CS352 Lecture - Efficient Query Processing / Query Processing Optimization

Last revised March 23, 2021

Objectives:

1. To understand why the choice of strategy for performing a query can have a huge impact on processing time
2. To be familiar with various strategies for performing selection operations
3. To be familiar with various strategies for performing join operations
4. To be familiar with how statistical information can be used for evaluating strategies

Materials:

1. Projectable of two different RA formulations of a query involving a select and a join
2. Projectable of query for join examples
3. Projectables of pseudo-code for 4 join strategies Rework!
4. Projectables of two equivalent forms of a query as a tree
5. Projectable of n and V values for join size estimation

I. Introduction

A. Given a query, the DBMS must interpret it and "plan" a strategy for carrying it out. For all but the simplest queries, there will probably be several ways of doing so - with total processing effort possibly varying by several orders of magnitude.

B. Some of the issues have to do with the way that data is physically stored on disk.

Recall that, for most queries, the cost of accesses to data on disk far exceeds any other other cost, and becomes the most significant factor in determining the time needed to process most queries.

C. Some of the issues have to do with the fact that several different, but equivalent, formulations of a query may be possible - perhaps with vastly different execution costs.

Example: Given the schemes: BookAuthor(callNo, authorName)
BookTitle(callNo, title)

1. The question "Give me the titles of all books written by Korth" can be answered by either of the following two relational algebra queries:

$\pi_{title}(\sigma_{authorName = 'Korth'}(BookTitle \,|X|\, BookAuthor))$

$\pi_{title}(BookTitle \,|X|\, \sigma_{authorName = 'Korth'}(BookAuthor))$

PROJECT

2. Because relational algebra is a procedural language, each of these queries implies a particular sequence of operations:

   a) The first query suggests that we should first do a natural join of BookAuthor and BookTitle, then select from it the tuples with authorName = 'Korth', then project out the title field.

   b) The second query suggests that we should first select only those tuples from Book Author where authorName = 'Korth', then join these with BookTitle, then project out the title field.

3. Suppose our database held 10,000 BookTitle tuples and 20,000 BookAuthor tuples (an average of two authors/book.) Suppose, further, that only 2 BookAuthor tuples contained 'Korth'. How would the cost of these two strategies compare?

   a) The first strategy would process all 10,000 BookTitle tuples at least once, and likewise all 20,000 BookAuthor tuples. Further, it would

involve creating a intermediate relation with 3 attributes (callNo, title, authorName) and (presumably) 20,000 tuples. Each of these would need to be examined to see if it pertains to 'Korth'. Thus, a total of 50,000 tuples would need to be processed - minimum. (And the minimum could only be achieved if the join is facilitated by an index on callNo for at least one of the two original schemes.)

b) On the other hand, the second strategy might involve processing only 2 BookAuthor tuples and the corresponding 2 BookTitle tuples (if appropriate indices exist) - for a total of 4 tuples. This is an effort ratio of 50,000: 4 = 12,500:1.

4. A low-performance DBMS might put the burden on the user to formulate his/her queries in such a way as to allow the most efficient processing of them. A good DBMS, however, will transform a given query into a more efficient equivalent one whenever possible.

   Example: If the first query above were given to a simple DBMS, it would perform very much less efficiently than if it were given the second. However, a sophisticated DBMS would transform the first query into something like the second before processing it if that were the form it was given.

D. The material assigned in the book goes into some detail about how one estimates the cost of various plans for executing a query. For a database that is stored on magnetic disk, it turns out that the cost of accessing the data on disk dominates the cost; but when the data is stored on SSD devices or even in memory, other factors such as computational cost have to be considered as well. A sophisticated DBMS has to consider these factors as well.

   However, for simplicity, in comparing ways to process a query, we will focus just on minimizing disk accesses, which will help us identify key ideas.

E. In the remainder of this series of lectures, we want to explore the following topics:

1. Strategies for performing selection

2. Strategies for performing joins

   Both of these, in turn, are influenced by issues such as the way the data is stored physically on the disk, and the availability of indices

3. Rules of equivalence for transforming queries

4. The use of statistical information to help evaluate query-processing strategies.

II. Selection Strategies

A. Consider a selection expression like

$$\sigma_{\text{SomeCondition}}(\text{SomeTable})$$

We consider several possibilities for the condition

1. It involves searching for an exact match for the value of some attribute (e.g. "borrowerID = '12345'"), and the attribute is a candidate key for the table, so we expect at most one match.

2. It involves searching for an exact match for the value of some attribute, but the attribute is <u>not</u> a candidate key for the table, so we can have any number of matches

3. It involves searching for a value of some attribute lying in some range (e.g."`where age between 21 and 65`" or "`where age < 21`"),

4. It involves some more complex condition - perhaps involving a compound condition ("and" or "or") or the values of two or more attributes.

