KTH Computer Science
and Communication

Evaluating the effect of cardinality estimates on two state-of-the-art query optimizer's selection of access method

Studying how MariaDB's and PostgreSQL's respective query optimizers select access method in correlation to the sample size used when estimating cardinality.

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Abstract

This is a skeleton for KTH theses. More documentation regarding the KTH thesis class file can be found in the package documentation.

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Chapter 1

Glossary

The terminology of databases often varies across literature and database vendors, this section therefore defines the terms used through this thesis. When it is the case that something commonly goes by other names as well, they will be included to a great an extent as possible.

Database

No distinction is made between the database and the Database Management Systems (DBMS) in this thesis as it is not relevant to separate them. If it is relevant to distinguish between the two it will be done explicitly.

Data

The *data* in a database is the values stored in the rows and columns of the database. This does not include additional information stored in the database such as indexes.

Dataset

A *dataset* is all information stored in the database, including both data and additional information such as indexes, primary and foreign keys etc.

Query optimizer

The terms query optimizer and optimizer are used interchangeably throughout the thesis. If an optimizer of some other kind is used this will be made explicit.

Host variable

A *host variable* is a variable declared in the program in which the SQL statement is embedded [6, p. 151]. Host variables are distinguished from normal columns by the fact that they begin with a colon. An example of a host variable is `:HEIGHT` in Figure 1.1.

```
SELECT  NAME
FROM    PERSONS
WHERE   HEIGHT = :HEIGHT
```

Figure 1.1: A simple query using a host variable.

Predicate

In order to get the data you need, you must be able to specify what conditions the data should fulfill to be relevant, this is done by specifying predicates. To illustrate, consider Figure 1.2 taken from [24].

```
WHERE   SEX = 'M'
AND
(WEIGHT = 90
OR
HEIGHT > 190)
```

Figure 1.2: The **WHERE** clause an SQL query containing three predicates and two compound predicates.

The **WHERE** clause in Figure 1.2 contains three predicates:

1. `SEX = 'M'`
2. `WEIGHT = 90`
3. `HEIGHT > 190`

A *compound predicate* is two or more predicates that are tied together in the form **AND**, **OR** or other similar operators. The **WHERE** clause in Figure 1.2 can be considered to have two different compound predicates:

1. `WEIGHT = 90 OR HEIGHT > 190`
2. `SEX = 'M' AND (WEIGHT = 90 OR HEIGHT > 190)`

Index slice

The term *index slice* comes from [24] and is defined as the number of index rows that need to be read for a predicate; the thinner the slice the less amount of index rows that need to be read, and consequently the number of reads to the table.

The thickness of the index slice will depend on the number of *matching columns*, that is the number of columns that exist both in the **WHERE** clause and the index. To illustrate why consider the query in Figure 1.3.

```
WHERE   WEIGHT = 90
AND
HEIGHT > 190
```

Figure 1.3: The **WHERE** clause of a query with two potential matching columns.

If there exists an index on only `HEIGHT`, no values for `WEIGHT` can be discarded in the index slice. If an index is added for `WEIGHT`, the thickness of the index slice will decrease as only values fulfilling both the `HEIGHT` and `WEIGHT` requirements remain.

Indexable predicate

A *indexable predicate* is a predicate that can be evaluated when the index is accessed (allowing a matching index scan) [39, 20]. Revisiting the example from earlier, both of the predicates in Figure 1.3 are examples of indexable predicates.

Matching predicate

A *matching predicate* is an indexable predicate with the corresponding necessary indexes [20]. In Figure 1.3 both predicates are indexable and would be matching if there exists an index for `WEIGHT` and `HEIGHT` respectively.

Non-indexable predicate

A *difficult predicate* (also sometimes called *nonsearch arguments*, *index suppression*, *difficult predicate*) is the opposite of an indexable predicate, and can as a consequence not define the index slice [24]. What predicates are non-indexable varies from database to database, but a typical example of one can be seen in Figure 1.4.

```
COL1 NOT BETWEEN :hv1 AND :hv2
```

Figure 1.4: A example of a commonly used non-indexable predicate.

Boolean term predicate

A *boolean term predicate* (BT predicate) is one that can reject a row because it does not match the predicate [24]. Conversely a non-BT predicate is a predicate that cannot reject a row. Non-BT predicates are typically the result of using **OR**. To illustrate when a predicate is BT respectively non-BT consider, assume there is an index `(A, B)` on **TABLE** and consider Figure 1.5 and Figure 1.6.

For the query in Figure 1.5 if the first predicate `A > :A` evaluates to false for a row the row can be rejected instantly, making it a BT predicate. For the query in

```
SELECT   A, B, C
FROM     ATABLE
WHERE    A > :A
AND
B > :B
```

Figure 1.5: A query with a BT predicate.

```
SELECT   A, B, C
FROM     ATABLE
WHERE    A > :A
OR
B > :B
```

Figure 1.6: An query with no BT predicates.

Figure 1.6 on the other hand it might be the case that `B > :B` evaluates to true even if `A > :A` does not, making both predicates non-BT predicates.

Index screening

A column may be in both the **`WHERE`** clause and the index, yet be unable to participate in defining the index slice due to other reasons [24]. Even if this is the case the column may still be able to reduce the amount of reads to the table anyway. A column fulfilling these criteria is a *screening column* as the presence of it in the index allows not reading from the table. The process of determining which columns might fulfill this is called *index screening*.

Cardinality

The *cardinality* is the number of distinct values for a column, or combination of columns [24]. The cardinality of the data is usually used when the query optimizer estimates the cost of different access paths.

Filter factor

The *filter factor* specifies what proportion of the rows that satisfy the conditions in a predicate [24]. The filter factor can be seen as the selectivity of a predicate and the lower it is, the more the number of rows that are filtered out by a predicate. For a predicate such as `HEIGHT = :HEIGHT` there are three ways to talk about filter factor:

- The *value specific filter factor* is the filter factor for one specific value of `:HEIGHT`;

- The *average filter factor* is the average value for all value specific filter factors;
- And the *worst-case filter factor* is the highest possible filter factor for a given value of `:HEIGHT`

Access path

The query optimizers output is an *access path*, which is an abstract representation of the path to access the data.

Execution plan

The *execution plan* corresponds to an access path but describes how to physically access the data.

Query plan

The *query plan* is the plan suggested by the database for how to access the data. It is the database-specific description of the access path.

Chapter 2

Introduction

> The person who gave us this book told us that the book describes a secret technology called a database.
> We hear that the database is a system that allows everyone to share, manage, and use data.
>
> *The King of Kod, from [40, p. 6]*

If you want to save data, you need a database. And almost every computer program need to save some form of data, consequently requiring them to use a database. The trend is also going towards us generating more and more data, putting higher strain on the databases and requiring better performance. To improve and develop databases is therefore a topic of much relevance in today's society.

One key component of databases is the query optimizer, the part of the database that analyses the users query and finds the optimal path to access it. Or rather, theoretically it finds the optimal path. Work has been done improving query optimizers since the early '70s [7], yet optimizers often select a bad access path, causing slow queries [25].

Guy Lohman identifies the cardinality estimate of the data to be main cause for bad plans:

"The root of all evil, the Achilles Heel of query optimization, is the estimation of the size of intermediate results, known as cardinalities"

The estimates can often be wrong by several orders of magnitude [26]. These incorrect estimates then propagate through the query and grow at an exponential rate [22], making the query optimizer base its decisions on completely false grounds.

The topic of improving the estimations has seen some study, yet the evaluation of new methods is often done on data that is easy to estimate, being uniformly distributed. It is only recently that a study has been done to analyze the performance of the optimizer end-to-end on complex real-world data [25]. The study found the optimizer to perform unnaturally well on the typically tested uniform data.

This thesis will therefore aim to provide further insight into performance of query optimizers by studying a previously unstudied metric and analysing the performance of state-of-the-art optimizers. The performance evaluation will be conducted on both the “easy” uniform data and complex real-world data.

2.1 Problem statement

In this thesis two open-source state-of-the-art databases are evaluated: MariaDB [27] and PostgreSQL [35]. One real-world dataset containing a large amount of data and with a complex schema and setup will be used in the evaluation. The database will be analyzed to measure the performance of the query optimizer in order to answer the question:

How much effect does the cost estimation have on the query optimizers selection of access method during the join enumeration?

The metric studied to evaluate this will be the number of different access methods used to access the same relation involved in a query. This metric gives a good indication to the cost estimation has on the query plan selected by the query optimizer. For a more in-depth description of how the metric is measured, see 5.1.

The exact setup and metrics of the dataset is described in Section 5.2. A motivation to why the databases are used is described in Section 5.1.1.

2.2 Purpose

Query optimizers make bad cardinality estimates, and as a consequence bad cost estimations of access paths [25] – but how much does this affect the actual selection of access method? Even though the errors may be large, they may not be large enough to actually cause the optimizer to generate different access paths.

There are three steps to the optimization – search space expansion, cost estimation and join enumeration (more about those in Section 4.3) – this thesis will focus on measuring what effect bad performance in the first two steps has on the third and final one. The study will be done by identifying the number of different access methods used for the same relation in order in order to identify the presence of the problem and if it differs between the databases studied. These two findings will give a good indication to what effect the cost estimation has on the final step of optimization.

Studying this is of relevance for the following reasons:

1. The tool developed for evaluation can be used in the future to measure the performance of query optimizers;

2. The evaluation will provide insight into what steps in the optimization process produce bad access paths;

3. The performance of query optimizers has not seen much study using actual real-world data;
4. The actual performance of the databases right now will be evident;
5. Since both databases compared are open-source, one performing better may guide development for the other.

The primary interest for academia is probably reasons 1, 2 and 3 whereas database vendors might be more interested in 4 and 5. This thesis will thus provide a foundation for further improving query optimizers and that is of relevance for everyone who uses a database.

2.3 Outline

Below is a brief outline of the chapters in the report and what can be expected to be found in each:

- The Introduction chapter gives an introduction to the subject of query optimizer, the problem statement discussed, the purpose of the thesis and why it is novel and relevant.
- The Related work chapter contains an overview of what previous and relevant work has been done in the area of improving and evaluating the performance of query optimizers.
- The Theory chapter gives a background and the information necessary to understand the thesis. The chapter begins with a background on how a modern query optimizer works. It then continues with a description of the individual characteristics of the databases analysed: MariaDB and PostgreSQL. It also defines some important terms used throughout the thesis.
- The Method chapter describes the performance tests that were run and how they were implemented. It also describes more in-detail the data used for the databases, the database configurations used and the environment the tests were run in.
- The Results chapter displays the results from the performance test in the form of graphs. It also gives some brief commentary on them.
- The Discussion chapter discusses the performance of the query optimizers and the consequences of it, as well as the validity of the results. It also answers the problem statement and provides suggestions for future research.

