

CS 245: Database System Principles

Notes 6: Query Processing

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Query Processing

Q → Query Plan

Focus: Relational System

- Others?

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Example

Select B,D

From R,S

Where $R.A = "c" \wedge S.E = 2 \wedge R.C=S.C$

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R	A	B	C	S	C	D	E
a	1	10	10	x	2		
b	1	20	20	y	2		
c	2	10	30	z	2		
d	2	35	40	x	1		
e	3	45	50	y	3		

Answer

B	D
2	x

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- How do we execute query?

One idea

- Do Cartesian product
- Select tuples
- Do projection

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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
	⋮					
Bingo! →	C	2	10	10	x	2
Got one...	⋮					

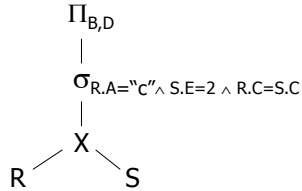
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Relational Algebra - can be used to describe plans...

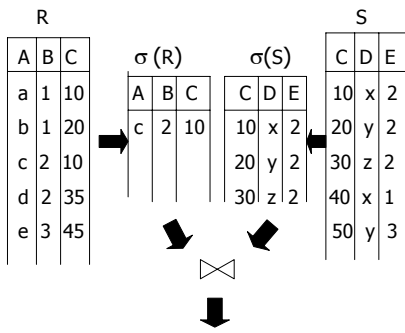
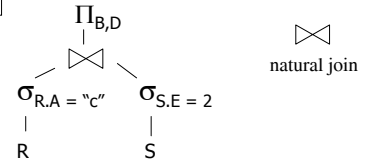
Ex: Plan I



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

Another idea:

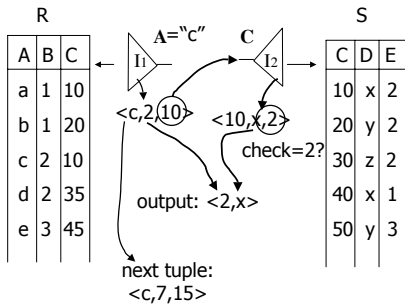
Plan II



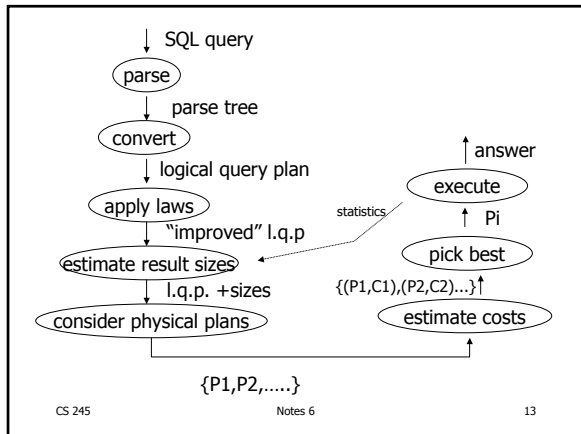
Plan III

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
- (3) Eliminate S tuples S.E ≠ 2
- (4) Join matching R,S tuples, project B,D attributes and place in result



