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CS 4604: Introduction to Database Management Systems

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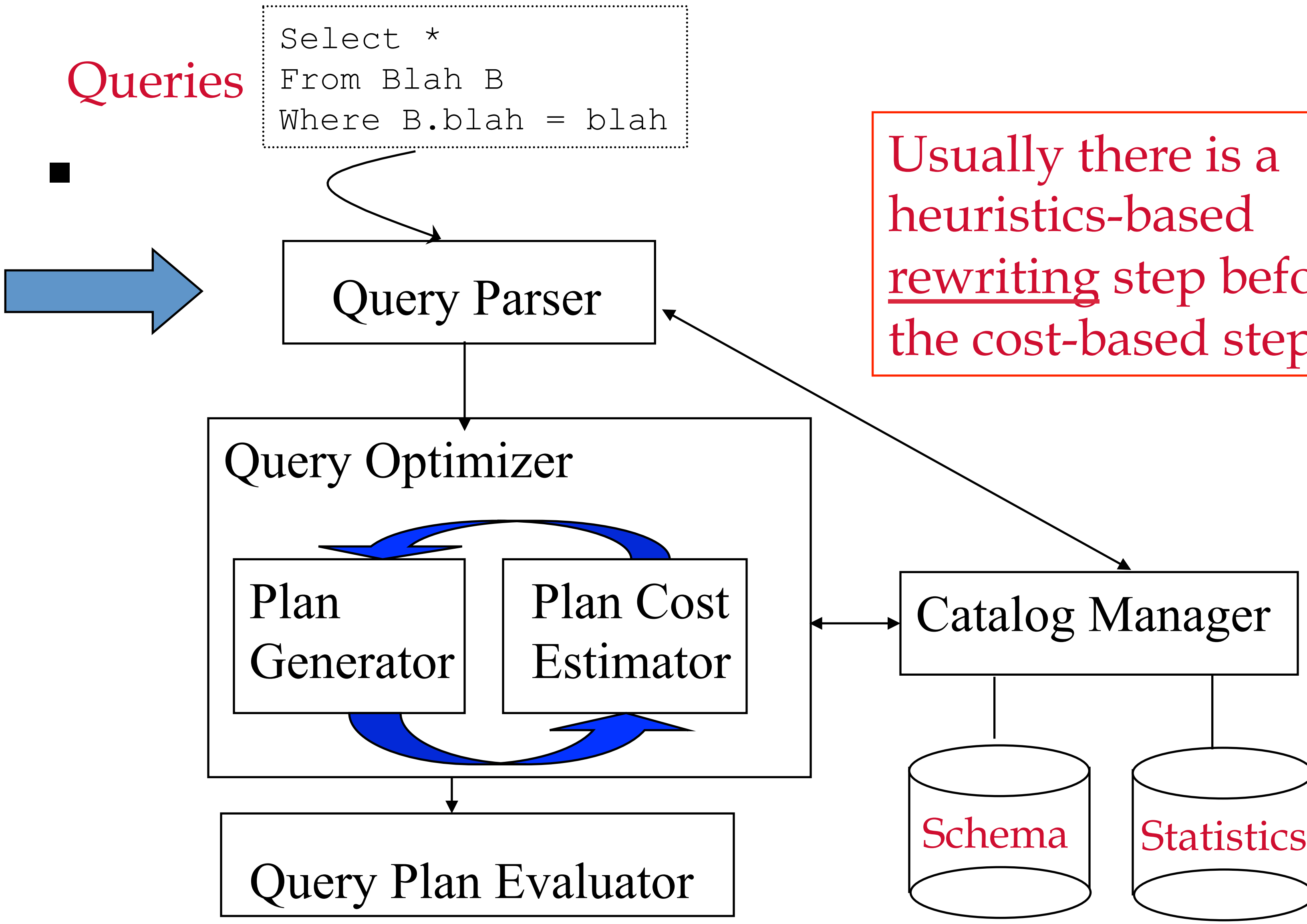
Lecture #19: Query Optimization

Notes

- **Material NOT in the book!**

- Some parts from (a copy of the paper is on the course webpage)
  - Selinger, Patricia, M. Astrahan, D. Chamberlin, Raymond Lorie, and T. Price. "Access Path Selection in a Relational Database Management System." In Proceedings of ACM SIGMOD, Boston, MA, 1979, pp. 22-34.

Cost-based Query Sub-System



Usually there is a heuristics-based rewriting step before the cost-based steps.

Multiple Algorithms: Range Searches

- Sequential Scan
- Hashes
- B-Trees
- ….

- Saw some of them in previous lecture

Multiple Algorithms: Joins

- Merge-Join (like merge-sort)
- Hash-Join (using hashes)
- Indexed-Join (using indexes)
- Nested loops Join (most obvious)
- ….

- We haven't covered them in class

Why Query optimization?

- SQL: ~declarative
- good q-opt -> big difference
  - eg., seq. Scan vs
  - B-tree index, on P=1,000 pages

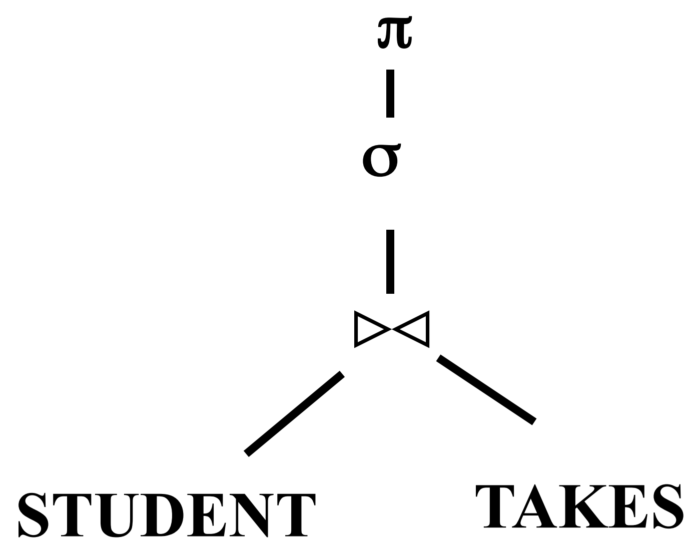
- We had some 'manual q-opt' in Project Assignment 3 → too much effort!

Q-opt steps

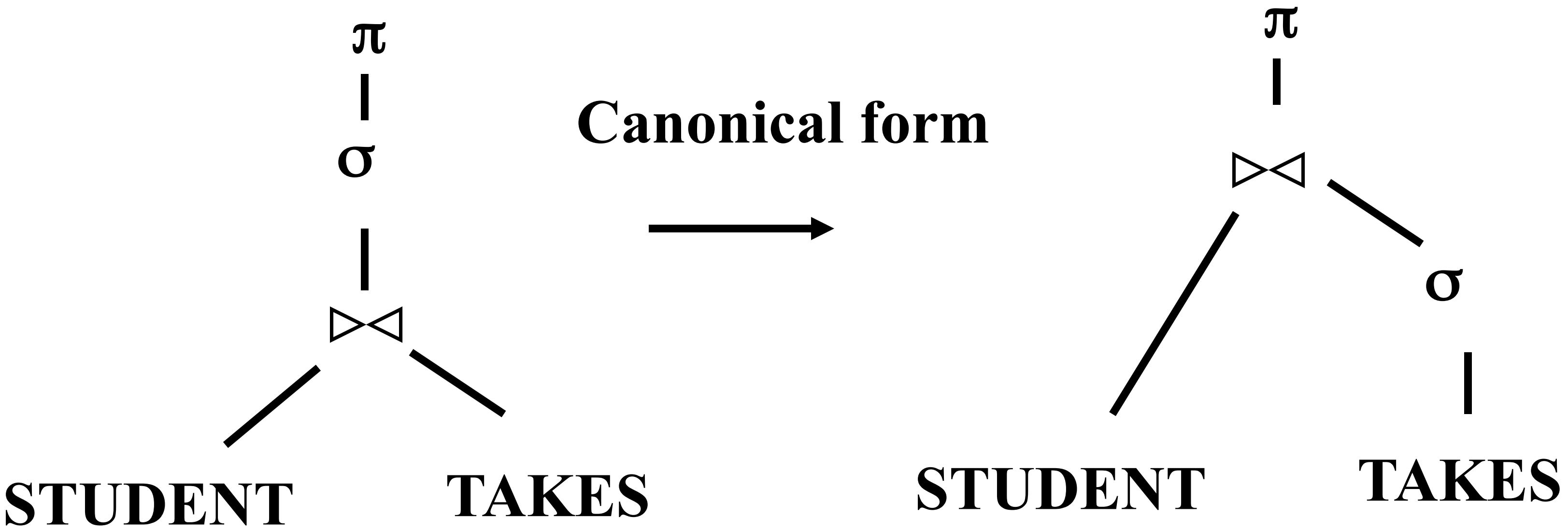
- bring query in internal form (eg., parse tree)
- … into ‘canonical form’ (syntactic q-opt)
- generate alt. plans
- estimate cost; pick best

