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Advanced Database Technology

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QUERY COMPILATION II

Lecture based on [GUW, 16.4-16.7] and [AGMS '99, sec. 1,2,4,5]

Slides based on
Notes 06-07: Query execution Part I-II
for Stanford CS 245, fall 2002
by Hector Garcia-Molina

Overview: Physical query planning

- We assume that we have an **algebraic expression** (tree), and consider:
  - Statistical estimates of the **size** of relations given by subexpressions.
  - Choosing an **order** for operations, using various optimization techniques.
  - Completing the **physical query plan**.

Estimating sizes of relations

The **sizes** of intermediate results are important for the choices made when planning query execution.

- Time for operations grow (at least) linearly with size of (largest) argument.
- The total size can even be used as a crude estimate on the running time.

Classical approach: Heuristics

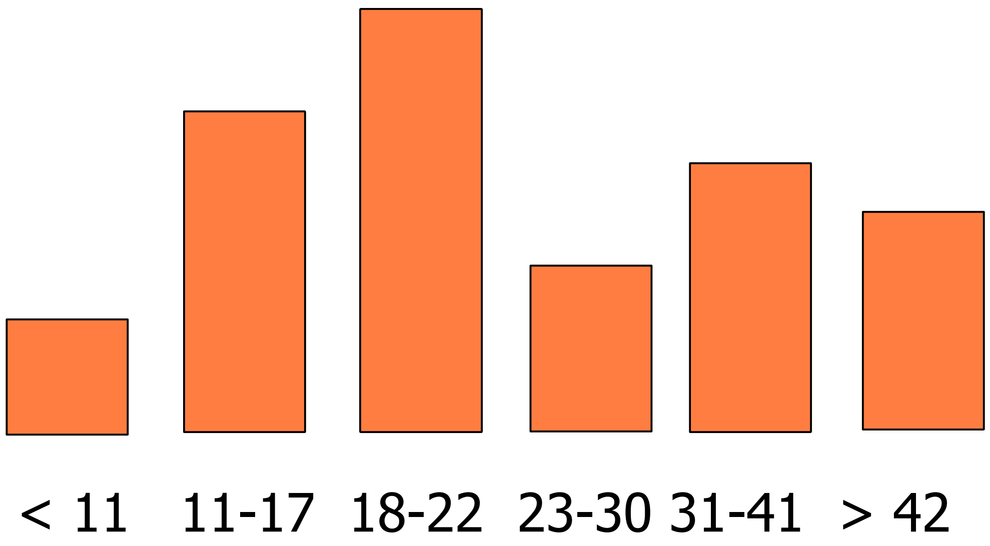
- In GUW section 16.4 a number of **heuristics** for estimating sizes of intermediate results are presented.
- This classical approach works well in some cases, but is unreliable in general.
- The modern approach is based on maintaining suitable **statistics** summarizing the data. (Focus of lecture.)

Some possible types of statistics

- Random sample of, say 1% of the tuples. (NB. Should fit main memory.)
- The 1000 most frequent values of some attribute, with tuple counts.
- Histogram with number of values in different ranges.
- The *"skew"* of data values.

Histogram

- Number of values/tuples in each of a number of intervals.



On-line vs off-line statistics

- **Off-line**: Statistics only computed periodically, often operator-controlled (e.g. Oracle). Typically involves sorting data according to all attributes.
- **On-line**: Statistics maintained automatically at all times by the DBMS. Focus of this lecture.

Maintaining a random sample

- To get a sample of expected size 1% of full relation:
  - Add a new tuple to the sample with probability 1%.
  - If a sampled tuple is deleted or updated, remember to remove from or update in sample.

Estimating selects

- To estimate the size of a select statement $\sigma_C(R)$:
  - Compute $|\sigma_C(R')|$, where R′ is the random sample of R.
  - If the sample is 1% of R, the estimate is 100 $|\sigma_C(R')|$, etc.
  - The estimate is reliable if $|\sigma_C(R')|$ is not too small (the bigger, the better).

Problem session

- Suppose you want to estimate the size of a join statement $R_1 \mid\!><\!\mid R_2$.
- You have random samples of 1% of each relation.
- How do you do the estimation?
- Warning: Answer on next slide!