B. One way to handle any selection condition is to use linear search - scan through all the tuples in the table, and find the ones that match.

If the tuples are blocked, then it suffices to perform one disk access for a block, and then scan the buffered copies of the records in turn.

Example: a table with 10,000 tuples - blocked 20 per block - would require 500 disk accesses - which would take on the order of 500*10ms = 5 seconds.

C. Linear search can often be avoided if the table has a relevant index.

1. Exact match queries can be facilitated if the table has an index on the attribute we are searching for. At this point, we need to consider a number of possibilities:

a) The attribute on which the search is based is a superkey. In this case, searching the index will take us directly to the one and only tuple desired. This requires one block access plus whatever accesses are needed to use the index.

b) The attribute on which the search is based is not a superkey - so there will likely be multiple matches.

(1)If the index is clustering (the primary index for the table) , then the index will take us to the first matching tuple. Since the index is in key order, it is likely that other matches will be in the same block, or perhaps the next block - so 1 (or sometimes more) block accesses plus whatever accesses are needed to use the index.

(2)If the index is non-clustering, then the index entry contains pointers to the relevant tuples, each of which is likely in a different block - so we need as many block accesses as there are matches plus whatever is needed to use the index.

2. If the query is a range query, an ordered index will take us to the first tuple that satisfies the query. (We search for the starting value of the range, and the index takes us to the first tuple greater than or equal to this.)

   (1)If the index is clustering (the primary index for the table), then successive tuples will lie in the same or successive blocks. Each block containing a tuple that matches the query will be processed just once.

   (2) If it is non-clustering but ordered (e.g. a B+ tree), then we can find successive matching tuples following pointers from successive index entries. The number of blocks read will be one per match found by the query.

   (3)However, if it is not ordered (a hashtable) then the index doesn't really help in this case.

3. If the query has a more complicated structure (e.g. involves and, or, not), it may be possible to make use of indexes to create a list of pointers to tuples and then perform the computation on the lists before retrieving the actual tuples.

4. Of course, when estimating the cost of a selection using an index, we need to consider both the cost of accessing the relevant block(s) of the index and the cost of accessing the data.

   a) For example, if a table is stored as a B-Tree of height 3, then access to a piece of data using the index involves - in principle - three disk accesses.

   b) However, we will almost certainly keep a copy of the root of the tree in a buffer - reducing the number of accesses to two. Moreover, we may be able to buffer the second level blocks of the index as well - in which case an access using the index only involves accessing the data block.

   c) Even if we can't do this, though, use of an index will still beat linear search - 3 disk accesses is a lot less than retrieving every block!

III. **Performing Joins Efficiently**

A. Joins are the most expensive part of query processing, because the number of tuples examined to do a join can approach the product of the size of the two relations involved. Thus, the query optimizer must give considerable attention to choosing the best join strategy.

B. As a worst-case example, consider the following SQL query, which finds the names of borrowers who have over due books:

```
select first_name, last_name
from Borrower join CheckedOut on
    Borrower.borrowerID = CheckedOut.borrowerID
where date_due < current date;
```

This is almost equivalent to the relational Algebra expression

π σ Borrower |X| CheckedOut
first_name book is overdue
last_name

PROJECT

(Actually, these are not quite equivalent - why?

ASK

RA eliminates duplicates, which would arise if a borrower had more than one overdue book. The SQL would need distinct, which would call for an extra processing step after the join to eliminate duplicates. We will ignore this for now (and not eliminate duplicates) but will talk about later.

1. Assumptions for examples:

   Borrower has 10.000 tuples blocked 20/block = 5000 blocks
   CheckedOut has 2000 tuples blocked 20/block = 100 blocks

a. Although the join is not a cartesian join, performing it will require examining 10,000 * 2000 = 20 million tuples to see if borrowerIDs match and the book is overdue.

b. One simplifying step - which a smart DBMS would do - is to do the selection based on the book being overdue before doing the join, which could result in fewer potential matches being considered (unless, of course, every book is overdue!). However, for this series of examples, we will not do this - considering that comes later.