Q-opt - example

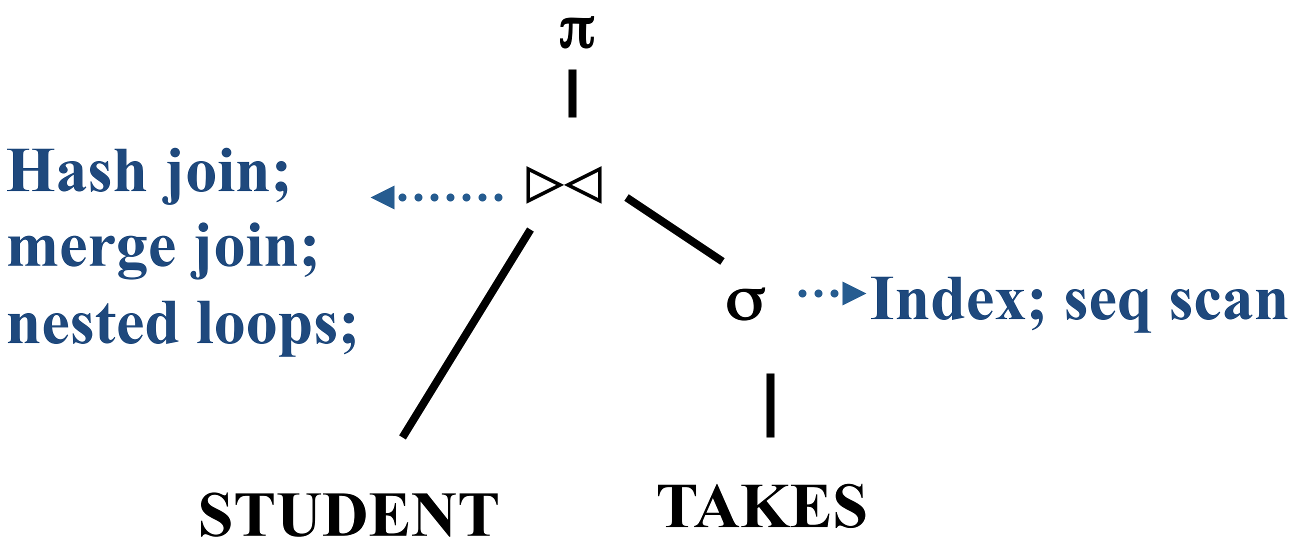
select name
from STUDENT, TAKES
where c-id = '4604' and
STUDENT.ssn = TAKES.ssn



Q-opt - example



Q-opt - example



Equivalence of expressions

- A.k.a.: syntactic q-opt
- in short: perform selections and projections early

Equivalence of expressions

- Q: How to prove a transformation rule?

$$\sigma_P(R1 \bowtie R2) \stackrel{?}{=} \sigma_P(R1) \bowtie \sigma_P(R2)$$

- A: use RA, to show that LHS = RHS, eg:

$$\sigma_P(R1 \cup R2) \stackrel{?}{=} \sigma_P(R1) \cup \sigma_P(R2)$$

Equivalence of expressions

$$\sigma_P(R1 \cup R2) \stackrel{?}{=} \sigma_P(R1) \cup \sigma_P(R2)$$

$$t \in LHS \Leftrightarrow$$

$$t \in \quad (R1 \cup R2) \wedge P(t) \quad \Leftrightarrow$$

$$(t \in \quad R1 \quad \vee \quad t \in R2) \wedge P(t) \quad \Leftrightarrow$$

$$(t \in \quad R1 \wedge P(t)) \quad \vee \quad (t \in R2) \wedge P(t)) \quad \Leftrightarrow$$

Equivalence of expressions

$$\sigma_P(R1 \cup R2) \stackrel{?}{=} \sigma_P(R1) \cup \sigma_P(R2)$$

...

$$(t \in R1 \wedge P(t)) \quad \vee \quad (t \in R2) \wedge P(t)) \quad \Leftrightarrow$$

$$(t \in \sigma_P(R1)) \quad \vee \quad (t \in \sigma_P(R2)) \quad \Leftrightarrow$$

$$t \in \sigma_P(R1) \cup \sigma_P(R2) \quad \Leftrightarrow$$

$$t \in RHS$$

$$QED$$

Equivalence of expressions

- Q: how to disprove a rule??

$$\pi_A(R1 - R2) \stackrel{?}{=} \pi_A(R1) - \pi_A(R2)$$

Construct a counter-example!

Equivalence of expressions

- Selections
  - perform them early
  - break a complex predicate, and push

$$\sigma_{p1 \wedge p2 \wedge \ldots pn}(R) = \sigma_{p1}(\sigma_{p2}(\ldots\sigma_{pn}(R))\ldots)$$

  - simplify a complex predicate
    - ('X=Y and Y=3') -> 'X=3 and Y=3'

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Equivalence of expressions

- Projections
  - perform them early (but carefully…)
    - Smaller tuples
    - Fewer tuples (if duplicates are eliminated)
  - project out all attributes except the ones requested or required (e.g., joining attr.)

Equivalence of expressions

- Joins
  - Commutative , associative

$$R \bowtie S = S \bowtie R$$

$$(R \bowtie S) \bowtie T = R \bowtie (S \bowtie T)$$

  - Q: n-way join - how many diff. orderings?

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Equivalence of expressions

- Joins - Q: n-way join - how many diff. orderings?
- A: Catalan number ~ 4^n
  - Exhaustive enumeration: too slow.

(Some) Transformation Rules (1)

1. Conjunctive selection operations can be deconstructed into a sequence of individual selections.

$$\sigma_{\theta_1 \wedge \theta_2}(E) = \sigma_{\theta_1}(\sigma_{\theta_2}(E))$$

2. Selection operations are commutative.

$$\sigma_{\theta_1}(\sigma_{\theta_2}(E)) = \sigma_{\theta_2}(\sigma_{\theta_1}(E))$$

3. Only the last in a sequence of projection operations is needed, the others can be omitted.

$$\Pi_{L_1}(\Pi_{L_2}(\ldots(\Pi_{Ln}(E))\ldots)) = \Pi_{L_1}(E)$$

4. Selections can be combined with Cartesian products and theta joins.
   a. $\sigma_{\theta}(E_1 \times E_2) = E_1 \bowtie_{\theta} E_2$
   b. $\sigma_{\theta 1}(E_1 \bowtie_{\theta 2} E_2) = E_1 \bowtie_{\theta 1 \wedge \theta 2} E_2$

(Some) Transformation Rules (2)

5. Theta-join operations (and natural joins) are commutative.

$$E_1 \bowtie_\theta E_2 = E_2 \bowtie_\theta E_1$$

6. (a) Natural join operations are associative:

$$(E_1 \bowtie E_2) \bowtie E_3 = E_1 \bowtie (E_2 \bowtie E_3)$$

(b) Theta joins are associative in the following manner:

$$(E_1 \bowtie_{\theta 1} E_2) \bowtie_{\theta 2 \wedge \theta 3} E_3 = E_1 \bowtie_{\theta 1 \wedge \theta 3} (E_2 \bowtie_{\theta 2} E_3)$$

where θ_2 involves attributes from only E_2 and E_3.

(Some) Transformation Rules (3)

7. The selection operation distributes over the theta join operation under the following two conditions:
   (a) When all the attributes in θ_0 involve only the attributes of one of the expressions (E_1) being joined.

   $$\sigma_{\theta 0}(E_1 \bowtie_{\theta} E_2) = (\sigma_{\theta 0}(E_1)) \bowtie_{\theta} E_2$$

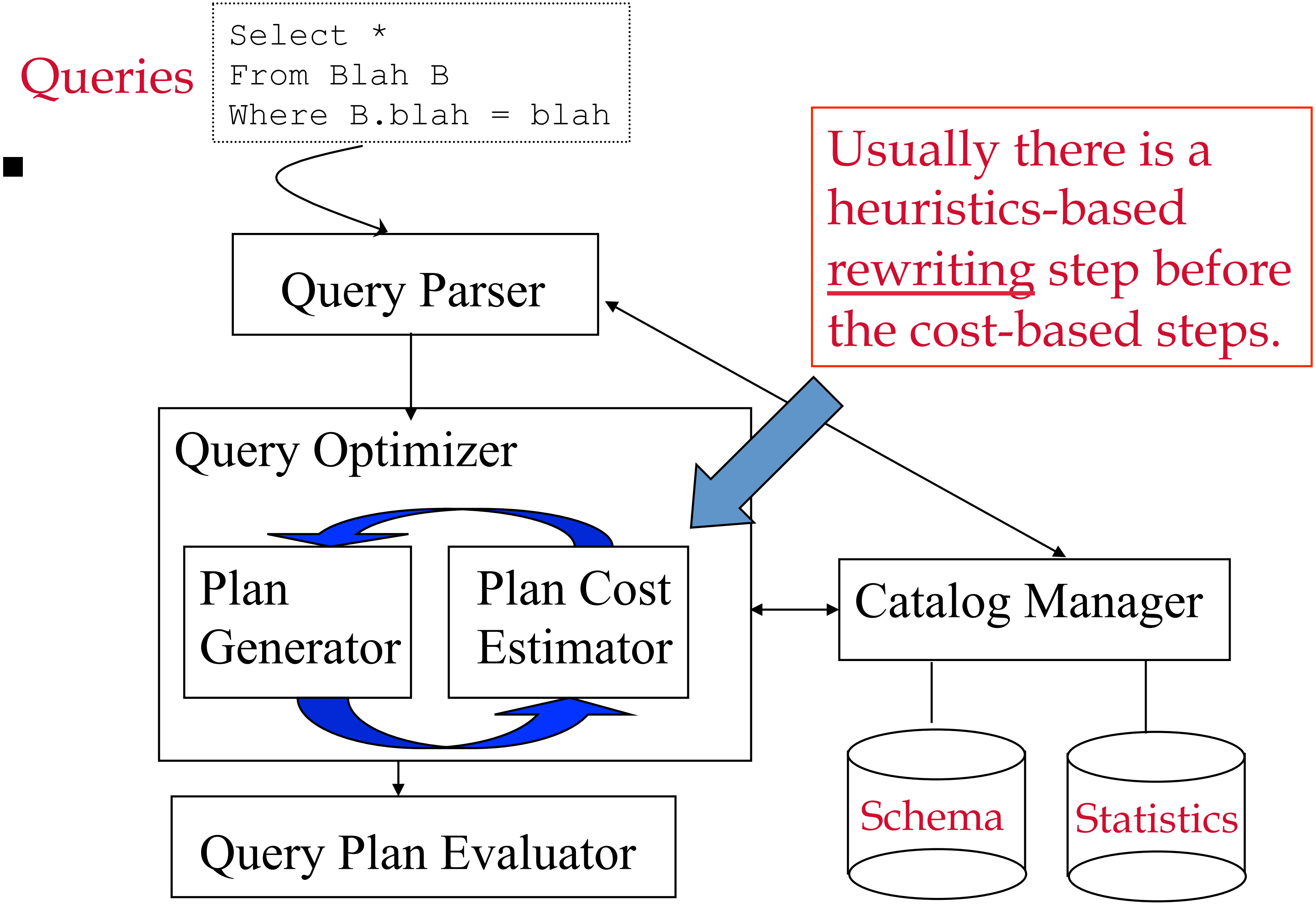
   (b) When θ_1 involves only the attributes of E_1 and θ_2 involves only the attributes of E_2.

