

SCHOOL OF COMPUTATION,
INFORMATION AND TECHNOLOGY -
INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatics

**Tuning Linear Programming Solvers for
Query Optimization**

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**Tuning Linear Programming Solvers for
Query Optimization**

**Anpassung von Linear Programming
Sollern für Anfrageoptimierung**

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I confirm that this bachelor's thesis in informatics is my own work and I have documented all sources and material used.

Munich, 15/10/2023

Sarra Ben Mohamed

Acknowledgments

Abstract

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1 Introduction

Our aim with this project is to investigate and compare different methods and techniques to solve small linear programming problems representing among others the problem of cardinality estimation. A way to estimate realistic and useful upper bounds of query sizes is through linear programming. Studies have shown that cardinality estimation is the major root of many issues in query optimization [Ngo22], which is why we want a practical estimate to choose the best from data plans to run efficient queries. For this purpose, we will introduce a formal description of the cardinality estimation problem, represent it in the form of a packing linear programming problem with the intention of maximizing the size of the query under some constraints. The result is hundreds of relatively small LP that we collect in datasets and solve them with different methods and algorithms. We then draw conclusions based on the results of our experiments, benchmarks and the previous work done on similar packing LP problems. This should guide us into constructing a thorough analysis of the particularities of these LP problems, what's unique about their structure and if their solution process follows any patterns. We then discuss and draw hypotheses on the ways this analysis can be exploited to further optimize the solution process: which methods or combination of methods deliver the best time and memory complexity.

2 Related work

2.1 Background

In this chapter we will talk about optimization, in particular the field of linear programming, we focus on the most widely used algorithms to tackle this problem, and we present some use cases and benchmarks for this technique.

2.1.1 Linear Programming

Informally, Linear Programming (LP) is a method to calculate the best possible outcome from a given set of requirements. A concrete real-world application of such a method is for instance aiming to maximize profit in a business, given some constraints on your variables like raw material availability, labor hours, etc.

Formally, LP is a mathematical modeling technique in which a linear function (called the objective function) $z : \mathbb{R}^n \rightarrow \mathbb{R}$ is maximized or minimized when subject to a set of linear constraints or inequalities. A maximization LP problem is then defined as: Maximize:

$$\begin{aligned} \text{Maximize} \quad & z = \mathbf{c}^T \mathbf{x} \\ \text{subject to} \quad & \mathbf{A}\mathbf{x} \leq \mathbf{b} \\ & \mathbf{x} \geq \mathbf{0} \end{aligned} \tag{2.1}$$

Where n is the number of decision variables and m is the number of constraints: $\mathbf{x} \in \mathbb{R}^n$ is the column vector of decision variables. $\mathbf{c} \in \mathbb{R}^n$ is the column vector of coefficients in the objective function. $\mathbf{A} \in \mathbb{R}^{m \times n}$ is the coefficient matrix in the constraints. $\mathbf{b} \in \mathbb{R}^m$ is the column vector of the right-hand sides of the constraints. In the following sections, we focus on LP problems that are maximization problems and we primarily use the matrix representation of the problem. To derive the setting for our contribution, we also explore a special instance of LP problems called packing LP.

Packing LP

One LP problem class that we are dealing with is called the packing LP problem. It is a special instance where: $\mathbf{c} = \mathbf{b} = [1 \ 1 \ \dots \ 1]$. Our specific problem is then expressed

as follows:

$$\begin{aligned}
& \text{Maximize} && \sum_{j=1}^n x_j \\
& \text{subject to} && \\
& && \sum_{j=1}^n a_{ij}x_j \leq 1, && i = 1, \dots, m \\
& && x_j \geq 0, && j = 1, \dots, n
\end{aligned} \tag{2.2}$$

This specific class of LPs has a simple structure that we can exploit, see Chapter 3, to further optimize our implementation.