2. This join can be computed in several different ways that differ in cost by orders of magnitude:

3. The simplest scheme would be

```
for (int i = 0; i < 10000; i ++)
{
   retrieve Borrower[i];
   for (int j = 0; j < 2000; j ++)
   {
      retrieve CheckedOut[j];
      if (Borrower[i].borrowerID==CheckedOut[j].borrowerID)
        check to see if overdue and if so add to result
   }
}
```

PROJECT

a) This scheme is called NESTED LOOP JOIN.

b) How many disk accesses does this strategy require?

i. Since we can buffer one block of borrower in memory, the 10,000 tuples we access from this table require 500 block readss.

ii. In the case of the inner relation (BookAuthor), we go through it 10,000 times. Each time through, we only need to need to read each of the 100

blocks once when retrieving the first tuple in the block, since the block we need is already buffered for the remaining 19 tuples. So we do 10,000 * 100 = 1,000,000 disk accesses to read the CheckedOut tuples

iii. we will ignore the number needed to write the result - which will hopefully be few!

iv. So we get a total of at least 1,010,000 disk accesses. If each disk access takes on the average 10 ms, we would estimate this amounts to 10100 seconds = 168 minutes = 2.8 hours

4. However, since the two relations are physically stored in blocks on disk containing several tuples, a MUCH BETTER scheme would be:

```
for (int i = 0; i < 10000; i += 20)
{
   retrieve block containing Borrower[i]..Borrower[i+19];
   for (int j = 0; j < j < 2000; j += 20)
   {
      retrieve block containing CheckedOut[j]..CheckedOut[j+19];
      for (int k = 0; k < 20; k ++)
         for (int l = 0; l < 20; l ++)
            if (Borrower[i+k].borrowerID ==
                  CheckedOut.[j+l].borrowerID)
               check to see if overdue and if so add to result
   }
}
```

PROJECT

a) At first glance, this looks like a much worse strategy - since we now have 4 nested loops!

b) However, when the relative cost of in-memory processing and disk accesses is taken into consideration, this strategy turns out to be much better.

(1)For the outer loop, this would require only 500 accesses to retrieve all the Borrower tuples.

(2)As before, the inner loop requires only 100 accesses each time through the BookAuthor table, but now this done only 500 times - for a total of 100*500 = 50,000 accesses

(3)The grand total is thus 50,500, plus writes needed for the result. This is almost 20 times better than the nested loop join. We're now down to 50,500 * 10ms = 505 seconds (about 8.4 minutes).

This strategy is called BLOCK NESTED JOIN.

5. However, if a moderate amount of internal memory is available for buffering, we could do even better. Note that the 2000 CheckedOut tuples could be stored using just 100 buffers (probably under a megabyte of RAM). We thus consider the following approach:

```
for (int j = 0; j < 2000; i += 20)
   retrieve and buffer block containing
      CheckedOut[j]..CheckedOut[j+19];

for (int i = 0; i < 10000; i += 20)
{
   retrieve block containing Borrower[i]..Borrower[i+19];
   for (int j = 0; j < j < 2000; j += 20)
   {
      // No need to retrieve CheckedOut blocks
      for (int k = 0; k < 20; k ++)
         for (int l = 0; l < 20; l ++)
            if (Borrower[i+k].borrowerID ==
                  CheckedOut.[j+l].borrowerID)
               check to see if overdue and if so add to result
   }
}
```

PROJECT

Now we only need 100 + 500 = 600 disk accesses for reading each of the two

relations exactly once! Further, it is clear that this is the best we can do, since we must consider each tuple of each relation at least once, and the two relations together occupy 600 blocks. Our time is now down to about 600*10 ms = 6 seconds!

Since we only need to buffer the smaller of the two tables, this strategy is applicable whenever there is enough memory to buffer at least one of the tables in its entirety.

C. Natural joins (or theta joins based on the equality of some attribute values) can be greatly expedited if indices are available

1. In computing a join, we can scan through the tuples of one relation. For each tuple, we find the tuple(s) of the other relation that join with it (if any) and construct a new tuple for each one found.

2. In the worst case, finding matching tuples in the second relation would require a sequential scan of that relation. Note that this means that we would have to read through the second relation one complete time FOR EACH TUPLE (OR MORE LIKELY EACH BLOCK) in the first relation.

3. However, if the second relation has an index or indices on the join field(s) (or even on one of the join fields if there is more than one), then the sequential scan of the second relation can be avoided. Instead, we use the index to locate tuples in the second relation that are candidates for joining with the current tuple in the first relation.

   Suppose our Borrower table has an index based on the borrowerID. Then we might use the following strategy:

```
for (int i = 0; i < 2000; i += 20)
{
```

```
   retrieve block containing
      CheckedOut[i]..CheckedOut[i+19];
   for (int j = 0; < j < 20; j ++)
   {
      look up CheckedOut[i+j].borrowerID in the
        borrowerID index of Borrower
      // There must be a match in Borrower table
      // due to foreign key constraint
      if book is overdue add to result
   }
}
```

(Obviously, we could reduce the number of index lookups by checking for overdue first - but so we can compare with the other strategies we will not do this.

