Query Processing and Advanced Queries

Query Optimization (1)

Improving Logical Query Plans

Introduction

- How to apply the algebraic laws to improve a logical query plan?
- Goal: minimize the size (number of tuples, number of attributes) of intermediate results.
- Push selections down in the expression tree as far as possible.
- Push down projections, or add new projections where applicable.

Improving Logical Query Plans

Pushing Selections

- Replace the left side of one of these (and similar) rules by the right side:

$$\sigma_{p1 \wedge p2}(R) \rightarrow \sigma_{p1}[\sigma_{p2}(R)]$$

$$\sigma_{p}(R \bowtie S) \rightarrow [\sigma_{p}(R)] \bowtie S$$

- Can greatly reduce the number of tuples of intermediate results.

Improving Logical Query Plans

Pushing Projections

- Replace the left side of one of these (and similar) rules by the right side:

$$\pi_x [\sigma_p (R)] \rightarrow \pi_x \{\sigma_p [\pi_{xz} (R)]\}$$

- Reduces the number of attributes of intermediate results and possibly also the number of tuples.

Improving Logical Query Plans

Pushing Projections

- Consider the following example:

  R(A,B,C,D,E)

  P: (A=3) $\wedge$ (B="cat")

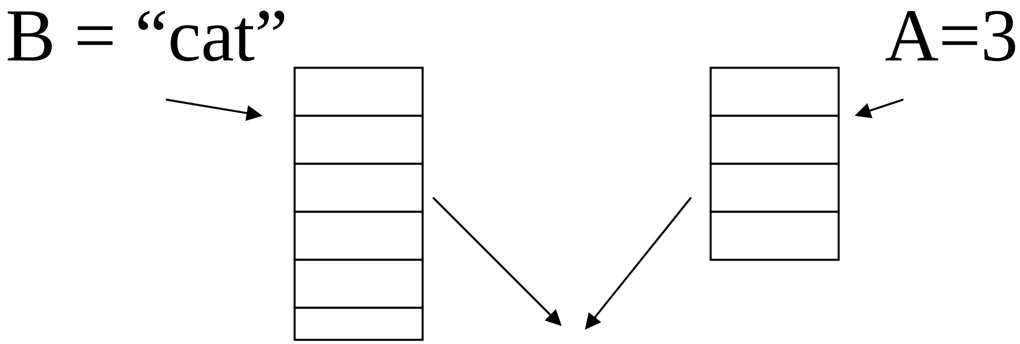
- Compare

  $\pi_E \{\sigma_p (R)\}$ vs. $\pi_E \{\sigma_p\{\pi_{ABE}(R)\}\}$

Improving Logical Query Plans

Pushing Projections

- What if we have indexes on A and B?



Intersect pointers to get pointers to matching tuples

- Efficiency of logical query plan may depend on choices made during refinement to physical plan.
- No transformation is always good!

