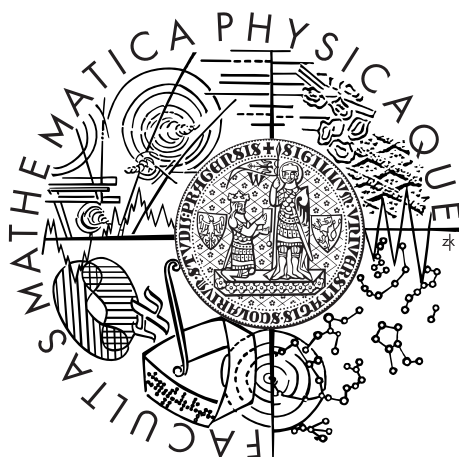


Charles University in Prague  
Faculty of Mathematics and Physics

## MASTER THESIS



Marcel Kikta

## Evaluating relational queries in pipeline-based environment

Department of Software Engineering

Supervisor of the master thesis: David Bednárek

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I would like to thank my parents for supporting me in my studies and my thesis supervisor David Bednárek for his advice and help with this thesis.

I declare that I carried out this master thesis independently, and only with the cited sources, literature and other professional sources.

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Autor: Marcel Kikta

Katedra: Katedra softwarového inženýrství

Vedoucí diplomové práce: RNDr. David Bednárek, Ph.D.

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Title:

Author: Marcel Kikta

Department: Název katedry či ústavu, kde byla práce oficiálně zadána

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# Introduction

Today's processors have multiple cores and it's single core performance is improving only very slow because of physical limitations. On the other hand number of cores is still increasing and we can assume that it will continue. That's why developing parallel software is crucial for improving overall performance.

Parallelization can be achieved manually or using some framework designed for it. For example there are frameworks like OpenMP or Intel TBB. Department of Software Engineering at Charles University in Prague developed it's own parallelization framework called Bobox[1].

Bobox is designed for parallel processing large amounts of data. It was specifically created to simplify and speed up parallel programming of certain class of problems - data computations based on non-linear pipeline. It was created to evaluate queries over relational data but it was successfully used in implementation of XQuery and TriQuery engines.

Bobox contains from runtime environment and operators. These operators are called boxes and they are C++ implementation of data processing algorithm. Boxes use messages called envelopes to send processed data to each other.

Bobox takes as input execution plan written in special language Bobolang[2]. It allows to define used boxes and simply connect them into directed acyclic graph. Bobolang specifies the structure of whole application and also the inner structure of each box. It can create highly optimized evaluation, which is capable of using the most of the hardware resources. The language has been tested in several applications and it turned out to be very powerful tool in data processing massive parallel application.

Most used databases are relational databases. They are based on the view of data organized in tables called relations. SQL[3] ("Structured query language") is very important language based on relation databases. It is used for querying data, modifying content of tables and also the structure of tables. When we want to evaluate query we need to parse query text input into parse tree. This form will be transformed to relational algebra, which we call logical query plan. It will be optimized and physical plan is generated. Physical plan indicates not only operation performed, but also which order are they performed and what kind of algorithms are used for execution.

The main goal of this thesis is to implement part of SQL compiler. The input is query written in XML format in form of relational algebra. Program validates input, optimizes and transforms it to physical plan of given query. The output is execution plan for Bobox written in Bobolang.

# 1. Architecture

## 1.1 Bobox

In the section we describe basic architecture of Bobox. Information source for this chapter is Doctoral thesis Parallel Processing of Data[4].

Overall Bobox architecture is displayed in figure 1.1. Framework contains of Boxes. Box is basically a C++ class containing implementation of data processing algorithm or it can be set of connected boxes. Box can have arbitrary number of inputs and outputs. All boxes are connected to a directed acyclic graph.

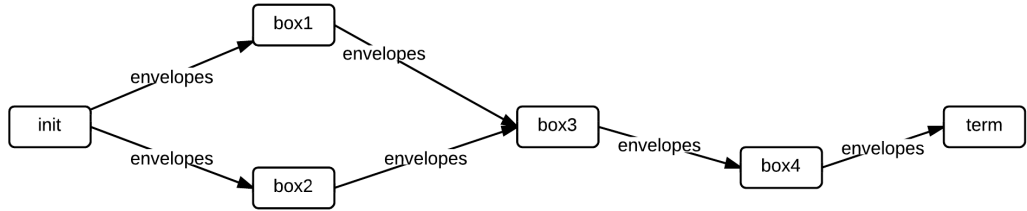


Figure 1.1: Bobox architecture.