   $$\sigma_{\theta 1 \wedge \theta 2}(E_1 \bowtie_{\theta} E_2) = (\sigma_{\theta 1}(E_1)) \bowtie_{\theta} (\sigma_{\theta 2}(E_2))$$

Q-opt steps

- bring query in internal form (eg., parse tree)
- … into 'canonical form' (syntactic q-opt)
- generate alt. plans
- estimate cost; pick best

Cost-based Query Sub-System

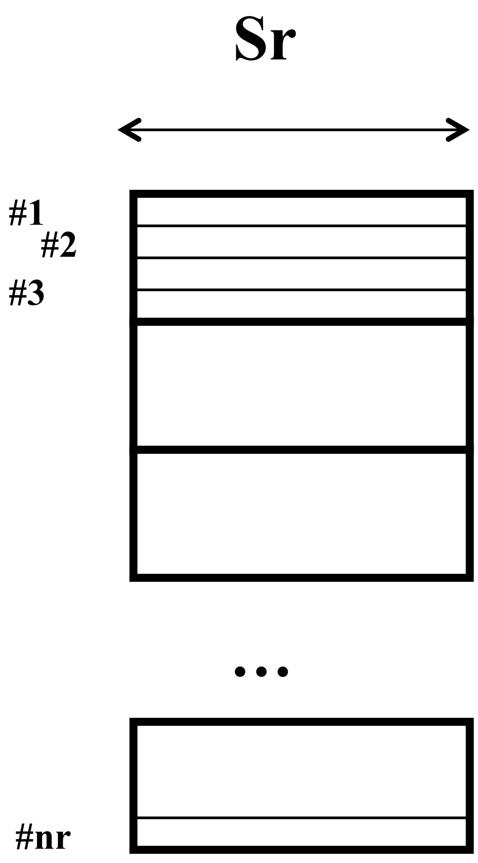


Cost estimation

- Eg., find ssn's of students with an 'A' in 4604 (using seq. scanning)
- How long will a query take?
  – CPU (but: small cost; decreasing; tough to estimate)
  – Disk (mainly, # block transfers)
- How many tuples will qualify?
- (what statistics do we need to keep?)

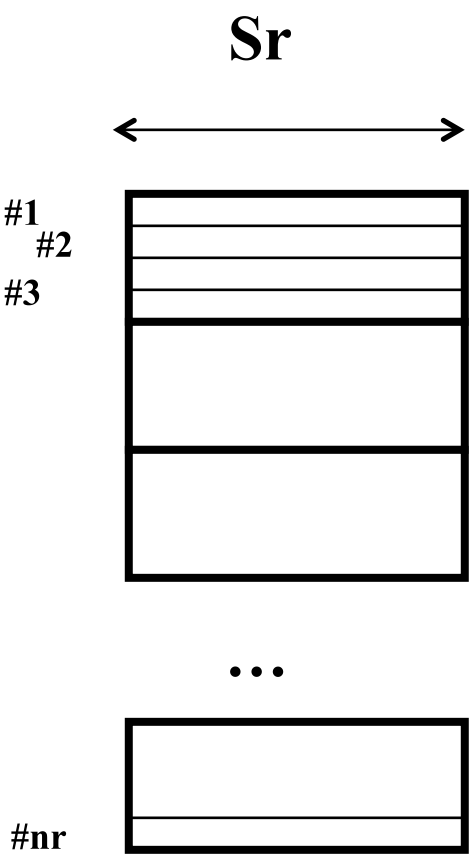
Cost estimation

- Statistics: for each relation 'r' we keep
  - nr : # tuples;
  - Sr : size of tuple in bytes



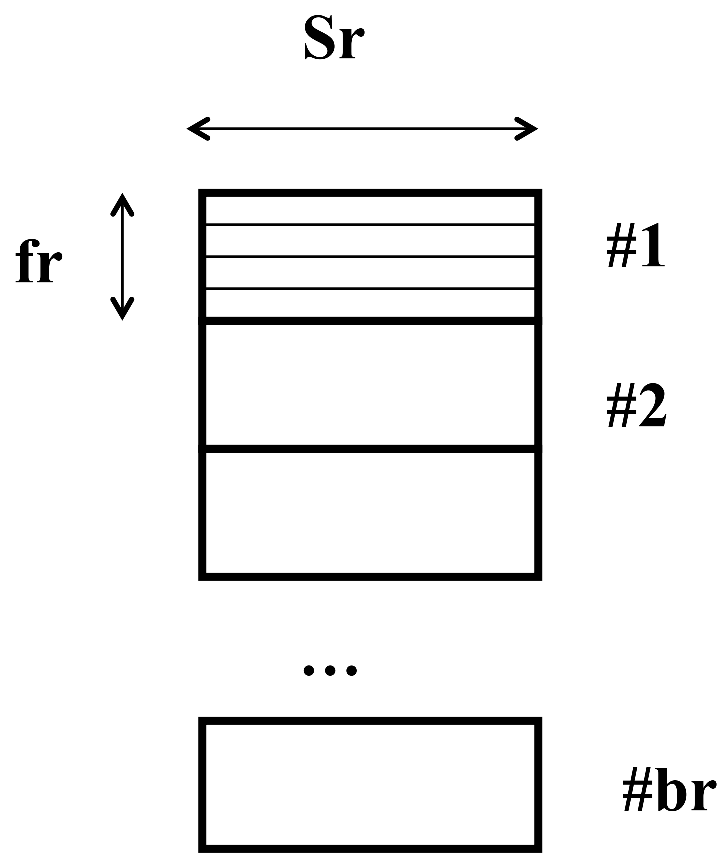
Cost estimation

- Statistics: for each relation 'r' we keep
  - …
  - V(A,r): number of distinct values of attr. 'A'
  - (recently, histograms, too)



Derivable statistics

- blocking factor = max# records/block (=??   )
- br: # blocks (=??   )
- SC(A,r) = selection cardinality = avg# of records with A=given (=??   )



Derivable statistics

- blocking factor = max# records/block (= B/Sr ; B: block size in bytes)
- br: # blocks (= nr / (blocking-factor))

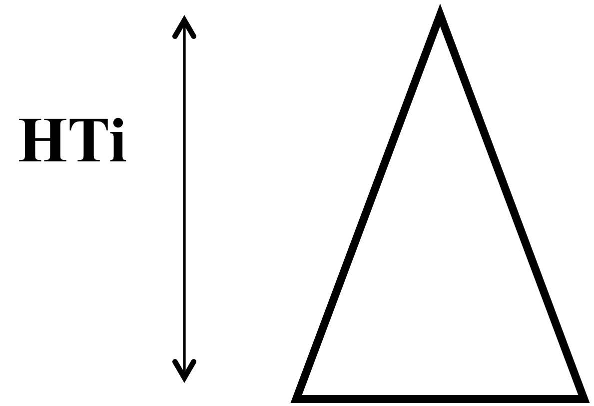
Derivable statistics

- SC(A,r) = selection cardinality = avg# of records with A=given (= nr / V(A,r)) (assumes uniformity...)

eg: 10,000 students, 10 departments – how many students in CS?

Additional quantities we need:

- For index 'i' :
  - fi: average fanout (~50-100)
  - HTi: # levels of index 'i' (~2-3)
    - ~ log(#entries)/log(fi)
  - LBi: # blocks at leaf level



Statistics

- Where do we store them?
- How often do we update them?