This strategy is called INDEXED LOOP JOIN

We now do 100 accesses to read the CheckedOut table, and a maximum of 2000 index lookups and retrievals. Assume the average cost of doing this is 2 disk accesses - then our total is 4100 accesses - which in this case is not as good as our previous example where we could buffer one whole table, but is a lot better than Nested Block Join and so would be preferred if we were dealing with tables too large to preclude buffering.

D. Because an appropriate index can greatly speed a join - especially if the index can be buffered in memory though the table cannot - it may be desirable in some cases for the query processor to create a TEMPORARY INDEX for one of the relations being joined - to be discarded when the query has been processed.

Example: Suppose neither Borrower nor CheckedOut has a relevant index. (An index on callNumber for CheckedOut wouldn't help) If we had to do the join Borrower |X| CheckedOut, we might choose to build a temporary index for the Borrower table. (We prefer this because there are fewer tuples in the CheckedOut table - and hence fewer accesses needed to the index.)

1. Each entry in the index for Borrower might occupy on the order of 10 bytes. If we use a dense index (as we must unless Borrower is physically ordered

by borrowerID) then the overall index will be about 100,000 bytes long - not a problem for main memory on a machine of any size.

2. Constructing the index, then, will require processing each of the tuples of Borrower once - for a total of 10000 tuples or 500 disk accesses

3. The join itself would require a maximum of 2000 accesses for the actual Borrower tuple (but none for the index since it's now in memory)- for a total of 2100 accesses in all - a worthwhile improvement over not using an index if we cannot buffer a whole table. (Which we probably could in this case :-))

E. Natural joins can also take advantage of the PHYSICAL ORDER of data in the database. In particular, if two relations being joined are both physically stored in ascending order of the join key, then a technique known as MERGE JOIN becomes possible.

Suppose, for the sake of illustration, that the Borrower table is stored in order of borrowerID, and the CheckedOut table is also stored in this order.

1. The following is the basic algorithm:

```
get first tuple from Borrower;
get first tuple from CheckedOut;
while (we still have valid tuples from both relations)
{
   if (Borrower.borrowerID == CheckedOut.borrowerID)
   {
      if the book is overdue output one tuple to the result;
      get next tuple from CheckedOut
      // We might have more matches for this borrower,
      // so keep current borrower tuple
   }
   else if (Borrower.borrowerID < CheckedOut.borrowerID)
      // Can't possibly be more matches for this borrower
      get next tuple from Borrower;
   else
      // See if this borrower has another book overdue
```

```
        get next tuple from CheckedOut;
    }
```

PROJECT

Notice that this is only applicable if both tables are clustered based on the attribute they have in common - and wouldn't work as written if duplicate names could occur in both tables!

2. Using this strategy, we only fetch each tuple once, for a total of 600 disk accesses - the same as what we could get if we were able to buffer one of the tables.

F. The book discusses another strategy called HASH JOIN which can be used with hash indices in which we use the hashing function(s) to identify sets of blocks that can contain the same values of the join attributes.

G. One other factor we need to consider when doing two or more joins is join order. When there are multiple joins involved, performance may be very sensitive to the order in which we do the joins.

Example: suppose we want to print out a list of borrowers together with the authors of books they have out. This would involve a query like:

π lastName, firstName, authorName (Borrower |X| BookAuthor |X| CheckedOut)

1. Suppose, for now, that there are 10,000 Borrowers, 2000 CheckedOuts, and 10,000 BookAuthor tuples. Suppose, further, that each Book has an average of two authors (so we expect each CheckedOut tuple to join with two BookAuthor tuples).

2. Natural join is a binary operation, so the three-way join would normally be done by joining two tables, then joining the result with the third. Since natural join is both associative and commutative, this means that there are

basically three ways to perform our joins:

(Borrower |X| BookAuthor) |X| CheckedOut
(BookAuthor |X| CheckedOut) |X| Borrower
(Borrower |X| CheckedOut) |X| BookAuthor

(each of these has commutative variants which have no effect on the actual work involved in performing the operation, so we ignore these variants).

3. In each case, we create a intermediate table by joining two tables, then join this with the third. What is interesting is to consider the size of the intermediate table created by each order.

   a. In the first case, we join two tables that have no attributes in common, so the natural join is equivalent to a cartesian join. The intermediate table has 100 million tuples!

   b. In the second case, since each book has, on the average, 2 authors, we expect the intermediate table to contain 2 x 2000 = 4000 tuples.

   c. In the third case, since each CheckedOut tuple is paired with exactly one Borrower, we expect the intermediate table to contain 2000 tuples.

      Clearly, one of these join orders is best, one is nearly as good, and one is really bad.