Data streams are implemented as data units called enveloped. Envelope structure is displayed in figure 1.2. It consists of sequence tuples, but internally data are stored by columns, that means envelope contains from sequence of columns and it's data is stored in separate list. So to read all attributes of the i-th tuple we have to access all column lists and read it's i-th element. There is special type of envelope having poisoned pill. It is send after all valid data indicating end of data stream.

There are two special boxes, which have to be in every execution plan:

- *init* - first box in topological order and it indicates starting box of execution plan
- *term* - last box in topological order and indicates that plan has been completely evaluated

Evaluation starts with scheduling *init* box, which sends poisoned pills to all of its output. All of it's output boxes will be scheduled. They can read data from hard drive or network, process it and sent it to other boxes for further processing. Other boxes usually receives data in envelopes in their inputs. Box *term* waits for every it's input to receive poisoned pill and then evaluation ends.

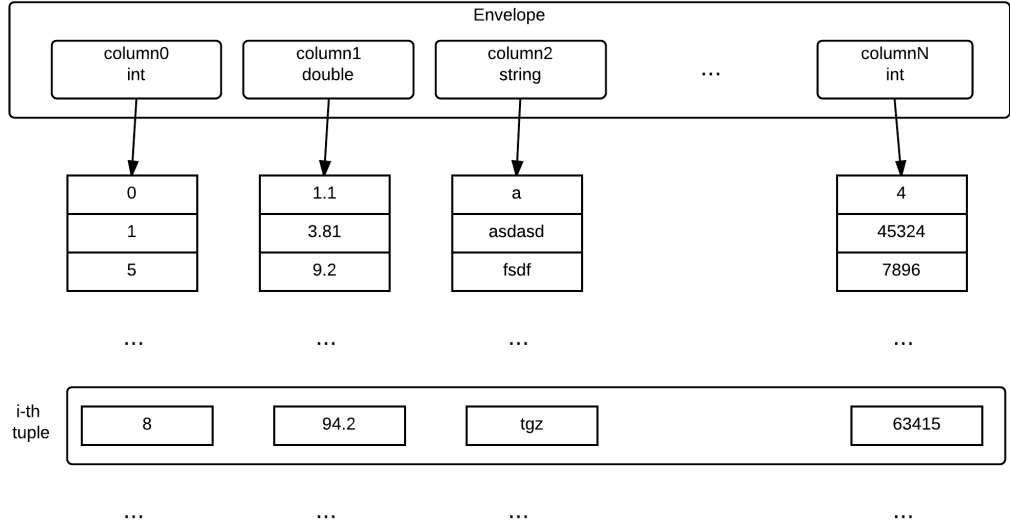


Figure 1.2: Envelope structure.

## 1.2 Bobolang

In this section we describe syntax and semantics of Bobolang language. We used paper Bobolang - a language for parallel streaming applications[2] as information source.

Bobolang is a formal description language for Bobox execution plan. Bobox environment provides implementation of basic operators (boxes). Bobolang let's programmer choose which boxes to used, what boxes to use, what type are passed and how the boxes are interconnected. Bobolang also provides possibility to create operators connecting existing ones.

In following example we show a definition using other operators:

```
operator process (int)->(int,int,int)
{
    preproc(int)->(int,int) pre;
    post(int,int)->(int,int,int) post;

    input -> pre;
    pre -> post -> output;
}
```

Code specifies that we are creating new operator called **process**. It takes one stream of integers as input and outputs one stream of triplets integers.

In the first part we declare sub operators, define type of input and output. For every declared sub operator we provide identifier. Second part specifies connec-



tion between declared operators. Code `op1 -> op2` indicates that output of `op1` is connected to input of operator `op2`. In this case output type of `op1` has equal to input type of `op2`. Bobolang syntax also allows to create chains of operators like `op1 -> op3` which has semantics like `op1 -> op2` and `op2 -> op3`.

There are explicitly defined operators called `input` and `output`. They represents input and output of declared operator `process`. The line `input -> pre;` represents that input of the operator `process` is connected to operator `pre`.

