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Multi-objective query optimization in Spark SQL

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ABSTRACT

Query optimization is a challenging process of DBMSs. When tackling query optimization in the cloud, there exists a simultaneous need of providing an optimal physical query execution plan, as well as an optimal resource configuration among available ones. Cloud computing features like resource elasticity and pricing make the process of finding this optimal query plan a multi-objective problem, with the monetary cost being an equally important factor to query execution time. Apache Spark is a popular choice for managing big data in the cloud. However, query optimization in its SQL module (Spark SQL) involves a number of limitations due to the rule-based nature of its optimizer, Catalyst. We propose a multi-objective cost model for the extension of the query optimizer of Apache Spark, aiming to minimize both objectives of query execution time and monetary cost, as well as a methodology for exploring the space of Pareto-optimal query plans and selecting one. The cost model is implemented and tuned, and an experimental study is conducted to validate its accuracy.

CCS CONCEPTS

• Information Systems → Query optimization; • Parallel data processing → Apache Spark.

KEYWORDS

query optimization, cost model, cloud computing, multi-objective optimization, Apache Spark, Catalyst optimizer

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1 INTRODUCTION

Query optimization is the most challenging step of query processing. A query optimizer can either be rule-based, using heuristics to convert the logical query plan to a physical one, or cost-based, using cost functions to compare alternative query plans and return

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the optimal according to its estimations. The architecture of a cost-based query optimizer consists of 3 key stages that determine the quality of its predictions [7]: cardinality estimation, cost modeling and plan enumeration.

The majority of works on query optimization aim to minimize query execution time on a fixed hardware configuration, which is a valid assumption in the on-premise world. Query processing in the Cloud, however, presents an extra challenge as a number of alternative hardware instances are available. Depending on the resource configuration that is used, the execution might be completely different. Decision making involves deciding on the type of the cluster (homogeneous or heterogeneous), the number of instances that will be used, their type, and their characteristics (e.g. RAM size). In such a scenario, a query optimizer should be able to pick both an optimal physical query execution plan, as well as a resource configuration among available hardware instances, thus bridging the gap between query and resource optimization [15].

In order to achieve this, optimizer cost models should be hardware-agnostic, being able to model the behaviour of a query plan in different clusters and systems. A hardware-agnostic cost model could lead to lower costs as well as better resource efficiency [11].

Query optimization is usually associated with minimizing query execution time. The performance of a query, however, can be evaluated in terms of more objectives. Features of the cloud, like resource elasticity and pricing increase the objectives that can be simultaneously optimized in a cloud setting. Adding instances to achieve maximum parallelization during query execution will in general lead to lower execution times, but may also lead to much higher monetary costs, as well as increased energy consumption. Monetary cost is one of the most prevalent query optimization objectives in the cloud [6, 8, 12]. Energy consumption has also been considered lately [10], as cloud providers yearn for reducing energy cost. Other objectives that can be considered in multi-objective query optimization are result precision [13], or data security.

Query optimization in big data systems, which are usually hosted in the cloud, is particularly challenging. As a result, it is necessary that the estimation components of query optimizers (cardinality estimator, cost model) are accurate. One of the most popular big data processing frameworks is Apache Spark, which is widely used in research and industry. However, the query optimizer of Spark’s SQL-based component, Spark SQL, has a limited cost model.

In this work, we propose a multi-objective cost model for Spark SQL. In order to achieve this, we re-implement an existing proposed cost model [2] for Spark SQL which shows promising accuracy in estimating query execution time. We validate its accuracy and extend it to provide estimations for the monetary cost of a given query plan.

The cost model receives a query and a set of Spark application configurations as an input, and returns the optimal query plans for each configuration, resulting in a Pareto front. The returned plans present different tradeoffs for the two objectives, and the user can either pick one or assign preference weights to the two objectives, and be provided with a single query plan that best meets them.

We also conduct an experimental study to validate the cost model estimation and prediction accuracy for a Spark-Yarn-HDFS architecture. We conducted our experiments on a real private cloud environment, using data and queries from the TPC-H benchmark.

