CS 245: Database System Principles

Notes 6: Query Processing

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Query Processing

Q → Query Plan

Query Processing

Q → Query Plan

Focus: Relational System

- Others?

Example

Select B,D
From R,S
Where R.A = “c” $\wedge$ S.E = 2 $\wedge$ R.C=S.C

R	A	B	C
	a	1	10
	b	1	20
	c	2	10
	d	2	35
	e	3	45

S	C	D	E
	10	x	2
	20	y	2
	30	z	2
	40	x	1
	50	y	3

R	A	B	C
	a	1	10
	b	1	20
	c	2	10
	d	2	35
	e	3	45

S	C	D	E
	10	x	2
	20	y	2
	30	z	2
	40	x	1
	50	y	3

Answer

B	D
2	x

- How do we execute query?

One idea

- Do Cartesian product
- Select tuples
- Do projection

RXS

R.A	R.B	R.C	S.C	S.D	S.E
a	1	10	10	x	2
a	1	10	20	y	2
.					
.					
C	2	10	10	x	2
.					
.					

RXS

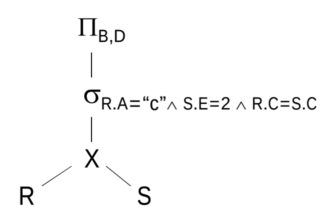
R.A	R.B	R.C	S.C	S.D	S.E
a	1	10	10	x	2
a	1	10	20	y	2
.					
.					
C	2	10	10	x	2
.					
.					

Bingo!

Got one...

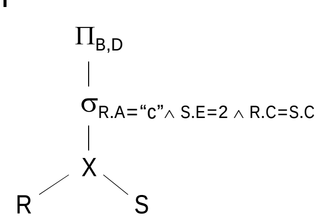
Relational Algebra - can be used to describe plans...

Ex: Plan I



Relational Algebra - can be used to describe plans...

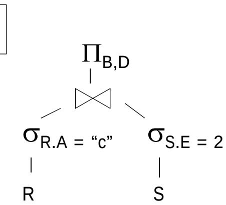
Ex: Plan I



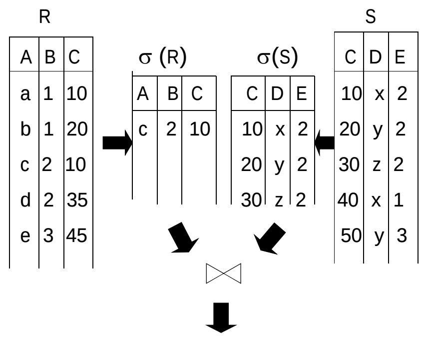
OR: $\Pi_{B,D}\ [\ \sigma_{R.A=\text{"c"} \wedge S.E=2 \wedge R.C = S.C}\ (RXS)]$

Another idea:

Plan II



$\bowtie$ natural join



Plan III

Use R.A and S.C Indexes

(1) Use R.A index to select R tuples with R.A = "c"

(2) For each R.C value found, use S.C index to find matching tuples

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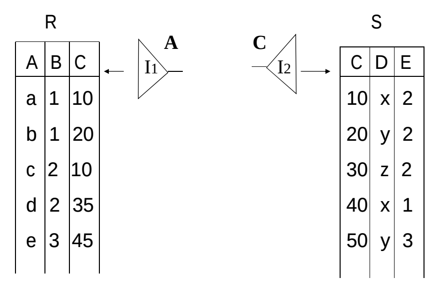
Use R.A and S.C Indexes

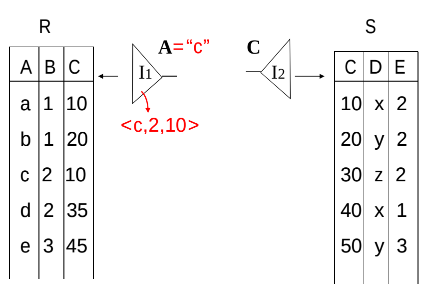
(1) Use R.A index to select R tuples with R.A = "c"