Q-opt steps

- bring query in internal form (eg., parse tree)
- … into 'canonical form' (syntactic q-opt)
- generate alt. plans
- estimate cost; pick best

Selections

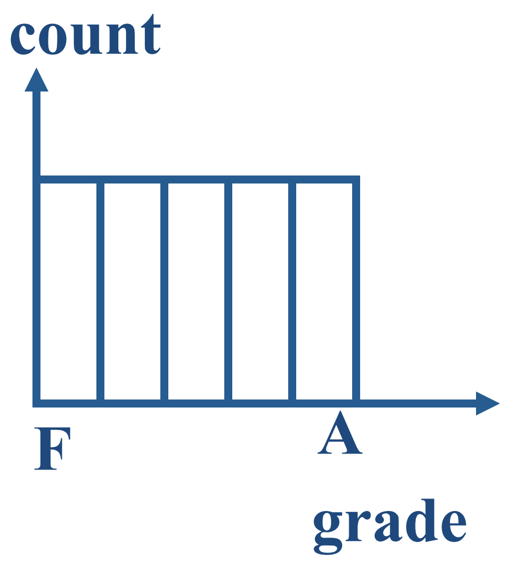
- we saw simple predicates (A=constant; eg., 'name=Smith')
- how about more complex predicates, like
  - 'salary > 10K'
  - 'age = 30 and job-code="analyst" '
- what is their selectivity?

Selections – complex predicates

- selectivity sel(P) of predicate P :
  - == fraction of tuples that qualify
  - sel(P) = SC(P) / nr

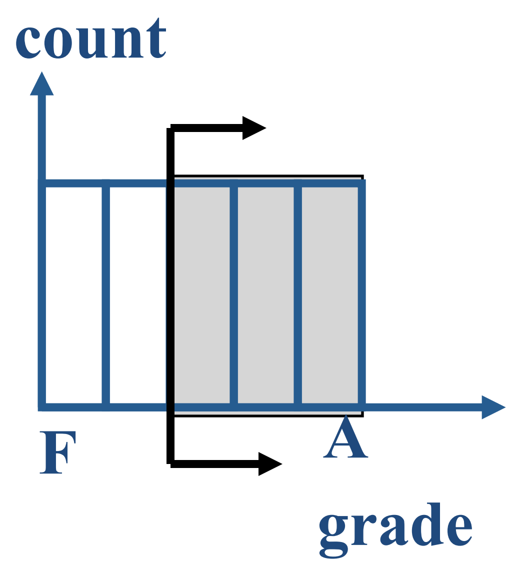
Selections – complex predicates

- eg., assume that V(grade, TAKES)=5 distinct values
- simple predicate P: A=constant
  - sel(A=constant) = 1/V(A,r)
  - eg., sel(grade= 'B') = 1/5
- (what if V(A,r) is unknown??)



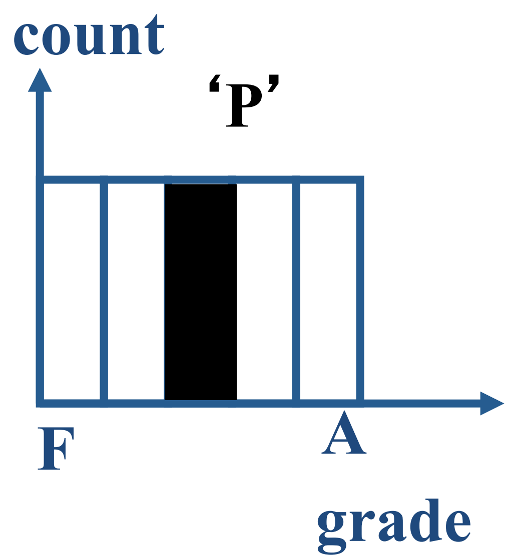
Selections – complex predicates

- range query: sel(grade >= 'C')
  - sel(A>a) = (Amax – a) / (Amax – Amin)



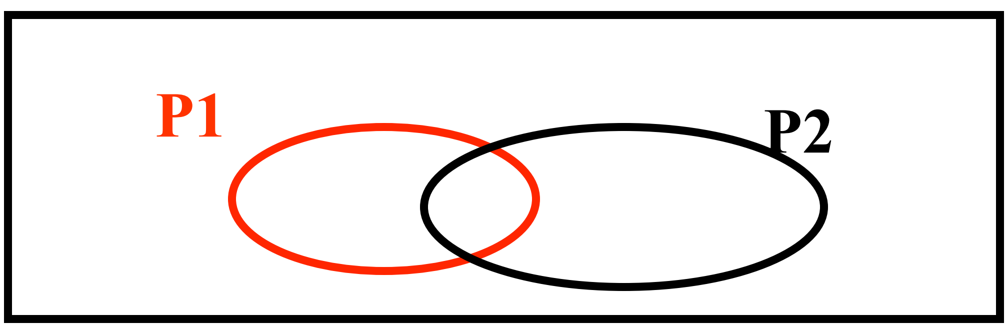
Selections - complex predicates

- negation: sel(grade != 'C')
  - sel(not P) = 1 – sel(P)
  - (Observation: selectivity =~ probability)



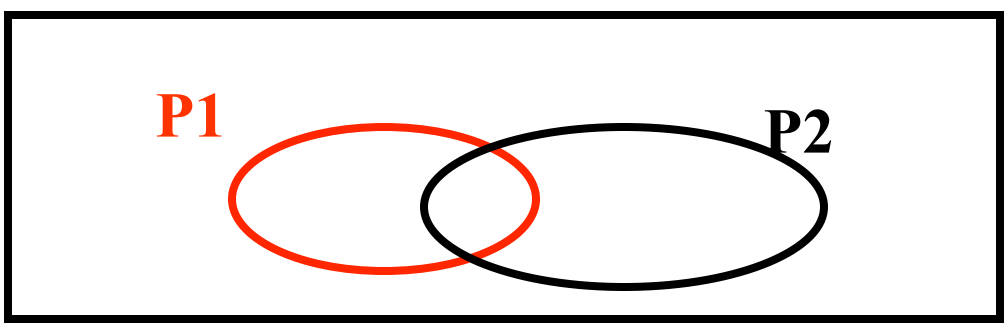
Selections - complex predicates

- Conjunction:
  - sel(grade = 'C' and course = '4604')
  - sel(P1 **and** P2) = sel(P1) * sel(P2)
  - INDEPENDENCE ASSUMPTION



Selections - complex predicates

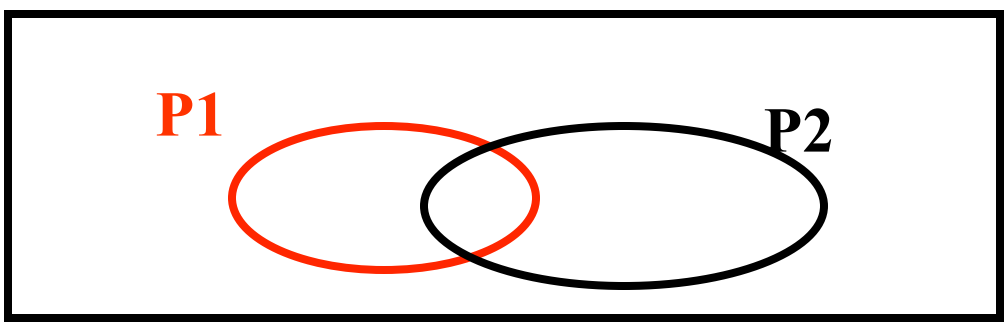
- Disjunction:
  – sel(grade = ‘C’ or course = ‘4604’)
  – sel(P1 **or** P2) = sel(P1) + sel(P2) – sel(P1 **and** P2)
  = sel(P1) + sel(P2) – sel(P1)*sel(P2)
  – INDEPENDENCE ASSUMPTION, again



Selections - complex predicates

- disjunction: in general
  - sel(P1 **or** P2 **or** … Pn) =

    1 - (1- sel(P1)) * (1 - sel(P2)) * … (1 - sel(Pn))



Selections – summary

- sel(A=constant) = 1/V(A,r)
- sel(A>a) = (Amax – a) / (Amax – Amin)
- sel(not P) = 1 – sel(P)
- sel(P1 **and** P2) = sel(P1) * sel(P2)
- sel(P1 **or** P2) = sel(P1) + sel(P2) – sel(P1)*sel(P2)
- sel(P1 **or** ... **or** Pn) = 1 - (1-sel(P1))*...*(1-sel(Pn))

- UNIFORMITY and INDEPENDENCE ASSUMPTIONS

Result Size Estimation for Joins

- Q: Given a join of R and S, what is the range of possible result sizes (in #of tuples)?
  - Hint: what if R_cols⋂S_cols = ∅?
  - R_cols ⋂ S_cols is a key for R (and a Foreign Key in S)?