Boblang also allows to declare operators with empty input or output. They have type `()` that means it doesn't transfer any data. Only data allowed is to transfer poisoned pill. When box receives poisoned pill, it means that it should start working, Sending it means that it's work is done.

We can define whole execution plan using operator `main` with empty input and output. Example of whole Bobolang plan:

```
operator main()->()
{
    source()->(int) src;
    process(int)->(int,int,int) proc;
    sink(int,int,int)->() sink;

    input -> src -> proc -> sink -> output;
}
```

In figure 1.3 we can seen structure of example execution plan. Operators `init` and `term` are added automatically. Operator `init` sends poisoned pill to `source`, which can read data from hard drive or network. These data are send to box `process`. Operator `sink` stores data and sends poisoned pill to box `term` and the computation ends.

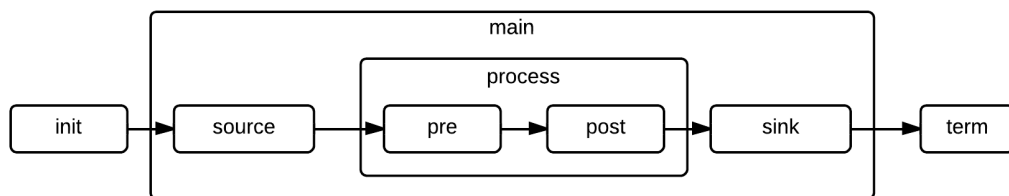


Figure 1.3: Example of execution plan.

## 1.3 SQL compiler architecture

In this section we describe planned SQL compiler. It's architecture is displayed in figure 1.4.

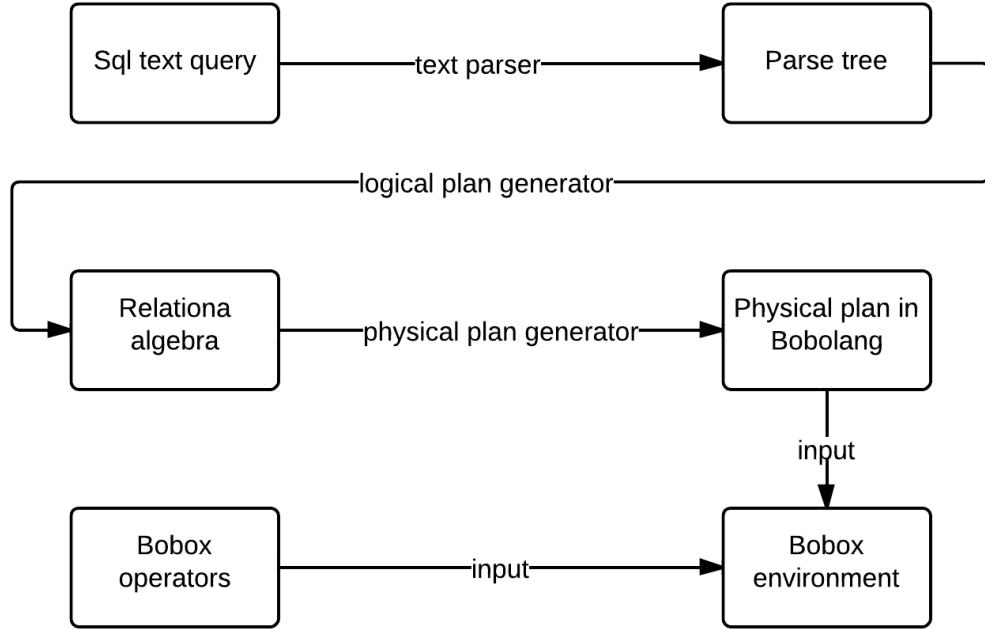


Figure 1.4: SQL compiler architecture.

SQL query is written in text. This text is parsed into parse tree, which is transformed into logical query plan (Relational algebra). Relational algebra is then optimized and this form is used for generating physical query plan. Physical plan written in Bobolang is input for Bobox for execution. Physical plan is not enough, we need to also provide implementation of physical algorithms (Bobox operators).

Since SQL is a pretty complicated language, this thesis aim is only implementing optimization and transformation of logical plan into physical plan.

## 2. Related work

In the chapter we introduce some theory of relational algebra, its optimizations and physical plan generation. This information was used for tool implementation.

### 2.1 Relational algebra

In this chapter we introduce and describe relational algebra[3]. We start with some basic definitions of relational model.