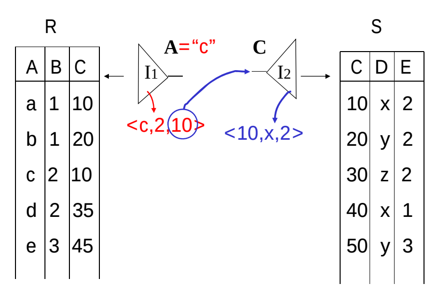
(2) For each R.C value found, use S.C index to find matching tuples

(3) Eliminate S tuples S.E $\neq$ 2

(4) Join matching R,S tuples, project B,D attributes and place in result

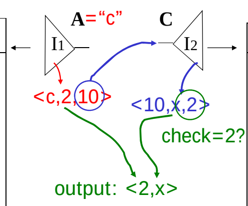






R

A	B	C
a	1	10
b	1	20
c	2	10
d	2	35
e	3	45

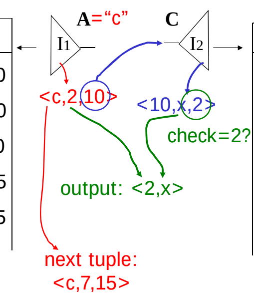


S

C	D	E
10	x	2
20	y	2
30	z	2
40	x	1
50	y	3

R

A	B	C
a	1	10
b	1	20
c	2	10
d	2	35
e	3	45



S

C	D	E
10	x	2
20	y	2
30	z	2
40	x	1
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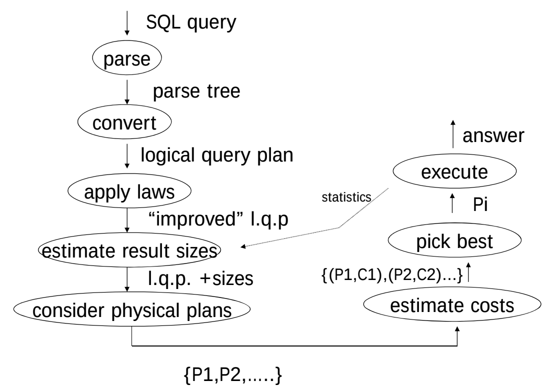
Overview of Query Optimization

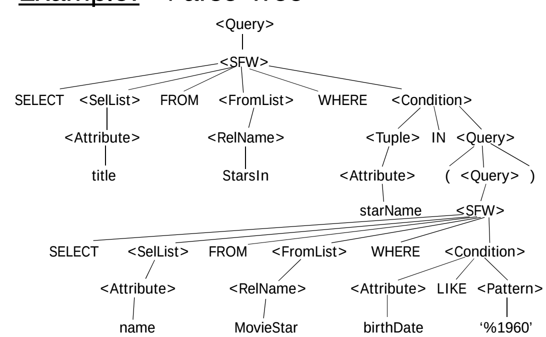


Example: SQL query

SELECT title
FROM StarsIn
WHERE starName IN (
    SELECT name
    FROM MovieStar
    WHERE birthdate LIKE '%1960'
);

(Find the movies with stars born in 1960)

Example: Parse Tree



Example: Generating Relational Algebra

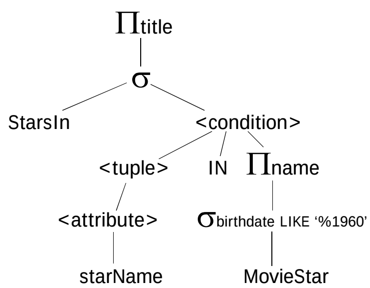


Fig. 7.15: An expression using a two-argument σ, midway between a parse tree and relational algebra