4. Actually. of course, each order ultimately produces the same number of tuples in the result. (If it didn't, something would be badly wrong)

   a. The first order joins a intermediate table of 100 million tuples with a table of only 2000. A given borrower appears in the intermediate table an average of two times - once for each author of each book in the library, and the natural join matches by borrowerID so the result table has 4000 tuples.

   b. In the second case, we join a intermediate table of 4000 tuples with the Borrower table. Since each tuple in the intermediate table contains a

borrowerID which matches just one borrower tuple, we again expect the result to have 4000 tuples.

c. In the third case, we join a intermediate table of 2000 tuples with the BookAuthor table. Since each tuple in the intermediate table contains a callNumber that matches an average of two tuples in the BookAuthor table, we again expect 4000 tuples in the result.

5. We will look at formalizing the reasoning we have done here by using statistical data about the database tables later in this lecture. For now we note that the amount of work needed to satisfy a query can be very sensitive to join order.

a) Simple DBMSs may simply perform joins in the order implied by the code.

b) Good DBMSs may rearrange joins in order to minimize the size of intermediate table(s).

IV. **Sorting**

A. While there is no inherent order to database tables, we often require the results to be put in some order before presenting them to the user.

1. One obvious reason for this is to implement the `order by` clause in SQL.

2. But this is also often done when we need to eliminate duplicates in a result - as specified by `distinct` in SQL. It turns out that often the fastest way to do this is to sort the table by result, which puts duplicate tuples next to each other.

B. We skipped the book section on sorting and will not discuss here, since sorting is a topic in CPS222.

V. **Rules of Equivalence For Queries**

A. The first step in processing a query is to convert it from the form input by the user into an internal form that the DBMS can process. This step is called query parsing.

1. This task is not different in principle from the parsing done by a compiler for a programming language, so we won't discuss it here.

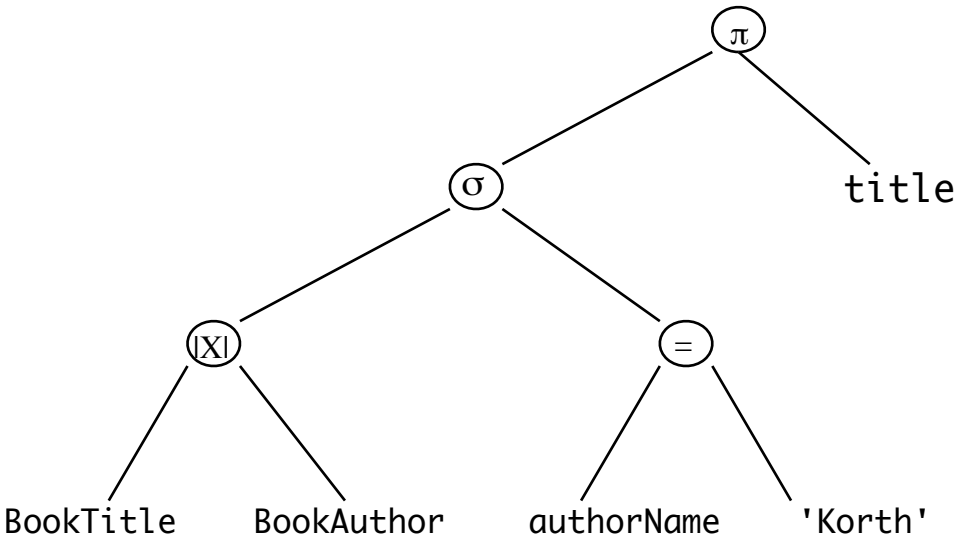
2. The internal form may well be some sort of tree - e.g. our first example (titles of books written by Korth), if formulated as

```
select title
   from BookTitle natural join BookAuthor
   where authorName = 'Korth'
```

is equivalent to the relational algebra expression

$\pi_{\text{title}}\ \sigma_{\text{authorName = 'Korth'}}$ (BookTitle |X| BookAuthor)