Chapter 3

Related work

Improving the query optimizer is a topic naturally tied to that of evaluating the query optimizer's performance. In spite of this, the optimizer's performance has not seen much study, while improving them on the other hand has. This section will start with a section about some of the more recent evaluations that have been done and then continue with a section about some improvements done to the query optimizer relating cardinality estimation. A final section describes some implementations to improve the performance of relational operators and make them more resistant to bad plans.

3.1 Evaluating the query optimizer's performance

In [25] Leis et. al. perform what they claim is:

"the first end-to-end study of the join ordering problem using a real-world data set and realistic queries".

In the study they create the a database setup based on the Internet Movie Database (IMDb), create a set of realistic queries for it and call it the Join Order Benchmark (JOB). Using this benchmark they then measure how PostgreSQL, HyPer and three unnamed commercial databases perform in terms of cardinality estimates, cost modelling and general performance. They also compare the results to TPC-H, the database setup previously mostly used for evaluation and show that the PostgreSQL optimizer performs unrealistically well for TPC-H because of the uniform data distribution. The results of their study show that relational databases produce large estimation errors and that primarily the cardinality estimate is to blame.

Another article that has evaluated optimizers is [47] where Wu et al. analyzed if the optimizer's cost model can be used to estimate the actual run-time of the query. They find that the optimizer consistently makes bad cost estimates, but show that for analyzing actual run-time a more costly and precise analysis can be conducted on the selected access path.

Evaluating a query optimizer's cardinality estimation is often done through a comparison with the actual cardinality. Calculating the exact cardinality can however be very costly for complex queries and datasets. A more efficient method that can find the exact cardinalities by studying a subset of all expressions i presented in [8].

One novel way of studying and analyzing the plans chosen by the query optimizer is a tool called Picasso, which allows query plans to be visualized as two-dimensional diagrams [19]. The tool provides a visualisation of the performance across the entire query plan space, thus providing another way of analysing queries or query optimizers.

An example of a visualisation done with Picasso can be seen in Figure 3.1. The colored regions represent a specific execution plan, the X and Y-axis represent the selectivity for the attributes `SUPPLIER.S_ACCTBAL` and `LINEITEM.L_EXTENDEDPRICE` respectively. The percentages in the legend correspond to the area covered by each plan.

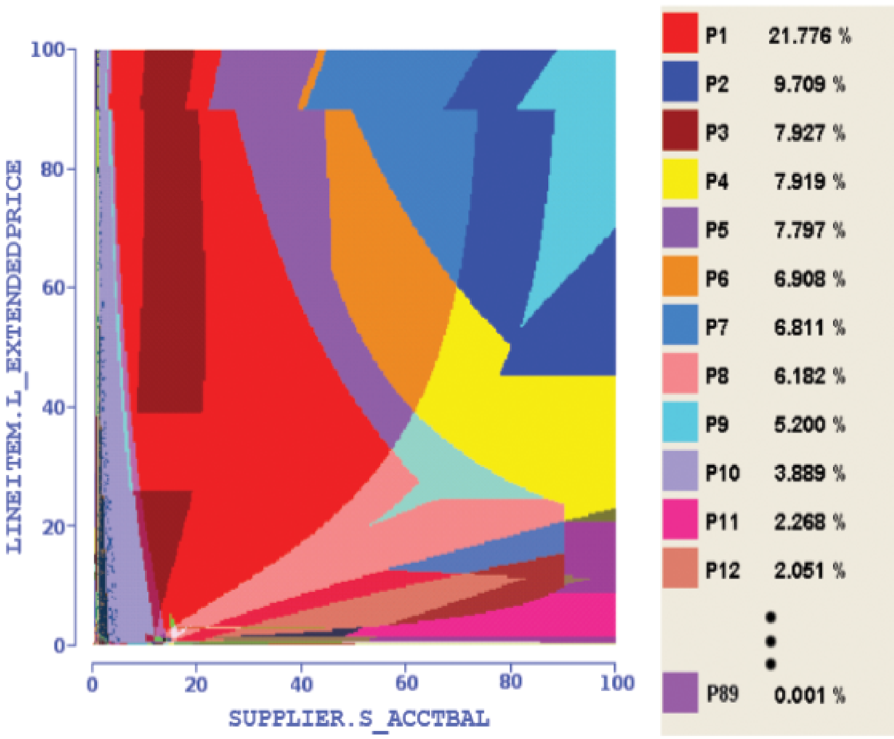


Figure 3.1: A query plan visualisation done by Picasso, image taken from [19].

Finally, on a more practical note Lahdenmäki et al. describe of how to identify queries where the selected access path is bad, and how to solve the problem [24]. The book gives a thorough introduction to many important aspects of the database and the chapter “Optimizers Are Not Perfect” focuses on incorrect cardinality estimates and other common query optimizer errors.

3.2 Bad statistics and cardinality estimates

In [22] Ionnidis et al. develop a framework to study how cardinality estimate errors propagate in queries. Their results indicate that the error increases exponentially with the number joins.

There are two different methods of improving how optimizers handle cardinality estimation:

- Reducing the effect of incorrect estimations by making plans more *robust*, which means they perform better over large regions of the search space;

- Or by improving the estimations.

3.2.1 Improving robustness

Harish et al. present a way to make plans more robust by allowing the optimizer to select the most robust plan that is not "too slow" compared to the calculated optimal path. [18]. They develop an external tool for this purpose and find that the tool indeed does improve performance by reducing the effect of selectivity errors.

A similar study is done by Abhirama et al. but they implement the selection directly in the PostgreSQL query optimizer [1]. Their results agree with those found by Harish et al. in that the performance is improved. The results they present show that robut plans often reduced the adverse effects of selectivity errors by more two-thirds while only providing a minor overhead in terms of time and memory.

3.2.2 Improving cardinality estimates

The most studied problem of cardinality estimate is that of finding the right balance between calculation time, memory overhead and correctness. One common method used in current state-of-the-art databases is histograms that assume attributes are independent of each other, an assumption that often is not correct [21]. Recent studies have been done to find alternatives method that do not assume independence.

Tzoumas et al. present one method that instead of the usual one-dimensional statistical summary, saves it as a small, two-dimensional distribution [45]. Their results show an small overhead, and an order of magnitude better selectivity estimates.

In [48] Yu et al. develop a method called *Correlated Sampling* that does not sample randomly, but rather save correlated sample tuples that retain join relationships. They further develop an estimator, called reverse estimator, that use correlated sample tuples for query estimation. Their results indicate that the estimator is fast to construct and provides better estimations than existing methods.

In [46] Vengerov et al. once again study Correlated Sampling, but improve on it by allowing it to only make a single pass over the data. They compare the algorithm to two other sampling approaches (independent Bernoulli Sampling and End-Biased Sampling, which is described in [12]) and find Correlated Sampling to give the best estimates in a large range of situations.

3.3 Improving operators

In [28] Müller et al. study the two implementations of relational operators: hashing and sorting (more about these in Section 4.1.4). Their study find that the two paradigms are in terms of cache efficiency actually the same and from this observation develop a relational aggregation algorithm that outperform state-of-the-art methods by up to 3.7 times.

A problem described in [25] is that the optimizer tends to pick nested-loop joins (more about these in Section 4.1.4) even though they provide a high risk but only a very small payoff. In [16] Goetz Graefe provides a generalized join algorithm that can replace both merge joins and hash joins in databases, thus avoiding the danger of mistaken join algorithm choices during query optimization.

Chapter 4

Theory

An SQL query walks into a bar
and sees two tables.
He walks up to them and asks
"Can I join you?"

– Source: Unknown, from [41]

In this chapter a background is given to relational databases with more focus on the areas of interest for this thesis. The first section will give a high-level introduction to relational databases and how they work in general. Following this is a section with a more in-depth description of indexes. After this comes the final section covering the query optimizer, detailing how it works, how it can be monitored and its limitations.

4.1 Relational databases

A database is a computerized record-keeping system, a way to save computerized data [11, p. 6]. The data stored in the database can then be accessed and modified by the user. Accessing and modifying the data is typically done through a layer of software called the database management system, which provides a method for accessing and modifying the data.

A database stores data in the form of rows in different tables. These rows are also sometimes referred to as tuples. In a relational database these tuples can then have relations between each other in the form of for example "Tuple A has one or more of Tuple B".

The following sections will describe some components of the database which are of the most relevant for this thesis. First comes a section describing the most common method to access data in a relational database, SQL, after this is is a section about how the query described by SQL is executed and finally a section about one of the most fundamental operations in SQL – the join operation.

4.1.1 SQL

SQL, or Structured Query Language in full, is the computer language most commonly used to query and modify the database, it is formally defined by ISO/IEC 9075 [15, p. 29][23]. The language came from research into manipulating databases in the early '70s and it is now one of the most popular database languages in existence [38].

4.1.2 Query execution

The execution of a query in the form of an SQL statement is split into four phases [37]:

1. *Parsing*, in which the input text is transformed into query blocks;
2. *Optimization*, in which an optimized way to access the data is found, called an *access path*;
3. *Code generation*, in which the access path is transformed a way to execute it, an *execution plan*;
4. And *execution*, when the code is executed;

The *parsing*, *code generation* and *execution phases* are all fairly trivial compared to the *optimization*. The optimization process is also the phase that has the potentially most effect on the execution time for the query. The query optimization process is performed by the query optimizer, which is described in more detail in Section 4.3.

4.1.3 The join operation

One of the most fundamental operations in SQL is that of joining two tables. An example of an inner join on the tables `EMPLOYEES` and `DEPARTMENTS` can be found in Figure 4.1.

```sql
SELECT *
FROM   EMPLOYEES, DEPARTMENTS
WHERE  EMPLOYEES.DEPARTMENT_ID =
 ↪  DEPARTMENTS.DEPARTMENT_ID
AND    EMPLOYEES.NAME = 'John';
```

Figure 4.1: An SQL query that will find the all employees by the name of John and info about their department.

There are four kinds of joins typically supported in databases. To illustrate this assume we have the following `Join(A, B)`, where `A` and `B` are tables and `Join` is one of the join operations.

- An inner join will return all rows in common between `A` and `B`;
- A left outer join will return all rows in `A` and all common rows in `B`;
- A right outer join will return all rows in `B` and all common rows in `A`;
- And a full outer join will return all rows in `A` and all rows in `B`.

See Figure 4.2 for a visualization of the joins using Venn diagrams.

