Query Optimization

Introduction to Databases
CompSci 316 Fall 2014
Announcements (Thu., Nov. 20)

• Project demo period Dec. 5-9
  • Early in-class demo
  • Watch for my email about signing up for a demo slot
• Homework #4 deadline extended by a week
Query optimization

• One logical plan → “best” physical plan

• Questions
  • How to enumerate possible plans
  • How to estimate costs
  • How to pick the “best” one

• Often the goal is not getting the optimum plan, but instead avoiding the horrible ones

Any of these will do

1 second 1 minute 1 hour
Plan enumeration in relational algebra

• Apply relational algebra equivalences
  ✏ Join reordering: \( \times \) and \( \bowtie \) are associative and commutative (except column ordering, but that is unimportant)

\[
\begin{align*}
R \bowtie S & = T \bowtie S \\
S \bowtie R & = T \bowtie R \\
R \bowtie T & = S \bowtie T \\
& \ldots
\end{align*}
\]
More relational algebra equivalences

• Convert $\sigma_p \times$ to/from $\bowtie_p$: $\sigma_p (R \times S) = R \bowtie_p S$
• Merge/split $\sigma$’s: $\sigma_{p_1} (\sigma_{p_2} R) = \sigma_{p_1 \land p_2} R$
• Merge/split $\pi$’s: $\pi_{L_1} (\pi_{L_2} R) = \pi_{L_1} R$, where $L_1 \subseteq L_2$
• Push down/pull up $\sigma$:
  $\sigma_{p \land p_r \land p_s} (R \bowtie_{p'} S) = (\sigma_{p_r} R) \bowtie_{p \land p'} (\sigma_{p_s} S)$, where
  • $p_r$ is a predicate involving only $R$ columns
  • $p_s$ is a predicate involving only $S$ columns
  • $p$ and $p'$ are predicates involving both $R$ and $S$ columns
• Push down $\pi$: $\pi_L (\sigma_p R) = \pi_L (\sigma_p (\pi_{L'} R))$, where
  • $L'$ is the set of columns referenced by $p$ that are not in $L$
• Many more (seemingly trivial) equivalences...
  • Can be systematically used to transform a plan to new ones
Relational query rewrite example

\[ \pi_{\text{Group.name}} \sigma_{\text{User.name}=\text{“Bart”} \land \text{User.uid} = \text{Member.uid} \land \text{Member.gid} = \text{Group.gid}} \]

\[ \times \]

\[ \pi_{\text{Group.name}} \sigma_{\text{Member.gid} = \text{Group.gid}} \]

\[ \times \]

\[ \pi_{\text{Group.name}} \]

\[ \sigma_{\text{User.uid} = \text{Member.uid}} \]

\[ \times \]

\[ \pi_{\text{Group.name}} \]

\[ \sigma_{\text{name} = \text{“Bart”}} \]

\[ \sigma_{\text{Member}} \]

\[ \sigma_{\text{User}} \]

Convert \( \sigma_p \times \) to \( \bowtie_p \)
Heuristics-based query optimization

• Start with a logical plan
• Push selections/projections down as much as possible
  • Why?
  • Why not?
• Join smaller relations first, and avoid cross product
  • Why?
  • Why not?
• Convert the transformed logical plan to a physical plan (by choosing appropriate physical operators)
SQL query rewrite

• More complicated—subqueries and views divide a query into nested “blocks”
  • Processing each block separately forces particular join methods and join order
  • Even if the plan is optimal for each block, it may not be optimal for the entire query

• Unnest query: convert subqueries/views to joins

We can just deal with select-project-join queries
  • Where the clean rules of relational algebra apply
SQL query rewrite example

• SELECT name
  FROM User
  WHERE uid = ANY (SELECT uid FROM Member);

• SELECT name
  FROM User, Member
  WHERE User.uid = Member.uid;
  • Wrong

• SELECT name
  FROM (SELECT DISTINCT User.uid, name
        FROM User, Member
        WHERE User.uid = Member.uid);
  • Right—assuming User.uid is a key
Dealing with correlated subqueries

- SELECT gid FROM Group
  WHERE name LIKE 'Springfield%'
  AND min_size > (SELECT COUNT(*) FROM Member
                  WHERE Member.gid = Group.gid);

- SELECT gid
  FROM Group, (SELECT gid, COUNT(*) AS cnt
               FROM Member GROUP BY gid) t
  WHERE t.gid = Group.gid AND min_size > t.cnt
  AND name LIKE 'Springfield%';
“Magic” decorrelation

- SELECT gid FROM Group
  WHERE name LIKE 'Springfield%'
  AND min_size > (SELECT COUNT(*) FROM Member
                   WHERE Member.gid = Group.gid);