Overall, the contributions of this work are the following:

- proposal of a multi-objective cost model for Spark SQL
- a user-interactive method for exploring the space of alternative query plans and choosing an optimal one
- reimplementing and extending a state of the art cost model
- a detailed experimental study on a real private cloud environment

The rest of this paper is organized as follows. Related work is discussed in Section 2. Section 3 describes the cost model that we implemented. The experimental evaluation and its results follow in Section 4, while Section 5 concludes the paper.

2 RELATED WORK

Optimization in Spark The Spark SQL query optimizer, Catalyst [1], is an extensible optimizer which can be extended with new rules. However, it is not ideal for cost-based query optimization. It only uses a limited cost model, being unable to provide analytical estimations for the execution time of a query plan. A number of research works have focused on improving specific limitations of the Catalyst optimizer [3, 14].

In 2018, Baldacci and Golfarelli proposed a cost model for Spark SQL [2], which showed promising results for the set of GPSJ queries, as it estimates their execution time with less than 20% error. It is a proposed improvement to the Catalyst optimizer which, as its authors state, is a first step into turning the Catalyst into a fully cost based optimizer. The cost model was not integrated into the Catalyst itself, but was evaluated manually. It includes a cardinality estimation technique, and it is also hardware and cluster-agnostic.

Although Spark is highly configurable, its manual tuning is time consuming and complex, due to the high-dimensional configuration space. A lot of works provide frameworks for tuning Spark applications [9, 12, 16], in most cases with learned methods. The proposed cost model can be useful in this perspective too, as apart from producing optimal query plans, it can also be used for tuning and comparing different application configurations.

Multi-objective query optimization Karampaglis et al. [4] proposed a bi-objective query cost model suitable for query optimization over a multi-cloud environment. It successfully provides estimates of both the expected execution time and monetary cost.

A number of works have considered multi-objective query optimization in the cloud. Killapi et al. [5] proposed a technique to optimize dataflow scheduling on a set of containers and form one schedule best meeting user constraints. Their work can also be used for query optimization, when the execution of a query can happen over multiple containers. Multi-objective parametric query optimization [13] takes a different approach to query optimization,

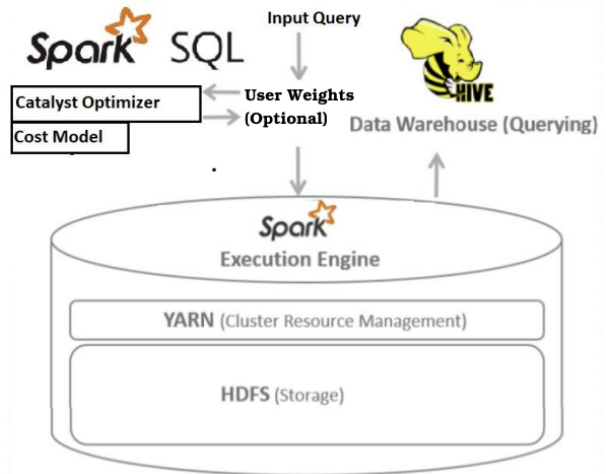


Figure 1: System architecture

	Catalyst C.M.	Proposed C.M.
Query types	ALL	GPSJ
Cost based join selection	YES	YES
Tables and Columns statistics	YES	YES
Considers cluster topology	NO	YES
Based on system disk access time	NO	YES
Takes into account network speed	NO	YES
Analytic estimation of QET	NO	YES

Table 1: Comparison of Catalyst and proposed cost model

which happens before runtime with the use of an exhaustive DP algorithm, and models queries as functions of parameters.

3 COST MODEL AND IMPLEMENTATION

In this work, we propose a cost model for cost-based multi-objective query optimization in Apache Spark. The cost model is based on a proposed cost model for Spark SQL [2], which is reimplemented, experimentally evaluated, and extended to include a formula for the estimation of the monetary cost of query plans. By using the extended cost model, the query optimization problem is tackled as a multi-objective optimization (MOO) problem aiming to minimize monetary cost together with query execution time, and using different methods to explore the space of Pareto-optimal query plans.