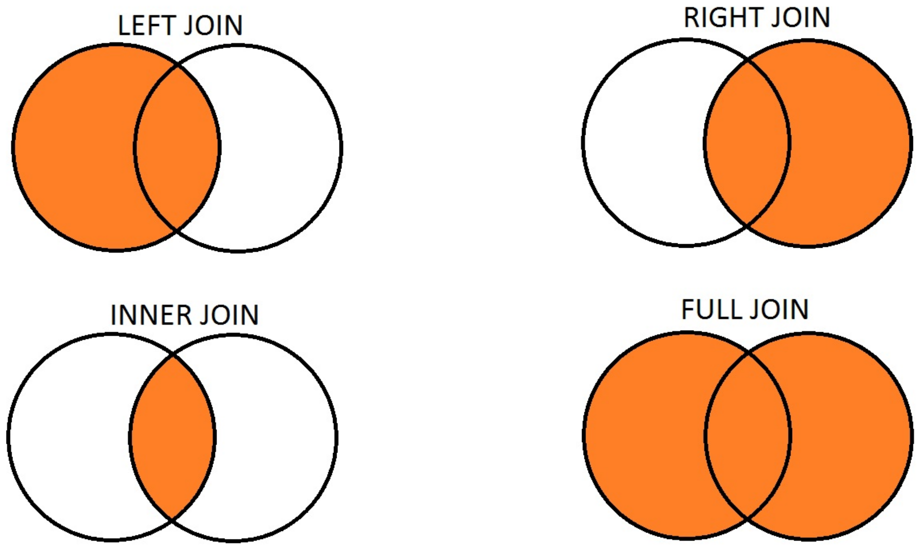


Figure 4.2: The four join operations illustrated using Venn diagrams, image taken from [5].

4.1.4 Implementation of operators

Operators can be divided into three classes:

1. *Sorting-based* methods;
2. *Hash-based* methods;
3. And *index-based* methods.

In general index-based methods are variations of class 1 or 2 that utilize indexes to speed up parts of the algorithm. Most notably when there exists an index, for example B-trees, that allows the data to be accessed sorted joins can be done very efficiently.

Furthermore the algorithms for the operators can be divided by the number of passes the algorithm does:

1. *One-pass algorithms* read the data from disk only once;

2. *Two-pass algorithms* reads the data once, processes it and saves it in some way before doing another pass;

3. And algorithms that do three or more passes, which are essentially generalizations of two-pass algorithms.

There are several operators to implement in a database, but the most relevant algorithms for this thesis are those implementing the join operator. Implementation of the join operator is typically done with three fundamental algorithms: nested loop join, merge join and hash join [33]. Many databases support more join algorithms, but they are typically variations of one of these three algorithms.

For the descriptions of the algorithms assume we have a query joining the tables `A` and `B`, `Join(A, B)`. The first table of the join operation, `A`, is referred to as the *outer table* and the second table, `B`, as the *inner table*.

Nested loop join

A nested loop join is essentially two nested loops, one over the outer table and inside it one over the inner table [15, p. 718-722]. The nested loop join is a bit of a special case as it is not necessarily of any of the classes. The number of passes it does can also be considered to be "one-and-a-half" as the outer table's tuples is read only once, while the inner table's tuples are read repeatedly.

If an index exists for the inner table the nested loop join could be considered to be of class 3 and is then called a *index nested loop join*.

Merge join

A merge join (sometimes also called *sort-merge join*) is a variation of a nested loop join that requires both tables to be sorted. The two tables can then be scanned in parallel, allowing each row to only be scanned once [15, p. 723-730]. The sorting of the tables can be achieved through an explicit sort step or through an index.

A merge join can be considered to be a two-pass algorithm of class 1.

Hash join

There are several types of hash joins but the general principle remains the same: build a hash table for the outer table, then scan the inner table to find rows that match the join condition [15, p. 732-738].

Hash joins are two-pass algorithms of class 2.

4.2 Indexes

This section will cover the basics behind indexes as described by Ramakrishnan et. al. in [36, Ch. 8].

An index is a data structure that allows data stored in the database to be accessed quicker through some retrieval operations. The data stored in the index is called the *data entry* and the value that is indexed – the value in the column – is called the *search key*. There are three alternatives for what to store as the data in the data entry:

1. A data entry is a the actual data saved;

2. A data entry is a pair containing a search key and record id;

3. A data entry is a pair containing a search key and a list of record ids corresponding to the key.

Which alternative is used depends on how the index is created and what kind of an index it is.

4.2.1 Composite indexes

Composite indexes are indexes containing more than one fields. A composite index can support a broader range of queries than a normal index and since they also contain more columns, they contain more information about the data saved.

4.2.2 Clustered index

A clustered index is an index on a column which is sorted in the same way as the index; otherwise it is an unclustered index. An index using Alternative 1 is sorted by definition, whereas Alternative 2 and 3 require the data stored to be sorted.

4.2.3 Data structures

The two most common indexes used are *hash-based indexes* and *tree-based indexes*. Below is a more detailed description of both.

Hash-based indexes

A hash-based index is implemented as a hash table, mapping the hashed value of a search key to a bucket containing one or more values. To search in the index the search key is hashed and the corresponding bucket is identified, all values in the bucket are then examined to identify the matching one.

Tree-based indexes

Tree-based indexes save the data as hierarchical sorted trees where the leaf nodes contain the values. To find a value the search starts at the root and all non-leaf nodes direct the search toward the correct leaf node. In practice the trees are often implemented as B^+-trees, which is a data structure that ensure that paths from the root to a leaf node are of the same length [10]. The efficiency of a B-tree index depends on the number of levels the B-tree has [15, p. 645].

4.3 The query optimizer

In order to access the data in an as efficient way as possible, the query is optimized by a built-in tool in the databases called the query optimizer. Below is a description of the fundamental operations performed by query optimizer, taken mostly from C., Surajits article on the topic [7].

Query evaluation is handled by two components: the *query optimizer* and the *query execution engine*. The input to the query optimizer is a parsed representation of the SQL query and the output is an execution plan that the query execution engine then performs.

In order for the query optimizer to find an access path it must be able to:

1. Expand the *search space* to find all access paths that are valid transformations of the query;
2. Perform a *cost estimation* for each access path to calculate its cost;
3. And finally *enumerate* the access paths to find which is the best.

A good query optimizer is one that does not cause too much overhead in the query execution in calculating the access path, while still finding a good access path. In order to do this each step must fulfill the criteria:

1. The search space includes plans with a low cost;
2. The cost estimation is accurate;
3. And the enumeration algorithm is efficient.

4.3.1 Expanding the search space

The first task of the query optimizer is that of taking the original search space containing just the original query, and expanding it through transformation rules. The expansion will thus generate a larger search space containing valid permutations of the join order. The output is a set of *operator trees*, which are binary trees where nodes represent operations and leaves values.

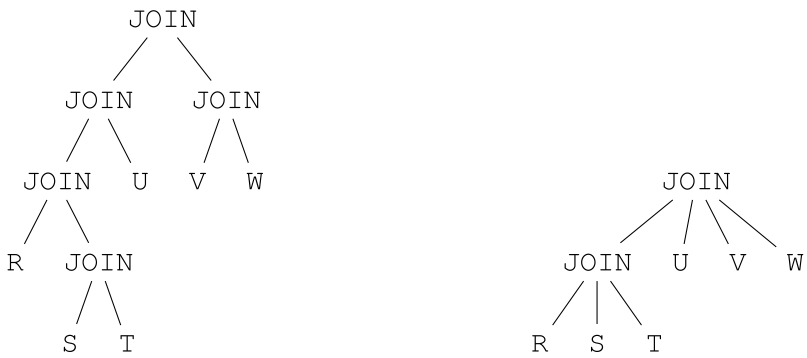
There are multiple rules that can be applied, most of which are complex and work only under some specific conditions. The most relevant rules for index-selection are described below, for a more in-depth description see [7].

Join reordering

One important rule is that both inner join and full join are:

- commutative: `Join(R1, R2)` is equivalent to `Join(R2, R1)`;
- Associative, `Join(R1, Join(R2, R3))` is equivalent to `Join(Join(R1, R2), R3)`.

This means that the joins can be grouped and reordered as the optimizer finds best. Another consequence of this is that the operators that can be seen as a single node with many children, see Figure 4.3 for an example.



(a) (b)

Figure 4.3: The `JOIN` operators are assumed to be associative and commutative, allowing Figure 4.3a to be transformed into Figure 4.3b, example taken from [15, p. 791].

Pushing operations up and down the tree

Another fundamental rule used by optimizers is that of pushing an operator down the expression tree in order to reduce the cost of performing it [15, p. 768-792]. For the example the selection operators tend to reduce the size of the relations, meaning pushing them down as far down the tree as possible is beneficial.

Another rule that can be applied is to pull an operator up the tree, in order to then be able to push it down again to reduce the size of more relations. See Figure 4.4, which illustrate how pulling a selection up the tree allows it to then be pushed down more branches.

The conditions for when these rules are applicable naturally varies a lot depending on the operator and it is beyond the scope of this thesis to list them all. See [15, p. 768-779] for an in-depth description of the rules and conditions.

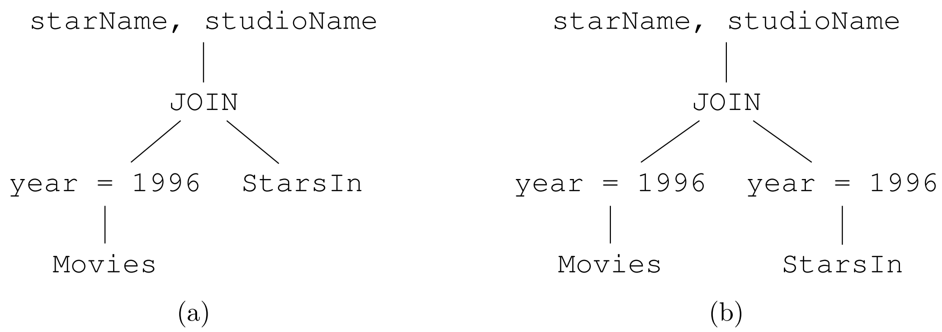


Figure 4.4: An expression tree representing a query to find which stars worked for which studios in 1996, example taken [15, p. 774]. The selection operator in Figure 4.4a is first pulled up the tree, allowing it to then be pushed down an additional branch as illustrated in Figure 4.4b.

Eliminating operators via an index

Several operations such as **`GROUP BY`**, **`ORDER BY`**, **`MAX`** etc can be eliminated because the the relation is known to already fulfill these criteria [15, p. 777-779]. One of the more common criteria is than index that allows the data to be retrieved sorted exists.

In combination with the ability to move operators up and down the tree this can be very powerful as potentially costly operations can be eliminated.

Accessing table data

For each read from a table there will be generated one access path per usable index, as well as one for a full table scan [15, p. 827-829].

