# Lab 4: Query Optimization

**Assigned: May 7th**  
  
**Due: May 21st, 23:59 PM**

In this lab, you will implement a query optimizer on top of SimpleDB.  
The main tasks include implementing a selectivity estimation framework  
and a cost-based optimizer. You have freedom as to exactly what you  
implement, but we recommend using something similar to the Selinger  
cost-based optimizer.

The remainder of this document describes what is involved in  
adding optimizer support and provides a basic outline of how  
you might add this support to your database.

As with the previous lab, we recommend that you start as **early** as possible.

## 1. Getting started

You should begin with the code you submitted for Lab 3 (if you did not submit code for Lab 3, or your solution didn't work properly, contact us to discuss options). We have provided you with extra test cases for this lab that are not in the original code distribution you received. We reiterate that the unit tests we provide are to help guide your implementation along, but they are not intended to be comprehensive or to establish correctness.

You will need to add these new test cases to your release. The easiest way to do this is to untar the new code in the same directory as your top-level simpledb directory, as follows:

* Make a copy of your Lab 3 solution by typing:

$ cp -r acmdb-lab3 acmdb-lab4

* Change to the directory that contains your top-level simpledb code:

$ cd acmdb-lab4

* Download the new tests and skeleton code for Lab 4 from [acmdb-lab4-supplement.tar.gz](assets/acmdb-lab4-supplement.tar.gz). (You can also find this file on Canvas.) Then place it in the acmdb-lab4 folder.
* Extract the new files for Lab 4 by typing:

$ tar -xvzf acmdb-lab4-supplement.tar.gz

### 1.1. Implementation hints

We suggest exercises along this document to guide your implementation, but you may find that a different order makes more sense for you. As before, we will grade your assignment by looking at your code and verifying that you have passed the test for the ant targets test and systemtest. See Section 3.4 for a complete discussion of grading and the tests you will need to pass.

Here's a rough outline of one way you might proceed with this lab. More details on these steps are given in Section 2 below.

* Implement the methods in the TableStats class that allow  
  it to estimate selectivities of filters and cost of  
  scans, using histograms (skeleton provided for the IntHistogram class) or some  
  other form of statistics of your devising.
* Implement the methods in the JoinOptimizer class that  
  allow it to estimate the cost and selectivities of joins.
* Write the orderJoins method in JoinOptimizer. This method must produce  
  an optimal ordering for a series of joins (likely using the  
  Selinger algorithm), given statistics computed in the previous two steps.

## 2. Optimizer outline

Recall that the main idea of a cost-based optimizer is to:

* Use statistics about tables to estimate "costs" of different  
  query plans. Typically, the cost of a plan is related to the cardinalities of  
  (number of tuples produced by) intermediate joins and selections, as well as the  
  selectivity of filter and join predicates.
* Use these statistics to order joins and selections in an  
  optimal way, and to select the best implementation for join  
  algorithms from amongst several alternatives.

In this lab, you will implement code to perform both of these  
functions.

The optimizer will be invoked from simpledb/Parser.java. Briefly, if you have a catalog file  
catalog.txt describing your tables, you can run the parser by  
typing:

java -jar dist/simpledb.jar parser catalog.txt

When the Parser is invoked, it will compute statistics over all of the  
tables (using statistics code you provide). When a query is issued,  
the parser  
will convert the query into a logical plan representation and then call  
your query optimizer to generate an optimal plan.

### 2.1 Overall Optimizer Structure

Before getting started with the implementation, you need to understand the overall structure of the SimpleDB optimizer.   
The overall control flow of the SimpleDB modules of the parser and optimizer is  
 shown in Figure 1.

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Figure 1: Diagram illustrating classes, methods, and objects used in the parser

The key at the bottom explains the symbols; you  
will implement the components with double-borders. The classes and  
methods will be explained in more detail in the text that follows (you may wish to refer back  
to this diagram), but  
the basic operation is as follows:

1. Parser.java constructs a set of table statistics (stored in the  
   statsMap container) when it is initialized. It then waits for a  
   query to be input, and calls the method parseQuery on that query.
2. parseQuery first constructs a LogicalPlan that  
   represents the parsed query. parseQuery then calls the method physicalPlan on the  
   LogicalPlan instance it has constructed. The physicalPlan method returns a DBIterator object that can be used to actually run  
   the query.