Result Size Estimation for Joins

- General case: R_cols∩S_cols = {A} (and A is key for neither)
  - match each R-tuple with S-tuples

    est_size <~ NTuples(R) * NTuples(S)/NKeys(A,**S**)

    <~ nr * ns / V(A,S)
  - symmetrically, for S:

    est_size <~ NTuples(R) * NTuples(S)/NKeys(A,**R**)

    <~ nr * ns / V(A,R)
  - Overall:

    est_size = NTuples(R)*NTuples(S)/MAX{NKeys(A,**S**), NKeys(A,**R**)}

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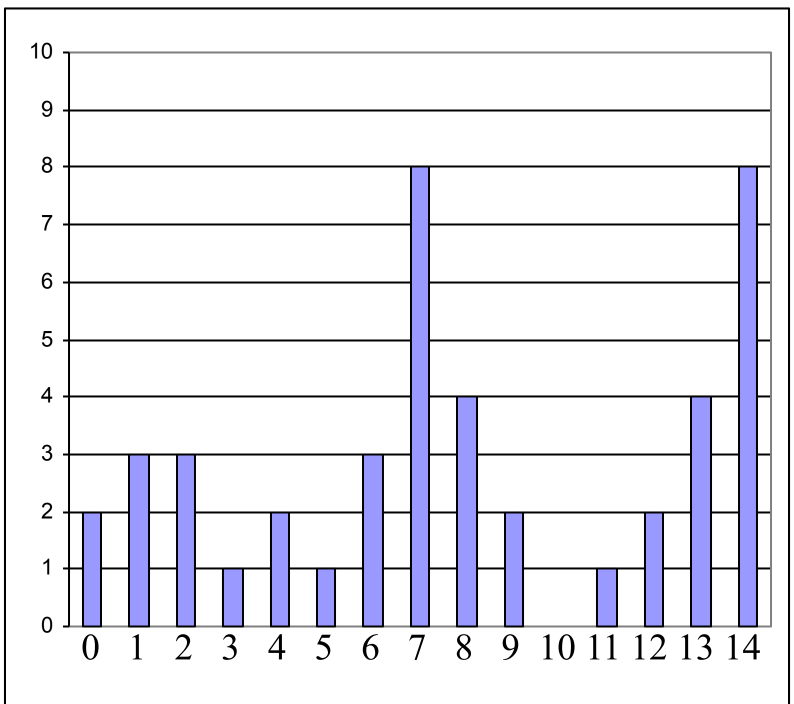
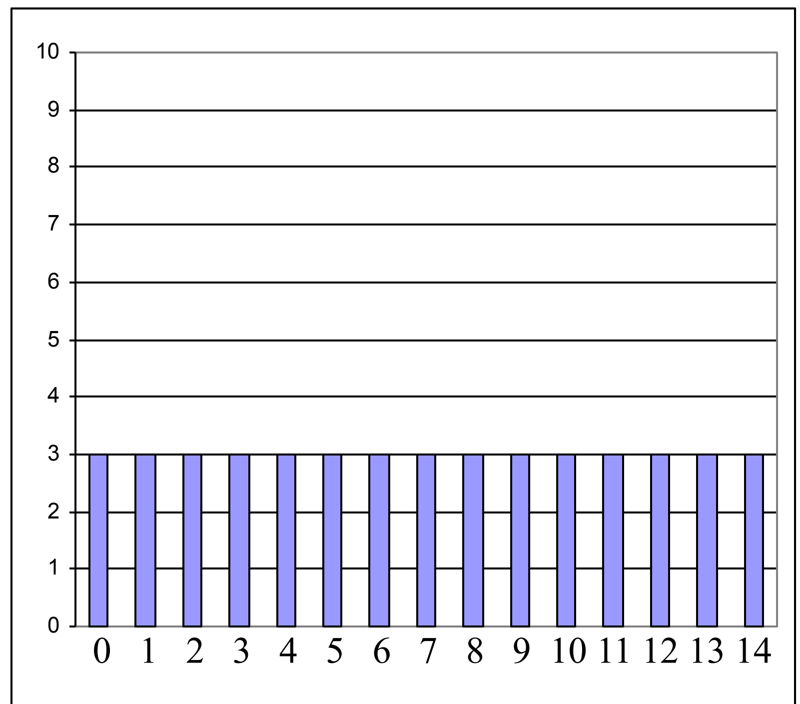
On the Uniform Distribution Assumption

- Assuming uniform distribution is rather crude

Distribution D



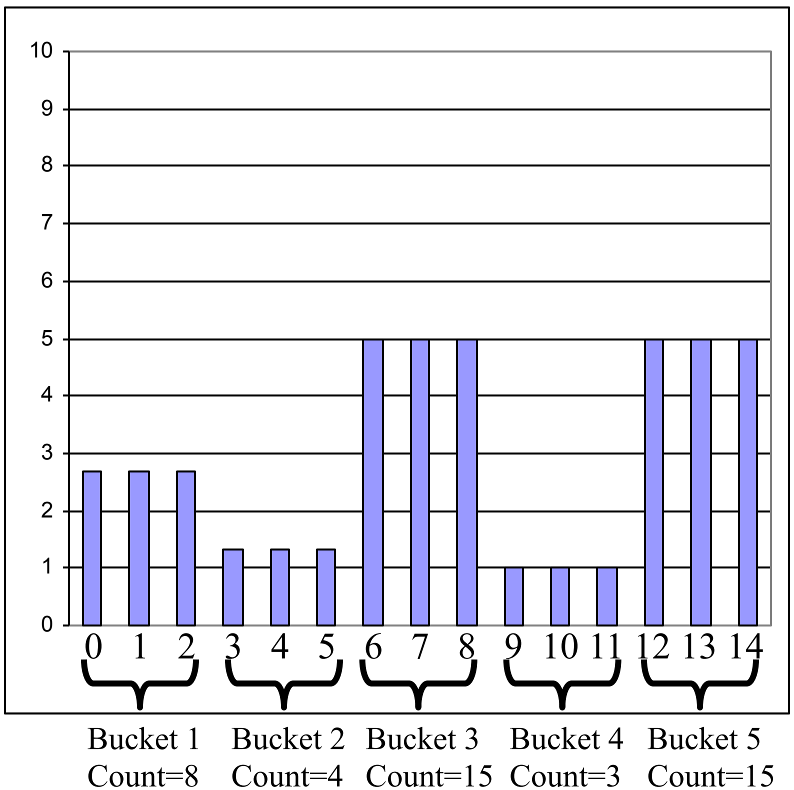
Uniform distribution approximating D



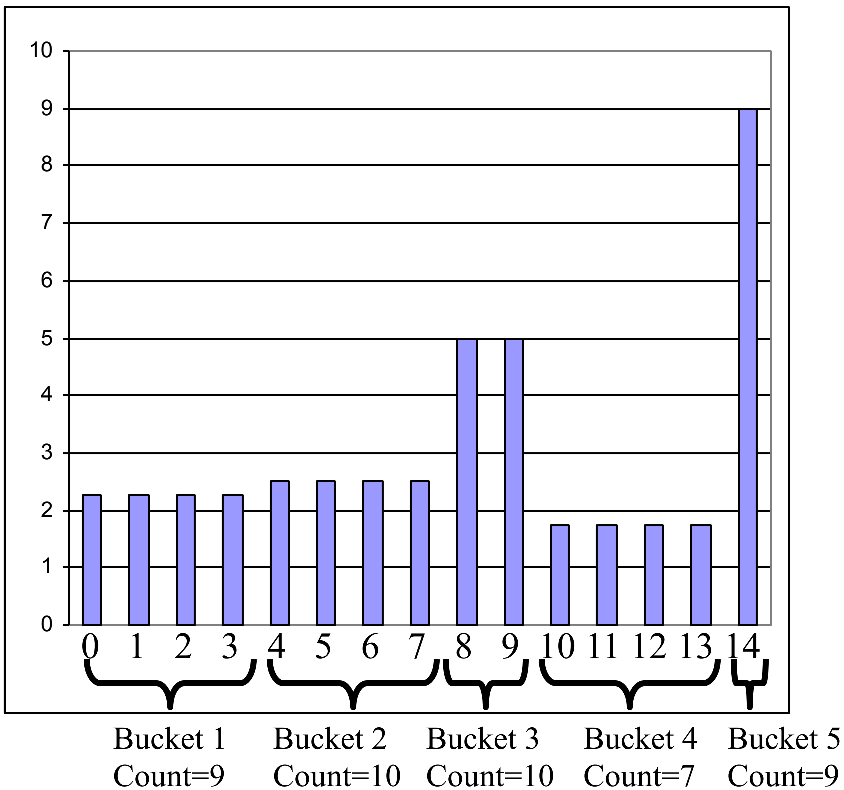
Histograms

- For better estimation, use a *histogram*

Equiwidth histogram



Equidepth histogram ~ quantiles



Q-opt Steps

- bring query in internal form (eg., parse tree)
- … into 'canonical form' (syntactic q-opt)
- **generate alt. plans**
  - **single relation**
  - multiple relations
- estimate cost; pick best

