., system resources, data freshness, data accuracy, response time, etc. Traditionally, only individual monetary values are associated with commodities.

In this paper, we focus on the first difference primarily and provide details about the proposed framework with respect to the overall system architecture, negotiation protocols, and negotiation contents. We also present the results of an extended number of simulation experiments that identify the key parameters affecting query optimization in very large autonomous federations of DBMSs and demonstrate the potential efficiency and performance of our method.

To the best of our knowledge, there is no other work that addresses the problem of distributed query optimization in a large environment of purely autonomous systems. Nevertheless, our experiments include a comparison of our technique with some of the currently most efficient techniques for distributed query optimization [2,4].

The rest of the paper is organized as follows. In section 2 we examine the way a general trading negotiation frameworks is constructed. In section 3 we present our query optimization technique. In section 4 we experimentally measure the performance of our technique and compare it to that of other relevant algorithms. In section 5 we discuss the results of our experiments and conclude.

2 Trading Negotiations Framework

A trading negotiation framework provides the means for buyers to request items offered by seller entities. These items can be anything, from plain pencils to advanced gene-related data. The involved parties (buyer and sellers) assign private valuations to each traded item, which in the case of traditional commerce, is usually their cost measured using a currency unit. Entities may have different valuations for the same item (e.g. different costs) or even use different indices as valuations, (e.g. the weight of the item, or a number measuring how important the item is for the buyer).

Trading negotiation procedures follow rules defined in a negotiation protocol [9] which can be bidding (e.g., [10]), bargaining or an auction. In each step of the procedure, the protocol designates a number of possible actions (e.g., make a better offer, accept offer, reject offer, etc.). Entities choose their actions based on (a) the strategy they follow, which is the set of rules that designate the exact action an entity will choose, depending on the knowledge it has about the rest of the entities, and (b) the expected surplus(utility) from this action, which is defined as the difference between the values agreed in the negotiation procedure and these held privately. Traditionally, strategies are classified as either *cooperative* or *competitive* (*non-cooperative*). In the first case, the involved entities aim to maximize the joint surplus of all parties, whereas in the second case, they simply try to individually maximize only their personal utility.

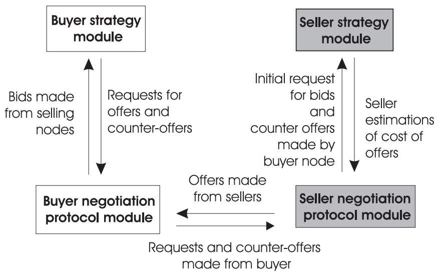

Buyer strategy module
Seller strategy module
Bids made from selling nodes
Requests for offers and counter-offers
Initial request for bids and counter offers made by buyer node
Seller estimations of cost of offers
Offers made from sellers
Buyer negotiation protocol module
Seller negotiation protocol module
Requests and counter-offers made from buyer

Fig. 1. Modules used in a general trading negotiations framework.

Figure 1 shows the modules required for implementing a distributed electronic trading negotiation framework among a number of network nodes. Each node uses two separate modules, a *negotiation protocol* and a *strategy* module (white and gray modules designate buyer and seller modules respectively). The first one handles inter-nodes message exchanges and monitors the current status of the negotiation, while the second one selects the contents of each offer/counter-offer.

3 Distributed Query Optimization Framework

Using the e-commerce negotiations paradigm, we have constructed an efficient algorithm for optimizing queries in large disparate and autonomous environments. Although our framework is more general, in this paper, we limit ourselves on select-project-join queries. This section presents the details of our technique, focusing on the parts of the trading framework that we have modified. The reader can find additional information on parts that are not affected by our algorithm, such as general competitive strategies and equilibriums, message congestion protocols, and details on negotiation protocol implementations in [5,6,11,12,13,7,8,9] and on standard e-commerce and strategic negotiations textbooks (e.g., [14,15,16]). Furthermore, there are possibilities for additional enhancements of the algorithm that will be covered in future work. These enhancements include the use of *contracting* to model partial/adaptive query optimization techniques, the design of a scalable *subcontracting* algorithm, the selection of advanced *cost functions*, and the examination of various *competitive and cooperative* strategies.

3.1 Overview

The idea of our algorithm is to consider queries and query-answers as commodities and the query optimization procedure as a trading of query answers between nodes holding information that is relevant to the contents of these queries. Buying nodes are those that are unable to answer some query, either because they lack the necessary resources (e.g. data, I/O, CPU), or simply because outsourcing the query is better than having it executed locally. Selling nodes are the ones offering to provide data relevant to some parts of these queries. Each node may play any of those two roles(buyer and seller) depending on the query been optimized and the data that each node locally holds.

Before going on with the presentation of the optimization algorithm, we should note that no query or part of it is physically executed during the whole optimization procedure. The buyer nodes simply ask from seller nodes for assistance in evaluating some *queries* and seller nodes make offers which contain their *estimated* properties of the answer of these queries (*query-answers*). These properties can be the total time required to execute and transmit the results of the query back to the buyer, the time required to find the first row of the answer, the average rate of retrieved rows per second, the total rows of the answer, the freshness of the data, the completeness of the data, and possibly a charged amount for this answer. The query-answer properties are calculated by the sellers' query optimizer and strategy module, therefore, they can be extremely precise, taking into account the available *network resources* and the *current workload* of sellers.