In the exercises to come, you will implement the methods that help  
physicalPlan devise an optimal plan.

### 2.2. Statistics Estimation

Accurately estimating plan cost is quite tricky. In this lab, we will  
focus only on the cost of sequences of joins and base table accesses. We  
won't worry about access method selection (since we only have one  
access method, table scans) or the costs of additional operators (like  
aggregates).

You are only required to consider left-deep plans for this lab.

#### 2.2.1 Overall Plan Cost

We will write join plans of the form p=t1 join t2 join ... tn,   
which signifies a left deep join where t1 is the left-most  
join (deepest in the tree).  
Given a plan like p, its cost  
can be expressed as:

scancost(t1) + scancost(t2) + joincost(t1 join t2) +  
scancost(t3) + joincost((t1 join t2) join t3) +  
...

Here, scancost(t1) is the I/O cost of scanning table t1,  
joincost(t1,t2) is the CPU cost to join t1 to t2. To  
make I/O and CPU cost comparable, typically a constant scaling factor  
is used, e.g.:

cost(predicate application) = 1  
cost(pageScan) = SCALING\_FACTOR x cost(predicate application)

For this lab, you can ignore the effects of caching (e.g., assume that  
every access to a table incurs the full cost of a scan). Therefore, scancost(t1) is simply the  
number of pages in t1 x SCALING\_FACTOR.

#### 2.2.2 Join Cost

When using nested loops joins, recall that the cost of a join between  
two tables t1 and t2 (where t1 is the outer) is  
simply:

joincost(t1 join t2) = scancost(t1) + ntups(t1) x scancost(t2) //IO cost  
 + ntups(t1) x ntups(t2) //CPU cost

Here, ntups(t1) is the number of tuples in table t1.

#### 2.2.3 Filter Selectivity

ntups can be directly computed for a base table by  
scanning that table. Estimating ntups for a table with  
one or more selection predicates over it can be trickier --   
this is the *filter selectivity estimation* problem. Here's one  
approach that you might use, based on computing a histogram over the  
values in the table:

* Compute the minimum and maximum values for every attribute in the table (by scanning  
  it once).
* Construct a histogram for every attribute in the table. A simple  
  approach is to use a fixed number of buckets *NumB*,  
  with  
  each bucket representing the number of records in a fixed range of the  
  domain of the attribute of the histogram. For example, if a field  
  *f* ranges from 1 to 100, and there are 10 buckets, then bucket 1 might  
  contain the count of the number of records between 1 and 10, bucket  
  2 a count of the number of records between 11 and 20, and so on.
* Scan the table again, selecting out all of fields of all of the  
  tuples and using them to populate the counts of the buckets  
  in each histogram.
* To estimate the selectivity of an equality expression,  
  *f=const*, compute the bucket that contains value *const*.  
  Suppose the width (range of values) of the bucket is *w*, the height (number of  
  tuples) is *h*,  
  and the number of tuples in the table is *ntups*. Then, assuming  
  values are uniformly distributed throughout the bucket, the selectivity of  
  the  
  expression is roughly *(h / w) / ntups*, since *(h/w)*  
  represents the expected number of tuples in the bin with value  
  *const*.
* To estimate the selectivity of a range expression *f>const*,  
  compute the  
  bucket *b* that *const* is in, with width *w\_b* and height  
  *h\_b*. Then, *b* contains a fraction *b\_f = h\_b / ntups* of the  
  total tuples. Assuming tuples are uniformly distributed throughout *b*,  
  the fraction *b\_part* of *b* that is *> const* is  
  *(b\_right - const) / w\_b*, where *b\_right* is the right endpoint of  
  *b*'s bucket. Thus, bucket *b* contributes *(b\_f x*  
   *b\_part)* selectivity to the predicate. In addition, buckets  
  *b+1...NumB-1* contribute all of their  
  selectivity (which can be computed using a formula similar to  
  *b\_f* above). Summing the selectivity contributions of all the  
  buckets will yield the overall selectivity of the expression.   
  Figure 2 illustrates this process.
* Selectivity of expressions involving *less than* can be performed  
  similar to the greater than case, looking at buckets down to 0.

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Figure 2: Diagram illustrating the histograms you will implement in Lab 5

In the next two exercises, you will code to perform selectivity estimation of  
joins and filters.