Example: Logical Query Plan

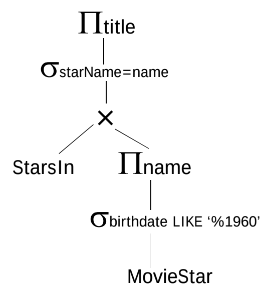


Fig. 7.18: Applying the rule for IN conditions

Example: Improved Logical Query Plan

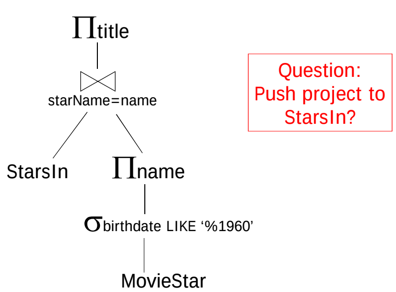
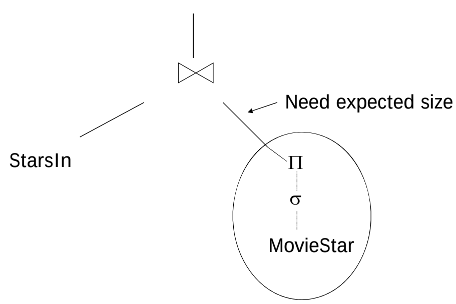
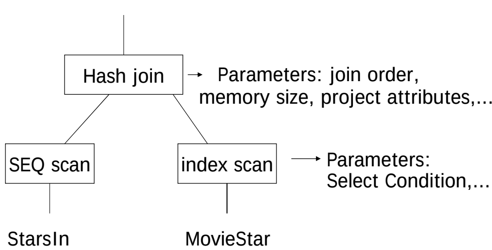


Fig. 7.20: An improvement on fig. 7.18.

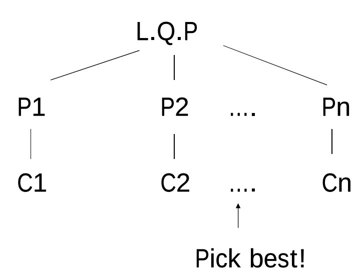
Example: Estimate Result Sizes



Example: One Physical Plan



Example: Estimate costs



Textbook outline

Chapter 15

5 [Ch 5] Algebra for queries [bags vs sets]
- Select, project, join, ... [project list a,a+b->x,...]
- Duplicate elimination, grouping, sorting

15.1 [15.1] Physical operators
- Scan,sort, ...

15.2 - 15.6 [15.2-15.6] Implementing operators + estimating their cost

Chapter 16

16.1[16.1] Parsing
16.2[16.2] Algebraic laws
16.3[16.3] Parse tree -> logical query plan
16.4[16.4] Estimating result sizes
16.5-7[16.5-7] Cost based optimization

Reading textbook - Chapters 15, 16

Optional:
- Sections 15.7, 15.8, 15.9 [15.7, 15.8]
- Sections 16.6, 16.7 [16.6, 16.7]

Optional: Duplicate elimination operator grouping, aggregation operators

Query Optimization - In class order

- Relational algebra level
- Detailed query plan level

Query Optimization - In class order

- Relational algebra level
- Detailed query plan level
  - Estimate Costs
    - without indexes
    - with indexes
  - Generate and compare plans

Relational algebra optimization

- Transformation rules (preserve equivalence)
- What are good transformations?

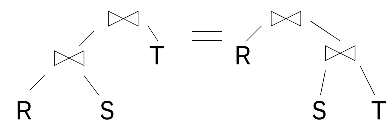
Rules: Natural joins & cross products & union

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

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

Note:

- Carry attribute names in results, so order is not important
- Can also write as trees, e.g.:



Rules: Natural joins & cross products & union

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

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

R x S = S x R

(R x S) x T = R x (S x T)

R U S = S U R

R U (S U T) = (R U S) U T

Rules: Selects

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

$\sigma_{p1 \vee p2}(R) =$

Rules: Selects

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

$\sigma_{p1 \vee p2}(R) = [\sigma_{p1}(R)] \cup [\sigma_{p2}(R)]$

Bags vs. Sets

R = {a,a,b,b,b,c}

S = {b,b,c,c,d}

RUS = ?