3.1 System Architecture

Figure 1 shows the system upon which the cost model operates. The storage layer includes a number of datanodes inside an HDFS filesystem. Data is processed in Spark, and Yarn is the resource negotiator between HDFS and Spark. For data management, data is stored in Apache Hive tables and accessed through Spark SQL queries. As for the optimizer, we envision an extended version of the Catalyst, operating cost-based by using the proposed cost model. We implemented the cost model outside Spark and used it manually.

3.2 Cost Model Preliminaries

The proposed Spark SQL cost model [2] can provide more than Catalyst when it comes to estimating the execution time for a query execution plan, as highlighted by Table 1. It is based on disk access time and network speed, as disk and network performance is critical in one-pass workloads, like Spark SQL queries. This means that it is a reconfigurable model, that can be tuned for any cluster (as long as it is homogeneous) and system. It also performs traditional SQL optimizations by collecting table and columns statistics from the database. It is also aware of the cluster topology, and takes into account Spark application parameters that influence query execution time. The Spark application parameters considered are the number of Spark executors, and the number of cores inside each executor.

One of its limitations is that it only covers the class of Generalized Projection, Selection, and Join (GPSJ) queries, which are a subset of SQL queries. This means that the use of specific SQL operators like UNION ALL or OUTER JOIN are not supported by the cost model. In addition to that, it is also limited to homogeneous clusters, not being able to make estimations for clusters involving different computing instances.

The cost model is capable of analytically estimating the execution time of the five essential RDD transformations that occur in Spark SQL GPSJ queries: (1) Full table scan (2) Full table scan and broadcast (3) Shuffle hash join (4) Broadcast hash join (5) Group by. Each of the transformations is modeled as a function, in the cost model code. Precisely modeling these operations is challenging, so the cost model focuses on a set of basic bricks that determine transformations and actions cost, for which it provides cost estimates (Read, Write, Shuffle Read, Broadcast). Each one of these functions receives a data table set as an input (or two, in case of a join operator), as well as the table’s cardinality, size, partitions and any filtering predicates. It returns the estimated time needed to execute the transformation, the columns returned, the cardinality and the adjusted size of the table set, as well as the number of partitions of the output. The estimated execution time for a query is obtained by summing up the time needed to execute each RDD transformation forming the query physical plan.

3.3 Bi-objective cost model

In the Spark-Yarn-HDFS architecture, query execution involves two parts. A user submits a query, and then specifies some parameters to configure the Spark application. Spark application tuning usually occurs manually and empirically and is a complex decision to make, as Spark has a considerable number of parameters that can be configured. One of the most critical parameters is the number of executors that will be allocated for an application. Each Spark executor runs within a Yarn container. Yarn containers are provided by Yarn on demand at the start of each Spark Application. Each one hosts a Spark executor as well as a number of cores that are assigned to it. They are deallocated when the Spark application completes.

If the Spark application were to be deployed on a public cloud, assigning each executor on a different computing instance would allow us to benefit from maximum parallelization. It would require renting a number of homogeneous computing instances from a

public cloud provider, using them during the runtime of a query and leasing them when execution is completed. The monetary cost of running a Spark application with 4 executors and 4 cores on each executor in a 4-node cluster in a public cloud is equivalent with the cost of renting 4 homogeneous computing instances with 4 vCPUs each, for the time needed for the query to execute.

As a result, we model the monetary cost of a query plan with the following formula:

$$cost = \#executors * runtime * ec2cost(\$/hour)/3600 \quad (1)$$

with $ec2cost$ being the hourly cost of using a given instance on Amazon EC2, which we divide by 3600 to scalarize it to seconds. If we use two a1.xlarge instances, for example, we can simulate the execution of a Spark query with 2 executors and 4 cores (a1.xlarge includes 4 vCPUs). The formula assumes per-second billing.