- WITH Supp_Group AS
  (SELECT * FROM Group WHERE name LIKE 'Springfield%'),
  Magic AS
  (SELECT DISTINCT gid FROM Supp_Group),
  DS AS
  ((SELECT Group.gid, COUNT(*) AS cnt
     FROM Magic, Member WHERE Magic.gid = Member.gid
     GROUP BY Member.gid) UNION
   (SELECT gid, 0 AS cnt
     FROM Magic WHERE gid NOT IN (SELECT gid FROM Member)))
  SELECT Supp_Group.gid FROM Supp_Group, DS
  WHERE Supp_Group.gid = DS.gid
  AND min_size > DS.cnt;

  Process the outer query without the subquery
  Collect bindings
  Evaluate the subquery with bindings
  Finally, refine the outer query
Heuristics-vs. cost-based optimization

• **Heuristics-based optimization**
  • Apply heuristics to rewrite plans into cheaper ones

• **Cost-based optimization**
  • Rewrite logical plan to combine “blocks” as much as possible
  • Optimize query block by block
    • Enumerate logical plans (already covered)
    • Estimate the cost of plans
    • Pick a plan with acceptable cost
  • Focus: select-project-join blocks
Cost estimation

Physical plan example:

Input to SORT(gid):

- PROJECT (Group.title)
- MERGE-JOIN (gid)
- SORT (gid)
- SCAN (Group)
- MERGE-JOIN (uid)
- SORT (uid)
- SCAN (Member)
- SCAN (User)
- FILTER (name = “Bart”)

• We have: cost estimation for each operator
  • Example: \( 	ext{SORT}(gid) \) takes \( O(B(\text{input}) \times \log_M B(\text{input})) \)
    • But what is \( B(\text{input}) \)?
• We need: size of intermediate results
Cardinality estimation

http://www.learningresources.com/product/estimation+station.do
Selections with equality predicates

• $Q$: $\sigma_{A=v} R$

• Suppose the following information is available
  • Size of $R$: $|R|$
  • Number of distinct $A$ values in $R$: $|\pi_A R|$

• Assumptions
  • Values of $A$ are uniformly distributed in $R$
  • Values of $v$ in $Q$ are uniformly distributed over all $R.A$ values

• $|Q| \approx \frac{|R|}{|\pi_A R|}$
  • Selectivity factor of $(A = v)$ is $\frac{1}{|\pi_A R|}$
Conjunctive predicates

• $Q: \sigma_{A=u} \land B=v^R$

• Additional assumptions
  • $(A = u)$ and $(B = v)$ are independent
    • Counterexample: major and advisor
  • No “over”-selection
    • Counterexample: $A$ is the key
Negated and disjunctive predicates

• $Q$: $\sigma_{A \neq v} R$
  - $|Q| \approx |R| \cdot \left(1 - \frac{1}{|\pi_A R|}\right)$
    - Selectivity factor of $\neg p$ is $(1 - \text{selectivity factor of } p)$

• $Q$: $\sigma_{A=u \lor B=v} R$
  - $|Q| \approx |R| \cdot \left(\frac{1}{|\pi_A R|} + \frac{1}{|\pi_B R|}\right)$?
Range predicates

• $Q: \sigma_{A>\nu} R$

• Not enough information!
  • Just pick, say, $|Q| \approx |R| \cdot \frac{1}{3}$

• With more information
  • Largest R.A value: $\text{high}(R.A)$
  • Smallest R.A value: $\text{low}(R.A)$
  • $|Q| \approx |R| \cdot \frac{\text{high}(R.A) - \nu}{\text{high}(R.A) - \text{low}(R.A)}$
  • In practice: sometimes the second highest and lowest are used instead
Two-way equi-join

• \( Q: R(A, B) \bowtie S(A, C) \)

• Assumption: containment of value sets
  • Every tuple in the “smaller” relation (one with fewer distinct values for the join attribute) joins with some tuple in the other relation
  • That is, if \(|\pi_A R| \leq |\pi_A S|\) then \(\pi_A R \subseteq \pi_A S\)
  • Certainly not true in general
  • But holds in the common case of foreign key joins

\[ |Q| \approx \frac{|R| \cdot |S|}{\max(|\pi_A R|,|\pi_A S|)} \]
• Selectivity factor of \( R. A = S. A \) is \(\frac{1}{\max(|\pi_A R|,|\pi_A S|)}\)
Multiway equi-join

• \( Q: R(A, B) \bowtie S(B, C) \bowtie T(C, D) \)

• What is the number of distinct \( C \) values in the join of \( R \) and \( S \)?