The buyer ranks the offers received using an administrator-defined weighting aggregation function and chooses those that minimize the total cost/value of the query. In the rest of this section, the valuation of the offered query-answers will be the total execution time (cost) of the query, thus, we will use the terms cost and valuation interchangeably. However, nothing forbids the use of a different cost unit, such as the total network resources used (number of transmitted bytes) or even monetary units.

3.2 The Query-Trading Algorithm

The execution plans produced by the query-trading (QT) algorithm, consist of the query-answers offered by remote seller nodes together with the processing operations required to construct the results of the optimized queries from these offers. The algorithm finds the combination of offers and local processing operations that minimizes the valuation (cost) of the final answer. For this reason, it runs iteratively, progressively selecting the best execution plan. In each iteration, the buyer node asks (Request for Bids -RFBs) for some queries and the sellers reply with offers that contain the estimations of the properties of these queries (query-answers). Since sellers may not have all the data referenced in a query, they are allowed to give offers for only the part of the data they actually have. At the end of each iteration, the buyer uses the received offers to find the best possible execution plan, and then, the algorithm starts again with a possibly new set of queries that might be used to construct an even better execution plan.

The optimization algorithm is actually a kind of bargaining between the buyer and the seller nodes. The buyer asks for certain queries and the sellers counter-offer to evaluate some (modified parts) of these queries at different values. The difference between our approach and the general trading framework, is that in each iteration of this bargaining the negotiated queries are different, as the buyer **and** the sellers progressively identify additional queries that may help in the optimization procedure. This difference, in turn, makes necessary to change selling nodes in each step of the bargaining, as these additional queries may be better offered by other nodes. This is in contrast to the traditional trading framework, where the participants in a bargaining remain constant.

Figure 2 presents the details of the distributed optimization algorithm. The input of the algorithm is a query q with an initially estimated cost of C_i. If no estimation using the available local information is possible, then C_i is a predefined constant (zero or something else depending on the type of cost used). The output is the estimated best execution plan P_* and its respective cost C_* (step B8). The algorithm, at the buyer-side, runs iteratively (steps B1 to B7). Each iteration starts with a set Q of pairs of queries and their estimated costs, which the buyer node would like to purchase from remote nodes. In the first step (B1), the buyer strategically estimates the values it should ask for the queries in set Q and then asks for bids (RFB) from remote nodes (step B2). The seller nodes after receiving this RFB make their offers, which contain query-answers concerning parts of the queries in set Q (step S2.1 - S2.2) or other relevant queries that they think it could be of some use to the buyer (step S2.3). The winning offers are then selected using a small nested trading negotiation (steps B3 and S3). The buyer uses the contents of the winning offers to find a set of candidate execution plans P_m and their respective estimated costs C_m (step B4), and an enhanced set Q of queries-costs pairs (q_e, c_e) (steps B5 and B6) which they could possibly be used in the next iteration of the algorithm for further improving the plans produced at step B4. Finally, in step B7, the best execution plan P_* out of the candidate plans P_m is selected. If this is not better than that of the previous iteration (i.e., no improvement) or if step B6 did not find any new query, then the algorithm is terminated.

As previously mentioned, our algorithm looks like a general bargaining with the difference that in each step the sellers and the queries bargained are different. In steps B2, B3 and S3 of each iteration of the algorithm, a complete (nested) trading negotiation

Buyer-side algorithm	**Sellers-side algorithm**
B0. Initialization, set $Q = \{\{q, C_i\}\}$	
B1. Make estimations of the values of the queries in set Q, using a trading strategy.	
B2. Request offers for the queries in set Q	
	S1. For each query q in set Q do the following:
	S2.1. Find sub-queries q_k of q that can be answered locally.
	S2.2. Estimate the cost c_k of each of these sub-queries q_k.
	S2.3. Find other (sub-)queries that may be of some help to the buyer node.
B3. Select the best offers $\{q_i, c_i\}$ using **one of the three** methods (bidding, auction, bargaining) of the query trading framework	S3. Using the query trading framework, make offers and try to sell some of the subqueries of step S2.2 and S2.3.
B4. Using the best offers, find possible execution plans P_m and their estimated cost C_m	
B5. Find possible sub-queries q_e and their estimated cost c_e that, if available, could be used in step B4.	
B6. Update set Q with sub-queries $\{q_e, c_e\}$.	
B7. Let P_* be the best of the execution plans P_m. If P_* is better than that of the previous iteration of the algorithm, or if step B6 modified the set Q, then go to step B1.	
B8. Inform the selling-nodes, which offered queries used in the best execution plan P_*, to execute these queries.	

Fig. 2. The distributed optimization algorithm.

is conducted to select the best seller nodes and offers. The protocol used can be any of the ones discussed in section 2.