2.1.2 The Standard Simplex Algorithm

In this subsection we will present the most widely used algorithm for solving LP problems, the simplex algorithm, as introduced by George Dantzig in 1947 [Dan90]. We have implemented our version of this algorithm in the C++ language and we use it, among others, to solve our dataset.

The algorithm

To be approachable by the simplex algorithm, the LP problem 2.1 needs to be cast in a computational form 2.3, that fulfills the requirement of the constraint matrix having to have full row rank and only equality constraints are allowed. To convert the inequalities to equations, we introduce slack variables s_1, s_2, \dots, s_m :

$$\begin{aligned}
& \text{Maximize} && z = \sum_{j=1}^n x_j \\
& \text{subject to} && \sum_{j=1}^n a_{1j}x_j + s_1 = b_1 \\
& && \sum_{j=1}^n a_{2j}x_j + s_2 = b_2 \\
& && \vdots \\
& && \sum_{j=1}^n a_{mj}x_j + s_m = b_m \\
& && x_1, x_2, \dots, x_n, s_1, s_2, \dots, s_m \geq 0
\end{aligned} \tag{2.3}$$

We then have a LP problem in the appropriate form and can be used as input for the simplex algorithm. To develop an intuition for how this algorithm works, it is helpful to view the strategy of the simplex algorithm as that of successive improvements until reaching an optimum. For instance, a maximization problem is optimized when the slack variables are “squeezed out,” maximizing the true variables’ effect on the objective function. Conversely, a minimization problem is optimized when the slack variables are “stuffed,” minimizing the true variables’ effect on the objective function.

Let’s start by defining the concepts of feasibility and unboundedness.

The simplex method is first initialized by an initial feasible solution \bar{x} , which is a vector of nonnegative numbers. This constitutes a feasible dictionary (or tableau), formally defined in [Chv83]. The simplex method then constructs a sequence of feasible dictionaries until reaching an optimum. This is how a simplex algorithm broadly looks like:

Algorithm 1 Simplex Algorithm

```

1: procedure SIMPLEX( $c, A, b$ )
2:   Initialize a feasible basic solution
3:   if no entering variable with positive reduced cost exists then
4:     return "Optimal solution found"
5:   end if
6:   if no positive pivot element in the column then
7:     return "Unbounded"
8:   end if
9:   Choose a leaving variable using the minimum ratio test
10:  Perform a pivot operation
11:  Update the basic and non-basic variables
12:  return current basic solution
13: end procedure

```

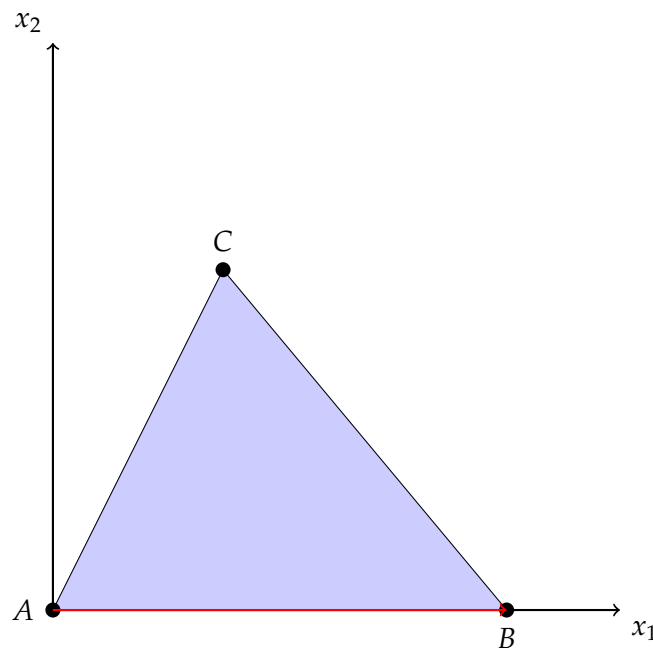
We call this a feasible dictionary [Chv83], or a feasible tableau. This is apparent, since all values in the RHS are positive, and the constraint matrix A also has positive coefficients.