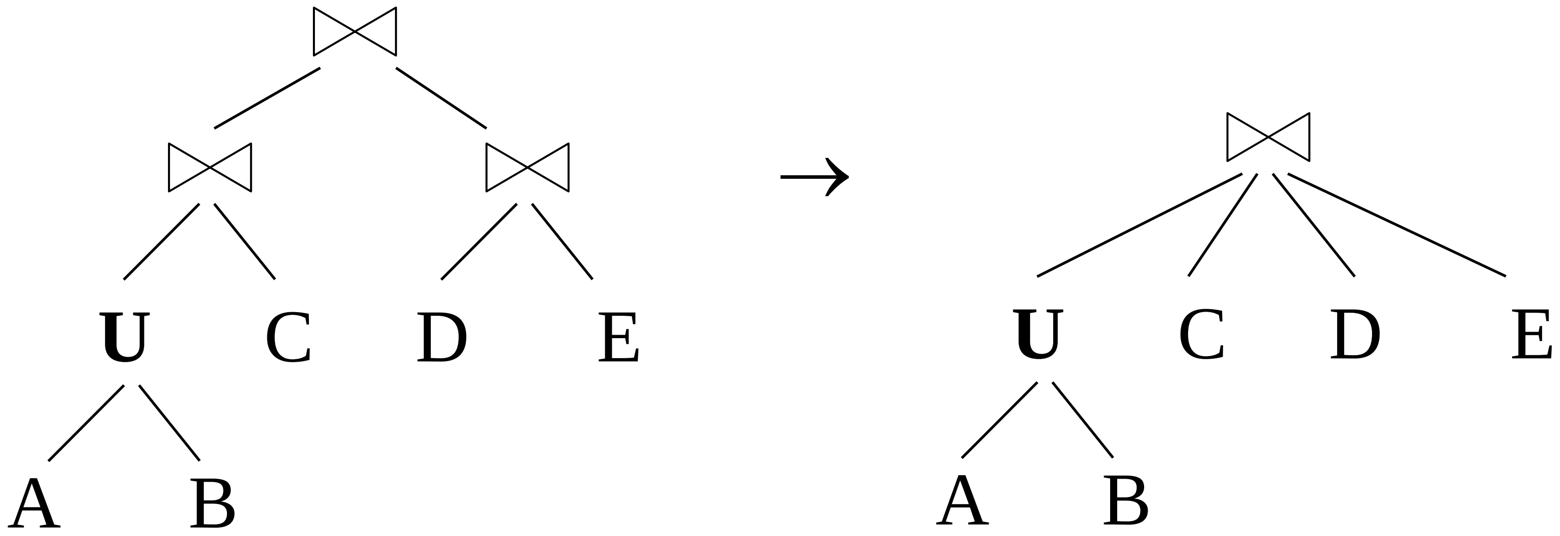
Improving Logical Query Plans

Grouping Associative / Commutative Operators

- For operators which are commutative and associative, we can order and group their arguments arbitrarily.
- In particular: natural join, union, intersection.
- As the last step to produce the final logical query plan, group nodes with the same (associative and commutative) operator into one n-ary node.
- Best grouping and ordering determined during the generation of physical query plan.

Improving Logical Query Plans

Grouping Associative / Commutative Operators



From Logical to Physical Plans

- So far, we have parsed and transformed an SQL query into an optimized logical query plan.
- In order to refine the logical query plan into a physical query plan, we
  - consider alternative physical plans,
  - estimate their cost, and
  - pick the plan with the least (estimated) cost.
- We have to estimate the cost of a plan without executing it. And we have to do that efficiently!

From Logical to Physical Plans

- When creating a physical query plan, we have to decide on the following issues.
  - order and grouping of operations that are associative and commutative,
  - algorithm for each operator in the logical plan,
  - additional operators which are not represented in the logical plan, e.g. sorting,
  - the way in which intermediate results are passed from one operator to the next, e.g. by storing on disk or passing one tuple at a time.

Estimating the Cost of Operations

- *Intermediate relations* are the output of some relational operator and the input of another one.
- The size of intermediate relations has a major impact on the cost of a physical query plan.
- It impacts in particular
  - the choice of an implementation for the various operators and
  - the grouping and order of commutative / associative operators.

Estimating the Cost of Operations

- A method for estimating the size of an intermediate relation should be
  - reasonably accurate,
  - efficiently computable,
  - not depend on how that relation is computed.
- We want to rank alternative query plans w.r.t. their estimated costs.
- Accuracy of the absolute values of the estimates not as important as the accuracy of their ranks.

Estimating the Cost of Operations

- Size estimates make use of the following *statistics* for relation R:

  T(R) : # tuples in R

  S(R) : # of bytes in each R tuple

  B(R): # of blocks to hold all R tuples

  V(R, A) : # distinct values for attribute A in R.

  MIN(R,A): minimum value of attribute A in R.

  MAX(R,A): maximum value of attribute A in R.

- Statistics need to be maintained up-to-date under database modifications!