3.3 Algorithm Details

Figure 3 shows the modules required for an implementation of our optimization algorithm (grayed boxes concern modules running at the seller nodes) and the processing workflow between them. As Figure 3 shows, the buyer node initially assumes that the value of query q is C_i, and asks its *buyer strategy* module to make a (strategic) estimation of its value using a traditional e-commerce trading reasoning. This estimation is given to the *buyer negotiation protocol* module that asks for bids (RFB) from the selling nodes. The seller, using its *seller negotiation protocol* module, receives this RFB and forwards it to the *partial query constructor and cost estimator* module, which builds pairs of a possible part of query q together with an estimate of its respective value. The pairs are forwarded to the *seller predicates analyser* to examine them and find additional queries (e.g., materialized views) that might be useful to the buyer. The output of this module (set of (sub-)queries and their costs) is given to the *seller strategy module* to decide (using again an e-commerce trading reasoning) which of these pairs is worth attempting to sell to the buyer node, and in what value. The *negotiation protocols* modules of both the seller and the buyer then run though the network a predefined trading protocol (e.g. bidding) to find the winning offers (q_i, c_i). These offers are used by the buyer as input to the *buyer query plan generator*, which produces a number of candidate execution plans P_m and their respective buyer-estimated costs C_m. These plans are forwarded to the *buyer*

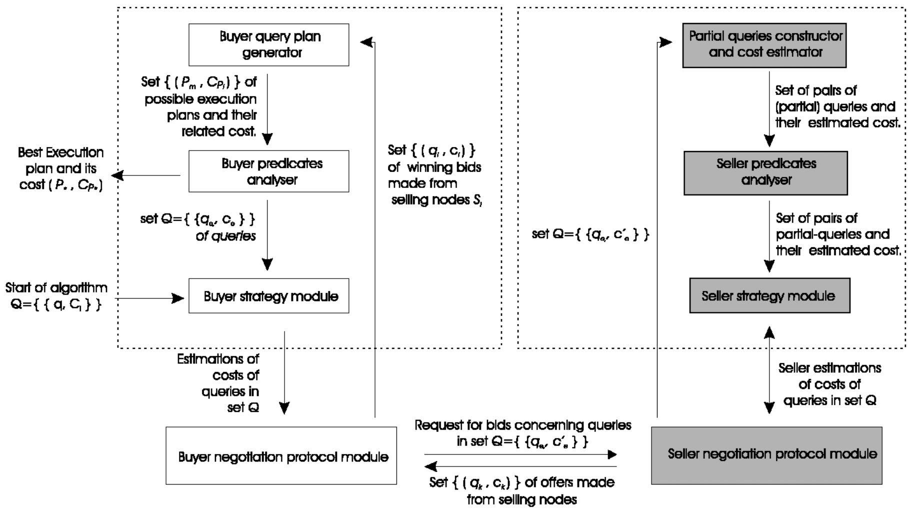

Buyer query plan generator
Set { (P_m , C_{P_i}) } of possible execution plans and their related cost.
Best Execution plan and its cost (P_* , C_{P_*})
Buyer predicates analyser
Set { (q_i , c_i) } of winning bids made from selling nodes S_i
set Q={ {q_e, c_e } } of queries
Start of algorithm Q={ { q, C } }
Buyer strategy module
Estimations of costs of queries in set Q
Buyer negotiation protocol module
Request for bids concerning queries in set Q={ {q_e, c'_e } }
Set { (q_k , c_k) } of offers made from selling nodes
Partial queries constructor and cost estimator
Set of pairs of (partial) queries and their estimated cost.
Seller predicates analyser
set Q={ {q_e, c'_e } }
Set of pairs of partial-queries and their estimated cost.
Seller strategy module
Seller estimations of costs of queries in set Q
Seller negotiation protocol module

Fig. 3. Modules used by the optimization algorithm.

predicates analyser to find a new set Q of queries q_e and then, the workflow is restarted unless the set Q was not modified by the *buyer predicates analyser* and the *buyer query plan generator* failed to find a better candidate plan than that of the previous workflow iteration. The algorithm fails to find a distributed execution plan and immediately aborts, if in the first iteration, the *buyer query plan generator* cannot find a candidate execution plan from the offers received.

It is worth comparing Figure 1, which shows the typical trading framework, to Figure 3, which describes our query trading framework. These figures show that the buyer strategy module of the general framework is enhanced in the query trading framework with a query plan generator and a buyer predicates analyser. Similarly, the seller strategy module is enhanced with a partial query constructor and a seller predicates analyser. These additional modules are required, since in each bargaining step the buyer and seller nodes make (counter-)offers concerning a different set of queries, than that of the previous step.

To complete the analysis of the distributed optimization algorithm, we examine in detail each of the modules of Figure 3 below.