Estimating join sizes

- To estimate the size of a join statement $R_1 \mid\!\!><\!\!\mid R_2$:
  - Compute $|R'_1 \mid\!\!><\!\!\mid R'_2|$, where R'_1 and R'_2 are samples of R_1 and R_2.
  - If samples are 1% of the relations, estimate is $100^2\ |R'_1 \mid\!\!><\!\!\mid R'_2|$. (Why?)
  - Shortly, you will see a considerably more reliable method, especially when we can store only a very small fraction of relations internally.

Keeping a sample of bounded size

Reservoir sampling (Vitter '85):

- Initial sample consists of s tuples.
- A tuple inserted in R is stored in sample with probability s/(|R|+1).
- When storing a new tuple, it *replaces* a randomly chosen tuple in existing sample (unless sample has size < s due to a deletion).

Next: Statistics for join estimation (AGMS '99)

Goal:

- Maintain information that "summarizes" or "sketches" each relation.
- Should be able to compute (reliable) join size estimates from sketches of **two** relations. (General case will not be covered.)

Special case: Joining R with itself

- Assume at most t distinct join values.
- Observation:
  - If all values are equally frequent, self-join size SJ(R) is smallest.
  - If data is *skewed* SJ(R) is bigger. Worst case is where there is only 1 join value.
- Intuitively, we need to measure skew.

Tug-of-war

- Each join value **v** is assigned a random team: All occurences of **v** are members of that team.
- Compute Z=difference between number of members of the two teams.
- Estimate for SJ(R) is Z^2. (Outside of scope of this course: Provably good.)

Computing Z on-line

- Pick hash function h ”assigns teams”, i.e., maps join value **i** to $\varepsilon_i=h(i)\in\{-1,1\}$.
- When new tuple arrives with join value i, add h(i) to current value of Z.
- When tuple with join value i is deleted, subtract h(i) from Z.

Estimating size of a join

- Have: Sketches Z_R and Z_S of relations R and S.
- Estimator for $|R \bowtie S|$ is $Z_R \cdot Z_S$. (Outside of scope of this course: Provably good.)
- Standard deviation is $\sqrt{(SJ(R) \cdot SJ(S))}$ - roughly "how much we expect the estimate to deviate from the true value".
- AGMS uses **Var**iance, which is the square of the standard deviation.

Boosting reliability

- The reliability of estimates can be improved by storing **k** sketches $Z_1,..,Z_k$, and taking the mean of the resulting k estimates.
- Decreases standard deviation by a factor of $\sqrt{k}$.