Overview of Query Optimization



Example: SQL query

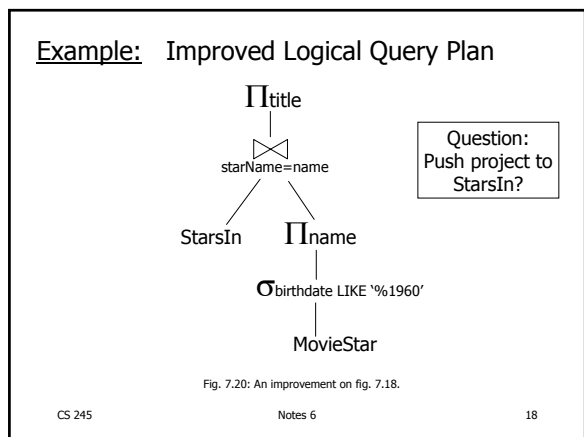
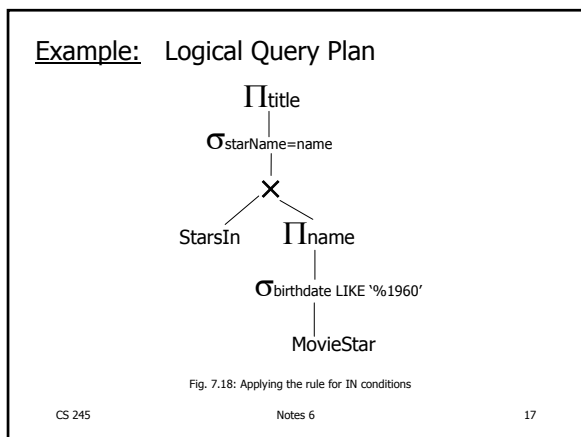
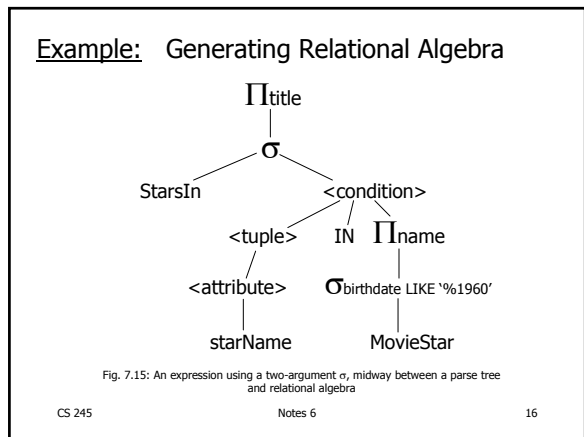
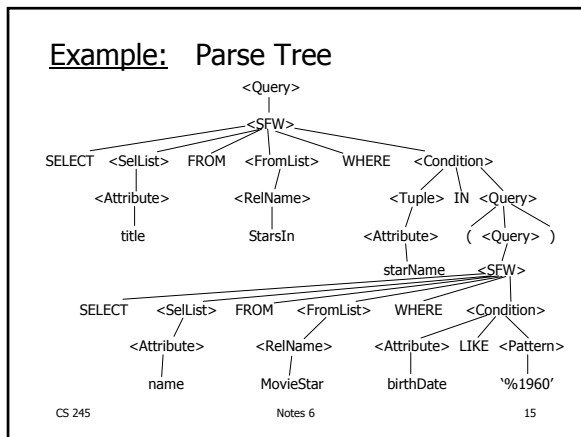
```

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

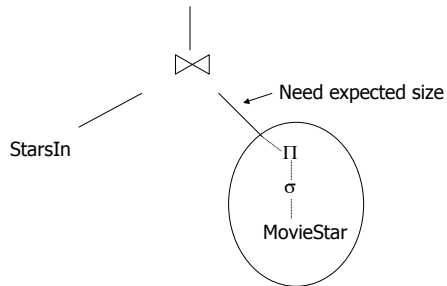
```

(Find the movies with stars born in 1960)

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Example: Estimate Result Sizes

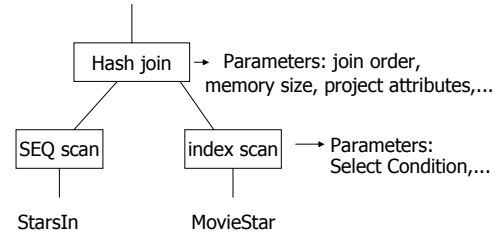


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Example: One Physical Plan

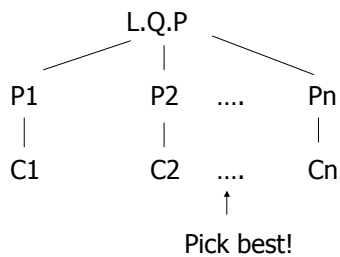


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Example: Estimate costs



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Textbook outline

Chapter 6

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

6.2 Physical operators

[15.1] - Scan, sort, ...