**Exercise 1: IntHistogram.java**

You will need to implement  
some way to record table statistics for selectivity estimation. We have  
provided a skeleton class, IntHistogram that will do this. Our   
intent is that you calculate histograms using the bucket-based method described   
above, but you are free to use some other method so long as it provides  
reasonable selectivity estimates.

We have provided a class StringHistogram that uses  
IntHistogram to compute selecitivites for String  
predicates. You may modify StringHistogram if you want to   
implement a better estimator, though you should not need to in order to   
complete this lab.

After completing this exercise, you should be able to pass the   
IntHistogramTest unit test.

**Exercise 2: TableStats.java**

The class TableStats contains methods that compute  
the number of tuples and pages in a table and that estimate the  
selectivity of predicates over the fields of that table. The  
query parser we have created creates one instance of TableStats per  
table, and passes these structures into your query optimizer (which  
you will need in later exercises).

You should fill in the following methods and classes in TableStats:

* Implement the TableStats constructor:  
  Once you have  
  implemented a method for tracking statistics such as histograms, you  
  should implement the TableStats constructor, adding code  
  to scan the table (possibly multiple times) to build the statistics  
  you need.
* Implement estimateSelectivity(int field, Predicate.Op op,  
  Field constant): Using your statistics (e.g., an IntHistogram  
  or StringHistogram depending on the type of the field), estimate  
  the selectivity of predicate field op constant on the table.
* Implement estimateScanCost(): This method estimates the  
  cost of sequentially scanning the file, given that the cost to read  
  a page is costPerPageIO. You can assume that there are no  
  seeks and that no pages are in the buffer pool. This method may  
  use costs or sizes you computed in the constructor.
* Implement estimateTableCardinality(double  
  selectivityFactor): This method returns the number of tuples  
  in the relation, given that a predicate with selectivity  
  selectivityFactor is applied. This method may  
  use costs or sizes you computed in the constructor.

You may wish to modify the constructor of TableStats.java to, for  
example, compute histograms over the fields as described above for  
purposes of selectivity estimation.

After completing these tasks you should be able to pass the unit tests  
in TableStatsTest.

#### 2.2.4 Join Cardinality

Finally, observe that the cost for the join plan p above  
includes expressions of the form joincost((t1 join t2) join  
t3). To evaluate this expression, you need some way to estimate  
the size (ntups) of t1 join t2. This *join*  
*cardinality estimation* problem is harder than the filter selectivity  
estimation problem. In this lab, you aren't required to do anything  
fancy for this, though it is possible to  
include a histogram-based method for join selectivity estimation.

While implementing your simple solution, you should keep in mind the following:

* For equality joins, when one of the attributes is a primary key, the number of tuples produced by the join cannot  
  be larger than the cardinality of the non-primary key attribute.
* For equality joins when there is no primary key, it's hard to say much about what the size of the output  
  is -- it could be the size of the product of the cardinalities of the tables (if both tables have the  
  same value for all tuples) -- or it could be 0. It's fine to make up a simple heuristic (say,  
  the size of the larger of the two tables).
* For range scans, it is similarly hard to say anything accurate about sizes.  
  The size of the output should be proportional to  
  the sizes of the inputs. It is fine to assume that a fixed fraction  
  of the cross-product is emitted by range scans (say, 30%). In general, the cost of a range  
  join should be larger than the cost of a non-primary key equality join of two tables  
  of the same size.

**Exercise 3: Join Cost Estimation**

The class JoinOptimizer.java includes all of the methods  
for ordering and computing costs of joins. In this exercise, you  
will write the methods for estimating the selectivity and cost of  
a join, specifically:

* Implement   
  estimateJoinCost(LogicalJoinNode j, int card1, int card2, double  
  cost1, double cost2): This method estimates the cost of  
  join j, given that the left input is of cardinality card1, the  
  right input of cardinality card2, that the cost to scan the left  
  input is cost1, and that the cost to access the right input is  
  card2. You can assume the join is an NL join, and apply  
  the formula mentioned earlier.
* Implement estimateJoinCardinality(LogicalJoinNode j, int  
  card1, int card2, boolean t1pkey, boolean t2pkey): This  
  method estimates the number of tuples output by join j, given that  
  the left input is size card1, the right input is size card2, and  
  the flags t1pkey and t2pkey that indicate whether the left and  
  right (respectively) field is unique (a primary key).