To further improve estimates

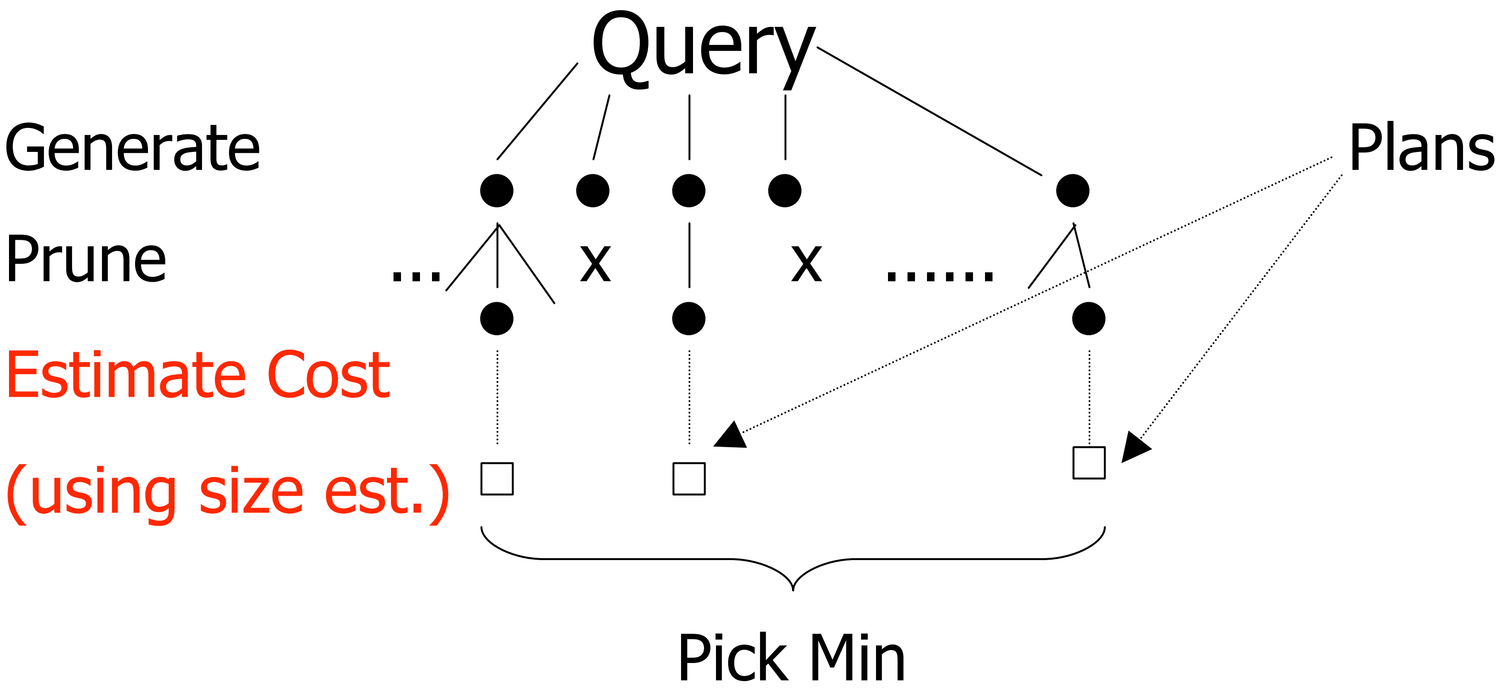
- ”Intelligently split” the domain of the join attribute in several parts, and estimate join sizes for each part. (Dobra et al, 2002)
- ”Skim” the most frequent values (by sampling) and use tug-of-war only for less frequent elements. (Ganguly et al, 2004)

Next: Physical query planning

- Have:
  - Relational algebra expression
  - Size estimates
- Need to determine:
  - In which order to compute subexpressions.
  - What algorithm to use for each operation.

Choosing a physical plan

Option 1: "Branch and bound".



Choosing a physical plan

Option 2: "Dynamic programming".

- Find best plans for subexpressions in bottom-up order.
- Might find several best plans:

  - The best plan that produces a sorted relation wrt. a later join or grouping attribute.

  - The best plan in general.

Choosing a physical plan

Options 3,4,...:

Other (heuristic) techniques from combinatorial optimization.

- Greedy plan selection.
- Hill climbing.
- ...

Order for grouped operations

- Recall that we **grouped** commutative and associative operators, e.g.
  R1 |><| R2 |><| R3 |><|... |><| Rk.
- For such expressions we must choose an evaluation order (a parenthesized expression), e.g.
  (R1 |><| R4) |><|(R3 |><|...) ... (... |><| Rk).

Order for grouped operations

- Book recommends considering just **left balanced** expressions
  (...((R4 |><| R2) |><| R7) |><| ...) |><| Rk.
- This gives **k!** possible expressions.
- Considering all possible expressions gives around **$2^k k!$** possibilities - not so many more.

Choosing final algorithms

- Usually best to use existing indexes.
- Sometimes building indexes or sorting on the fly is advantageous.
- Sorting based algorithms may beat hashing based algorithms if one of the relations is already sorted.
- Just do the calculation and see!

Pipelining and materialization

- Some algorithms (e.g. σ implemented as a scan) require little internal memory.
- **Idea:** Don't write result to disk, but feed it to the next algorithm immediately.
- Such **pipelining** may make many algorithms run "at the same time".
- Sometimes even possible with algorithms using more memory, such as sorting.

Influencing the query plan

- One of the great things about DBMSs is that the user does **not** need to know about query compilation/optimization.
- ...unless things turn out to run too slowly - then manual tuning may be needed.
- Tuning can use statistics and query plans to suggest the creation of certain indexes, for example.

Summary

- **Size estimation** (using statistics) is an important part of query optimization.
- Given size estimates and a relational algebra expression, **query optimization** essentially consists of computing the (estimated) cost of all possible query plans.
- Other issues are **pipelining** and memory usage during execution.