plan generation

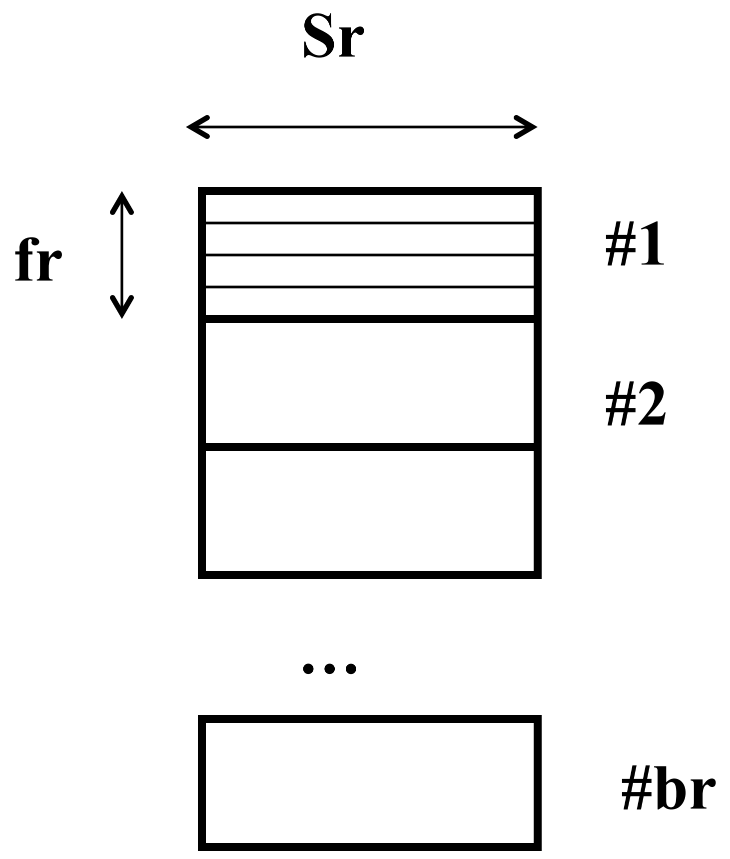
- Selections – eg.,

  select *

  from TAKES

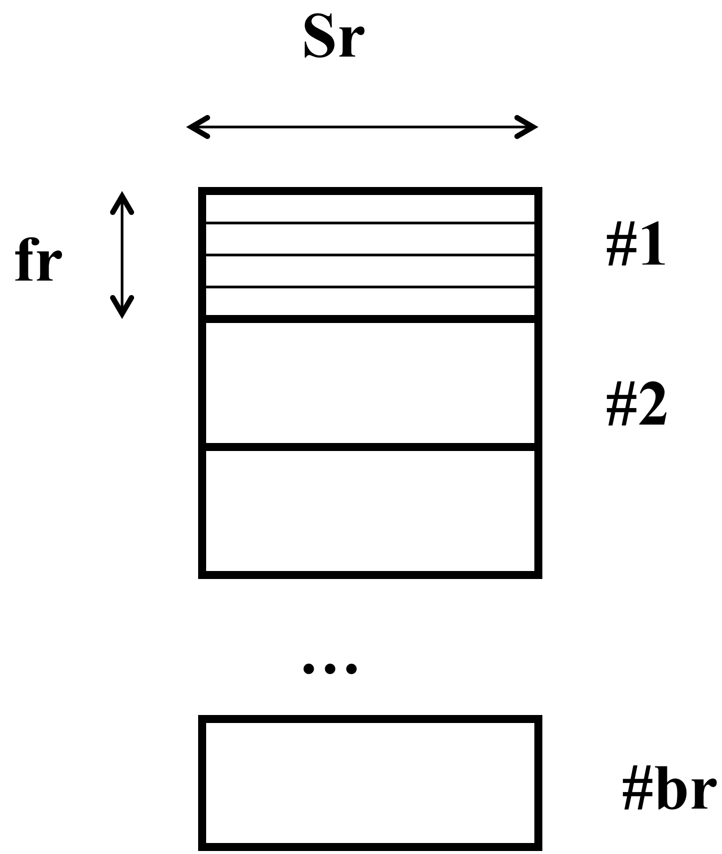
  where grade = ‘A’

- Plans?



plan generation

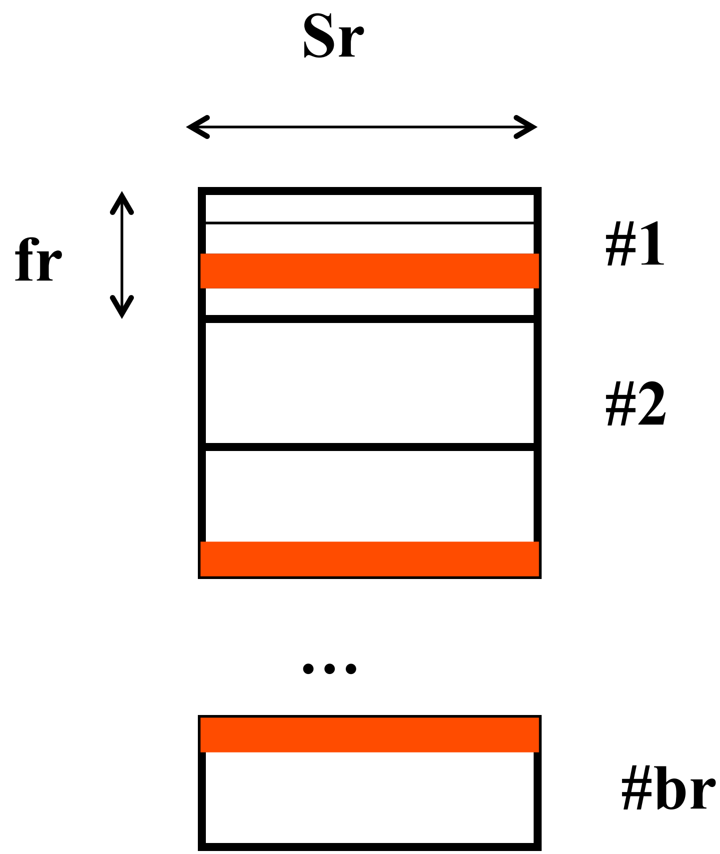
- Plans?
  - seq. scan
  - binary search
    - (if sorted & consecutive)
  - index search
    - if an index exists



plan generation

seq. scan – cost?

- br (worst case)
- br/2 (average, if we search for primary key)

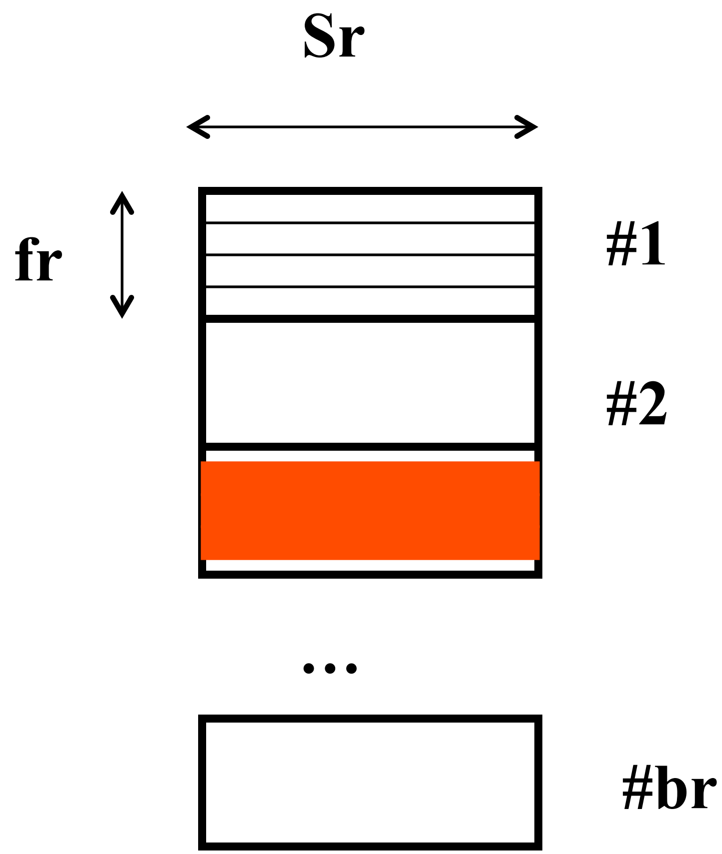


plan generation

binary search – cost?

if sorted and consecutive:

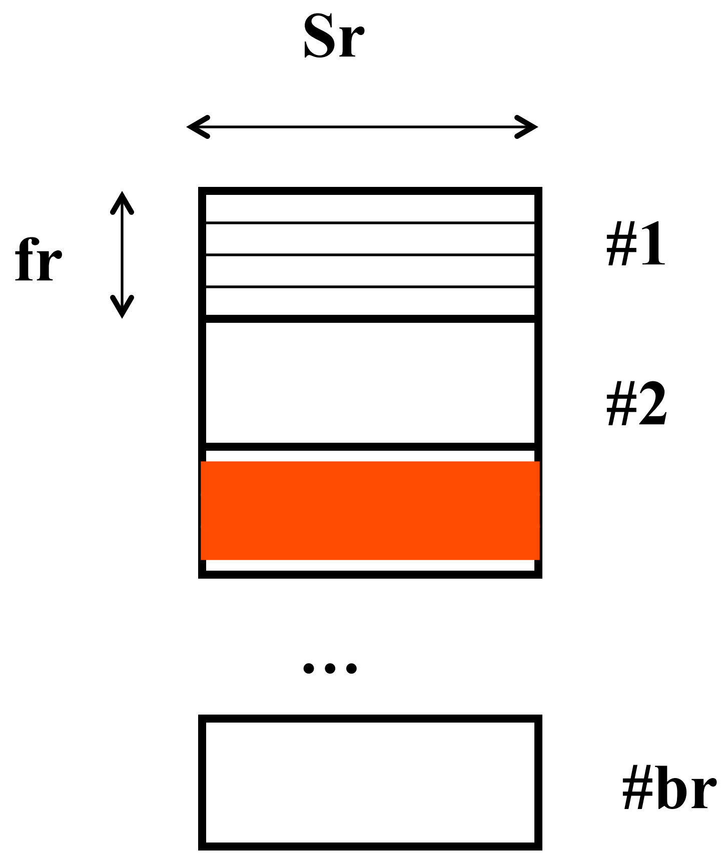
- ~log(br) +
- SC(A,r)/fr (=blocks spanned by qual. tuples)



plan generation

estimation of selection cardinalities SC(A,r):