6.3-6.10 Implementing operators +
[15.2-15.9] estimating their cost

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Chapter 7

- 7.1[16.1] Parsing
- 7.2[16.2] Algebraic laws
- 7.3[16.3] Parse tree -> logical query plan
- 7.4[16.4] Estimating result sizes
- 7.5-7[16.5-7] Cost based optimization

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Reading textbook - Chapters 6,7

Optional: 6.8, 6.9, 6.10, 7.6, 7.7
[15.7, 15.8, 15.9, 16.6, 16.7]

Optional: Duplicate elimination operator
grouping, aggregation operators

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Query Optimization - In class order

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

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Relational algebra optimization

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

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Rules: Natural joins & cross products & union

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

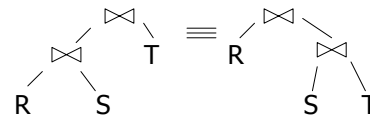
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Note:

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



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Rules: Natural joins & cross products & union

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

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

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

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Rules: Selects

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

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

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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}

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Option 2 (MAX) makes this rule work:

$$\sigma_{p_1 \vee p_2}(R) = \sigma_{p_1}(R) \cup \sigma_{p_2}(R)$$

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

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

$$\sigma_{p_1 \vee p_2}(R) = \{a,a,b,b,b,c\}$$

$$\sigma_{p_1}(R) = \{a,a,b,b,b\}$$

$$\sigma_{p_2}(R) = \{b,b,b,c\}$$

$$\sigma_{p_1}(R) \cup \sigma_{p_2}(R) = \{a,a,b,b,b,c\}$$

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"Sum" option makes more sense:

Senators (.....)

Rep (.....)

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

T1	Yr	State	T2	Yr	State
	97	CA		99	CA
	99	CA		99	CA
	98	AZ		98	CA

Union?

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Executive Decision

- > Use "SUM" option for bag unions
- > Some rules cannot be used for bags

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Rules: Project

Let: X = set of attributes

Y = set of attributes

XY = X U Y

~~$$\pi_{xy}(R) = \pi_x[\pi_y(R)]$$~~

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Rules: $\sigma + \bowtie$ combined

Let p = predicate with only R attribs

q = predicate with only S attribs

m = predicate with only R,S attribs

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

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

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

Some Rules can be Derived:

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

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

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

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Do one, others for homework:

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

$$\sigma_{p \wedge q \wedge m} (R \bowtie S) = \sigma_m [(\sigma_p R) \bowtie (\sigma_q S)]$$

$$\sigma_{p \vee q} (R \bowtie S) = [(\sigma_p R) \bowtie S] \cup [R \bowtie (\sigma_q S)]$$

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--> Derivation for first one:

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

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

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

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

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Rules: π, σ combined

Let x = subset of R attributes

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

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

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Rules: π, \bowtie combined

Let x = subset of R attributes

y = subset of S attributes

z = intersection of R, S attributes

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

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

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

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

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

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Rules for σ, π combined with X

similar...

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

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Rules σ, \cup combined:

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

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

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Which are "good" transformations?

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

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Conventional wisdom:
do projects early

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

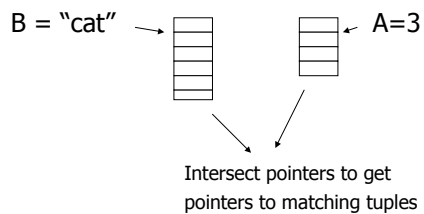
$\pi_x\{\sigma_p(R)\}$ vs. $\pi_E\{\sigma_p\{\pi_{ABE}(R)\}\}$

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But What if we have A, B indexes?