4.3.2 Cost estimation

The second task of the query optimizer is to be able to assign a cost to a given search plan. This cost estimation will be repeated several times as it is called for each operator tree in the search space that the query optimizer considers relevant, thus it is important that the estimation is efficient. The cost estimation is done in three steps:

1. Collect statistics of stored data;

2. For each node in the tree calculate the cost of applying the operation;

3. And then the calculate the statistics for the resulting output.

There are two important statistics that need to be calculated for the data: the number of tuples in a relation and the number of different values in the column of a relation for an attribute [15, p. 807-808]. Common methods of saving the data is through a histogram describing the data distribution for an attribute. If histograms are not used the second highest and lowest values are used – this is because the highest and lowest values often are outliers

Modern databases can contain huge amounts of data and thus calculating the exact histograms is impossible, requiring them to be estimated, usually through *sampling* [15, p. 807-808]. When estimating via sampling only a subset of the data is read and used to estimate. Furthermore the statistics are usually only computed periodically as they:

- Tend not to change radically in a short time;
- Even if inaccurate, they are used consistently for all cost estimations;
- And keeping them up to date may cause their calculations to take up the most of the database's time.

Finally the statistics need to be propagated upwards in the tree. There are several ways of performing this propagation and they are described in more detail in [7].

4.3.3 Enumeration

The enumeration is the final task of the optimizer and the one that will perform the actual expansion and cost estimation, as it selects in what way to expand the search space. It would be too costly to expand the entire search space and for each plan estimate the cost, instead the search space is expanded heuristically in a way that the optimizer believes will give cheap plans.

When expanding the search space the general principle is to find paths where the size of relations is reduced as early as possible. For example pushing an operation down the tree, as shown in Figure 4.4, can reduce the size of the relation and thus reduce the cost of performing a join later on [15, p. 772-774].

If the enumeration algorithm estimates the cost for a new plan to be more expensive than a previously found one, it can discard it right away. The main goal for the enumeration algorithm is therefore to expand the search space in such a way that the best plans are generated early, so that the more expensive plans can be discarded quickly later on [29].

Most modern query optimizers use a dynamic programming algorithm first proposed in 1979 for the System R database [37]. The algorithm is built on the observation that the join methods are independent, that is the best join method for joining the composite to relation i is independent of joining of the first $i-1$ relations. The method used is then to construct a tree with all permutations of joins by searching from smaller to successively larger subsets.

One final optimization done during this step is also to heuristically prune subtrees that the heuristic consider too bad to even consider [30].

4.3.4 Monitoring

It is often useful to monitor and see what decisions the query optimizer make and why; most databases implement the ability to do so via an SQL statement [24, p. 34]. In PostgreSQL and MariaDB the statement is called **EXPLAIN** [34] [13], but it is also called **SHOW** PLAN or **EXPLAIN** PLAN. For an example of how **EXPLAIN** is used see Figure 4.5, which shows the code for a query, and Figure 4.6, which shows the corresponding trace.

```sql
EXPLAIN
SELECT  title.title
FROM    movie_info, title
WHERE   movie_info.info IN ('Bulgaria') AND
 ↪  movie_info.movie_id=title.id;
```

Figure 4.5: An example of a query done on the IMDb dataset, requesting the title of all movies filmed in Bulgaria. See Figure 4.6 for the output.

```
Merge Join  (cost=2.25..921735.28 rows=19682252 width
   =17)
Merge Cond: (title.id = movie_info.movie_id)
->  Index Scan using title_pkey on title  (cost
   =0.43..155884.96 rows=3572150
width=21)
->  Index Only Scan using movie_info_idx_mid on
   movie_info
(cost=0.44..511110.22 rows=19682252 width=4)
(4 rows)
```

Figure 4.6: The access path as shown by PostgreSQL's EXPLAIN statement, corresponding to the the query in Figure 4.5.

4.3.5 Limitations

Even though much work has been done on improving query optimizers they may not always choose the correct access path. This section will describe some of the primary reasons why an incorrect access path path is chosen, as described in [24, Ch. 14].

The optimizer can't see the best path

One reason the query optimizer cannot find the best path is because it is unable to see all alternatives because the query is too complicated for it.

- If a predicate is non-indexable it cannot by definition participate in defining the index slice. Furthermore it might also be the case when the predicate is even more difficult that the the optimizer is unable to perform an index screening, forcing it to read a table row.
- If a compound predicate contains **`OR`** it may become non-BT, which in turn mean the predicate cannot be used to define the index slice. This means the query optimizer cannot make full use of potential indexes that exist.
- Sometimes the optimizer will add an **`ORDER BY`** to data that is already sorted thanks to an index.

The optimizer's cost estimate is wrong

Even if the optimizer is able to see all alternatives it might be the case that the filter factor is incorrectly estimated, resulting in an incorrect access path.

- If the filter factor is not estimated for a host variable, it must use a default value which often results in a poor estimate. However, if the filter facotr is estimated evewry time the query is executed it adds a large overhead.
- If the optimizer is unaware of the true distribution of the data it might make a guess based on the cardinality, if the distribution is skewed this guess may very well become very incorrect.
- In a compound predicate such as `HEIGHT = :HEIGHT` **`AND`** `WEIGHT = :WEIGHT` the optimizer can only produce a good estimate of the filter factor only if it knows the cardinality of the combination of the `HEIGHT` and `WEIGHT` columns. If it does not, it must somehow estimate this.

Chapter 5

Method

In this chapter, the method used to investigate the problem statement is presented. First, the choice of method is described, motivating the dataset and technologies used. Following this the problems used for benchmarking are presented, including a more in-depth description of the dataset. After these motivations, the actual implementation details are presented, showing how the database's are evaluated.

5.1 Choice of method

This section will motivate the methods' three primary questions:

1. What databases are evaluated?
2. What dataset is used to evaluate the databases?
3. How are the databases evaluated?

The following three sections will answer these questions in order, motivating choice of databases, dataset and implementation.

5.1.1 Choice of databases

The two databases chosen to evaluated are PostgreSQL and MariaDB. The choice was made based on the the fact that they are:

1. Modern databases with widespread use and active development;
2. Open-source projects allowing anyone to read and modify the source code;
3. And they implement state-of-the-art algorithms and methods.

In addition to this they both cover two common use-cases: academia and enterprises. All research papers mentioned in Chapter 3 that have implemented new algorithms or modified old ones have done so in PostgreSQL. On the other hand

MariaDB is compatible with MySQL, making it a common alternative for companies to use.

An evaluation of both of these database will give a good indication of the performance of a modern state-of-the-art query optimizer. Furthermore, as mentioned in Section 2.2 since both of them are open-source, if one performs better than the other the code can be studied to identify areas of improvement.

5.1.2 Choice of dataset

The primary focus when selecting the dataset was to use a dataset which could capture the complexity of a real-world database and provide a realistic challenge for the query optimizer. The primary requirements are that the dataset feature:

1. Many relations with multiple indexes each;

2. More than just trivial indexes on a single row;

3. Skewed and non-uniform data for which the cardinality is not trivially estimated;

4. A sufficiently large amount of data such that the database must estimate cardinality;

The datasets most commonly used for evaluation of database implementations are TPC-H [43], TPC-DS [42] and more recently JOB [25]. However, none of these datasets meet requirement 2 making the problem of selecting access methods for these databases trivial.

Instead, the dataset chosen was one taken from the real world: the dataset for TriOptima's product triReduce which fulfill all the requirement. The metrics of the dataset are presented in more detail in Section 5.2.

Another important aspect of the dataset is the queries used for evaluation. Selecting these was done based on the following critera:

- The relations involved in the query must be sufficiently large as to require the cardinality to be estimated via sampling;

- The data most be accessible via one or more index so that the actual index selection is not trivial for the query optimizer.

The two criteria are not fulfilled for more than a few relations in a database, reducing the amount of queries relevant for evaluation. However, the queries that do fulfill the above requirements are also those that are most interesting to study for a database as they are the ones that will have the longest execution time.

5.1.3 Choice of implementation

The focus when implementing the tool used to evaluate the databases was to find a tool that would allow a high-level description of the data transformations necessary. Additionally the language must be sufficiently stable and be able to handle potentially large amounts of simultaneous data.

The language chosen that fulfill these requirements is Clojure. Clojure compiles to bytecode that runs on the JVM, which is stable and well-used. Additionally the language is well-suited to describing data transformations as it provides many high-level functions for doing so.

More information regarding Clojure and the tool developed will be presented in Section 5.3, which also shows how some of the data transformations are done in practice.

5.2 Benchmark problems

This section describe the problems used for benchmarking, starting with specification of the hardware that the tests were ran on. Following this is first a description of the metrics of the dataset used.

5.2.1 Hardware specs

All evaluations were ran on a dedicated computer running only the databases. The most important part of the hardware is to ensure that there is sufficient data for both the databases and the results of the tests. For all evaluations three hard drives were used, one for each database and one for the tool itself.

The exact specifications are:

- 2 *Intel®Xeon®Processor E5-2643 (10M Cache, 3.30 GHz, 8.00 GT/s Intel®QPI)*, featuring 4 cores each;
- 1 *Seagate Savvio 15K.3 ST9146853SS 146GB 15000 RPM 64MB Cache SAS 6Gb/s 2.5"*, used to store the project itself on;
- 1 *Seagate Constellation ES.3 ST4000NM0023 4TB 7200 RPM 128MB Cache SAS 6Gb/s 3.5"*, used to store the PostgreSQL database on;
- And 1 *Seagate Constellation ES ST2000NM0001 2TB 7200 RPM 64MB Cache SAS 6Gb/s 3.5"*, used to store the MariaDB database on.

As a final note it is worth pointing out that the effect of the hardware should have none, or very little, effect on the query optimizer's plan selection.

5.2.2 The dataset

As detailed in Section 5.1.2 the dataset should be sufficiently complex in terms of indexes, table size and table values. Table 5.1 presents the number of indexes, the

	#index	#rows	size (MB)
database total	1130	305	1165290
mm	6	64882651	9448
book	6	51709	10
resamb	3	40598	5
cmm	2	17335822	1219
cmt	9	52808814	12811
t	35	115851469	92633
est	32	33726190	19434
ct	23	115751571	72320
mt	9	21721256	4284

Table 5.1: The metrics for the dataset used for evaluation of the databases. Both the metrics for the entire database and those of individual relations are shown. Note that the relation names have been anonymized and are only referred to by an identifier.

number of rows and the size in MB of the entire database and all relations involved in the benchmarking, the names of the relations have anonymized and are referred to by an identifier such as "mm" or "book".

The original dataset was stored in a MySQL database and was ported to PostgreSQL and MariaDB. MariaDB is made as an add-on to MySQL and thus required no tooling, the data was just copied into a fresh install of MariaDB using a *mysql-dump*. For PostgreSQL *py-mysql2pgsql* [31] was used to create a dump of the MySQL database with all MySQL specific data types converted to their most similar PostgreSQL equivalents. The data was then read into a fresh install of PostgreSQL.