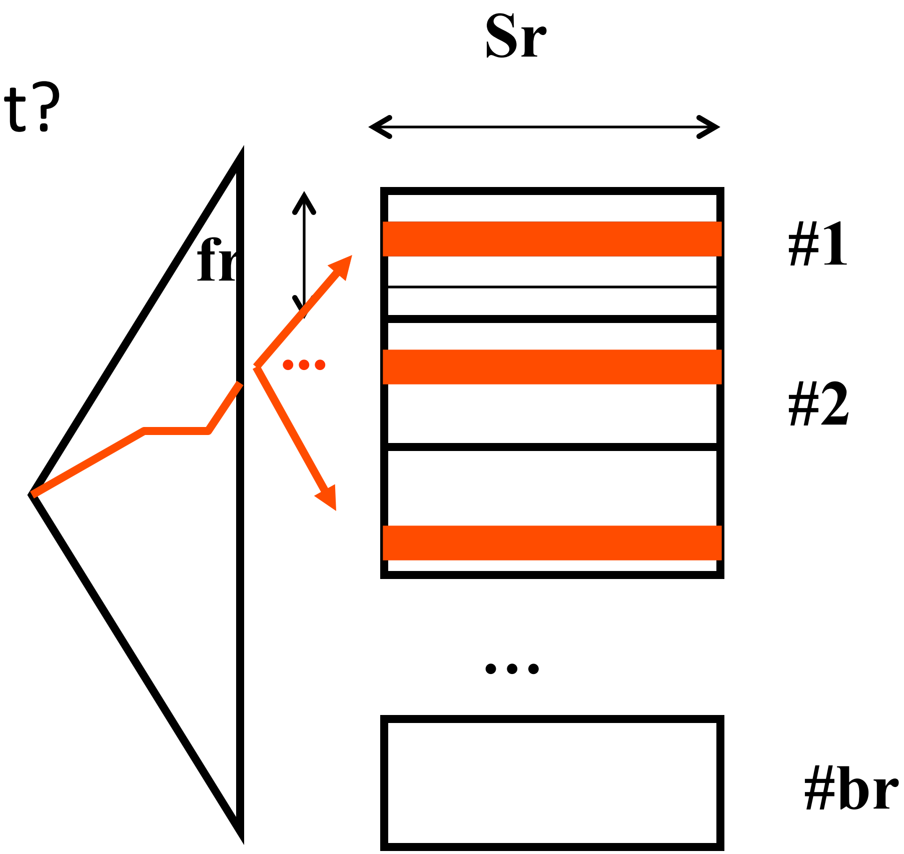
non-trivial – we saw it earlier



plan generation

method#3: index – cost?

- **Tricky**



Q-opt Steps

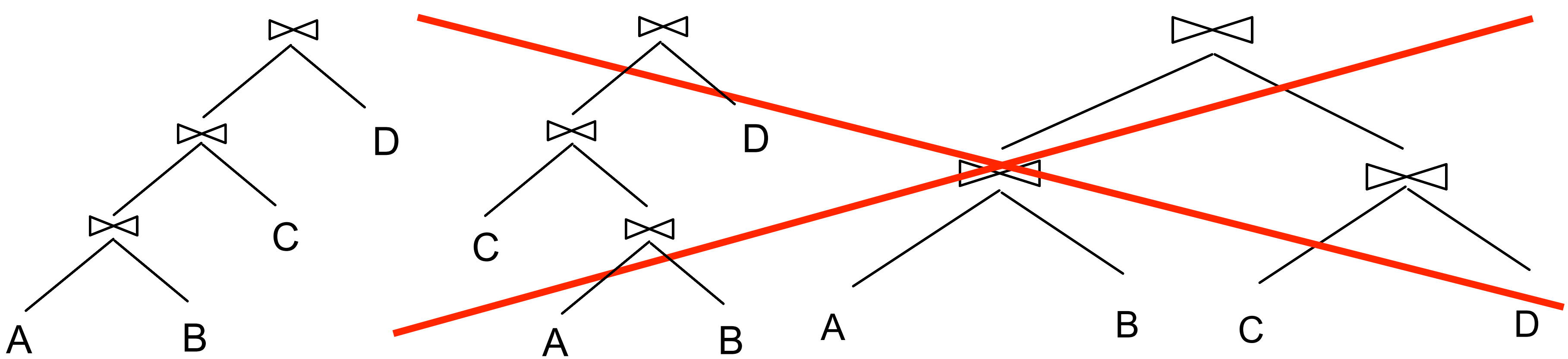
- bring query in internal form (eg., parse tree)
- … into 'canonical form' (syntactic q-opt)
- **generate alt. plans**
  - single relation
  - **multiple relations**
- estimate cost; pick best

n-way joins

- r1 JOIN r2 JOIN ... JOIN rn
- typically, break problem into 2-way joins
  - choose between NL, sort merge, hash join, ...

Queries Over Multiple Relations

- As number of joins increases, number of alternative plans grows rapidly → *need to restrict search space*
- Fundamental decision in System R (IBM): *only left-deep join trees* are considered. Advantages?



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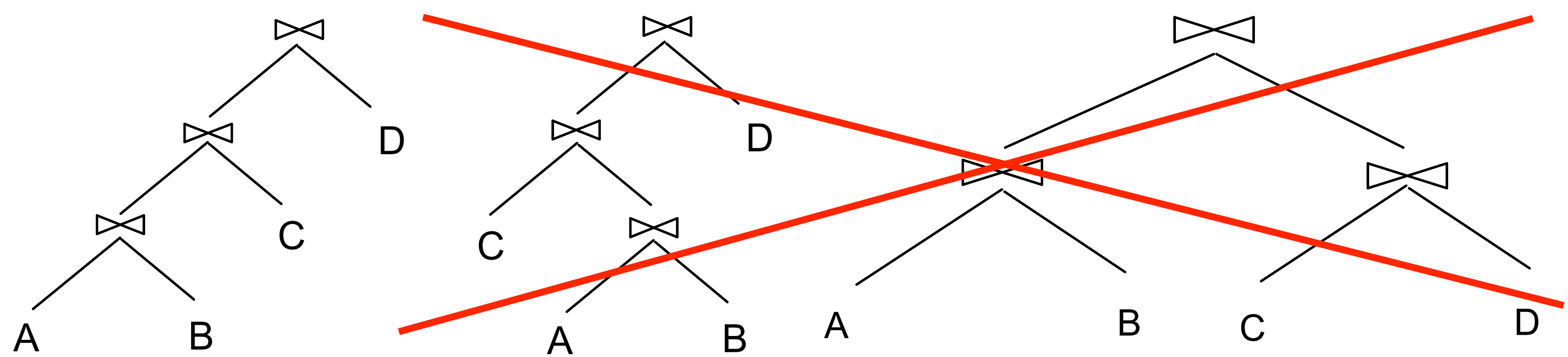
Queries Over Multiple Relations

- As number of joins increases, number of alternative plans grows rapidly → *need to restrict search space*
- Fundamental decision in System R (IBM): *only left-deep join trees* are considered. Advantages?
  - *fully pipelined* plans.
    - Intermediate results not written to temporary files.



Queries over Multiple Relations

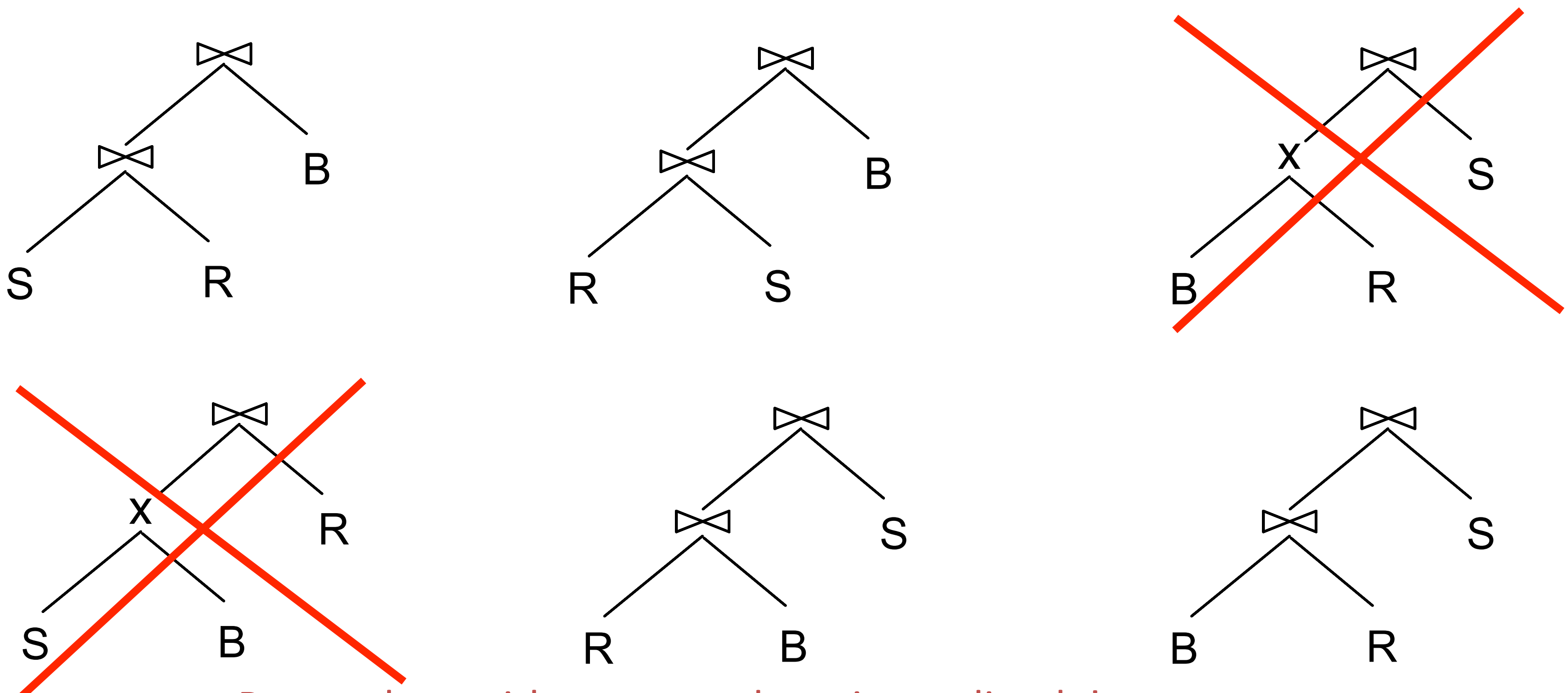
- Enumerate the orderings (= left deep tree)
- enumerate the plans for each operator
- enumerate the access paths for each table