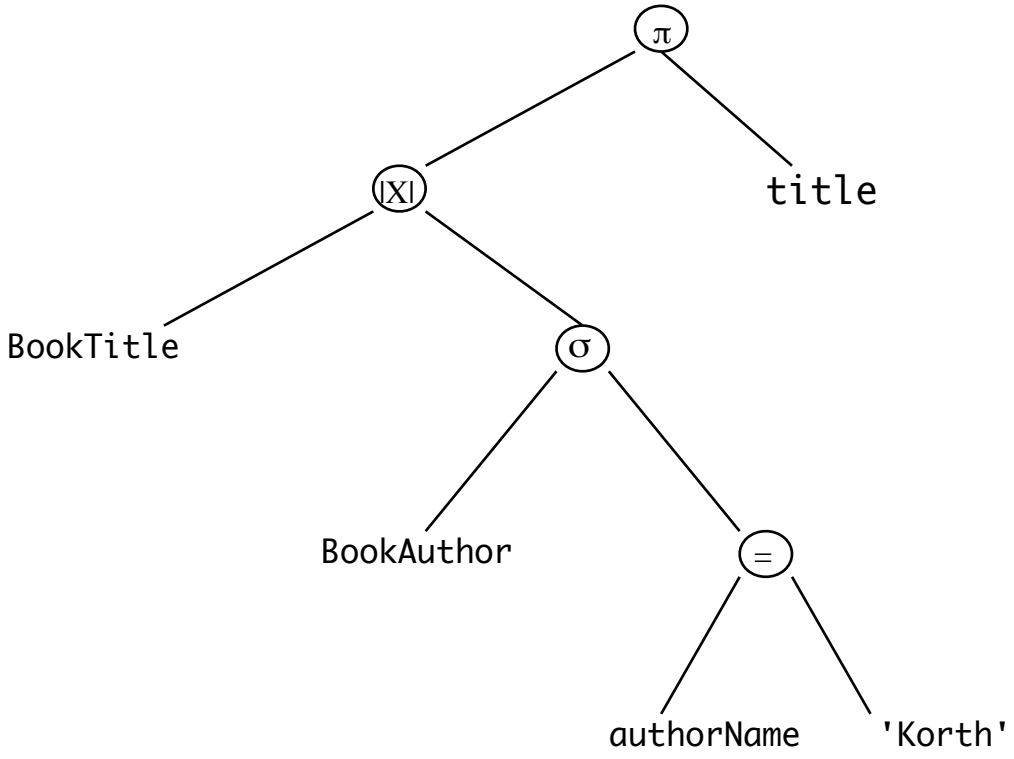
which in turn is equivalent to the following tree



PROJECT SQL, RA, TREE

3. However, the relational algebra expression could be transformed into a second, equivalent query by an operation on the tree (moving selection inside join)

π BookTitle |X| σ BookAuthor
title authorName = 'Korth'



PROJECT RA, TREE

4. However, for our purposes it will suffice to proceed as if relational algebra were the internal form, since a tree like this can always be uniquely constructed from a given relational algebra query.

B. Because relational algebra is a procedural language, each formulation of a query implies a certain plan for evaluating it.

1. For example:

   $\pi_{title}\ \sigma_{authorName = 'Korth'}\ (BookTitle \bowtie BookAuthor)$

   implies that we first join BookTitle and BookAuthor, then select tuples for which the authorName is Korth (discarding the rest), and then project the title from these.

2. But:

   $\pi_{title}\ (BookTitle \bowtie\ \sigma_{authorName = 'Korth'}\ BookAuthor)$

   implies that we first select tuples from BookAuthor for which the authorName is Korth, then join only these with BookTitle, and the project the title from the result of the join.

3. We say that two formulations of a query are EQUIVALENT if they produce the same final answer, except for a possibly different order of the rows (relations are sets, so order is not important.) Thus, both of our formulations in the previous example were equivalent.

   The book goes into an extensive discussion of rules of equivalence, but we will not pursue this further.

4. It turns out that there are some transformations that are almost always beneficial:

   a) Do selection as early as possible (move selection inward).

(1)Example: if we have

σ RelationA |X| RelationB
SomeExpression

and SomeExpression involves only attributes from one of the two relations (say RelationB), then we can convert the query to an equivalent - and usually more efficient - form:

RelationA |X| σ RelationB
SomeExpression

(This is, in fact, the transformation that was used in the above example)

(2)Suppose, however, we have a selection expression which involves attributes from BOTH relations in the join. In this case, it may not be possible to move the selection operation inward.

Example: we considered the following query earlier:

σ Borrower X BookAuthor
Borrower.lastName = BookAuthor.authorName

Clearly, this requires us to do the join before we can do the selection.

(3)However, sometimes when a selection expression involves attributes from both relations in a join we can still more selection inward by looking at the structure of the selection expression itself.

Example: we might want to find out what books (if any) that cost us more than $100.00 to buy are now overdue. This requires the query:

σ Book |X| CheckedOut
purchasePrice > 20.00 and dateDue < today

By taking advantage of the fact that any selection condition of the form:

$$\sigma_{\text{ConditionA and ConditionB}}$$

is equivalent to

$$\sigma_{\text{ConditionA}}\left(\sigma_{\text{ConditionB}}\right)$$

our query is equivalent to:

$$\sigma_{\text{purchasePrice} > 20.00}\left(\sigma_{\text{dateDue} < \text{today}}\left(\text{Book} \mid X \mid \text{CheckedOut}\right)\right)$$

or

$$\left(\sigma_{\text{purchasePrice} > 20.00}\left(\text{Book}\right)\right) \mid X \mid \left(\sigma_{\text{dateDue} < \text{today}}\left(\text{CheckedOut}\right)\right)$$

b) A second heuristic is similar to the first: do projection as early as possible (move projection inward.)