- feasible dictionaries?
- (Bland’s rule, zero tolerance, ...)
- feasibility, boundedness,
- largest coefficient rule vs. largest increase rule.

- the problem of stalling, degeneracy
- Bland's rule guarantees termination.

Geometric Interpretation

The simplex algorithm can be understood geometrically as a method to navigate the vertices (corners) of a polytope defined by the feasible region of a linear programming problem. The algorithm starts at an initial vertex and moves along the edges of the polytope to vertices with better objective values until the optimal solution is reached.



In the above figure, the shaded region represents the feasible region of a linear programming problem. The simplex algorithm starts at vertex A and moves to vertex B because B offers a better objective value. The algorithm would continue navigating the vertices until the optimal solution is found.

- The simplex algorithm only evaluates the objective function at the vertices of the feasible region.
- At each step, the algorithm selects an adjacent vertex with a better objective value and moves to it.
- The algorithm terminates when it reaches a vertex where all adjacent vertices have worse objective values, indicating an optimal solution.

The complexity

Klee and Minty (1972) [KM72] constructed a worst-case example that showed that the simplex algorithm for linear programming has a number of iterations or pivots that is not majorized by any polynomial function of the two parameters that specify the size of the program, i.e. the number of decision variables n and the number of linear inequalities m . In particular, they showed that $2^m - 1$ iterations may be required, making the simplex' worst-case time complexity exponential, which we denote by $O(2^m)$. It can be however argued that this is only one worst-case example. Indeed, the number of iterations usually encountered in practice or even in formal experimental studies of the simplex algorithm is much lower. For packing linear programs, the worst-case time complexity of the Simplex algorithm remains exponential, even though there exists polynomial time implementations for it. [Sti10].

2.1.3 The Revised Simplex Algorithm

As explained in the book [Chv83], while Standard Simplex algorithm maintains and updates the entire tableau in its dense form, which includes both basic and non-basic variables, at each iteration. In contrast, the Revised Simplex algorithm focuses on tracking only the basic variables and their corresponding basis matrix B , thereby reducing memory requirements. The Revised Simplex algorithm often employs the product form update method to efficiently update the inverse of the basis matrix B^{-1} without having to recompute it from scratch, making it computationally more efficient for large-scale problems. Finally, we primarily use the Compressed Column Representation (CCR) of the, which greatly benefits the performance of the implementation.

The product form update method

We will discuss the PFI, introduced by George Dantzig [DO54].

Data structures

Compressed Storage Formats: We use the CSC format to store sparse matrices. These formats store the non-zero values, along with their corresponding row and column indices, in a compact way. This reduces memory usage and speeds up operations on sparse matrices

```
struct CCRMatrix {  
    float *values; // Non-zero values in the matrix
```

Algorithm 2 Revised Simplex Algorithm

1. **Input:** A feasible basic solution, B , c , A , and b
 2. **Output:** Optimal solution or a certificate of unboundedness
 3. Initialize B^{-1} , the inverse of the basis matrix B
 4. **While True:**
 - Step 1:* Solve the system $yB = c_B$ (BTRAN)
 - Step 2:* Choose an entering column. This may be any column a of A_N such that ya is less than the corresponding component of c_N . If there is no such column, then the current solution is optimal. In other words: Choose first j such that $c_j - yA_j > 0$ then $a = A_j$ is the enterig column.
 - Step 3:* Solve the system $Bd = a$ (FTRAN)
 - Step 4:* Let $x_B^* = B^{-1}b$ the current basic variables' values. Find the largest t such that $x_B^* - td \geq 0$ if there is no such t , then the problem is unbounded; otherwise, at least one component of $x_B^* - td$ equals zero and the corresponding variable is leaving the basis.
 - Step 5:* Set the value of the entering variable at t and replace the values x_B^* of the basic variables by $x_B^* - td$. Replace the leaving column of B by the entering column, and in the basis heading, replace the leaving variable by the entering variable.
 5. **Return** Optimal solution $B^{-1}b$
-

```

    int *rowIdx; // Row indices corresponding to the non-zero values
    int *colPtr; // Points to the index in 'values' where each column starts
};