Dynamic programming, to save cost estimations

Candidate Plans

SELECT S.sname, B.bname, R.day
FROM Sailors S, Reserves R, Boats B
WHERE S.sid = R.sid AND R.bid = B.bid

1. Enumerate relation orderings:

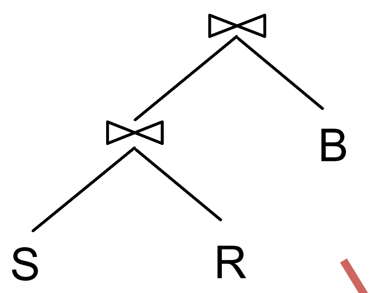


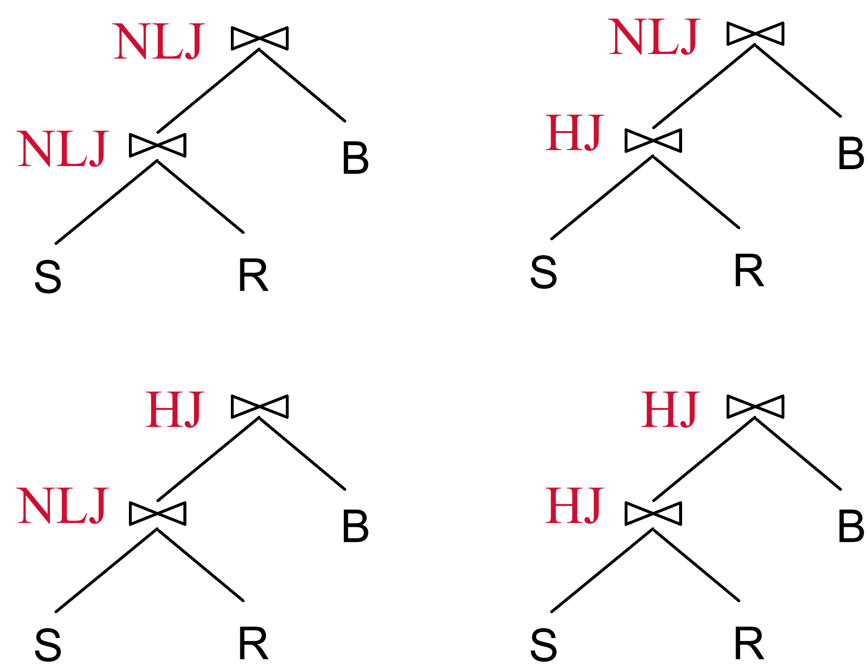
Prune plans with cross-products immediately!

Candidate Plans

SELECT S.sname, B.bname, R.day
FROM Sailors S, Reserves R, Boats B
WHERE S.sid = R.sid AND R.bid = B.bid

2. Enumerate join algorithm choices:





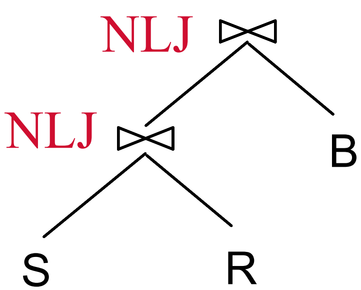
+ do same for
4 other plans

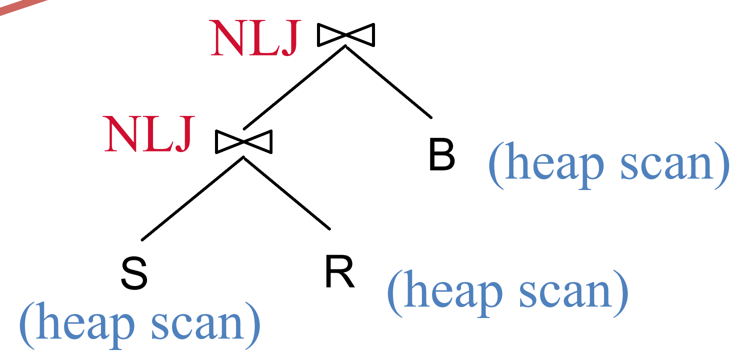
→ 4*4 = 16 plans so far..

Candidate Plans

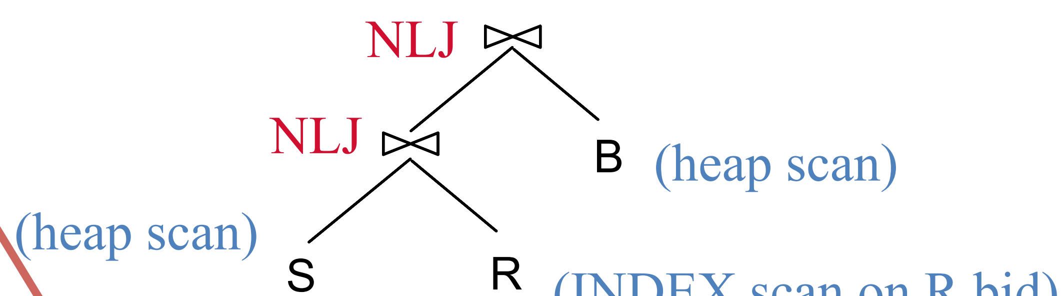
SELECT S.sname, B.bname, R.day
FROM Sailors S, Reserves R, Boats B
WHERE S.sid = R.sid AND R.bid = B.bid

3. Enumerate access method choices:





+ do same for other plans



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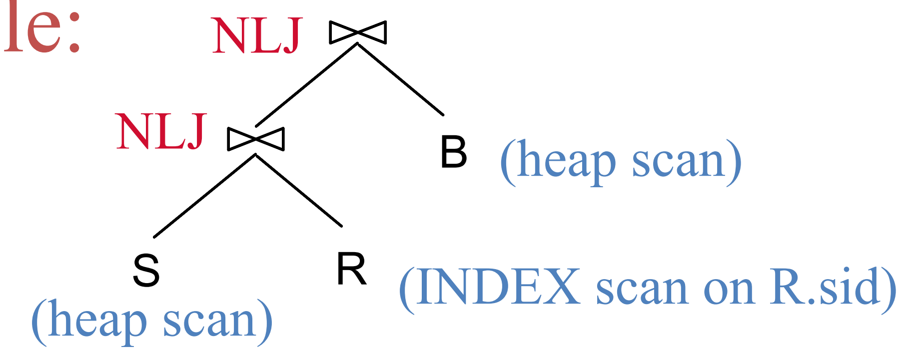
Now estimate the cost of each plan

Example:



Query Re-writing

- Re-write nested queries
- to: **de-correlate** and/or **flatten** them

Reminder

Correlated vs Uncorrelated

- The previous subqueries did not depend on anything outside the subquery
  - …and thus need to be executed just once.
  - These are called uncorrelated.

- A correlated subquery depends on data from the outer query
  - … and thus has to be executed for each row of the outer table(s)

Example: Decorrelating a Query

```
SELECT CourseName, Enrollment
FROM Courses
WHERE EXISTS
(SELECT *
FROM Teaches T
WHERE (T.name = 'Smith')
AND(Courses.num = T.num));
```

Equivalent uncorrelated query:

SELECT CourseName, Enrol
FROM Courses
WHERE Courses.Num IN
(SELECT T.num
FROM Teaches T
WHERE T.name = 'Smith')

- Advantage: nested block only needs to be executed once (rather than once per S tuple)

Example: "Flattening" a Query

```
SELECT  CourseName, Enrol
FROM Courses
WHERE  Courses.Num IN
  (SELECT  T.num
   FROM  Teaches T
   WHERE  T.name = 'Smith')
```

Equivalent non-nested query:

```
SELECT  CourseName, Enrol
FROM Courses C, Teaches T
WHERE  Courses.Num=T.num
AND  T.name = 'Smith'
```

- Advantage: can use a join algorithm + optimizer can select among join algorithms & reorder freely

Conclusions

- Ideas to remember:
  - syntactic q-opt – do selections early
  - selectivity estimations (uniformity, indep.; histograms; join selectivity)
  - left-deep joins
    - dynamic programming
  - handling correlated sub-queries