Bags vs. Sets

R = {a,a,b,b,b,c}

S = {b,b,c,c,d}

RUS = ?

- Option 1 SUM

  RUS = {a,a,b,b,b,b,b,c,c,c,d}
- Option 2 MAX

  RUS = {a,a,b,b,b,c,c,d}

Option 2 (MAX) makes this rule work:

$\sigma_{p1 \vee p2}$ (R) = σ_{p1}(R) U σ_{p2}(R)

Example: R={a,a,b,b,b,c}

P1 satisfied by a,b; P2 satisfied by b,c

Option 2 (MAX) makes this rule work:

$\sigma_{p1 \vee p2}$ (R) = σ_{p1}(R) U σ_{p2}(R)

Example: R={a,a,b,b,b,c}

P1 satisfied by a,b; P2 satisfied by b,c

$\sigma_{p1 \vee p2}$ (R) = {a,a,b,b,b,c}

σ_{p1}(R) = {a,a,b,b,b}

σ_{p2}(R) = {b,b,b,c}

σ_{p1}(R) U σ_{p2} (R) = {a,a,b,b,b,c}

"Sum" option makes more sense:

Senators (......) Rep (......)

T1 = $\pi_{yr,state}$ Senators; T2 = $\pi_{yr,state}$ Reps

T1

Yr	State
97	CA
99	CA
98	AZ

T2

Yr	State
99	CA
99	CA
98	CA

Union?

Executive Decision

-> Use "SUM" option for bag unions

-> Some rules cannot be used for bags

Rules: Project

Let: X = set of attributes

Y = set of attributes

XY = X U Y

π_{xy} (R) =

Rules: Project

Let: X = set of attributes
Y = set of attributes
XY = X U Y

π_{xy} (R) = π_x [π_y (R)]

Rules: Project

Let: X = set of attributes
Y = set of attributes
XY = X U Y

π_{xy} (R) = π_x [$\cancel{\pi_y}$ (R)]

Rules: $\sigma + \bowtie$ combined

Let p = predicate with only R attribs
q = predicate with only S attribs
m = predicate with only R,S attribs

σ_p (R $\bowtie$ S) =

σ_q (R $\bowtie$ S) =

Rules: $\sigma + \bowtie$ combined

Let p = predicate with only R attribs
q = predicate with only S attribs
m = predicate with only R,S attribs

σ_p (R $\bowtie$ S) = [σ_p (R)] $\bowtie$ S

σ_q (R $\bowtie$ S) = R $\bowtie$ [σ_q (S)]

Rules: $\sigma + \bowtie$ combined (continued)

Some Rules can be Derived:

$\sigma_{p \wedge q}$ (R $\bowtie$ S) =

$\sigma_{p \wedge q \wedge m}$ (R $\bowtie$ S) =

$\sigma_{p \vee q}$ (R $\bowtie$ S) =

Do one, others for homework:

$\sigma_{p \wedge q}$ (R $\bowtie$ S) = [σ_p (R)] $\bowtie$ [σ_q (S)]

$\sigma_{p \wedge q \wedge m}$ (R $\bowtie$ S) =

σ_m [(σ_p R) $\bowtie$ (σ_q S)]

$\sigma_{p \vee q}$ (R $\bowtie$ S) =

[(σ_p R) $\bowtie$ S] U [R $\bowtie$ (σ_q S)]

--> Derivation for first one:

$\sigma_{p \wedge q} (R \bowtie S) =$

$\sigma_p [\sigma_q (R \bowtie S)] =$

$\sigma_p [R \bowtie \sigma_q (S)] =$

$[\sigma_p (R)] \bowtie [\sigma_q (S)]$

<u>Rules:</u> π,σ combined

Let x = subset of R attributes
z = attributes in predicate P
(subset of R attributes)