In the copying process all indexes and relations were maintained, thus maintaining the same metrics for both of the copies as for the original.

5.2.3 The queries

To evaluate the databases only one query was used. The reason is that, as described in Section 5.1.2, there are few relations that can be involved in the query as they must fulfill the important critera in terms of indexes and size. As such one query covering all of the most complex relations were constructed, this query can be considered to be the most complex query for the dataset. Subsets are then used to simulate simpler scenarios.

The original query used for evaluation can be seen in Figure 5.1, the relation names are once again anonymized. For the metrics of the relations involved see Figure 5.1. The variations of the query simply remove one or more relations involved.

```
SELECT *
FROM ct JOIN t JOIN mt JOIN mm JOIN book JOIN cmt JOIN cmm
 ↪  JOIN est JOIN resamb
WHERE ct.key = :KEY
```

Figure 5.1: The query used for evaluation, simplified and anonymized. The relations are joined on rows in common.

5.3 Implementation

This section will cover the implementation details of the tool used for evaluation. The section starts with a general overview of the process of evaluation, breaking it down into steps. Following this is a description of the tool developed, showing how it is used and what technologies are used. After this section is three sections describing each of the three steps of evaluation. Finally implementation details are provided for PostgreSQL and MariaDB.

Evaluating a database for a given query can be broken down into three primary steps:

1. Repeatedly forcing the database to re-estimate the cardinalities and then generate query plans;

2. Parsing the query plans to find what access methods are used for all relations;

3. And finally analyzing the parsed plans to find the number of unique access methods used for each relation;

These three steps must be executed in order, but they can be executed independently of each other — it is possible to only generate plans at a time and save them for later parsing and analysis.

5.3.1 Overview of the tool

The tool was implemented so as to be executed from the command line, providing all the necessary parameters via flags. As mentioned in Section 5.1.3 the tool was developed using Clojure and is therefore typically ran via Leiningen, as shown in Figure 5.2.

```
lein run steps='generate parse analyze' query=queryid
 ↪  repetitions=100 samplesizes='10 100'
 ↪  --database=postgresql
```

Figure 5.2: An example of using the tool to generate, parse and analyze a query with some given parameters, such as the sample sizes to use.

As the steps can be executed one at a time, the results for each are saved and the tool allows the execution of only a specific set of steps at a time. An example of this can be seen in Figure 5.3 where a previously generated plan is parsed and analyzed.

```
lein run plans/xxx-000000000 steps='parse analyze'
```

Figure 5.3: An example of how the tool can be used to parse and analyze a previously generated file containing query plans.

The tool is open-source and can be found at [2]. The repository has further documentation regarding project structure etc.

5.3.2 Generating plans

The task of generating query plans can be broken down in the following steps:

1. Set the sample size used to estimate cardinalities;
2. Generate new statistics, and thus new cardinality estimates, for all relations involved in the query used for evaluation;
3. Find the query plan for each possible value of the query.

These steps are then repeated a number of times to ensure that all query plans are found.

The most relevant parts of the code used to generate plans can be found in Figure 5.4. In the figure two functions can be seen: `generate-plans` and `sample-and-query`, additional functions are referenced but not seen.

The generation step is handled by `generate-plans`, which is provided the options for the evaluation. This function will then for each sample size to use, repeated the number of times specified, call `sample-and-query`.

The `sample-and-query` function will in turn perform all of the steps outlined above; set the statistics target and generate new statistics via `resample-with!` and then find the query plan for all possible predicate values via repeated calls to `explain-query`.

Each plan found is directly saved to file for later use in parsing.

5.3.3 Parsing the plans

Parsing the generated plans is done by simply stripping all information but the access methods from the query plans, after this is done the access methods are grouped by what relation they access. The code for the parsing can be seen in Figure 5.5.

Parsing a plan is done with the function `parse-plan`, which will find all access methods with `find-relation-accesses` and group these by their relation with

```
(defn- sample-and-query [save-plan options]
  (resample-with! options)
  (doseq [param param-range]
    (save-plan (explain-query options param))))

(defn generate-plans [opts save-plan]
  (j/with-db-connection [db-con (opts->db-info opts)]
    (doseq [sample-size (:samplesizes opts)]
      (dotimes [i (:repetitions opts)]
       (sample-and-query save-plan
                         (assoc
                          opts
                          :sample-size sample-size
                          :connection db-con))))))
```

Figure 5.4: The relevant parts of the Clojure code used to generate the query plans. Some function definitions have been removed to improve readability.

`group-by-relation`. Finding the access methods in the query plan is done by traversing the plan as a tree and calling `save-if-relation-access` on each value — storing it, if it describes an access method.

Each generated plan is parsed and the new plan saved to another file. The main purpose is to transform the data into something more easily analyzed. Additionally the size of the query plans are reduced in size, reducing the time taken to analyze all plans.

5.3.4 Analyzing the plans

Analyzing the plans is done by merging all access methods found when parsing the plans, keeping the distinct methods for each relation. The code for analysis can be seen in Figure 5.6.

Analyzing all generated plans for a sample size is done by the function `analyze-plans`, which is provided an identifier for the database evaluated, a function to read the next plan and the total number of plans to read. The analysis is done by reading the next plan and merging it with the previous one. If the same relation is found in both the function `conj-distinct` will add only the new access methods found that are distinct from those previously found. Only the index used is considered in terms of two plans being distinct from each other.

The analysis is done for each sample size, and the resulting map of relation to access methods is saved for study.

```clojure
(defn- save-if-relation-access [db-id o]
  (if (and (map? o) (contains? o db-id))
    (swap! relation-accesses conj o))
  o)

(defn- find-relation-accesses [db-id plan]
  (reset! relation-accesses [])
  (postwalk #(save-if-relation-access db-id %) plan)
  @relation-accesses)

(defn- group-by-relation [db-id accesses]
  (group-by
   #(get % db-id)
   accesses))

(defn parse-plan [db plan]
  (let [db-id (access-key db)]
    (group-by-relation db-id (find-relation-accesses db-id
     ↪  plan))))
```

Figure 5.5: The Clojure code used to parse the query plan output from the generation step.

5.3.5 PostgreSQL

In PostgreSQL the SQL commands used are quite straightforward, one is used to delete all previously gathered statistics, one to set the sample size and finally an **ANALYZE** is called for each relation involved in the query being evaluated. The specific commands used can be seen in Figure 5.7, the value of the sample size is provided as a host variable, as it will depend on the options used when evaluating a database and query.

5.3.6 MariaDB

In MariaDB the commands used to estimate cardinality are storage engine specific, in this case InnoDB is the storage engine used. It is worth noting that InnoDB only supports MariaDB with estimates, it is then MariaDB that performs the actual query optimization.

It is necessary in InnoDB to ensure that the statistics used are those generated, to do this no persistent statistics are saved. Furthermore, no data is deleted between estimates as it is neither possible nor necessary — the old statistics are overwritten by the new. Finally the relations are all analyzed in one single **ANALYZE** call.

The specific commands used can be seen in Figure 5.8.

```clojure
(defn conj-distinct [f x y]
  (reduce
   (fn [coll v]
     (if (some #(= (f %) (f v)) coll)
       coll
       (conj coll v)))
   x y))

(defn analyze-plans [db next-plan plans-to-read]
  (loop [m {} plans-left plans-to-read]
    (if (zero? plans-left)
      m
      (recur
       (merge-with
        #(conj-distinct (fn [access] (get access (idx-key
         ↪  db)))
                        %1 %2)
        m (next-plan))
       (dec plans-left)))))
```

Figure 5.6: The Clojure code used to analyze the parsed output. The code will merge the maps generated, only keeping the unique access methods for each relation.

```sql
DELETE FROM pg_statistics;
SET default_statistics_target TO :SAMPLE_SIZE;
ANALYZE table1;
ANALYZE table2;
```

Figure 5.7: The SQL commands used to first delete all statistics in PostgreSQL, set the statistics target and finally analyze all relations involved in the query.

5.4 Evaluation

In order to evaluate the database the dataset described in 5.1.2 and the queries described in 5.2.3 were used. The tool supports several options to be set and the values used for the evaluation can be seen in Table 5.2, which shows the initial tests conducted. The results from these tests warranted further evaluation and the options for these tests can be seen in Table 5.3. The same values were used when testing both PostgreSQL and MariaDB.

In order to find a possible correlation between sample size and the number of of different access methods for the same relation, the tests were done with a very small sample size and a large one, both with a large number of repetitions This was only

```sql
SET GLOBAL innodb_stats_persistent='OFF';
SET GLOBAL innodb_stats_auto_recalc='OFF';
SET GLOBAL innodb_stats_transient_sample_pages =
 ↪  :SAMPLE_SIZE;
ANALYZE TABLE table1, table2;
```

Figure 5.8: The SQL commands used to first ensure that MariaDB will not use some other stats than those we gather, then set the statistics target and finally analyze all relations involved in the query.

query	repetitions	sample sizes
#1	50	1
#1	50	100

Table 5.2: The number of repetitions and sample size used for the evaluation. The tests are conducted with a low and high value for the sample size in order to capture the difference when analyzing cardinality with few samples versus many samples.

queries	repetitions	sample sizes
#1 — #9	1	1

Table 5.3: The number of repetitions and sample size used for the evaluation. Two tests with a large number of repetitions were done for the original, and the other queries evaluated with a lesser number of repetitions.

done for the original query as it is the most complex, making tests on the subsets unnecessary. The options used can be seen in Table 5.2.

Additional tests done were on the subsets to further evaluate the behavior identified in the first evaluation. As can be seen in the table, a small number of repetitions is used and the sample size is minimal, this is as neither of these two options seemed to affect the query plans chosen. For a further discussion about this see Section 7.2, where the results found for the initial tests is discussed in detail.

Chapter 6

Results

This chapter contains the results of using the tool to evaluate the two databases. This chapter will start with a section showing the results when evaluating the databases to identify a correlation between sample size and selection of different access methods. Following this are further results showing the results when evaluating subsets of the original query.

6.1 Correlation between sample size and selection of access methods

This section contains the results of the evaluation done in order to determine a correlation between sample size and the number of different access methods used to access the same relation. The evaluation consisted of a total of four tests, two tests per database. For the options used in the tests see Section 5.4 and more specifically Table 5.2. The results will be presented in the form of two bar charts, one for each of the sample sizes used.

The first test done can be seen in Figure 6.1. Each relation involved in the query is represented by a three different bars — one for the number of possible access methods and one for the actual access methods used for either of the two databases. From the figure it can be seen that there are six possible access methods for `ct` (one full table scan and five usable indexes) and that MariaDB will vary between three of these methods, whereas PostgreSQL consistently selects the same one.