**Definition 1.** *Relation is a two dimensional table.*

**Definition 2.** *Attribute is column of a table.*

**Definition 3.** *Schema name of the relations and a set of attributes. For example:  $Movie(id, name, length)$ .*

**Definition 4.** *Tuple of a relation is a row other than header row.*

An algebra in general consists of operators and atomic operands. For example in arithmetic algebra variables like  $x$  or constant like 15 and operators are addition multiplication, subtraction and division. We can build expression by applying operators on operands or other expressions. Example of an expression in arithmetic algebra is  $(15 + x) * x$ .

Relational algebra has atomic operands:

- Variables, that are relations.
- Constants, that are finite relations.

In classical relational algebra all operators and expression results are set. All these operations can be applied also to bags. Relation algebra operators are:

- Set operations - union, difference, intersection.
- Removing operators - selection, which removes rows and projection that eliminates columns from given relation.
- Operations that combine two relations, all kinds of joins.
- Renaming operations, that doesn't change tuples of the relation but changes schema.

Expressions in relational algebra are called *queries*.

### 2.1.1 Classical relational algebra operators

#### Set operations on relations

Sets operations are:

- Union  $R \cup S$  is a set of tuples that are in  $R$  or  $S$ .
- Intersection  $R \cap S$  is a set of tuples that are in both  $R$  and  $S$ .
- Difference  $R - S$  is a set of tuples that are in  $R$  but not in  $S$ .

Lets have relations  $R$  and  $S$ . If we want to apply some set operation both relations must have the same set of attributes. If we want to compute set theoretic union, difference or intersections the order of columns must be the same in both relations. We can also use renaming operations if relations doesn't have same number of attributes.

#### Projection

*Projection* operator  $\pi$  produces from relation  $R$  new Relations with reduced set of attributes. Result of a expression  $\pi_{A_1, A_3, A_4, \dots, A_N}(R)$  is relation  $R$  with attributes  $A_1, A_3, A_4, \dots, A_N$ .

#### Selection

If we apply operator selection  $\sigma$  on Relation  $R$  with condition  $C$  we get a new relation with same attributes and tuples, which satisfy given condition. For example  $\sigma_{A_1=4}(R)$ .

#### Cartesian product

Cartesian product of two sets  $R$  and  $S$  creates a set of pairs by choosing the first element of pair to be any element from  $R$  and second element of pair to be any element of  $S$ . Cartesian product of relations similar. We pair tuples from  $R$  with all tuples from  $S$ .

#### Natural joins

We usually don't want to pair all of the tuples from  $R$  to all tuples from  $S$ . We can pair tuple in some other way. The simplest join is called natural join of  $R$  and  $S$  ( $R \bowtie S$ ). Let schema of  $R$  be  $R(r_1, r_2, \dots, r_n, c_1, c_2, \dots, c_n)$  and schema of  $S$  be  $S(s_1, s_2, \dots, s_n, c_1, c_2, \dots, c_n)$ . In natural join we pair tuple  $r$  from relation  $R$  to tuple  $s$  from relation  $S$  only if  $r$  and  $s$  agree on all attributes with same name (in this case  $c_1, c_2, \dots, c_n$ ).

## Theta joins

Natural join forces us to use one specific condition. In many cases we want to join a relation with some other condition. For this purpose we have theta-join. The notation for joining relation  $R$  and  $S$  based on condition  $C$  is  $R \bowtie_C S$ . The result is constructed in the following way:

1. Make Cartesian product of  $R$  and  $S$
2. Use selection with condition  $C$ .

Basically  $R \bowtie_C S = \sigma_C(R \times S)$

## Renaming

In order to control the name of attributes or relation name we have the renaming operator. We can use operator  $\rho_{S(A_1, A_2, \dots, A_n)}(R)$ . Result will have the same tuples as  $R$  but the relation will be called  $S$  and attributes will be renamed to  $(A_1, A_2, \dots, A_n)$ .

### 2.1.2 Relational operations on bags

Commercial database systems almost never are based purely on bags. *Bag* is a multi-set. Only operations that behave differently are intersection, union, and difference.

#### Union

Bag union of  $R \cup S$  we just add all tuples from  $S$  and  $R$  together. If tuple  $t$  appears in  $R$   $m$ -times and in  $S$   $n$ -times then in  $R \cup S$  will  $t$  appear  $m + n$  times. Both  $m$  and  $n$  can be zero.