$\pi_x[\sigma_p (R)] =$

<u>Rules:</u> π,σ combined

Let x = subset of R attributes
z = attributes in predicate P
(subset of R attributes)

$\pi_x[\sigma_p (R)] = \quad \{\sigma_p [\pi_x (R)]\}$

<u>Rules:</u> π,σ combined

Let x = subset of R attributes
z = attributes in predicate P
(subset of R attributes)

$\pi_x[\sigma_p (R)] = \pi_x \{\sigma_p [\overset{\pi_{xz}}{\cancel{\pi_x}} (R)]\}$

<u>Rules:</u> $\pi, \bowtie$ combined

Let x = subset of R attributes
y = subset of S attributes
z = intersection of R,S attributes

$\pi_{xy} (R \bowtie S) =$

<u>Rules:</u> $\pi, \bowtie$ combined

Let x = subset of R attributes
y = subset of S attributes
z = intersection of R,S attributes

$\pi_{xy} (R \bowtie S) =$

$\pi_{xy}\{[\pi_{xz} (R)] \bowtie [\pi_{yz} (S)]\}$

$\pi_{xy} \{\sigma_p (R \bowtie S)\} =$

$\pi_{xy} \{\sigma_p (R \bowtie S)\} =$

$\pi_{xy} \{\sigma_p [\pi_{xz'} (R) \bowtie \pi_{yz'} (S)]\}$

$z' = z \cup \{\text{attributes used in } P\}$

<u>Rules</u> for σ, π combined with X

similar...

e.g., $\sigma_p (R \times S) = ?$

<u>Rules</u> $\sigma, \cup$ combined:

$\sigma_p(R \cup S) = \sigma_p(R) \cup \sigma_p(S)$

$\sigma_p(R - S) = \sigma_p(R) - S = \sigma_p(R) - \sigma_p(S)$

Which are "good" transformations?

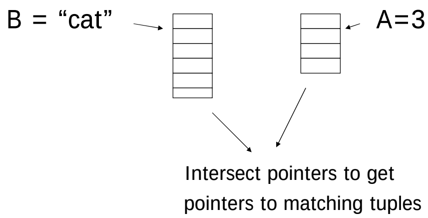
- □ $\sigma_{p1 \wedge p2} (R) \rightarrow \sigma_{p1} [\sigma_{p2} (R)]$
- □ $\sigma_p (R \bowtie S) \rightarrow [\sigma_p (R)] \bowtie S$
- □ $R \bowtie S \rightarrow S \bowtie R$
- □ $\pi_x [\sigma_p (R)] \rightarrow \pi_x \{\sigma_p [\pi_{xz} (R)]\}$

Conventional wisdom:
do projects early

<u>Example</u>: R(A,B,C,D,E) x={E}
P: (A=3) $\wedge$ (B="cat")

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

$\boxed{\text{But}}$ What if we have A, B indexes?



Bottom line:

- No transformation is always good
- Usually good: early selections

In textbook: more transformations

- Eliminate common sub-expressions
- Other operations: duplicate elimination

Outline - Query Processing

- Relational algebra level
  - transformations
  - good transformations
- Detailed query plan level
  - estimate costs
  - generate and compare plans

- Estimating cost of query plan

(1) Estimating size of results
(2) Estimating # of IOs

Estimating result size

- Keep 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 in R for attribute A

Example

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

Example

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 S(R) = 37
V(R,A) = 3 V(R,C) = 5
V(R,B) = 1 V(R,D) = 4

Size estimates for W = R1 x R2

T(W) =

S(W) =

Size estimates 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)

S(W) = S(R)

T(W) = ?

Example

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

V(R,A)=3
V(R,B)=1
V(R,C)=5
V(R,D)=4

W = $\sigma_{z=val}$(R) T(W) =

Example

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

V(R,A)=3
V(R,B)=1
V(R,C)=5
V(R,D)=4

what is probability this tuple will be in answer?