• Assumption: preservation of value sets
  • A non-join attribute does not lose values from its set of possible values
  • That is, if \( A \) is in \( R \) but not \( S \), then \( \pi_A (R \bowtie S) = \pi_A R \)
  • Certainly not true in general
  • But holds in the common case of foreign key joins (for value sets from the referencing table)
Multiway equi-join (cont’d)

- \( Q: R(A, B) \bowtie S(B, C) \bowtie T(C, D) \)

- Start with the product of relation sizes
  - \(|R| \cdot |S| \cdot |T|\)

- Reduce the total size by the selectivity factor of each join predicate
  - \( R.B = S.B: \frac{1}{\max(\pi_B R, \pi_B S)} \)
  - \( S.C = T.C: \frac{1}{\max(\pi_C S, \pi_C T)} \)
  - \(|Q| \approx \frac{|R| \cdot |S| \cdot |T|}{\max(\pi_B R, \pi_B S) \cdot \max(\pi_C S, \pi_C T)}\)
Cost estimation: summary

• Using similar ideas, we can estimate the size of projection, duplicate elimination, union, difference, aggregation (with grouping)

• Lots of assumptions and very rough estimation
  • Accurate estimate is not needed
  • Maybe okay if we overestimate or underestimate consistently
  • May lead to very nasty optimizer “hints”
    
    SELECT * FROM User WHERE pop > 0.9;
    SELECT * FROM User WHERE pop > 0.9 AND pop > 0.9;

• Not covered: better estimation using histograms
Search strategy

http://1.bp.blogspot.com/-Motdu8reRKs/TgyAi4ki5QI/AAAAAAAAAEK/mi8ejfZ8S7U/s1600/cornMaze.jpg
Search space

• Huge!

• “Bushy” plan example:

• Just considering different join orders, there are \( \frac{(2n-2)!}{(n-1)!} \) bushy plans for \( R_1 \bowtie \cdots \bowtie R_n \)

  • 30240 for \( n = 6 \)

• And there are more if we consider:
  • Multiway joins
  • Different join methods
  • Placement of selection and projection operators
Left-deep plans

- Heuristic: consider only “left-deep” plans, in which only the left child can be a join
  - Tend to be better than plans of other shapes, because many join algorithms scan inner (right) relation multiple times—you will not want it to be a complex subtree
- How many left-deep plans are there for $R_1 \bowtie \cdots \bowtie R_n$?
### A greedy algorithm

- $S_1, \ldots, S_n$
  - Say selections have been pushed down; i.e., $S_i = \sigma_p(R_i)$
- Start with the pair $S_i, S_j$ with the smallest estimated size for $S_i \bowtie S_j$
- Repeat until no relation is left:
  - Pick $S_k$ from the remaining relations such that the join of $S_k$ and the current result yields an intermediate result of the smallest size

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Pick most efficient join method
Minimize expected size
Current subplan

... $S_k, S_l, S_m, \ldots$
Remaining relations to be joined
A dynamic programming approach

• Generate optimal plans **bottom-up**
  • Pass 1: Find the best single-table plans (for each table)
  • Pass 2: Find the best two-table plans (for each pair of tables) by combining best single-table plans
  • ...
  • Pass $k$: Find the best $k$-table plans (for each combination of $k$ tables) by combining two smaller best plans found in previous passes
  • ...

• Rationale: Any subplan of an optimal plan must also be optimal (otherwise, just replace the subplan to get a better overall plan)

☞ Well, not quite...
The need for “interesting order”

• Example: \( R(A, B) \bowtie S(A, C) \bowtie T(A, D) \)
• Best plan for \( R \bowtie S \): hash join (beats sort-merge join)
• Best overall plan: sort-merge join \( R \) and \( S \), and then sort-merge join with \( T \)
  • Subplan of the optimal plan is not optimal!
• Why?
  • The result of the sort-merge join of \( R \) and \( S \) is sorted on \( A \)
  • This is an interesting order that can be exploited by later processing (e.g., join, dup elimination, GROUP BY, ORDER BY, etc.)!
Dealing with interesting orders

When picking the best plan

• Comparing their costs is not enough
  • Plans are not totally ordered by cost anymore

• Comparing interesting orders is also needed
  • Plans are now partially ordered
  • Plan $X$ is better than plan $Y$ if
    • Cost of $X$ is lower than $Y$, and
    • Interesting orders produced by $X$ “subsume” those produced by $Y$

• Need to keep a set of optimal plans for joining every combination of $k$ tables
  • At most one for each interesting order
Summary

- Relational algebra equivalence
- SQL rewrite tricks
- Heuristics-based optimization
- Cost-based optimization
  - Need statistics to estimate sizes of intermediate results
  - Greedy approach
  - Dynamic programming approach