After implementing these methods, you should be able to pass the unit  
tests estimateJoinCostTest and estimateJoinCardinality in JoinOptimizerTest.java.

### 2.3 Join Ordering

Now that you have implemented methods for estimating costs, you will  
implement the Selinger optimizer. For these methods, joins are  
expressed as a list of join nodes (e.g., predicates over two tables)  
as opposed to a list of relations to join as described in class.

An outline in pseudocode would be:

1. j = set of join nodes  
2. for (i in 1...|j|):  
3. for s in {all length i subsets of j}  
4. bestPlan = {}  
5. for s' in {all length d-1 subsets of s}  
6. subplan = optjoin(s')  
7. plan = best way to join (s-s') to subplan  
8. if (cost(plan) < cost(bestPlan))  
9. bestPlan = plan  
10. optjoin(s) = bestPlan  
11. return optjoin(j)

To help you implement this algorithm, we have provided several classes and methods to assist you. First,  
the method enumerateSubsets(Vector v, int size) in JoinOptimizer.java will return  
a set of all of the subsets of v of size size. This method is not particularly efficient but is enough for this lab.

Second, we have provided the method:

private CostCard computeCostAndCardOfSubplan(HashMap<String, TableStats> stats,   
 HashMap<String, Double> filterSelectivities,   
 LogicalJoinNode joinToRemove,   
 Set<LogicalJoinNode> joinSet,  
 double bestCostSoFar,  
 PlanCache pc)

Given a subset of joins (joinSet), and a join to remove from  
this set (joinToRemove), this method computes the best way to  
join joinToRemove to joinSet - {joinToRemove}. It  
returns this best method in a CostCard object, which includes  
the cost, cardinality, and best join ordering (as a vector).  
computeCostAndCardOfSubplan may return null, if no plan can  
be found (because, for example, there is no left-deep join that is  
possible), or if the cost of all plans is greater than the  
bestCostSoFar argument. The method uses a cache of previous  
joins called pc (optjoin in the pseudocode above) to  
quickly lookup the fastest way to join joinSet -  
{joinToRemove}. The other arguments (stats and  
filterSelectivities) are passed into the orderJoins  
method that you must implement as a part of Exercise 4, and are  
explained below. This method essentially performs lines 6--8 of the  
pseudocode described earlier.

Third, we have provided the method:

private void printJoins(Vector<LogicalJoinNode> js,   
 PlanCache pc,  
 HashMap<String, TableStats> stats,  
 HashMap<String, Double> selectivities)

This method can be used to display a graphical representation of a join plan (when the "explain" flag is set via  
the "-explain" option to the optimizer, for example).

Fourth, we have provided a class PlanCache that can be used  
to cache the best way to join a subset of the joins considered so far  
in your implementation of Selinger (an instance of this class is  
needed to use computeCostAndCardOfSubplan).

**Exercise 4: Join Ordering**

In JoinOptimizer.java, implement the method:

Vector<LogicalJoinNode> orderJoins(HashMap<String, TableStats> stats,   
 HashMap<String, Double> filterSelectivities,   
 boolean explain)

This method should operate on the joins class member,  
returning a new Vector that specifies the order in which joins  
should be done. Item 0 of this vector indicates the left-most,  
bottom-most join in a left-deep plan. Adjacent joins in the  
returned vector should share at least one field to ensure the plan  
is left-deep. Here stats is an object that lets you find  
the TableStats for a given table name that appears in the  
FROM list of the query. filterSelectivities  
allows you to find the selectivity of any predicates over a table;  
it is guaranteed to have one entry per table name in the  
FROM list. Finally, explain specifies that you  
should output a representation of the join order for informational purposes.

You may wish to use the helper methods and classes described above to assist  
in your implementation. Roughly, your implementation should follow  
the pseudocode above, looping through subset sizes, subsets, and  
sub-plans of subsets, calling computeCostAndCardOfSubplan and  
building a PlanCache object that stores the minimal-cost  
way to perform each subset join.

After implementing this method, you should be able to pass all the unit tests in  
JoinOptimizerTest. You should also pass the system test  
QueryTest.

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### 2.4 Extra Credit

In this section, we describe several optional excercises that you may  
implement for extra credit. These are less well defined than the  
previous exercises but give you a chance to show off your mastery of  
query optimization!