$W = \sigma_{z=val}(R) \quad T(W) =$

Example

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

V(R,A)=3
V(R,B)=1
V(R,C)=5
V(R,D)=4

$W = \sigma_{z=val}(R) \quad T(W) = \frac{T(R)}{V(R,Z)}$

Assumption:

Values in select expression Z = val
are uniformly distributed
over possible V(R,Z) values.

Alternate Assumption:

Values in select expression Z = val
are uniformly distributed
over domain with DOM(R,Z) values.

Example

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

Alternate assumption
V(R,A)=3 DOM(R,A)=10
V(R,B)=1 DOM(R,B)=10
V(R,C)=5 DOM(R,C)=10
V(R,D)=4 DOM(R,D)=10

$W = \sigma_{z=val}(R) \quad T(W) = ?$

Example

R

A	B	C	D
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what is probability this tuple will be in answer?

$W = \sigma_{z=val}(R) \quad T(W) = ?$

Example

R

A	B	C	D
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Alternate assumption
V(R,A)=3 DOM(R,A)=10
V(R,B)=1 DOM(R,B)=10
V(R,C)=5 DOM(R,C)=10
V(R,D)=4 DOM(R,D)=10

$$W = \sigma_{z=val}(R) \qquad T(W) = \frac{T(R)}{DOM(R,Z)}$$

Selection cardinality

SC(R,A) = average # records that satisfy equality condition on R.A

$$SC(R,A) = \begin{cases} \dfrac{T(R)}{V(R,A)} \\ \\ \dfrac{T(R)}{DOM(R,A)} \end{cases}$$

What about $W = \sigma_{z \geq val}(R)$?

T(W) = ?

What about $W = \sigma_{z \geq val}(R)$?

T(W) = ?

- Solution # 1:
  T(W) = T(R)/2

What about $W = \sigma_{z \geq val}(R)$?

T(W) = ?

- Solution # 1:
  T(W) = T(R)/2
- Solution # 2:
  T(W) = T(R)/3

- Solution # 3: Estimate values in range

Example R

	Z

Min=1

Max=20

V(R,Z)=10

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

- Solution # 3: Estimate values in range

Example R

	Z

Min=1

Max=20

V(R,Z)=10

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

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

T(W) = f × T(R)

Equivalently:

f×V(R,Z) = fraction of distinct values

$T(W) = [f \times V(Z,R)] \times \frac{T(R)}{V(Z,R)} = f \times T(R)$

<u>Size estimate</u> for W = R1 ⋈ R2

Let x = attributes of R1

y = attributes of R2

<u>Size estimate</u> for W = R1 ⋈ R2

Let x = attributes of R1

y = attributes of R2

$\boxed{\text{Case 1}}$ $X \cap Y = \emptyset$

Same as R1 x R2

$\boxed{\text{Case 2}}$ W = R1 ⋈ R2 $X \cap Y = A$

R1

A	B	C

R2

A	D

$\boxed{\text{Case 2}}$ W = R1 ⋈ R2 $X \cap Y = A$

R1

A	B	C

R2

A	D

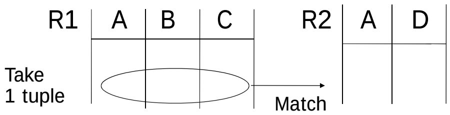
<u>Assumption:</u>

V(R1,A) ≤ V(R2,A) ⇒ Every A value in R1 is in R2

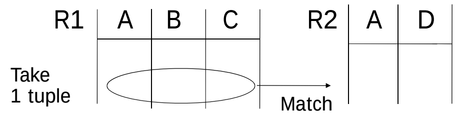
V(R2,A) ≤ V(R1,A) ⇒ Every A value in R2 is in R1

"containment of value sets" Sec. 7.4.4

Computing T(W) when $V(R1,A) \leq V(R2,A)$



Computing T(W) when $V(R1,A) \leq V(R2,A)$



1 tuple matches with $\frac{T(R2)}{V(R2,A)}$ tuples...