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Bottom line:

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

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In textbook: more transformations

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

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Outline - Query Processing

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

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- Estimating cost of query plan

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

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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

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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

$$T(R) = 5 \quad S(R) = 37$$

$$V(R,A) = 3 \quad V(R,C) = 5$$

$$V(R,B) = 1 \quad V(R,D) = 4$$

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Size estimates for $W = R1 \times R2$

$$T(W) = T(R1) \times T(R2)$$

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

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Size estimate for $W = \sigma_{A=a}(R)$

$$S(W) = S(R)$$

$$T(W) = ?$$

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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	

$$V(R,A)=3$$

$$V(R,B)=1$$

$$V(R,C)=5$$

$$V(R,D)=4$$

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

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Assumption:

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

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Alternate Assumption:

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

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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
 $V(R,A)=3 \quad DOM(R,A)=10$
 $V(R,B)=1 \quad DOM(R,B)=10$
 $V(R,C)=5 \quad DOM(R,C)=10$
 $V(R,D)=4 \quad DOM(R,D)=10$

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

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$$C=val \Rightarrow T(W) = (1/10)1 + (1/10)1 + \dots = (5/10) = 0.5$$

$$B=val \Rightarrow T(W) = (1/10)5 + 0 + 0 = 0.5$$

$$A=val \Rightarrow T(W) = (1/10)2 + (1/10)2 + (1/10)1 = 0.5$$

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

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

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Selection cardinality

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

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

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

$$T(W) = ?$$

- Solution # 1:

$$T(W) = T(R)/2$$

- Solution # 2:

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

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- Solution # 3: Estimate values in range

Example R

	Z

Min=1 $V(R,Z)=10$
 $W = \sigma_{z \geq 15}(R)$
 Max=20

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

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

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Equivalently:

$f \times V(R,Z)$ = fraction of distinct values

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

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Size estimate for $W = R1 \bowtie R2$

Let x = attributes of R1

y = attributes of R2

Case 1

$$X \cap Y = \emptyset$$

Same as $R1 \times R2$

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Case 2 $W = R1 \bowtie R2$ $X \cap Y = A$

A	B	C

A	D

Assumption:
 $V(R1,A) \leq V(R2,A) \Rightarrow$ Every A value in R1 is in R2
 $V(R2,A) \leq V(R1,A) \Rightarrow$ Every A value in R2 is in R1

"containment of value sets" Sec. 7.4.4

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

A	B	C

A	D

Take 1 tuple Match

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

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

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

[A is common attribute]

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In general $W = R1 \bowtie R2$

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

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Case 2 with alternate assumption

Values uniformly distributed over domain

A	B	C

A	D

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

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In all cases:

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

size of attribute A

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Using similar ideas,
we can estimate sizes of:

$\Pi_{AB}(R)$ Sec. 7.4.2 [16.4.2]

$\sigma_{A=a, B=b}(R)$ Sec. 7.4.3 [16.4.3]

$R \bowtie S$ with common attribs. A,B,C
 Sec. 7.4.5 [16.4.5]

Union, intersection, diff,
 Sec. 7.4.7 [16.4.7]

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

E.g. $W = [\sigma_{A=a}(R1)] \bowtie R2$

Treat as relation U

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

Also need $V(U, *)$!!

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To estimate Vs

E.g., $U = \sigma_{A=a}(R1)$

Say R1 has attribs A,B,C,D

$V(U, A) =$

$V(U, B) =$

$V(U, C) =$

$V(U, D) =$

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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

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

$V(U,A) = 1$

$V(U,B) = V(R,B)$

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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]

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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

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$$\text{Partial Result: } U = R1 \bowtie R2$$

$$T(U) = \frac{1000 \times 2000}{200} \quad V(U,A) = 50$$
$$V(U,B) = 100$$
$$V(U,C) = 300$$

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$$Z = U \bowtie R3$$

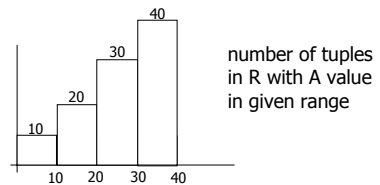
$$T(Z) = \frac{1000 \times 2000 \times 3000}{200 \times 300} \quad V(Z,A) = 50$$
$$V(Z,B) = 100$$
$$V(Z,C) = 90$$
$$V(Z,D) = 500$$

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A Note on Histograms



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

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Summary

- Estimating size of results is an "art"
- Don't forget:
Statistics must be kept up to date...
(cost?)

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Outline

- Estimating cost of query plan
 - Estimating size of results ← done!
 - Estimating # of IOs ← next...
- Generate and compare plans

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