#### Intersection

Let's have tuple  $t$  that appears in  $R$   $m$ -times and  $S$   $n$ -times. In the Bag intersection  $R \cap S$  will be  $t$   $\min(m, n)$ -times.

#### Difference

Every tuple  $t$  that appears in  $R$   $m$ -times and  $S$   $n$ -times, will appear  $\max(0, m - n)$  times in bag  $R - S$ .

### 2.1.3 Extended operators of Relational algebra

We will introduce extended operators that proved useful in many query languages like SQL.

## Duplicate elimination

This operator  $\delta(R)$  returns set consisting of one copy of every tuple that appears in bag  $R$  one or more times.

## Aggregate operations

Aggregate operators such as sum are not relational algebra operator but are used by grouping operator. They apply on column and produce one number as result. The standard operators are *SUM*, *AVG*(average), *MIN*, *MAX* and *COUNT*.

## Grouping operator

We often doesn't want to compute aggregation function for entire column. We rather compute this function on for some group of columns. For example we can compute average salary for every person in database, or we can group them by companies and get every salary in every company.

For this purpose we have grouping operator  $\gamma_L(R)$ .  $L$  is a list of:

1. Attribute of  $R$  by which  $R$  will be grouped.
2. Aggregation operator applied on a attribute of relation.

Relation computed by expression  $\gamma_L(R)$  is constructed:

1. Relation will be partitioned into groups. Every group contains all tuples which have same value in all grouping attributes. If there is no grouping attributes, all tuples will be in one group.
2. For each group operator produces one tuple consisting of:
  - (a) Grouping attributes values for group.
  - (b) Results of aggregations over all tuple of processed group.

Duplicate elimination operator is a special case of grouping operator. We can express  $\delta(R)$  with  $\gamma_L(R)$ , where  $L$  is a list of all attributes of  $R$ .

## Extended projection operator

We can extend classical projection operator  $\pi_L(R)$  introduced in chapter 2.1.1. We denote it also  $\pi_L(R)$  but projection list can have following elements:

1. Attribute of  $R$ , which means attribute will appear in output.
2. Expression  $x = y$ , attribute  $y$  will be renamed to  $x$ .

3. Expression  $x = E$ , where  $E$  is an expression created from attributes from  $R$ , constants, arithmetic, string and other operators.  $x$  is new name. For example  $x = e * (1 - l)$ .

### The sorting operator

In several situations we want the output of query to be sorted. Expression  $\tau_L(R)$ , where  $R$  is relation,  $L$  is list of attributes with additional information about sort order, is relation with same tuples like  $R$  but different order of tuples. Example:  $\tau_{A_1:A, A_2:D}(R)$  will sort relation  $R$  by attribute  $A_1$  ascending and tuples with same  $A_1$  value will be additionally sorted by their  $A_2$  value descending.

### Outer joins

Lets have join  $R \bowtie_C S$ . We call tuple  $t$  from relation  $R$  or  $S$  *dangling* if we didn't find any match in relation  $S$  or  $R$ . Outer join  $R \bowtie_C^\circ S$  is formed by creating  $R \bowtie_C S$  and adding dangling tuples from  $R$  and  $S$ . The added tuples must be filled with special *null* value in all attributes they don't have but appear in join result.

Left/right outer join is outer join but we only add dangling tuples from left/right relation.

## 2.2 Optimizations of relational algebra

After initial logical query plan is generated, we can apply some heuristics to improve it, using some algebraic laws that hold for relational algebra.

### 2.2.1 Commutative and associative laws

Commutative and associative operators are Cartesian product, natural join, union and intersection. Theta join is commutative but generally is not associative. But if the conditions makes sense where they where positioned, then theta join is associative. That means we can make following changes to algebra tree:

- $R \oplus S = S \oplus R$
- $(R \oplus S) \oplus T = R \oplus (S \oplus T)$

$\oplus$  stands for  $\times$ ,  $\cap$ ,  $\cup$ ,  $\bowtie$  or  $\bowtie_C$ .