3.4 Query plan enumeration

For a given query, the cost model is able to compare all valid query plans. In our case, two alternative join operators were available and we considered all their combinations, as well as all possible join orderings. We based our monetary cost estimations on the price of renting an a1.medium instance from Amazon EC2, considering cases of renting a different number of a1.medium instances, ranging from 1 to 8. The cost model is easily extensible therefore prices for more computing instance types can be included and different cluster and application scenarios can be compared, as long as the cluster is homogeneous. As a result, our search space for a query involving 3 join operators involved 2^3 join operator combinations, $3!$ join orderings, and 8 available application configurations, involving a different number of computing instances each time. We assumed that one Spark executor is allocated for each computing instance, resulting in a search space of $8*6*8=384$ query plans. Understandably, the search space can become extremely large for more complex queries. The search space can be reduced significantly if we assume that join ordering happens optimally, as the most recent Catalyst version can make cost-based join ordering decisions. A further reduction can be achieved by not considering query plans involving broadcast hash joins for joins involving table sets whose size exceeds a specific threshold, as well as the opposite, considering only broadcast hash joins for trivial cases, where a table set joined is considerably small. Applying these 2 steps can lead to a significant reduction of the search space.

In the experimental part, we also had to overcome the limitation of Catalyst returning a single query plan and not providing alternatives, which we did by reconfiguring certain configuration parameters (disabling broadcast joins, changing broadcast joins thresholds). This allowed us to produce and compare many query plans.

3.5 Multi-objective optimization

We follow a two-step process to achieve multi-objective optimization. In the first step, we apply single-objective optimization, to find the optimal query plan in terms of execution time for every one of the available system configurations. A single query plan is returned for each available Spark configuration. The point of this step is that as the monetary cost of the query is dependent on query execution

time, the fastest plan will also be the cheapest, for a fixed computing instance and a fixed number of Spark executors. Thus, the different tradeoffs are offered by the alternative configurations, and not by alternative query plans inside a certain application setting.

The second step is the multi-objective optimization one, as all the query plans from the first step are compared in terms of both objectives. Dominated plans are discarded, and the remaining, Pareto-optimal plans are the output of the cost model, forming a Pareto front. The query plan that will be selected will determine both the physical query plan that will be used for query execution, as well as the application configuration in Spark.

After the Pareto front is formed, the final step is the decision process, which will happen by the user. As the number of alternative query plans can be quite large, the process of visualizing the alternatives to the user, and assisting him/her to make a decision is another challenge.

The user can pick a query plan that best meets his/her needs. In order to reduce the number of alternatives, he/she can set maximum price and latency filters to adjust to his/her budget and needs. The cost model can also be used in the user-interactive mode. In this mode, the user submits preference weights to the objectives and the cost model returns a single plan best meeting them, having scalarized the problem back to a single-objective one, using a simple equation.

$$F(x) = w_1 * f_1(x) + w_2 * c * f_2(x) \quad (2)$$

where c is a constant that we set to an empirical value of 25000, used to normalize the values of time and money to the same order of magnitude. In that case, 25 seconds of query execution are equivalent with a monetary cost of 0.001 US dollars. In our experiments, execution time varied between 50-400 seconds depending on the query and configuration, and monetary cost between 0.001 - 0.01 US dollars per query, so in case no objective is weighted, a query plan near the middle of the Pareto curve is selected. The query plan that has the minimum value for F , is the one selected for execution. Before the user submits the preferred weights, he/she can also be provided with a value showing the time-money relationship for the weights he/she has selected.

4 EXPERIMENTAL EVALUATION

Methodology The cost model makes the following assumptions, which our work inherited too:

- It covers the class of GPSJ queries
- It assumes uniform distribution of data in table sets
- It performs single query optimization, assuming a cold start
- It assumes operating on a homogeneous cluster

We evaluated the cost model for a main-memory scenario, assuming that all data fits in memory, as well as intermediate results. We also assumed exclusion of exogenous factors potentially affecting cluster performance, and we calculated a Spark-Yarn initialization overhead in each query, which we did not take into account.

For the evaluation of the cost model, we follow a two step methodology. First, we examine the estimation accuracy of the cost model. Second, we evaluate the optimality of the cost model, aiming to see if it can point to an optimal query plan among alternatives.