3.4 Partial Query Constructor and Cost Estimator

The role of the partial query constructor and cost estimator of the selling nodes is to construct a set of queries q_k offered to the buyer node. It examines the set Q of queries asked by the buyer and identifies the parts of these queries that the seller node can contribute to. Sellers may not have all necessary base relations, or relations' partitions, to process all elements of Q. Therefore, they initially examine each query q of Q and rewrite it (if possible), using the following algorithm, which removes all non-local relations and restricts the base-relation extents to those partitions available locally:

Query rewriting algorithm

```
1. While there is a relation $R$ in query $q$ that is not available locally, do
1.1.  Remove $R$ from $q$.
1.2.  Update the SELECT-part of $q$ adding the attributes of the rest relations of $q$ that
       are used in joins with $R$.
1.3.  Update the WHERE-part of $q$ removing any operators referencing relation $R$.
1. End While
2. For each remaining relation $R$ in query $q$, do
2.1   Update the WHERE-part of $q$ adding the restriction operators of the partitions
      of $R$ that are stored locally.
2. End For
```

As an example of how the previous algorithm works, consider the example of the telecommunications company and consider again the example of the query asked by that manager at Athens. Assume that the Myconos node has the whole invoiceline table but only the partition of the customer table with the restriction `office='Myconos'`. Then, after running the query rewriting algorithm at the Myconos node and simplifying the expression in the WHERE part, the resulting query will be the following:

```
SELECT SUM(charge) FROM invoiceline i, customer c
WHERE i.custid=c.custid AND office='Myconos';
```

The restriction `office='Myconos'` was added to the above query, since the Myconos node has only this partition of the customer table.

After running the query rewrite algorithm, the sellers use their local query optimizer to find the best possible local plan for each (rewritten) query. This is needed to estimate the properties and cost of the query-offers they will make. Conventional local optimizers work progressively pruning sub-optimal access paths, first considering two-way joins, then three-way joins, and so on, until all joins have been considered [17]. Since, these partial results may be useful to the buyer, we include the optimal two-way, three-way, etc. partial results in the offer sent to the buyer. The modified dynamic programming (DP) algorithm [18] that runs for each (rewritten) query q is the following (The queries in set D are the result of the algorithm):

Modified DP algorithm

```
1. Find all possible access paths of the relations of $q$.
2. Compare their cost and keep the least expensive.
3. Add the resulting plans into set $D$.
3. For i=2 to number of joins in $q$, do
3.1.  Consider joining the relevant access paths found in previous iterations using all
       possible join methods.
3.2.  Compare the cost of the resulting plans and keep the least expensive.
3.3.  Add the resulting plans into set $D$.
3. End For
```

If we run the modified DP algorithm on the output of the previous example, we will get the following queries:

```
1. SELECT custid FROM customer
   WHERE office='Myconos';
2. SELECT custid,charge FROM invoiceline;
3. SELECT SUM(charge) FROM invoiceline i, customer c
   WHERE i.custid=c.custid AND office='Myconos';
```

The first two SQL queries are produced at steps 1-3 of the dynamic programming algorithm and the last query is produced in its first iteration (i=2) at step 3.3.

3.5 Seller Predicates Analyser

The seller predicates analyser works complementarily to the partial query constructor finding queries that might be of some interest to the buyer node. The latter is based on a traditional DP optimizer and therefore does not necessarily find all queries that might be of some help to the buyer. If there is a materialized view that might be used to quickly find a superset/subset of a query asked by the buyer, then it is worth offering (in small value) the contents of this materialized view to the buyer. For instance, continuing the example of the previous section, if Myconos node had the materialized view:

```
CREATE VIEW invoice AS
    SELECT custid, SUM(charge) FROM invoiceline
    GROUP by custid;
```

then it would worth offering it to the buyer, as the grouping asked by the manager at Athens is more coarse than that of this materialized view. There are a lot of non-distributed algorithms concerning answering queries using materialized views with or without the presence of grouping, aggregation and multi-dimensional functions, like for instance [19]. All these algorithms can be used in the seller predicates analyser to further enhance the efficiency of the QT algorithm and enable it to consider using remote materialized views. The potential of improving the distributed execution plan by using materialized views is substantial, especially in large databases, data warehouses and OLAP applications.

The seller predicates analyser has another role, useful when the seller does not hold the whole data requested. In this case, the seller, apart from offering only the data it already has, it may try to find the rest of these data using a subcontracting procedure, i.e., purchase the missing data from a third seller node. In this paper, due to lack of space, we do not consider this possibility.

3.6 Buyer Query Plan Generator

The query plan generator combines the queries q_i that won the bidding procedure to build possible execution plans P_m for the original query q. The problem of finding these plans is identical to the answering queries using materialized views [20] problem. In general, this problem is NP-Complete, since it involves searching though a possibly exponential number of rewritings.

The most simple algorithm that can be used is the dynamic programming algorithm. Other more advanced algorithms that may be used in the buyer plan generator include those proposed for the Manifold System (bucket algorithm [21]), the InfoMaster System (inverse-rules algorithm [22]) and recently the MiniCon [20] algorithm. These algorithms are more scalable than the DP algorithm and thus, they should be used if the complexity of the optimized queries, or the number of horizontal partitions per relation are large.