### 2.2.2 Laws involving selection

Selection are very important for improving logical plan. They usually reduce size of relation markedly so that's why we need to move them down the tree as far as possible. We can change order of selections:

- $\sigma_{C_1}(\sigma_{C_2}(R)) = \sigma_{C_2}(\sigma_{C_1}(R))$

Sometimes we cannot push whole condition but we can split it:

- $\sigma_{C_1 \text{ AND } C_2}(R) = \sigma_{C_1}(\sigma_{C_2}(R))$
- $\sigma_{C_1 \text{ OR } C_2}(R) = \sigma_{C_1}(R) \cup_S \sigma_{C_2}(R)$

Last law works only when  $R$  is a set.  $\cup_S$  stands for set union. We can push selection down union, it has to be pushed to both branches:

- $\sigma_C(R \cup S) = \sigma_C(R) \cup \sigma_C(S)$

When pushing selection through difference we must push it to first branch. Pushing to second branch optional. Laws for difference:

- $\sigma_C(R - S) = \sigma_C(R) - \sigma_C(S)$
- $\sigma_C(R - S) = \sigma_C(R) - S$

Following laws allow to push selection down both arguments. Let's have selection  $\sigma_C$ . We can push it to the branch, which contains all attributes used in  $C$ . If  $C$  contains only attributes of  $R$ :

- $\sigma_C(R \oplus S) = \sigma_C(R) \oplus S$

$\oplus$  stands for  $\times$ ,  $\cap$ ,  $\cup$ ,  $\bowtie$  or  $\bowtie_C$ . If relation  $S$  and  $R$  contains all attributes of  $C$  we can also use following law:

- $\sigma_C(R \bowtie S) = \sigma_C(R) \bowtie \sigma_C(S)$

### 2.2.3 Laws involving projection

Principle for manipulation with projections that we can add projection anywhere in the tree as long as it only eliminates attributes which are not used anymore and don't appear in query result.



### 2.2.4 Laws involving joins and products

We have more laws involving selection that follow directly from definition of the join:

- $\sigma_C(R \times S) = R \bowtie_C S$
- $R \bowtie S = \pi_L(\sigma_C(R \times S))$ ,  $C$  is condition that equates each pair of attributes of  $R$  and  $S$ , which have the same name and  $L$  is a list of attributes of relation  $R$ .

## 2.3 Physical plan generation

After we optimized logical plan, we need to create physical plan. We generate many physical plans and choose one with least estimated cost to run it. This approach is called cost-based enumeration.

For each physical plan we select

1. An order of grouping and joins.
2. An algorithm for each operator. For example if we use join based on hashing or sorting.
3. Additional operators which are not presented in logical plan. For example we can sort relation in order to use faster algorithm which assumes that its input is sorted.
4. The way in which arguments are passed to between operators. We can use iterators for it or store result on hard drive.

### 2.3.1 Size estimations

The costs of evaluating physical plan are based on estimated size of intermediate relations. Ideally we want our estimation to be accurate, easy to compute and logically consistent (size of relation doesn't depend on how relation is computed). We will present simple rules, which will give us good estimations in most situations. Goal of estimating sizes is not to predict exact size of relation, even an inaccurate size will help us with plan generation.

In this section we will use following conventions:

- $T(R)$  is number of tuples in relation  $R$ .
- $V(R, a)$  number of distinct values in attribute  $a$ .
- $V(R, [a_1, a_2, \dots, a_n])$  is number of tuples in  $\delta(\pi_{a_1, a_2, \dots, a_n}(R))$

### Estimating the size of projection

Projection is only operator which size of result is computable. It doesn't change number of tuples, only their lengths change.

### Estimating the size of selection

Selection usually reduces number of tuples. Lets have  $S = \sigma_{A=c}(R)$ , where  $A$  is a attribute of  $R$  and  $c$  is a constant. Recommended estimation is:

- $T(S) = T(R)/V(R, A)$

More problematic estimation is when selection involves inequality comparison. Lets have  $S = \sigma_{A < c}(R)$ . In average half the tuple satisfies condition, but usually queries select only a small fraction from all tuples. Therefore the estimation is:

- $T(S) = T(R)/3$

For selection where condition is in form  $C_1$  and  $C_2$  and ... and  $C_N$  we can treat selection as a cascade of simple selections and estimate size for every simpler condition.