The cost model can be used to produce a Pareto front, including plans that offer different time-money tradeoffs. The decision maker

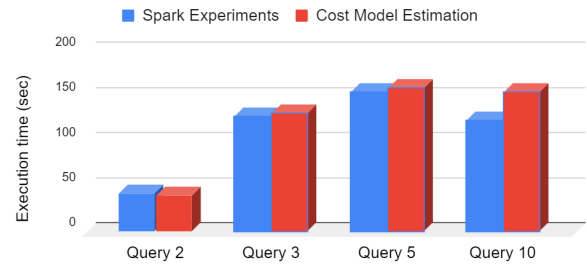


Figure 2: Execution time for different TPC-H queries

can choose the query plan that best suits his/her needs or can use the cost model in a user-interactive mode, and assign weights to the objectives, in order to be provided with a single query plan.

Setup We conducted our experiments in Grid ’5000 [], a large-scale and flexible platform for experiment-driven research in computer science, with a focus on parallel and distributed computing.

In our experiments Grid ’5000 was used as a private cloud, where we deployed up to 8 homogeneous computing nodes, each one containing 2 CPUs Intel Xeon E5-2630 v3, 8 cores/CPU, 128GB RAM, 5x558GB HDD, 186GB SSD, and 2 x 10Gb Ethernet. Inside our cluster, we set up an HDFS filesystem where each node worked as a datanode, and our dataset was stored in the SSDs.

Experimental Evaluation The cost model was reimplemented using the formulas described in the original paper to model each one of the five RDD transformations. For our experiments and estimations we used the TPC-H benchmark dataset and queries. The performance of the cost model was validated, when it comes to taking into account the impact of different factors. This allowed us to fine-tune the cost model for our system configuration, and also re-evaluate it and observe its strengths and inaccuracies. Figure 2 shows its performance for a number of TPC-H queries (7.7% error) in a scenario with 4 Spark executors and 4 executor cores. The estimations are quite accurate with the exception of Query 10, where there is a 20% overestimation error. After breaking down the query, which involves 5 tables and 4 join operations, we realize that the key overestimation occurs in the final broadcast join, which runs quicker than expected. Figure 3 shows that the cost model is also able to capture the impact adding Spark executors has for query execution, with an error rate of 12.1%. The query execution time values are an average of a set of TPC-H queries’ execution time. A more detailed evaluation of the cost model estimation accuracy can be found in the diploma thesis, upon which this paper is based [].

Inaccuracies mainly have to do with the fact that the cost model does not precisely model Spark data actions and transformations, but only provides estimates on key operations. Furthermore, in some cases it assumes linear relations between different factors not considering heuristics or overkills that occur in Spark. Finally, stochastic processes happening in the cluster might be influencing system characteristics like the read/write throughput or the network speed, causing minor inaccuracies. Tuning the cost model for a given cluster was a challenging task.

In terms of optimality (prediction accuracy), the cost model is able to make correct choices for trivial cases. For complex queries, when it did not point to the optimal plan, it was able to at least spot the trends and propose a near-optimal query plan, having small