The second evaluation of query #1, using a high sample size, can be seen in Figure 6.2, which can be read in the same way as the previous figure. The graph has three bars per relation once again. From this graph it can be seen that…

6.2 Evaluating subsets of the query

This section contains the results for the second evaluation conducted. The evaluation was done on queries #1 through #9, where #2 through #9 are subsets of

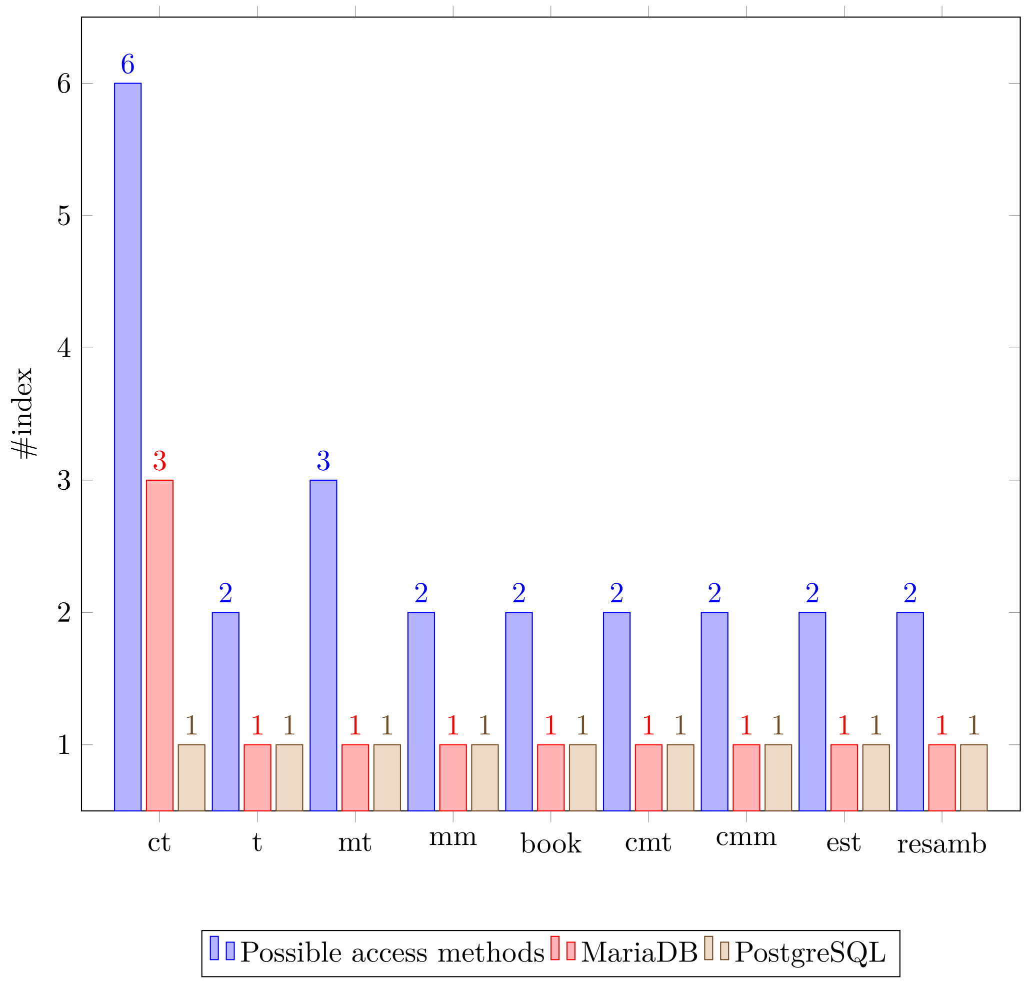


Figure 6.1: The index selections for query #1 are shown next to each other, showing the actual index selections next to the possible index selections.

query #1, and the results can be seen in Figure 6.3.

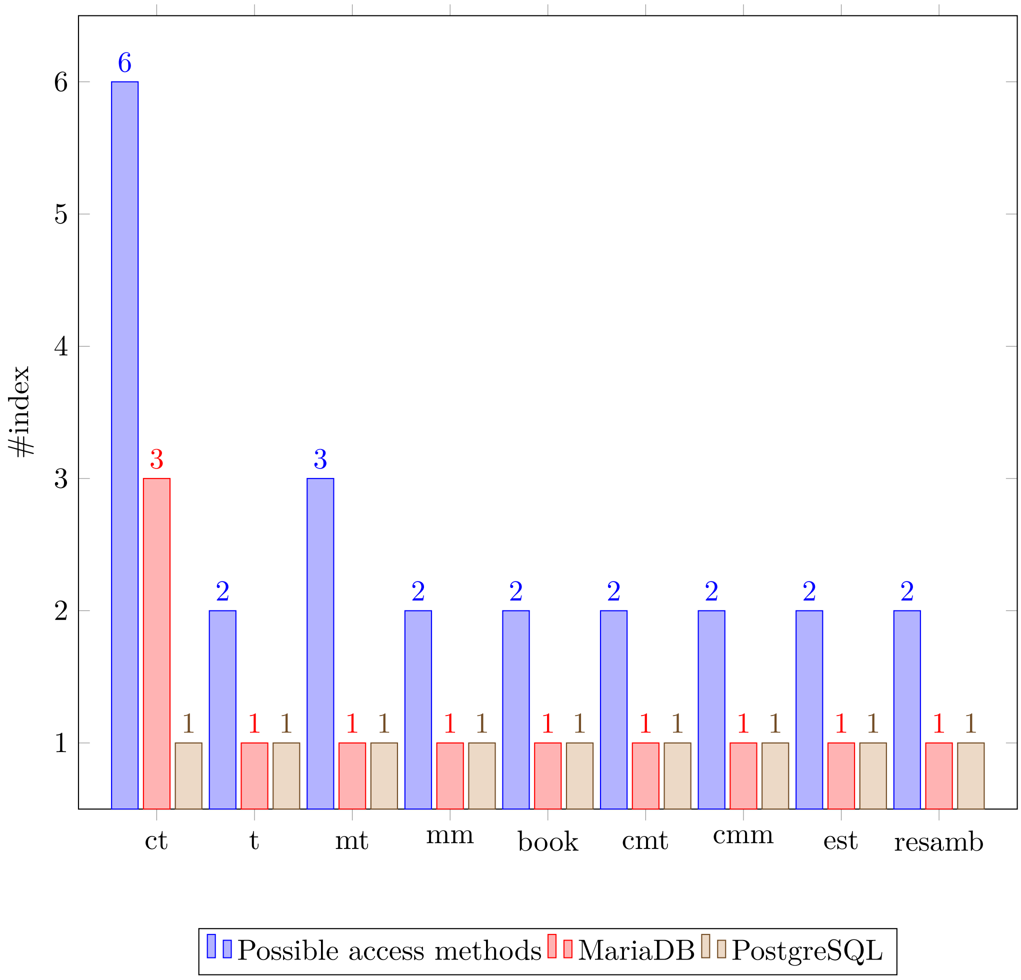


Figure 6.2: The index selections for query #1 are shown next to each other, showing the actual index selections next to the possible index selections.

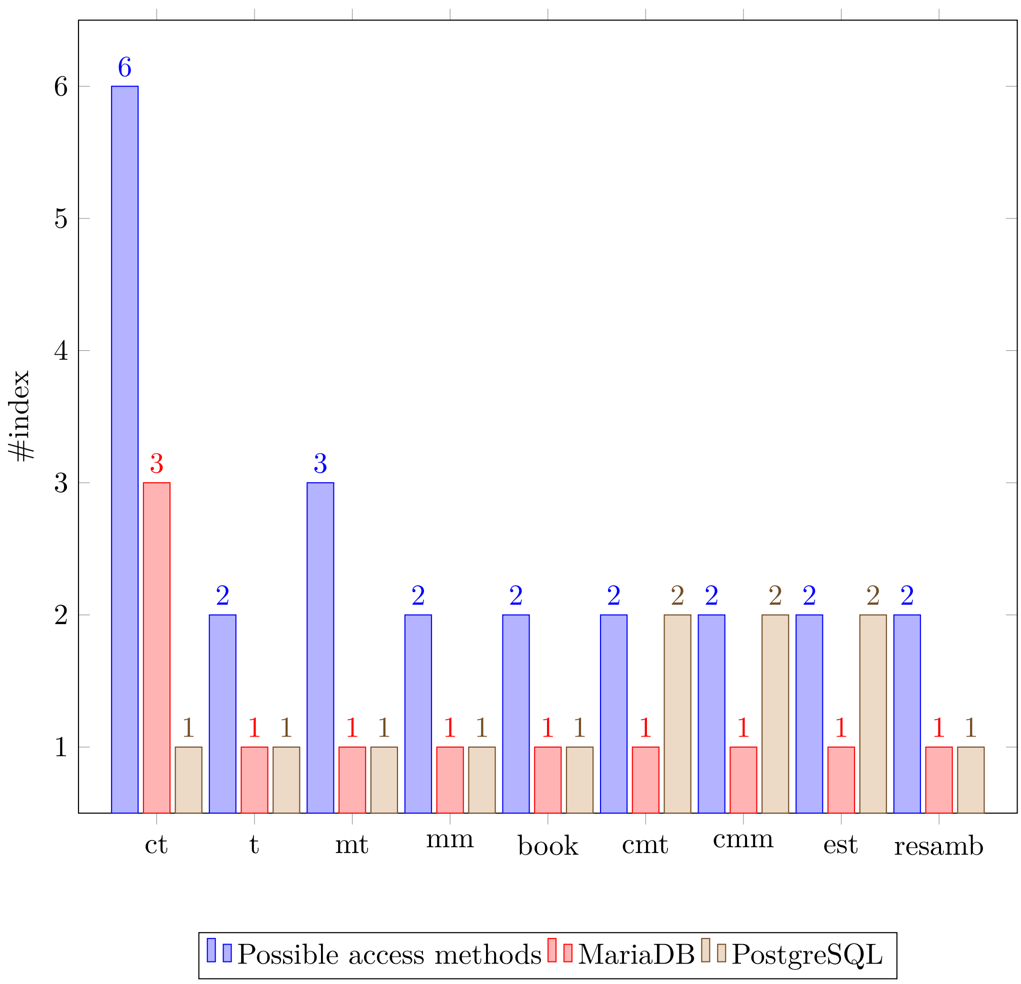


Figure 6.3: The index selections for query #1 are shown next to each other, showing the actual index selections next to the possible index selections.