(1)The motivation here is that projection reduces the number of columns in a relation - hence the amount of data that must be moved around between memory and disk, or stored in a temporary relation in memory. In particular, if a query involves constructing an intermediate result relation, then use of this heuristic may result in

(a)being able to keep the temporary relation in memory, rather than storing it on disk

(b)or allowing more tuples of the temporary relation to be stored in one block - thus reducing disk accesses.

(2)Example:

π Borrower |X| CheckedOut |X| Book
lastName,
firstName,
title,
dateDue

could be done somewhat more efficiently as:

π Borrower |X| (π CheckedOut |X| Book)
lastName borrowerID
firstName title
title dateDue
dateDue

which reduces the size of the intermediate table created by the first join. (Note that we need to keep one attribute from this join that we don't need in the final result to allow the second natural join to be done.)

(3)The benefits gained by this heuristic may not be as great as those from the move selection inward heuristic - but it's still worth considering.

C. Fortunately, the onus is not on the user to figure out the most efficient way to formulate a query.

1. In general, a commercial DBMS will develop a number of different strategies for equivalent ways of evaluating a given query, estimate the cost for each, and then choose the one that appears to have the lowest overall cost.

a. The simplest cost measure for a query is total disk accesses This is because the cost of a disk access is so high relative to other operations. In general, we will prefer the strategy that processes one of the equivalent forms of the original query with the fewest disk accesses.

b. With the increasing use of SSDs to store part or all of a database, disk accesses are no longer a sufficient measure of cost, though, since while SSD access times a greater than time for access to information in memory, the ratio is not nearly as great.

c. Sophisticated optimizers consider things like:

    i. Where relevant tables are stored (disk or SSD or possibly even main memory)

    ii. The existence of indexes and the possibility of creating a temporary index just for one query.

    iii. The order in which tables are stored.

    iv. Computationally-expensive computations.

2. A lot of effort goes into determining accurate cost measures and coding sophisticated optimizers - one reason why top DBMS's are quite expensive!

3. Nonetheless, giving some thought to formulating queries in a reasonably efficient style is just good practice, I think.

VI. Use of Statistical Information to Choose an Efficient Query Processing Strategy

A. We noted earlier that a DBMS may keep some statistical information about each relation in the database.

1. The following statistics may be kept for each table.

a) For each relation r, the total number of tuples in the relation. We denote this n_r.

b) For reach relation r, the total number of disk BLOCKS needed to store it. We denote this by b_r.

c) For each relation r, the size (in bytes) of a tuple. We denote this by l_r

d) For each relation r, the blocking factor (# of tuples per block). We denote this by f_r. Assuming tuples do not span across blocks, his is simply floor(blocksize / l_r)

(Actually, if we can compute some of these from the others, so we don't need to keep all of them - e.g. the following relationship holds among the above if the tuples of a relation are stored in a single file without being clustered with other relations.

b_r = ceiling(n_r / f_r)

2. The following statistics may be kept for each column of a table

a) For each attribute A of each relation r, the number of different values that appear for A in the relation. We denote this V(A,r).

Note that if A is a superkey for r, then V(A,r) = n_r

b) A corollary of this is the fact that, for any given value that actually occurs in r, if A is not a superkey then we can estimate the number of times the value occurs as:

$n_r / V(A, r)$

(where this is just an estimate, of course - the true count for a given value could be as small as 1, or as many as $n_r - V(A,r) + 1$.)

c) The formula above assumes that all values of an attribute are equally probable, but often some values (or even just one) are occur more frequently than others. For this reason, sophisticated DBMS may store more detail about the frequency of occurrence of different values such as a histogram of the relative frequency of values lying in different ranges. (This was discussed in the book.)

3. Fortunately, the table statistics are very easy to maintain - in fact, they're needed in the meta-data in any case. The column statistic is harder to maintain in general, but V(A,r) is relatively easy if the attribute A is indexed (just maintain a count of index entries). Fortunately, V(A,r) tends to be of most interest for those attributes A which also tend to be prime candidates for indices. Statistical information may also be updated during time periods when the DBMS is not busy processing user transactions.

B. We can use these statistics to estimate the size of a join.

1. In the case of the cartesian product r X s, the number of tuples is simply $n_r * n_s$, and the size of each tuple in the result is $l_r + l_s$.