In case we have following condition:  $S = \sigma_{not(C)}(R)$ , we use this estimation:

- $T(S) = T(R) - T(\sigma_C(R))$

Little more complicated is when condition involved an *or* of conditions. Lets have expression  $S = \sigma_{C_1 \text{ or } C_2}(R)$ . We assume that  $C_1$  and  $C_2$  are independent. Size of  $S$  is:

- $T(S) = T(R)(1 - (1 - \frac{m_1}{T(R)})(1 - \frac{m_2}{T(R)}))$

Expression  $1 - \frac{m_1}{T(R)}$  is fraction of tuples which doesn't satisfy condition  $C_1$  and  $1 - \frac{m_2}{T(R)}$  is fraction of tuples which doesn't satisfy condition  $C_2$ . Product of these numbers are the fraction of tuples from  $R$  which are not in result. One minus the product gives us fraction of tuples in  $S$ .

### Estimating the size of join

We start with natural join. Let's have expression  $X = R(X, Y) \bowtie S(Y, Z)$ . We join here by one attribute and we use estimation:

- $T(X) = \frac{T(R)T(S)}{\max(V(R, Y), V(S, Y))}$

We can generalize this rule for joining with multiple attributes. For join  $R \bowtie S$ , where we join  $R$  and  $S$  using following attributes  $a_1, a_2, \dots, a_n$ , we use this estimation:

$$\bullet T(R \bowtie S) = \frac{T(R)T(S)}{\prod_{k=1}^n \max(V(R, a_k), V(S, a_k))}$$

If we have other type of join (theta join), we can use following rules for it's estimation:

1. Size of product is product of sizes of relations involved.
2. Equality conditions can be estimated using techniques presented in natural joins.
3. An inequality compassion can be handled like inequality comparison in expression  $\sigma_{A < c}(R)$ . We assume that 1/3 of tuples will satisfy condition.

### Estimating the size of union

If we have bag union, then size of resulting relation is sum of sizes of input relations. Size of set union  $R \cup_S S$  can be between  $\max(T(R), T(S))$  and  $T(R) + T(S)$ . Recommended estimate is average of this numbers.

### Estimating the size of intersection

Size of relation  $R \cap S$  can be between 0 and  $\min(T(R), T(S))$ . We recommend to take half of size of smaller relation:

$$\bullet \min(T(R), T(S))/2.$$

### Estimating the size of difference

Result of expression  $R - S$  can be as big as  $T(R)$  and as small as  $T(R) - T(S)$ . Suggested estimate is:

$$\bullet T(R - S) = T(R) - T(S).$$

### Estimating the size of grouping

Size of the result of expression  $\gamma_L(R)$  is  $V(R, [g_1, g_2, \dots, g_n])$ , where  $g_x$  are grouping attributes of  $L$ . This statistics is almost never available so we need another estimate.  $T(\gamma_L(R))$  can be between 1 and  $\prod_{k=1}^n V(R, g_k)$ . Upper bound can larger than number of tuple in relation  $R$ . That's why we suggest:

$$\bullet T(\gamma_L(R)) = \min\left(\frac{T(R)}{2}, \prod_{k=1}^n V(R, g_k)\right)$$

Duplicate elimination can be handled exactly like grouping.

### 2.3.2 Enumerating plans

For every logical plan there is exponential many physical plans. in this section we present way to enumerate physical plans so we can choose plan with least estimated cost. There are two broad approaches:

- Top-down: We go down the algebra tree. For each possible implementation of operation, we consider best possible algorithms for it's subtrees. We compute costs of every combination and take the best.
- Bottom-up: We go up the tree and for every subexpression we enumerate plans based on plans generated for it's subexpressions.

There is not much difference between this approaches but one method eliminates plans that other method can't and vice versa.

#### Heuristic selection

We use same approach for generating physical plan as we used to improve logical plan. We make choices based on heuristics. Here are some heuristics that can be used:

- If there is selection  $\sigma_{A=c}$  and relation  $R$  has index on attribute  $A$ , then we use scanning by index instead of scanning table with filtering result.
- More general rule if selection contains condition  $A = c$  and selected relation contains index of  $A$ , then we use scanning by index and filtering result based on other parts of condition.
- If an join attribute has an index, we can use joining by index.
- If one argument of join is sorted, then we prefer merge join to hash join.
- If we compute intersection of union of more than 2 relations, we perform algorithm on smaller relations first.

#### Branch-and-bound plan enumeration

Branch-and-bound plan enumeration is often use in practice. We begin by finding physical plan using heuristics. We denote cost of this plan  $C$ . Then we can consider other plans for sub-queries. We can eliminate any plan for sub-query with cost greater than  $C$ . If we get plan with lower estimated cost than  $C$  we use this plan instead.