**Bonus Exercises.** Each of these bonuses is worth up to 5% extra credit:

* *Add code to perform more advanced join cardinality estimation*.  
  Rather than using simple heuristics to estimate join cardinality,  
  devise a more sophisticated algorithm.
* One option is to use joint histograms between  
  every pair of attributes *a* and *b* in every pair of tables *t1* and *t2*.  
  The idea is to create buckets of *a*, and for each bucket *A* of *a*, create a  
  histogram of *b* values that co-occur with *a* values in *A*.
* Another way to estimate the cardinality of a join is to assume that each value in the smaller table has a matching value in the larger table. Then the formula for the join selectivity would be: 1/(*Max*(*num-distinct*(t1, column1), *num-distinct*(t2, column2))). Here, column1 and column2 are the join attributes. The cardinality of the join is then the product of the cardinalities of *t1* and *t2* times the selectivity.
* *Improved subset iterator*. Our implementation of  
  enumerateSubsets is quite inefficient, because it creates  
  a large number of Java objects on each invocation. A better  
  approach would be to implement an iterator that, for example,  
  returns a BitSet that specifies the elements in the  
  joins vector that should be accessed on each iteration.  
  In this bonus exercise, you would improve the performance of  
  enumerateSubsets so that your system could perform query  
  optimization on plans with 20 or more joins (currently such plans  
  takes minutes or hours to compute).
* *A cost model that accounts for caching*. The methods to  
  estimate scan and join cost do not account for caching in the  
  buffer pool. You should extend the cost model to account for  
  caching effects. This is tricky because multiple joins are  
  running simultaneously due to the iterator model, and so it may be  
  hard to predict how much memory each will have access to using the  
  simple buffer pool we have implemented in previous labs.
* *Improved join algorithms and algorithm selection*. Our  
  current cost estimation and join operator selection algorithms  
  (see instantiateJoin() in JoinOptimizer.java)  
  only consider nested loops joins. Extend these methods to use one  
  or more additional join algorithms (for example, some form of in  
  memory hashing using a HashMap).
* *Bushy plans*. Improve the provided orderJoins() and other helper  
  methods to generate bushy joins. Our query plan  
  generation and visualization algorithms are perfectly capable of  
  handling bushy plans; for example, if orderJoins()  
  returns the vector (t1 join t2 ; t3 join t4 ; t2 join t3), this  
  will correspond to a bushy plan with the (t2 join t3) node at the top.

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You have now completed this lab.   
Good work!

## 3. Logistics

You must submit your code (see below) as well as a short (2 pages, maximum) writeup describing your approach. This writeup should:

* Describe any design decisions you made, including methods for selectivity estimation, join ordering.
* Discuss and justify any changes you made to the API.
* Describe any missing or incomplete elements of your code.
* Describe how long you spent on the lab, and whether there was anything you found particularly difficult or confusing.

### 3.1. Collaboration

This lab should be manageable for a single person. Therefore, teaming is prohibited in this project.

### 3.2. Submitting your assignment

To submit your code, please create a acmdb-lab4 directory in your github repo. Please submit your writeup as a PDF or plain text file (.txt) in the top level of your acmdb-lab4 directory. Please do not submit a .doc or .docx.

### 3.3. Submitting a bug

Please submit (friendly!) bug reports to both TAs. When you do, please try to include:

* A description of the bug.
* A .java file we can drop in the test/simpledb directory, compile, and run.
* A .txt file with the data that reproduces the bug. We should be able to convert it to a .dat file using HeapFileEncoder.

### 3.4. Grading

100% of your grade will be based on whether or not your code passes the test suite we will run over it. Before handing in your code, you should make sure it produces no errors (passes all of the tests) from both ant test and ant systemtest.

**Important:** before testing, we will replace your build.xml and the entire contents of the test directory with our version of these files. This means you cannot change the format of .dat files! You should also be careful changing our APIs. You should test that your code compiles the unmodified tests.

In other words, we will pull your repo, replace the files mentioned above, compile it, and then grade it. It will look roughly like this:

[replace build.xml and test]  
$ git checkout -- build.xml test\  
$ ant test  
$ ant systemtest

If any of these commands fail, we'll be unhappy, and, therefore, so will your grade. We've had a lot of fun designing this assignment, and we hope you enjoy hacking on it!