In the experiments presented at section 4, apart from the DP algorithm, we have also considered the use of the Iterative Dynamic Programming IDP-M(2,5) algorithm proposed in [2]. This algorithm is similar to DP. Its only difference is that after evaluating all 2-way join sub-plans, it keeps the best five of them throwing away all other 2-way join sub-plans, and then it continues processing like the DP algorithm.

3.7 Buyer Predicates Analyser

The buyer predicates analyser enriches the set Q (see Figure 3) with additional queries, which are computed by examining each candidate execution plan P_m (see previous subsection). If the queries used in these plans provide redundant information, it updates the set Q adding the restrictions of these queries which eliminate the redundancy. Other queries that may be added to the set Q are simple modifications of the existing ones with the addition/removal of sorting predicates, or the removal of some attributes that are not used in the final plan.

To make more concrete to the reader the functionality of the buyer predicate analyser, consider again the telecommunications company example, and assume that someone asks the following query:

```
SELECT custid FROM customer
WHERE office in (‘Corfu’, ‘Myconos’, ’Santorini’);
```

Assume that one of the candidate plans produced from the buyer plan generator contains the union (distrinct) of the following queries:

```
1a. SELECT custid FROM customer
    WHERE office in (‘Corfu’, ‘Myconos’);
2a. SELECT custid FROM customer c
    WHERE office in (‘Santorini’, ‘Myconos’);
```

The buyer predicates analyser will see that this union has redundancy and will produce the following two queries:

```
1b. SELECT custid FROM customer WHERE office=‘Corfu’;
2b. SELECT custid FROM customer WHERE office=‘Santorini’;
```

In the next iteration of the algorithm, the buyer will also ask for bids concerning the above two SQL statements, which will be used in the next invocation of the buyer plan generator, to build the same union-based plan with either query (1a) or (2a) replaced with the cheaper queries (1b) or (2b) respectively.

3.8 Negotiation Protocols

All of the known negotiation protocols, such as bidding, bargaining and auctions can be used in the query trading environment. Bidding should be selected if someone wishes to keep the implementation as simple as possible. However, if the expected number of selling nodes is large, bidding will lead to flooding the buying nodes with too many bids. In this case, a better approach is to use an agent based auction mechanism, since it reduces the number of bids. On the other hand, an auction may produce sub-optimal results if the bidders are few or if some malicious nodes form a *ring* agreeing not to compete against each other. The latter is possible, if our query trading framework is used for commercial purposes. This problem affects all general e-commerce frameworks and is solved in many different ways (e.g., [23]).

Bargaining, instead of bidding, is worth using only when the number of expected offers is small and minor modifications in the offers are required (e.g., a change of a single query-answer property), since this will avoid the cost of another workflow iteration. If major modifications in the structure of the offered queries are required, the workflow (by definition) will have to run at least one more iteration and since each iteration is actually a generalized bargaining step, using a nested bargaining within a bargaining will only increase the number of exchanged messages.

4 Experimental Study

In order to assert the quality of our algorithm (QT), we simulated a large network of interconnected RDBMSs and run a number of experiments to measure the performance of our algorithm. To the best of our knowledge, there is no other work that addresses the problem of distributed query optimization in large networks of purely autonomous nodes. Hence, there is no approach to compare our algorithm against on an equal basis with respect to its operating environment.

As a matter of comparison, however, and in order to identify the potential "cost" for handling true autonomy, we have also implemented the SystemR algorithm, an instance of the optimization algorithm used by the Mariposa distributed DBMS [4] and a variant of the Iterative Dynamic Programming (IDP) algorithm [2]. These are considered three of the most effective algorithms for distributed query optimization and serve as a solid basis of our evaluation.

4.1 Experiments Setup

Simulation parameters. We used C++ to build a simulator of a large Wide Area Network (WAN). The parameters of this environment, together with their possible values, are displayed in Table 1. The network had 5,000 nodes that exchanged messages with a simulated latency of 10-240ms and a speed of 0.5-4Mbits. Each node was equipped with a single CPU at 1200Mhz (on average) that hosted an RDBMs capable of evaluating joins using the nested-loops and the merge-scan algorithms. 80% of the simulated RDBMSs could also use the hash-join method. The local I/O speed of each node was not constant and varied between 5 and 20 Mbytes/s.

Table 1. Simulation parameters.

Parameter type	Parameter	Value
Network	Total size of Network (WAN)	5,000 nodes
	Minimum duration of each network message	1 ms
	WAN network packet latency	10 - 240ms (120 ms average)
	WAN interconnection speed	0.5 - 4Mbits/s
RDBMs	Join capabilities	Nested-loops, merge-scan and Hash-join
	Operators pipelining support	Yes
	CPU resources	One 700-1500 MHz CPU
	Sorting/Hashing buffer size	10,000 tuples
	I/O Speed per node	5-20Mbytes
Dataset	Size of relations	1-400,000 tuples
	Number of attributes per relation	20 attributes
	Number of partitions per relation	1-8
	Number of mirrors per partition	1-3
	Indices per partition per node	3 single-attribute indices
Workload	Joins per query	0 - 7
	Partitions per relation	1 - 8

The data-set used in the experiment was synthetically constructed. We constructed the metadata of a large schema consisting of 10,000 relations. There was no need to actually build the data since our experiments measured the performance of query optimization, not that of query execution. Each relation had 200,000 tuples on average and was horizontally range-partitioned in 1-8 disjoint partitions that were stored in possibly different nodes in such a way that each partition had 0-3 mirrors. The nodes were allowed to create 3 local indices per locally stored partition.