```

2.1.4 Cardinality Estimation

In the pipeline of query execution, cardinality estimation serves as a cornerstone for the optimization process. Cardinality, defined as the number of tuples in the output, plays a pivotal role in the selection of an optimal query plan. Modern Database Management Systems (DBMSs) often rely on cost-based Query Optimizers to make this selection. For example, the SQL Server Query Optimizer [Mic23] employs a cost-based approach, aiming to minimize the estimated processing cost of executing a query.

The cost estimation is influenced by two primary factors: the cardinality of the query plan and the algorithmic cost model dictated by the operators used in the query. The former serves as an input parameter for the latter, creating a dependency between the two. Enhanced cardinality estimation can lead to more accurate cost models, which in turn results in more efficient query execution plans. Consequently, accurate and reliable cardinality estimates are crucial in achieving faster query execution times. The objective is to develop a Linear Programming (LP) solver designed specifically for cardinality estimation. This solver aims to maximize a cost function that represents the upper bound of the output size, optimizing for both time and memory complexity. The performance of this solver will be evaluated using the Query-per-Hour Performance Metric (QphH@Size).

To set the stage for our implementation, we focus on the problem of upper-bounding the cardinality of a join query Q . We begin by considering the worst-case join size and then proceed to add some constraints that keep some of our main variables in check. The motivation behind this work is to frame the problem of estimating the size of a multi-join query as a packing linear programming problem.

Scenario

To elucidate the core concepts, suppose we have two relation R and S with attributes

$$Q(a, b, c) = R(a, b) \bowtie S(b, c)$$

where we denote the sizes of the relations as $|R|$ and $|S|$ respectively. It is easy to see that the largest possible output is $|R| \cdot |S|$, which occurs when the join behaves like a cartesian product, i.e. have a selectivity equals to 1. So, this is the worst-case upper bound.

Now the maximum sizes of these relations (i.e. the number of tuples, in our case pairs) depend on the variables a , b and c , their respective types and domains. It can also be affected by the nature of the data or business rules.

If there are constraints on the domains of the attributes, the join size can be limited. For example:

- If B in R and B in S have domain constraints such that they can only take on k distinct values, then the maximum number of join results for a single value of B is $\frac{|R|}{k} \times \frac{|S|}{k}$ (assuming uniform distribution). Therefore, the worst-case join size is $k \times \left(\frac{|R|}{k} \times \frac{|S|}{k} \right) = \frac{|R| \times |S|}{k}$.
- If there are foreign key constraints, such as B in S being a foreign key referencing B in R , then each tuple in S can join with at most one tuple in R . This means the worst-case join size is $\min(|R|, |S|)$.

If there are multiple constraints, they can be combined to provide a tighter bound on the join size. For instance, if there's both a domain constraint and a foreign key constraint, the worst-case join size would be the minimum of the sizes derived from each constraint.

We start with the inequality 2.4. Applying the natural logarithm to both sides yields 2.5. We then rename the variables, simplifying the inequality to 2.6. Normalizing by dividing both sides by r' , we obtain 2.7. This leads us to the objective function for our packing LP problem.

$$|a| \cdot |b| \leq |R| \tag{2.4}$$

$$\ln |a| + \ln |b| \leq \ln |R| \tag{2.5}$$

$$a' + b' \leq r' \tag{2.6}$$

$$\frac{1}{r'} a' + \frac{1}{r'} b' \leq 1 \tag{2.7}$$

$$\text{maximize } a' + b' + c' + d' \quad \text{s.t.} \quad \frac{1}{r'} a' + \frac{1}{r'} b' \leq 1 \tag{2.8}$$

And in this simple abstracted way we get a sample packing LP from our dataset.