2. In the case of a natural join r |X| s, where r and s have some attribute A in common, we can estimate the size of the join two ways:

a) Estimate that each of the n_s tuples of s will join with

n_r / V(A, r) tuples of r

b) Estimate that each of the n_r tuples of r will join with

n_s / V(A, s) tuples of s

c) The first formulation is equivalent to $n_r * n_s$ / V(A, r) and the second is equivalent to $n_r * n_s$ / V(A, s). Clearly, these are two different numbers if V(A,r) ≠ V(A, s). However, if this is the case, then it must be that some of the values of A that occur in one table don't occur in the other - so we want to use the smaller of the two estimates - leading to the following estimate for the size of r |X| s:

min($n_r * n_s$ / V(A,r), $n_r * n_s$ / V(A, s)) =
$n_r * n_s$ / max(V(A,r), V(A,s))

d) Of course, this estimate could be far from correct in a particular case.

Example: suppose we performed a natural join between tables for CSMajorsAtGordon and PsychologyMajorsAtGordon, based on studentID.

Since V(id, CSMajorsAtGordon) = $n_{CSMajorsAtGordon}$ and
V(id, PsychologyMajorsAtGordon) = $n_{PsychologyMajorsAtGordon}$

and since $n_{PsychologyMajorsAtGordon} > n_{CSMajorsAtGordon}$, we would estimate the size of the join to be $n_{CSMajorsAtGordon}$ - but it was actually 2 when I consulted the data two years ago while revising this lecture.

However, as a tool for selecting query strategies, these estimates are still very useful - since the alternative of actually carrying out the various strategies and then comparing the costs is hardly helpful!

e) In order to make further estimations, it is also helpful to note that we can estimate V(A, r |X| s) = min(V(A, r), V(A, s)) - i.e. some tuples in the relation having the larger number of values don't join with any tuples in the other relation, and thus don't appear in the result.

C. We now consider how these statistics may be used to help us decide on the order in which to perform multiple joins

1. Earlier, we considered a a query that prints borrower names an authors of books they have checked out.

   π Borrower |X| BookAuthor |X| CheckedOut
   lastName,
   firstName,
   authorName

2. We saw that the total amount of effort in processing the query varied greatly depending on the order in which the joins are performed. We established this by using informal reasoning to assess the various strategies. We now want to see how statistical data could be used to arrive at the same conclusions algorithmically. To review, the join orders we want to compare are:

   (Borrower |X| BookAuthor) |X| CheckedOut
   (BookAuthor |X| CheckedOut) |X| Borrower
   (Borrower |X| CheckedOut) |X| BookAuthor

3. Suppose the relevant statistics have the following values (all recorded in the meta-data or calculated form the meta-data):

   a) $n_{Borrower} = 10{,}000$

   b) $n_{CheckedOut} = 2000$

   c) $n_{BookAuthor} = 10{,}000$

   (these are the values we used in the example)

d) V(borrowerID, Borrower) = 10,000 (since borrowerID is a key for Borrower, each tuple must have a distinct value)

e) V(borrowerID, CheckedOut) = 1000 - so we expect each borrowerID that occurs at all to occur in 2000/1000 = 2 CheckedOut tuples - i.e. each borrower who has books out has an average of 2 out

f) V(callNo, CheckedOut) = 1666 - so we expect each callNo that occurs at all to occur in 2000/1666 = 1.2 CheckedOut tuples. (Remember that we have multiple copies of any given book. I chose the particular number I did to simplify calculations!)

g) V(callNo, BookAuthor) = 5000 - so we expect each callNo to occur in 10000/5000 = 2 BookAuthor tuples

PROJECT

4. Let's now consider how many intermediate result tuples we would expect each join order to produce:

a) (Borrower |X| BookAuthor) |X| CheckedOut

Intermediate table needed for Borrower |X| BookAuthor - no attributes in common (cartesian join)

estimated $n_{\text{Borrower |X| BookAuthor}} = n_{\text{Borrower}} * n_{\text{BookAuthor}} =$

10,000 * 10,000 = 100 million

b) (BookAuthor |X| CheckedOut) |X| Borrower

Intermediate table needed for BookAuthor |X| CheckedOut - join attribute = callNo

$n_{\text{BookAuthor}} = 10{,}000$; $n_{\text{CheckedOut}} = 2000$,
V(callNo, BookAuthor) = 5000; V(callNo, CheckedOut) = 1666

Using the larger V value, we get

estimated $n_{BookAuthor \, |X| \, CheckedOut} = 10{,}000 * 2000 / 5000 = 4000$

c) (Borrower |X| CheckedOut) |X| BookAuthor

Intermediate table needed for Borrower |X| CheckedOut - join attribute = borrowerID

$n_{Borrower} = 10000$; $n_{CheckedOut} = 2000$,
V(borrowerID, Borrower) = 10000; V(borrowerID, CheckedOut) = 1000

Using the larger V value, we get

estimated $n_{Borrower \, |X| \, CheckedOut} = 10000*2000 / 1000 = 2000$

d) These are the same numbers as we got before, but this time using a less ad-hoc approach.