In order for the nodes to be aware of all currently active RFBs, we used a directory service using a publish-subscribe mechanism, since these are widely used in existing agent-based e-commerce platforms [13] and have good scalability characteristics. This type of architecture is typical for small e-commerce negotiation frameworks [24].

Query optimization algorithms. In each experiment, we studied the execution plans produced by the following four algorithms: SystemR, IDP(2,5), Mariposa, and Query Trading. More specifically:

SystemR. The SystemR algorithm [17] was examined as it produces optimal execution plans. However, it is not a viable solution in the large autonomous and distributed environments that we consider for two reasons. The first one is that it cannot cope with the complexity of the optimization search space. The second one is that it requires cost estimations from remote nodes. Not only this makes the notes not autonomous, but for a query with n joins, it will take n rounds of message exchanges to find the required information. In each round, the remote nodes will have to find the cost of every feasible k-way join (k=1..N), which quickly leads to a network bottleneck for even very small numbers of n.

We implemented SystemR so that we have a solid base for comparing the quality of the plans produced by the rest algorithms. Our implementation assumed that nodes running the algorithm had exact knowledge of the state of the whole network. This made possible running the algorithm without the bottleneck of network throughput, which would normally dominate its execution time.

IDP-M(2,5). Recently, a heuristic extension of the SystemR algorithm, the IDP-M(k,m), was proposed for use in distributed environments [2]. Therefore, we choose to include an instance of this algorithm in our study. Given an n-way join query, it works like this [2]: First, it enumerates all feasible k-way joins, i.e., all feasible joins that contain less than or equal to k base tables and finds their costs, just like SystemR does. Then, it chooses the best m subplans out of all the subplans for these k-way joins and purges all others. Finally, it continues the optimization procedure by examining the rest $n - k$ joins in a similar to SystemR way. The IDP algorithm is not suitable for autonomous environment as it shares the problems of SystemR mentioned above. For instance, for an n-way star join query ($k \ll n$), where each relation has p horizontal partitions ($p \geq 2$) each with M mirrors ($M \geq 2$), at least $O(M2^{p}mn^{k})$ plans [2] would have to be transmitted through the network.

Our implementation assume that nodes running the algorithm have exact knowledge of the state of the whole network and thus avoids the bottleneck of network throughput, which similar to SystemR, would normally dominate its execution time [2].

Mariposa. The Mariposa query optimization algorithm [25,26] is a two-step algorithm that considers conventional optimization factors (such as join orders) separately from distributed system factors (such as data layout and execution location). First, it uses information that it keeps locally about various aspects of the data to construct a locally optimal plan by running a local optimizer over the query, disregarding the physical distribution of the base relations and fixing such items as join order and the application of join and restriction operators. It then uses network yellow-pages information to parallelize the query operators, and a bidding protocol to select the execution sites, all in a single interaction with the remote nodes. The degree of parallelism is statistically determined by the system administrator before query execution and is independent of the available distributed resources.

The Mariposa System was initially designed to cover a large range of different requirements. In this paper, we implemented the Mariposa algorithm as described in [27] with the difference that in the second phase of the algorithm, the optimization goal was set to minimize the total execution time of the query, which is the task of interest in our experiments. We included Mariposa in our study as it is one of the fastest-running known algorithm for distributed query optimization. Nevertheless, it is not suitable for true autonomous environments as it requires information from nodes that harm their autonomy, such as their cost functions, their join capabilities, and information on the data and indices they have.

Query trading. We instantiated the Query Trading Algorithm using the following properties:

- For the Negotiation protocol, we choose the bidding protocol as the expected number of offered bids for each RFB was not large enough for an auction protocol to be beneficiary. We ranked each offer based only on the time required to return the complete query answer. In this way, our optimization algorithm produced plans that had the minimum execution time, reflecting the traditional optimization task.

- We used a plain cooperative strategy. Thus nodes replied to RFBs with offers matching exactly their available resources. The seller strategy module had a small buffer that held the last 1,000 accepted bids. These bids were collected from past

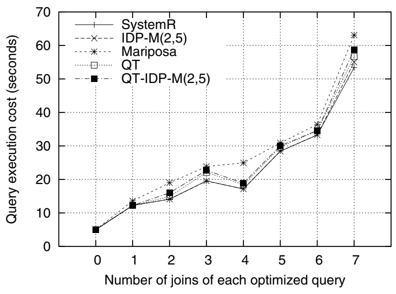
biddings that the node had participated in. Using the contents of this buffer, nodes estimated the most probable value of the offer that will win a bidding and never made offers with value more than 20% of this estimation. This strategy helped to reduce the number of exchanged messages.
- In the Buyer query plan generator we used a traditional answering queries using views dynamic programming algorithm. However, to decrease its complexity we also tested the plan generator with the IDP-M(2,5) algorithm.