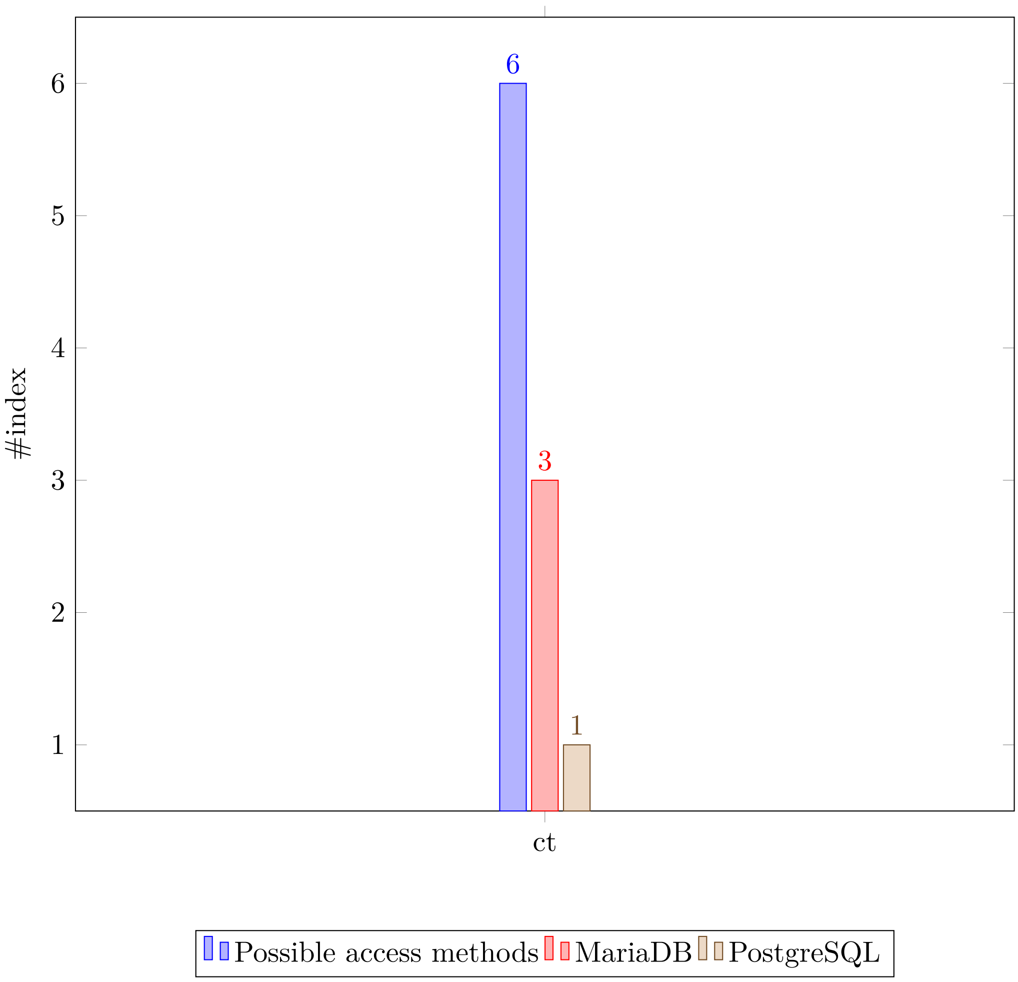


Figure 6.4: The index selections for query #9 are shown next to each other, showing the actual index selections next to the possible index selections.

Chapter 7

Discussion

This chapter contains a discussion regarding the validity of the results and the ability to use these to draw more general conclusions. Furthermore the results and the conclusions that can be drawn from these are discussed. Finally some suggestions for future research is given.

7.1 Validity of the results

Two main criticisms concerning the validity of the results can be raised:

1. Only a few number of queries were used for evaluation;
2. And only one dataset was used for evaluation.

Both of these criticisms will be answered in turn below. Finally a motivation is provided as to why the results can be considered usable to draw general conclusions from.

7.1.1 Only a few queries were used

Only one single query and subsets of that query were used, this is hardly a large set of tests for evaluation.

To answer this criticism it is important to consider the fact that the possibility for multiple access methods for the same relation depends on the criteria outlined in Section 5.1.2. The tables fulfilling these criteria are few, reducing the possibility to use multiple queries as they will only involve the same tables anyway.

Furthermore, the query constructed can be considered to be sufficiently complex as to capture a problematic query that the problem would realistically arise for. From this it can be said that if the problem does not arise for that query, then it is highly unlikely that it would for any simpler query.

So while only one query and subsets of it are used, these queries cover a good range of queries from simple to more complex for the query optimizer. This means that the results from these can be considered valid.

7.1.2 Only one dataset was used

Only one dataset was used for evaluation, the results found for the problem studied could be very different for another dataset.

This criticism is one related to the problem of evaluating databases in general: the performance of the database is often dependent on the dataset used for testing. While it is correct that the results could vary depending on dataset, this problem applies to all studies of databases.

Furthermore, the dataset used to test the databases is one taken from the real world, making it more realistic than those often otherwise used. As such, the validity of the results of this study are well on par with those of other studies using less realistic datasets like TPC-H.

While only one dataset is used for evaluation, the results found can be seen as an indication of a specific behavior and should warrant future research. Additionally, the results found are based on a dataset taken from the real world further giving validity to the results.

7.1.3 Applicability

The results found in this study do, as all other studies of databases do, suffer from the problem of the possibility of the results depending on the dataset used. However, the results found in this study show indicate two things:

- Different access methods are used to access the same relation;
- And the behavior of when this is done differs between MariaDB and PostgreSQL.

These results will be discussed in more detail in Section 7.2, but both of these results highlight an existing behavior in the databases. Having more datasets to test against would not have added anything to these findings except for an indication of how common it is for the database's to use different access methods.

7.2 Selection of access method

This section will discuss the main findings of the evaluation, starting with a discussion regarding the correlation between sample size and the number of different access methods used for the same relation. Following this a section describing the second set of results identified: the correlation between predicate values and access methods used.

7.2.1 Sample size vs access methods used

- index selections tend to not be ambiguous, the optimizer remains consistent regardless of sample size used

7.2.2 Predicate value vs access methods used

One finding that is clear from the results is that the access method used often depend on the predicate value used, rather than the statistics causing the query optimizer to pick the incorrect one. An example of this can be seen in Figure 6.1 where several different access methods are used for MariaDB depending on the predicate value used. A total of three different access methods are used out of a total of 6 possible.

The fact that the query optimizer is sensitive to predicate value can be seen as both intuitive and unintuitive — the filter factor might vary considerably between different predicate values but the same index should always be the best for accessing the same relation.

A clear different can be seen between the two databases as PostgreSQL, while sensitive to predicate value always selects the same access method for the relations where MariaDB differs. Instead PostgreSQL sometimes deems all indexes insufficient and opts instead to just do a full table scan. This is another contrast between the two as MariaDB always picks an index if one exists, never opting to do a full table scan.

As can be seen in Figure 6.4 this behavior remains consistent for both databases' query optimizers regardless of the complexity of the query in terms of number of joins and tables involved. This indicates that the behavior is intended, and not the cause of incorrect statistics.

7.3 Future research

This section will cover some suggestions for future research on the topic of databases, both in general and specifically for the problem of index selection.

As discussed in Section 7.1 one problem when evaluating databases is the dataset used for evaluation. In this study a dataset based on a product for the company TriOptima was used to evaluate the databases with a real-world dataset. However, this dataset can't be made public. Other datasets like TPC-H or to more recently create JOB suffer from the problem that they are simpler than a database used by a company; as an example both of them have only one index per relation on the primary key.

One important area of research in databases would therefore be to create one or more realistic datasets with complex data, relations and indexes that could be used for research. Using these datasets for evaluation would then provide results that could be considered more general and correct.

The most important results indicated by this study is that query optimizer selects different access methods depending on the predicate values. If this is the correct choice or not to do is not evaluated as a performance study is beyond the scope of this thesis. A suggestion for future research would therefore be to evaluate the performance of this behavior — is it the right decision to use different indexes depending on predicate values?

Finally it is important to also note that the problem of different access methods for the same relation because of small sample size, or incorrect estimation of statistics, seem to not be common. As such, future study into the area should probably avoid this topic in favor of other topics, for example that of optimizers being sensitive to predicate values.

Chapter 8

Conclusions

This thesis concerns the evaluation of two modern, state-of-the-art database's, and the effect of estimating statistics on the index selection. The thesis question was: *How much effect does the cost estimation have on the query optimizers selection of indexes during the join enumeration?*

Two databases — PostgreSQL and MariaDB — were chosen as a good representation of state-of-the-art query optimizers. A large enterprise dataset was ported to both of these two databases. Finally, a query was constructed using the most complex tables in the dataset.

A tool was then implemented in Clojure to allow the two databases to be evaluated. With the tool the index selections for a given query can be tested for a number of different sample sizes. By testing over an increasing sample size the cost estimation can be simulated to range from bad to good, allowing the testing of databases in a realistic scenario.

Using the tool to evaluate the databases with the query we find that the cost estimation have little effect on the index selection. For all the queries used, regardless of sample size, no correlation is found between the sample size and the number of different indexes used to access the same relation.

Instead the results indicate that predicate values can cause the databases to select different indexes. Furthermore, it is found that this behavior is different for the two databases with neither being sensitive to the same value as the other. This shows that the query optimizer's perform different for the two databases, indicating that further study should be done to identify which of the two behaviors might be considered best.

In conclusion we have found results indicating that the cost estimations have little effect on the query optimizers selection of access method. We have also found results indicating that instead the predicate value used for filtering does effect the index selection.

Bibliography

[1] M. Abhirama et al. “On the stability of plan costs and the costs of plan stability”. In: *Proceedings of the VLDB Endowment* 3.1-2 (2010), pp. 1137–1148. URL: http://dl.acm.org/citation.cfm?id=1920983 (visited on 01/21/2016).

[2] Martin Barksten. *mbark/ambiguous-index-finder*. GitHub. URL: https://github.com/mbark/ambiguous-index-finder (visited on 05/02/2016).

[3] Srikanth Bellamkonda et al. “Adaptive and big data scale parallel execution in oracle”. In: *Proceedings of the VLDB Endowment* 6.11 (2013), pp. 1102–1113. URL: http://dl.acm.org/citation.cfm?id=2536235 (visited on 02/08/2016).

[4] Renata Borovica-Gajic et al. “Smooth scan: Statistics-oblivious access paths”. In: *Data Engineering (ICDE), 2015 IEEE 31st International Conference on*. IEEE, 2015, pp. 315–326. URL: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=7113294 (visited on 02/08/2016).

[5] Brian. *Better Queries: Joins*. Bounded Index. 2014-07-01T03:38:40+00:00. URL: http://bilquist.com/better-queries-joins/ (visited on 02/10/2016).