so $T(W) = \frac{T(R2)}{V(R2,\ A)} \times T(R1)$

- $V(R1,A) \leq V(R2,A)$ $\quad T(W) = \frac{T(R2)\ T(R1)}{V(R2,A)}$
- $V(R2,A) \leq V(R1,A)$ $\quad T(W) = \frac{T(R2)\ T(R1)}{V(R1,A)}$

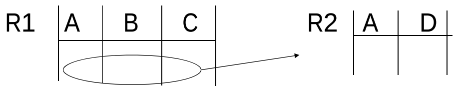
[A is common attribute]

In general $W = R1 \bowtie R2$

$$T(W) = \frac{T(R2)\ T(R1)}{\max\{\ V(R1,A),\ V(R2,A)\ \}}$$

$\boxed{\text{Case 2}}$ with alternate assumption

Values uniformly distributed over domain



This tuple matches T(R2)/DOM(R2,A) so

$$T(W) = \frac{T(R2)\ T(R1)}{DOM(R2,\ A)} = \frac{T(R2)\ T(R1)}{DOM(R1,\ A)}$$

Assume the same

In all cases:

$S(W) = S(R1) + S(R2) - S(A)$

size of attribute A

Using similar ideas,
we can estimate sizes of:

Π_{AB} (R) ..... Sec. 16.4.2 (same for either edition)

$\sigma_{A=a \wedge B=b}$ (R) .... Sec. 16.4.3

R $\bowtie$ S with common attribs. A,B,C
Sec. 16.4.5

Union, intersection, diff, ...
Sec. 16.4.7

Note: for complex expressions, need intermediate T,S,V results.

E.g. $W = \underbrace{[\sigma_{A=a} (R1)]}_{\text{Treat as relation U}} \bowtie R2$

T(U) = T(R1)/V(R1,A) S(U) = S(R1)

Also need V (U, *) !!

To estimate Vs

E.g., U = $\sigma_{A=a}$ (R1)
Say R1 has attribs A,B,C,D
V(U, A) =
V(U, B) =
V(U, C) =
V(U, D) =

Example

R1

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)

Example

R1

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 V(U,B) =1 V(U,C) = $\frac{T(R1)}{V(R1,A)}$

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

Possible Guess U = $\sigma_{A=a}$ (R)

V(U,A) = 1
V(U,B) = V(R,B)

For Joins U = R1(A,B) $\bowtie$ R2(A,C)

V(U,A) = min { V(R1, A), V(R2, A) }
V(U,B) = V(R1, B)
V(U,C) = V(R2, C)

[called “preservation of value sets” in section 7.4.4]

Example:

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

R1	T(R1) = 1000	V(R1,A)=50	V(R1,B)=100
R2	T(R2) = 2000	V(R2,B)=200	V(R2,C)=300
R3	T(R3) = 3000	V(R3,C)=90	V(R3,D)=500

Partial Result: U = R1 $\bowtie$ R2

$$T(U) = \frac{1000 \times 2000}{200}$$

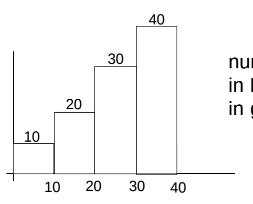
V(U,A) = 50
V(U,B) = 100
V(U,C) = 300

Z = U $\bowtie$ R3

$$T(Z) = \frac{1000 \times 2000 \times 3000}{200 \times 300}$$

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

A Note on Histograms



number of tuples in R with A value in given range

$\sigma_{A=val}(R)$ = ?

Summary

- Estimating size of results is an “art”
- Don’t forget:
  Statistics must be kept up to date…
  (cost?)

Outline

- Estimating cost of query plan
  - Estimating size of results ← done!
  - Estimating # of IOs ← next...

- Generate and compare plans