Simulated scenarios. We initially run some experiments to assert the scalability of our algorithm in terms of network size. As was expected, the performance of our algorithm was not dependent on the total number of network nodes but on (a) the number of nodes which replied to RFBs and (b) the complexity of the queries. Thus we ended up running three sets of experiments: In the first set, the workload consisted of star-join queries with a varying number of 0-7 joins. The relations referenced in the joins had no mirrors and only one partition. This workload was used to test the behavior of the optimization algorithms as the complexity of queries increased. In the second set of experiments, we considered 3-way-join star-queries that referenced relations without mirrors but with a varying number of 1-8 horizontal partitions. This test measured the behavior of the algorithms as relations' data were split and stored (data spreading) in different nodes. Finally, in the last set of experiments we considered 3-way-join star-queries that referenced relations with three partitions and a varying number of mirrors (1-3). This experiment measured the behavior of the algorithms in the presence of redundancy.

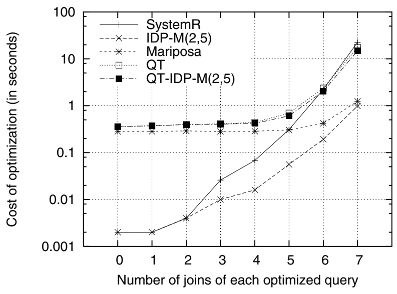
We run each experiment five times and measured the average execution time of the algorithms and the average plan cost of the queries, i.e., the time in seconds required to execute the produced queries as this was estimated by the algorithms. We should note that the execution times of SystemR and IDP are not directly comparable to those of other algorithms, as they do not include the cost of network message exchanges. The numbers presented for them are essentially for a non-autonomous environment with a centralized node for query optimization.

4.2 The Results

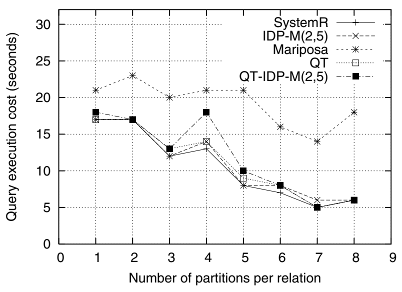
Number of joins. Figures 4(a) and 4(b) present the results of the first set of tests. The first figure presents the average execution cost of the plans produced by the SystemR, IDP(2,5), Mariposa and the two instances of the QT algorithm. It is surprising to see that even for such simple distributed data-sets (no mirrors, no partitions) all algorithms (except SystemR) fail to find the optimal plan (the deviation is in average 5% for IDP, 8% for QT and 20% for Mariposa)). As expected, IDP(2,5) algorithm deviates from the optimal plan when the number of joins is more than two. The Mariposa algorithm makes the largest error producing plans that require on average 20% more time than those produced by SystemR. This is because in its first phase of the optimization procedure, Mariposa is not aware of network costs and delays and thus, fails to find the best joins order for the base tables. The rest of the algorithms usually selected the proper joins order, taking into account that the delay caused by slow data sources may be masked if the joins related with these sources are executed last in the subplans pipeline. The



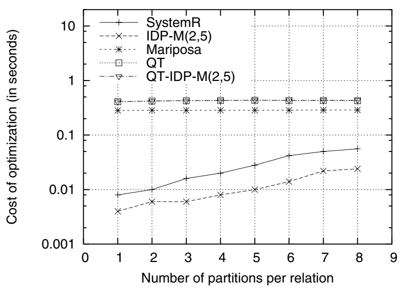
(a) Average execution cost of plans vs number of joins.



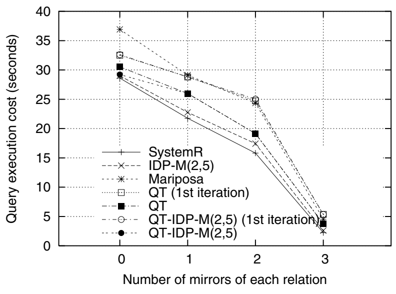
(b) Cost of optimization in seconds vs number of joins.



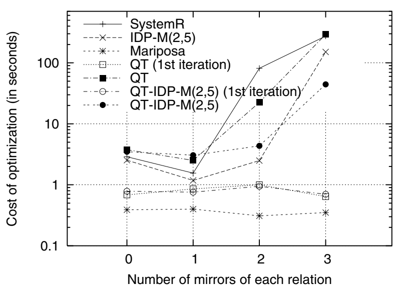
(c) Average execution cost of plans vs number of horizontal partitions.



(d) Cost of optimization in seconds vs number of horizontal partitions.



(e) Average execution cost of plans vs number of mirrors per partition.



(f) Cost of optimization in seconds vs number of mirrors per partition.