The great advantage is we can choose when to cut search for better plan. If  $C$  is low then we don't continue searching other plan. On the other hand when  $C$  is large, it is better to invest some time in finding a better plan.

## Hill climbing

First we start with heuristically selected plan. Then we try to do some changes, for example changing order of joins or replacing operator using hash table for sort-based operator. When we find a plan where no small modification give up better plan, then we make this plan out chosen physical plan.

## Dynamic programming

Dynamic programming is variation of bottom-up strategy. For each subexpression we keep only one plan of least cost.

## Selinger-Style Optimization

This is a improvement of dynamic programming approach. We keep for every subexpression not only best plan, but also other plans with higher cost, which result is in some way sorted. This might be useful in following situation:

1. The sort operator  $\tau_L$  is on the root of tree and we have plan, which is sorted by some or all attributes in  $L$ .
2. Plan is sorted by attribute used later in grouping.
3. We are joining by some sorted attribute.

In this situation we don't have to sort input or we need only partial sort and we can use faster algorithm, which takes advantage of sorted input.

### 2.3.3 Choosing join order

We have three choices how to choose order of join of multiple relation:

1. Consider all possible options.
2. Consider only subset of join orders.
3. Use heuristic to pick one.

In this section we present algorithm that can be used for choosing join order.

## Dynamic programming to select a join order

For this algorithm we need a table, where we store information following information:

1. Estimated size of relation.

2. Cost to compute current relations.
3. Expression how was current relation computed.

We store every single relation  $R$  with estimated cost 0. For every pair of relations we compute their estimated size of join and store it into table. For that we use estimation describe in section 2.3.1.

After that we compute entry of all subset of sizes  $(3, 4, \dots, n)$ . If we want to consider all possible trees, we need to partition relations in join  $R$  into two non empty disjoint sets. For each pair of sets we compute estimated size and cost of their join to get join  $R$ . For this we use data already in our table. We are estimating join of  $k$  relations and all joins of  $k - 1$  relations are already estimated. The join tree with least estimated cost will be stored in the table.

Example: for estimating join  $A \bowtie B \bowtie C \bowtie D$  we try to join following subsets:

1.  $A$  and  $B \bowtie C \bowtie D$
2.  $B$  and  $A \bowtie C \bowtie D$
3.  $C$  and  $A \bowtie B \bowtie D$
4.  $D$  and  $A \bowtie B \bowtie C$
5.  $A \bowtie B$  and  $C \bowtie D$
6.  $A \bowtie C$  and  $B \bowtie D$
7.  $A \bowtie D$  and  $B \bowtie C$

We don't have to consider all trees but only so called left-deep join tree. Tree is called left-deep tree if all of its right children are leaves. Right-deep tree is tree, where all left children are leaves.

We do it the same way like we wanted to include all possible trees, but with one exception. When partitioning  $R$  into two non empty disjoint sets, we make sure that one set has only one relation.

Example: for estimating join  $A \bowtie B \bowtie C \bowtie D$  we try to join following subsets:

1.  $A$  and  $B \bowtie C \bowtie D$
2.  $B$  and  $A \bowtie C \bowtie D$
3.  $C$  and  $A \bowtie B \bowtie D$
4.  $D$  and  $A \bowtie B \bowtie C$

### Greedy algorithm for selecting a join order

Time complexity of using dynamic programming to select an order of join is exponential. We can use it for small amount of relations (maybe maximal 5 or 6). If we don't want to invest time we can use greedy algorithm. This algorithm has to store same information as dynamic programming algorithm for every relation.

We start with a pair of relations  $R_i, R_j$ , for which size of  $R_i \bowtie R_j$  is smallest. This join is our current tree.

For other relations that are not yet included we find relation  $R_k$ , so that its join with current tree gives us smallest estimated size. We continue until we include all relations into tree.

This algorithm will also create left-deep or right-deep join tree.

There are examples where dynamic algorithm finds plans with lower estimated cost than greedy algorithm.

### 2.3.4 Choosing physical algorithms

table

select

join

other

## 3. Analysis

3.1 Format of relational algebra

3.2 Type resolving

3.3 Architecture

3.4 Optimization

3.5 Generating physical plan



## 4. Implementation

# Conclusion

# Bibliography

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# List of figures

# Attachments