Estimating the Cost of Operations

R

A	B	C	D
cat	1	10	a
cat	1	20	b
dog	1	30	a
dog	1	40	c
bat	1	50	d

A: 20 byte string

B: 4 byte integer

C: 8 byte date

D: 5 byte string

T(R) = 5

V(R,A) = 3

V(R,B) = 1

S(R) = 37

V(R,C) = 5

V(R,D) = 4

Estimating the Cost of Operations

- Size estimate for W = R1 x R2
- $T(W) = T(R1) \times T(R2)$

  $S(W) = S(R1) + S(R2)$
- Size estimate for $W = \sigma_{A=a}(R)$
- Assumption: values of A are uniformly distributed over the attribute domain

  $T(W) = T(R)/V(R,A)$

  $S(W) = S(R)$

Estimating the Cost of Operations

- Size estimate for $W = \sigma_{z \geq val}(R)$
- Solution 1: on average, half of the tuples will satisfy an inequality condition

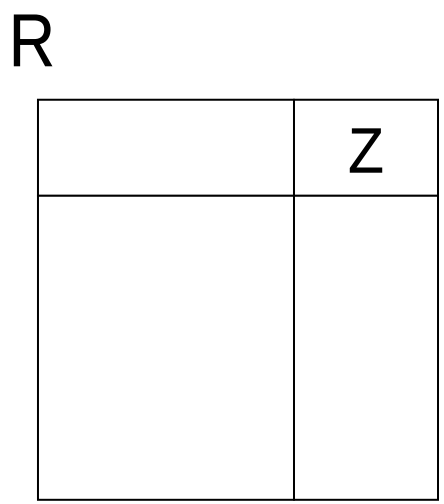
  $T(W) = T(R)/2$
- Solution 2: more selective queries are more frequent, e.g. professors who earn more than $200,000 (rather than less than $200,000)

  $T(W) = T(R)/3$

Estimating the Cost of Operations

- Solution 3: estimate the number of attribute values in query range
- Use minimum and maximum value to define range of the attribute domain.
- Assume uniform distribution of values over the attribute domain.
- Estimate is the fraction of the domain that falls into the query range.

Estimating the Cost of Operations



MIN(R,Z)=1

V(R,Z)=10

$W = \sigma_{Z \geq 15}(R)$

MAX(R,Z)=20

$$f = \frac{20-15+1}{20-1+1} = \frac{6}{20} \qquad \text{(fraction of range)}$$

$$T(W) = f \times T(R)$$

Estimating the Cost of Operations

- Size estimate for $W = R1 \bowtie R2$
- Consider only *natural join* of R1(X,Y) and R2(Y,Z).
- We do not know how the Y values in R1 and R2 relate:

  - disjoint, i.e. $T(R1 \bowtie R2) = 0$,
  - Y may be a foreign key of R1 and the primary key of R2, i.e. $T(R1 \bowtie R2) = T(R1)$,
  - all the R1 and all the R2 tuples have the same Y value, i.e. $T(R1 \bowtie R2) = T(R1) \times T(R2)$.

Estimating the Cost of Operations

- Make several simplifying assumptions.
- *Containment of value sets*:

  $V(R1,Y) \le V(R2,Y) \Rightarrow$

  every Y value in R1 is in R2

  $V(R2,Y) \le V(R1,Y) \Rightarrow$

  every Y value in R2 is in R1
- This assumption is satisfied when Y is foreign key in R1 and primary key in R2.
- Is also approximately true in many other cases.

Estimating the Cost of Operations

- *Preservation of value sets*:
  If A is an attribute of R1 but not of R2, then
  $V(R1 \bowtie R2, A) = V(R1, A)$.
- Again, holds if the join attribute Y is foreign key in R1 and primary key in R2.
- Can only be violated if there are "dangling tuples" in R1, i.e. R1 tuples that have no matching partner in R2.