[6] Don Chamberlin. *A Complete Guide to DB2 Universal Database*. Morgan Kaufmann, 1998. 820 pp. ISBN: 978-1-55860-482-7.

[7] Surajit Chaudhuri. “An overview of query optimization in relational systems”. In: *In PODS*. 1998, pp. 34–43.

[8] Surajit Chaudhuri, Vivek Narasayya, and Ravi Ramamurthy. “Exact cardinality query optimization for optimizer testing”. In: *Proceedings of the VLDB Endowment* 2.1 (2009), pp. 994–1005. URL: http://dl.acm.org/citation.cfm?id=1687739 (visited on 01/21/2016).

[9] *Clojure*. URL: https://clojure.org/ (visited on 05/03/2016).

[10] Douglas Comer. “Ubiquitous B-Tree”. In: *ACM Comput. Surv.* 11.2 (June 1979), pp. 121–137. ISSN: 0360-0300. DOI: 10.1145/356770.356776. URL: http://doi.acm.org/10.1145/356770.356776 (visited on 02/02/2016).

[11] C.J. Date. *An Introduction to Database Systems*. 8th ed. Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc., 2003. ISBN: 0-321-19784-4.

[12] Cristian Estan and Jeffrey F. Naughton. "End-biased samples for join cardinality estimation". In: *Data Engineering, 2006. ICDE'06. Proceedings of the 22nd International Conference on*. IEEE, 2006, pp. 20–20. URL: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1617388 (visited on 02/08/2016).

[13] *EXPLAIN - MariaDB Knowledge Base*. URL: https://mariadb.com/kb/en/mariadb/explain/ (visited on 02/03/2016).

[14] Nicholas L. Farnan et al. "PAQO: a preference-aware query optimizer for PostgreSQL". In: *Proceedings of the VLDB Endowment* 6.12 (2013), pp. 1334–1337. URL: http://dl.acm.org/citation.cfm?id=2536309 (visited on 01/21/2016).

[15] Hector Garcia-Molina, Jeffrey D Ullman, and Jennifer Widom. *Database systems: the complete book*. Upper Saddle River, NJ: Prentice Hall, 2002. ISBN: 0-13-031995-3 978-0-13-031995-1.

[16] Goetz Graefe. "A Generalized Join Algorithm." In: *BTW*. Citeseer, 2011, pp. 267–286. URL: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.401.1510&rep=rep1&type=pdf#page=285 (visited on 02/08/2016).

[17] Peter J. Haas et al. "Sampling-based estimation of the number of distinct values of an attribute". In: *VLDB*. Vol. 95. 1995, pp. 311–322. URL: http://www.vldb.org/conf/1995/P311.PDF (visited on 02/08/2016).

[18] D. Harish, Pooja N. Darera, and Jayant R. Haritsa. "Identifying robust plans through plan diagram reduction". In: *Proceedings of the VLDB Endowment* 1.1 (2008), pp. 1124–1140. URL: http://dl.acm.org/citation.cfm?id=1453976 (visited on 01/21/2016).

[19] Jayant R. Haritsa. "The Picasso database query optimizer visualizer". In: *Proceedings of the VLDB Endowment* 3.1-2 (2010), pp. 1517–1520. URL: http://dl.acm.org/citation.cfm?id=1921027 (visited on 02/08/2016).

[20] *IBM Knowledge Center - Indexable and non-indexable predicates*. Jan. 1, 2013. URL: https://www-01.ibm.com/support/knowledgecenter/SSEPEK_10.0.0/com.ibm.db2z10.doc.perf/src/tpc/db2z_indexablepredicates.dita (visited on 02/03/2016).

[21] Yannis Ioannidis. "The history of histograms (abridged)". In: *Proceedings of the 29th international conference on Very large data bases-Volume 29*. VLDB Endowment, 2003, pp. 19–30. URL: http://dl.acm.org/citation.cfm?id=1315455 (visited on 02/08/2016).

[22] Yannis E. Ioannidis and Stavros Christodoulakis. "On the Propagation of Errors in the Size of Join Results". In: *Proceedings of the 1991 ACM SIGMOD International Conference on Management of Data*. SIGMOD '91. New York, NY, USA: ACM, 1991, pp. 268–277. ISBN: 0-89791-425-2. DOI: `10.1145/115790.115835`. URL: `http://doi.acm.org/10.1145/115790.115835` (visited on 02/08/2016).

[23] *ISO/IEC 9075-1:2011 - Information technology – Database languages – SQL – Part 1: Framework (SQL/Framework)*. URL: `http://www.iso.org/iso/home/store/catalogue_ics/catalogue_detail_ics.htm?csnumber=53681` (visited on 02/01/2016).

[24] Tapio Lahdenmäki and Michael Leach. *Relational database index design and the optimizers: DB2, Oracle, SQL server, et al.* Hoboken, NJ: Wiley, 2005. 310 pp. ISBN: 978-0-471-71999-1.

[25] Viktor Leis et al. "How good are query optimizers, really?" In: *Proceedings of the VLDB Endowment* 9.3 (2015), pp. 204–215. URL: `http://dl.acm.org/citation.cfm?id=2850594` (visited on 01/21/2016).

[26] Guy M. Lohman. *Is Query Optimization a "Solved" Problem?* ACM SIGMOD Blog. URL: `http://wp.sigmod.org/?p=1075` (visited on 02/08/2016).

[27] *MariaDB.org*. MariaDB.org. URL: `https://mariadb.org` (visited on 01/27/2016).

[28] Ingo Müller et al. "Cache-Efficient Aggregation: Hashing Is Sorting". In: *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data*. SIGMOD '15. New York, NY, USA: ACM, 2015, pp. 1123–1136. ISBN: 978-1-4503-2758-9. DOI: `10.1145/2723372.2747644`. URL: `http://doi.acm.org/10.1145/2723372.2747644` (visited on 02/09/2016).

[29] A. Nica, I. Charlesworth, and M. Panju. "Analyzing Query Optimization Process: Portraits of Join Enumeration Algorithms". In: *2012 IEEE 28th International Conference on Data Engineering (ICDE)*. 2012 IEEE 28th International Conference on Data Engineering (ICDE). Apr. 2012, pp. 1301–1304. DOI: `10.1109/ICDE.2012.132`.

[30] Kiyoshi Ono and Guy M. Lohman. "Measuring the Complexity of Join Enumeration in Query Optimization." In: *VLDB*. 1990, pp. 314–325. URL: `http://www.researchgate.net/profile/Kiyoshi_Ono/publication/221311358_Measuring_the_Complexity_of_Join_Enumeration_in_Query_Optimization/links/0fcfd50bfe86d75dfc000000.pdf` (visited on 01/27/2016).

[31] *philipsoutham/py-mysql2pgsql*. GitHub. URL: `https://github.com/philipsoutham/py-mysql2pgsql` (visited on 05/03/2016).

[32] *Portfolio compression service for OTC derivative dealers - triReduce | TriOptima*. URL: `http://www.trioptima.com/services/triReduce.html` (visited on 05/03/2016).

[33] *PostgreSQL: Documentation: 9.0: Planner/Optimizer*. URL: http://www.postgresql.org/docs/9.0/static/planner-optimizer.html (visited on 01/26/2016).

[34] *PostgreSQL: Documentation: 9.3: EXPLAIN*. URL: http://www.postgresql.org/docs/9.3/static/sql-explain.html (visited on 02/03/2016).

[35] *PostgreSQL: The world's most advanced open source database*. URL: http://www.postgresql.org/ (visited on 01/27/2016).

[36] Raghu Ramakrishnan and Johannes Gehrke. *Database management systems*. 3. ed., international ed. Boston, Mass.: McGraw-Hill, 2003. 1065 pp. ISBN: 978-0-07-246563-1 978-0-07-115110-8 978-0-07-123057-5.

[37] P. Griffiths Selinger et al. "Access Path Selection in a Relational Database Management System". In: *Proceedings of the 1979 ACM SIGMOD International Conference on Management of Data*. SIGMOD '79. New York, NY, USA: ACM, 1979, pp. 23–34. ISBN: 0-89791-001-X. DOI: 10.1145/582095.582099. URL: http://doi.acm.org/10.1145/582095.582099 (visited on 01/29/2016).

[38] *SQL | computer language*. Encyclopedia Britannica. URL: http://www.britannica.com/technology/SQL (visited on 02/01/2016).

[39] *Summary of predicate processing*. Oct. 2014. URL: https://www-01.ibm.com/support/knowledgecenter/api/content/nl/en-us/SSEPEK_10.0.0/com.ibm.db2z10.doc.perf/src/tpc/db2z_summarypredicateprocessing.dita (visited on 02/03/2016).

[40] Mana Takahashi, Shoko Azuma, and Ltd Trend-Pro Co. *The Manga Guide to Databases*. 1 edition. Tokyo, Japan; San Francisco, Calif.: No Starch Press, Feb. 7, 2009. 224 pp. ISBN: 978-1-59327-190-9.

[41] *The Join Operation*. URL: http://Use-The-Index-Luke.com/sql/join (visited on 02/09/2016).

[42] *TPC-DS - Homepage*. URL: http://www.tpc.org/tpcds/ (visited on 05/02/2016).

[43] *TPC-H - Homepage*. URL: http://www.tpc.org/tpch/ (visited on 01/26/2016).

[44] Immanuel Trummer and Christoph Koch. "Multi-Objective Parametric Query Optimization". In: VLDB. 2015. URL: https://infoscience.epfl.ch/record/206967 (visited on 01/21/2016).

[45] Kostas Tzoumas, Amol Deshpande, and Christian S. Jensen. "Lightweight graphical models for selectivity estimation without independence assumptions". In: *Proceedings of the VLDB Endowment* 4.11 (2011), pp. 852–863. URL: http://www.vldb.org/pvldb/vol4/p852-tzoumas.pdf (visited on 02/08/2016).

[46] David Vengerov et al. "Join size estimation subject to filter conditions". In: *Proceedings of the VLDB Endowment* 8.12 (2015), pp. 1530–1541. URL: http://dl.acm.org/citation.cfm?id=2824051 (visited on 02/09/2016).

[47] Wentao Wu et al. "Predicting query execution time: Are optimizer cost models really unusable?" In: *2013 IEEE 29th International Conference on Data Engineering (ICDE)*. 2013 IEEE 29th International Conference on Data Engineering (ICDE). Apr. 2013, pp. 1081–1092. DOI: 10.1109/ICDE.2013.6544899.

[48] Feng Yu et al. "CS2: a new database synopsis for query estimation". In: *Proceedings of the 2013 ACM SIGMOD International Conference on Management of Data*. ACM, 2013, pp. 469–480. URL: http://dl.acm.org/citation.cfm?id=2463701 (visited on 02/09/2016).

Appendix A

Source code

The appendix.