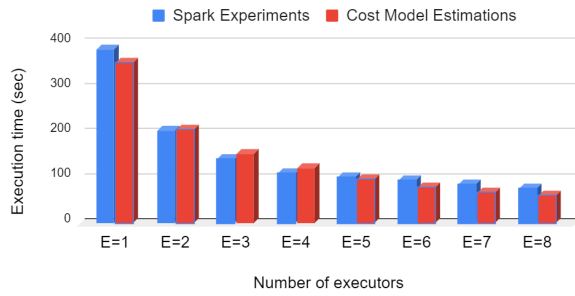


Figure 3: Query Execution times for different number of Spark executors

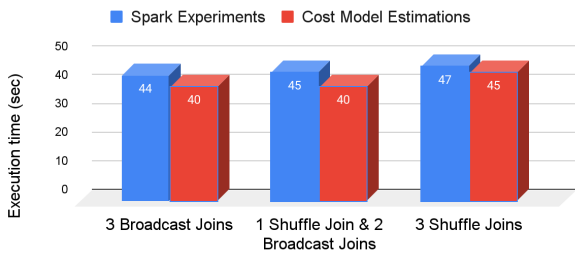


Figure 4: Execution times for three alternative TPC-H Query 2 query plans

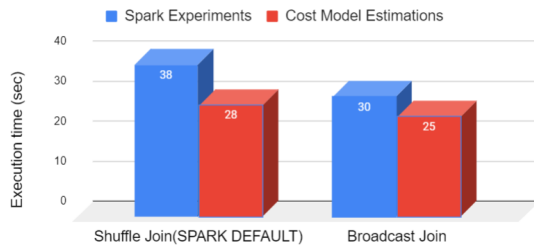


Figure 5: The cost model corrects the Catalyst

impact in query execution time. Figure 4 shows the performance of the cost model when it comes to comparing 3 good enough query plans for TPC-H Query 2, for a configuration involving 4 Spark executors and 4 executor cores. As the table sets considered in Query 2 are quite small, the query plan involving only broadcast joins performs slightly better than the alternatives. Shuffle joining in every case results in a slightly worse execution time, whereas operating the first join with a shuffle join operator and the other two with a broadcast one has similar execution time with the optimal case. The cost model gives equally good estimates for the two best execution plans.

In comparison with the Catalyst, it is able to make better choices than the Spark SQL optimizer in many cases. For example, for a very simple query involving just a join operation (Fig. 5), we can see that a broadcast hash join is a better choice, as it results in an 8 seconds faster query execution than using a shuffle hash join. However, the Catalyst will by default choose to shuffle join these tables. The cost model is able to point to the broadcast hash join as the better option. In the experimental study, the cost model proved that it can be a "relevant first step for turning Catalyst into a fully cost based optimizer", showing significant estimation accuracy while

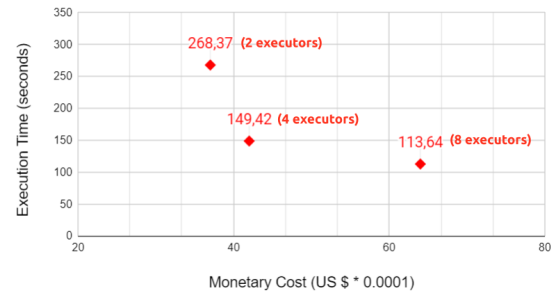


Figure 6: Pareto Front of the optimal query plans

staying on point when it comes to optimality, and comparison of alternative query plans.

When it comes to performing multi-objective optimization, Figure 6 shows the outcome of the extended cost model for a scenario with 3 alternative Spark application configurations with a varying number of executors (2,4 and 8), and 4 executor cores.

The cost model returns the fastest query plan for each application configuration, and then the plans are compared in terms of both objectives. In that case, all three query plans are Pareto optimal and form a Pareto front, as they present different time-money tradeoffs. Thus, the problem is formulated to a multi-objective optimization one. The user can either decide himself/herself which query plan best fits his/her application, or can assign weights of preferences to the objectives in the user-interactive mode of the cost model. For the case of $w_1 = w_2$, the plan with the 4 executors is picked. In case of $w_1 = 2 * w_2$, the plan with the 8 executors is picked, and in case of $w_2 = 2 * w_1$ the selected plan is the one with 2 executors, as the time-money relationship changes each time.

5 FUTURE WORK - CONCLUSION

In the future, we aim to extend the cost model to consider heterogeneous resources. This will require modeling the execution costs on different hardware, like GPUs. We also aim to explore more optimization goals, like energy consumption, which is a critical objective in green and sustainable data centers. Finally, a long term goal is to try to integrate the cost model into the Catalyst.

In this paper we proposed a multi-objective cost model for query optimization in Spark SQL. We built on a proposed cost model that showed promising results, which we extended by introducing a formula for estimating the monetary cost of query plans in Spark. The cost model is able to produce and compare query plans providing different time-money tradeoffs, and we also introduce a method for assisting the user into picking a single one. The cost model was implemented and tested, as a detailed experimental study was conducted in a private cloud environment.

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