Fig. 4. Performance of various distributed query optimization algorithms.

QT-IDP-M algorithm produces plans that are only marginally inferior to those of plain QT.

The execution time (Figure 4(b)) of all algorithms depends exponentially on the number of joins. The QT, QT-IDP and Mariposa algorithms have a start-up cost of a single round of message exchanges (approx. 400ms and 280ms respectively) caused by the bidding procedure. The QT and QT-IDP algorithms never had to run more than one round of bids.

Data partitioning. Figures 4(c) and 4(d) summarize the results of the second set of experiments, which evaluate the algorithm as the partitioning and spreading of information varied. The first figure shows that the QT algorithm is little affected by the level of data spreading and partitioning. This was expected since the bidding procedure completely masks data spreading. The performance of the Mariposa algorithm is substantially affected by the level of data partitioning, producing plans that are up to three times slower than those of SystemR. This is because as the number of partitions increase, the chances that some remote partitions may have some useful remote indices (which are disregarded by Mariposa as each node has different indices) are increased. Moreover, Mariposa does not properly splits the join operators among the different horizontal partitions and nodes, as operators splitting is statically determined by the database administrator and not by the Mariposa algorithm itself.

The execution times of all algorithms depend on the number of relations partitions, as they all try to find the optimal join and unions orders to minimize the execution cost. Figure 4(d) shows the execution time of the QT, QT-IDP-M and Mariposa algorithm constant due to the logarithmic scale and the fact that the cost of the single bid round was much larger than that of the rest costs. Similarly to the previous set of experiments, the QT and QT-IDP-M algorithms run on average a single round of bids.

Data mirroring. Figures 4(e) and 4(f) summarize the results of the last set of experiments, where the level of data mirroring is varied. Data mirroring substantially increases the complexity of all algorithms as they have to horizontally split table-scan, join and union operators and select the nodes which allow for the best parallelization of these operators. The QT algorithm is additionally affected by data mirroring, as it has to run multiple rounds of bid procedures. On average, three rounds per query were run. For comparison reasons we captured the execution time and plan produced both at the end of the first iteration and at the end of the final one.

Figures 4(e) and 4(f) shows that although the first iteration of the QT algorithm completed in less than a second, the plans produced were on average the worse ones. Mariposa completed the optimization in the shortest possible time (less that 0.5s) and produced plans that were usually better than those produced in the first iteration of QT and QT-IDP, but worst than those produced in their last iteration. Finally, the best plans were produced by SystemR and IDP-M(2,5).

As far as the optimization cost is concerned, the SystemR, QT, and IDP-M(2,5) algorithms were the slowest ones. The QT-IDP-M algorithm was substantially faster than QT and yet, produced plans that were close to those produced by the latter. Finally, Mariposa was the fastest of all algorithms but produced plans that were on average up to 60% slower than those of SystemR.

5 Discussion

In large database federations, the optimization procedure must be distributed, i.e., all (remote) nodes must contribute to the optimization process. This ensures that the search space is efficiently divided to many nodes. The QT algorithm cleverly distributes the optimization process in many remote nodes by asking candidate sellers to calculate the cost of any possible sub-queries that might be useful for the construction of the global plan. Network flooding is avoided using standard e-commerce techniques. For instance, in our experiments, the strategy module disallowed bids that had (estimated) few chances of being won. The degree of parallelism of the produced distributed execution plans is not statically specified, like for instance in Mariposa, but is automatically found by the DP algorithm run at the buyer query plan generator. Nevertheless, the results of the experiments indicated that the bidding procedure may severely limit the number of possible combinations.

The SystemR and IDP-M centralized algorithms attempt to find the best execution plan for a query by examining several different solutions. However, the results of the experiments (even when not counting network costs) show that the search space is too large. Thus, SystemR and IDP-M are inappropriate for optimizing (at run-time) queries in large networks of autonomous nodes when relations are mirrored and partitioned. For these environments, the Mariposa algorithm should be used for queries with small execution times, and the QT and QT-IDP algorithms should be selected when the optimized queries are expected to have long execution times.

The Mariposa algorithm first builds the execution plan, disregarding the physical distribution of base relations and then selects the nodes where the plan will be executed using a greedy approach. Working this way, Mariposa and more generally any other two-step algorithm that treats network interconnection delays and data location as second-class citizens produce plans that exhibit unnecessarily high communication costs [3] and are arbitrarily far from the desired optimum [25]. Furthermore, they violate the autonomy of remote nodes as they require all nodes to follow a common cost model and ask remote nodes to expose information on their internal state. Finally they cannot take advantage of any materialized views or advanced access methods that may exist in remote nodes.

The QT algorithm is the only one of the four algorithms examined that truly respects the autonomy and privacy of remote nodes and. It treats them as true black boxes and runs without any information (or assumption) on them, apart from that implied by their bids.

6 Conclusions and Future Work

We discussed the parameters affecting a framework for trading queries and their answers, showed how we can use such a framework to build a WAN distributed query optimizer, and thoroughly examined its performance characteristics.

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