Variables

Objective

Constraints

2.2 Previous Work

Here we will discuss alternative approaches that are superseded by my work.

2.2.1 Comparative studies of different update methods

We will focus on one study [HH15].

2.2.2 Other techniques

The primal simplex method starts from a trial point that is primal feasible and iterates until dual feasibility. The dual simplex method starts from a trial point that is dual feasible and iterates until primal feasibility. ALGLIB implements a three-phase dual simplex method with additional degeneracy-breaking perturbation:

- Forrest-Tomlin updates for faster LU refactorizations
- A bound flipping ratio test (also known as long dual step) for longer steps
- Dual steepest edge pricing for better selection of the leaving variable
- Shifting (dynamic perturbations applied to cost vector) for better stability

3 Tuning Linear Programming Solvers for Query Optimization

3.1 Proposal

Our contribution consists in conducting experiments on small packing LP problems that are generated from real-life queries as mentioned in 2.1.4 as well as randomly generated LPs with varying sizes. We use different LP solvers, and different update methods to solve these LPs. We then proceed to compare results based on time and memory performance. We also build an analysis of our datasets' properties. Finally, we aim to give a recommendation on how to build the best performing LP solver based on the particularities of the LP problems.

3.2 Experimental Design

3.2.1 Analysis of dataset properties

In this subsection we will conduct an analysis of our dataset properties. What are the particularities of the structure of these LP problems, is there any patterns in their solution process. This analysis is based on observing the statistical results we obtained from running different solvers on these problems. This will later provide us with insight regarding optimization of these problems. TPC-H is a Decision Support Benchmark. The TPC-H is a decision support benchmark. It consists of a suite of business oriented ad-hoc queries and concurrent data modifications. The performance metric reported by TPC-H is called the TPC-H Composite Query-per-Hour Performance Metric (QphH@Size)

Mention zero tolerances: A zero tolerance epsilon safeguards against divisions by extremely small numbers, which tend to produce the most dangerous rounding errors, and may even lead to degeneracy. diagonal entry in eta matrix should be fairly far from otherwise (in our experiment) degeneracy.

Algorithm 3 Tableau Simplex Algorithm

```
1: Input: Packing LP maximisation problem in computational form
2: Output: Optimal value  $z$ 
3: Step 1: Pricing: Find pivot column, or entering variable using Bland's rule
4:    $enteringVars \leftarrow \text{findPivotColumnCandidates}()$ 
5:   if no entering variable found then
6:     print "Optimal value reached."
7:     return  $z$ 
8:   end if
9:    $pivotColumn \leftarrow enteringVars[0]$ 
10: Step 2: Find pivot row, or leaving variable using the ratio test
11:    $pivotRow \leftarrow \text{findPivotRow}(pivotColumn)$ 
12:   if no leaving variable then
13:     print "The given LP is unbounded."
14:     return  $\infty$ 
15:   end if
16: Step 3: Update the tableau using pivoting and update the objective function value
17:    $\text{doPivoting}(pivotRow, pivotColumn, z)$ 
18: Goto Step 1
```

3.2.2 Dataset Structure

Our dataset structure: as opposed to what the linear programming research has dealt with, which is very large problems, we are dealing with hundreds of small problems. These are represented in the revised simplex algorithm by sparse matrices but not as sparse as it would have been if the problem was large, small matrices that are not small enough to be dense. (they still have quite a number of non-zeroes).

3.3 Analysis

Some metrics:

- number of iterations
- runtime
- number of loops ?
- for matrix : number of columns and rows, nonzeros and density

3.4 Results

All the following results have been obtained on a personal computer with AMD 4000 series RYZEN, 16GB RAM running Ubuntu. Using the following settings:

- Presolve techniques are not used
- scaling techniques are not used
- The computed optimal solutions have been validated using the scipy python library.

4 Evaluation

4.1 Setup

4.1.1 Evaluation metrics

4.1.2 Evaluation baselines

4.2 Results

4.3 Discussion

5 Conclusion

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