Estimating the Cost of Operations

- *Uniform distribution of attribute values*: the values of attribute A are uniformly distributed over their domain, i.e. P(A=a1) = P(A=a2) = . . . = P(A=ak).
- This assumption is necessary to make cost estimation tractable.
- It is often violated, but nevertheless allows reasonably accurate ranking of query plans.

Estimating the Cost of Operations

- *Independence of attributes*:
  the values of attributes A and B are independent from each other, i.e. $P(A=a \mid B=b) = P(A=a)$ and $P(B=b \mid A=a) = P(B=b)$.
- This assumption is necessary to make cost estimation tractable.
- Again, often violated, but nevertheless allows reasonably accurate ranking of query plans.

Estimating the Cost of Operations

- Suppose that t1 is some tuple in R1, t2 some tuple in R2.
- What is the probability that t1 and t2 agree on the join attribute Y?
- If $V(R1,Y) \leq V(R2,Y)$, then the Y value of t1 appears in R2, because of the containment of value sets.
- Assuming uniform distribution of the Y values in R2 over their domain, the probability of t2 having the same Y value as t1 is $1/V(R2,Y)$.

Estimating the Cost of Operations

- If $V(R2,Y) \le V(R1,Y)$, then the Y value of t2 appears in R1, and the probability of t1 having the same Y value as t2 is $1 / V(R1,Y)$.
- $T(W)$ = number of pairs of tuples from R1 and R2 times the probability that an arbitrary pair agrees on Y.
- $T(R1 \bowtie R2) = T(R1)\, T(R2) / \max(V(R1,Y), V(R2,Y))$.

Estimating the Cost of Operations

- For complex query expressions, need to estimate T,S,V results for intermediate results.
- For example, $W = \underbrace{[\sigma_{A=a} (R1)]}_{\text{treat as relation U}} \bowtie R2$
- $T(U) = T(R1)/V(R1,A)$
  $S(U) = S(R1)$
- Also need V (U, *) for all attributes of U(R1)!

Estimating the Cost of Operations

R 1

A	B	C	D
cat	1	10	10
cat	1	20	20
dog	1	30	10
dog	1	40	30
bat	1	50	10

$V(R1,A)=3$

$V(R1,B)=1$

$V(R1,C)=5$

$V(R1,D)=3$

$U = \sigma_{A=a}(R1)$

$V(U,A) = 1 \quad V(U,B) = 1 \quad V(U,C) = T(R1)/V(R1,A)$

V(U,D) ... somewhere in between

Estimating the Cost of Operations

- R1(A,B), R2(A,C).
- Consider join U = R1 $\bowtie$ R2.
- Estimate V results for U.
- V(U,A) = min { V(R1, A), V(R2, A) }

  Holds due to containment of value sets.
- V(U,B) = V(R1, B)

  V(U,C) = V(R2, C)

  Holds due to preservation of value sets.

Estimating the Cost of Operations

- Consider the following example:

  $Z = R1(A,B) \bowtie R2(B,C) \bowtie R3(C,D)$

  $T(R1) = 1000 \quad V(R1,A)=50 \quad V(R1,B)=100$

  $T(R2) = 2000 \quad V(R2,B)=200 \quad V(R2,C)=300$

  $T(R3) = 3000 \quad V(R3,C)=90 \quad V(R3,D)=500$

- Group and order as $(R1 \bowtie R2) \bowtie R3$

Estimating the Cost of Operations

- Partial result: $U = R1 \bowtie R2$

  $T(U) = 1000 \times 2000 \ / \ 200$

  $V(U,A) = 50$

  $V(U,B) = 100$

  $V(U,C) = 300$

Estimating the Cost of Operations

- Final result: $Z = U \bowtie R3$

  $T(Z) = 1000 \times 2000 \times 3000 \quad / \; (200 \times 300)$

  $V(Z,A) = 50$
  $V(Z,B) = 100$
  $V(Z,C) = 90$
  $V(Z,D) = 500$