CSE544
Data Management

Lectures 10
Query Optimization (part 2)

Announcements

- HW2 was due last night
- HW3 is posted, due on Friday, May 7
- Review 5 was due today
- Review 6 due on Monday, May 3rd

Query Optimization

Three major components:

1. Cardinality and cost estimation
2. Search space
3. Plan enumeration algorithms

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1. Cardinality and cost estimation
2. Search space
3. Plan enumeration algorithms

First, let's discuss the paper

Discuss the paper

- Why do they use the IMDB database instead of TPC-H?
- Do cardinality estimators typically under- or over-estimate?
- From cardinality to cost: how critical is that?

[How good are they]

Single Table Estimation

	median	90th	95th	max
PostgreSQL	1.00	2.08	6.10	207
DBMS A	1.01	1.33	1.98	43.4
DBMS B	1.00	6.03	30.2	104000
DBMS C	1.06	1677	5367	20471
HyPer	1.02	4.47	8.00	2084

Table 1: Q-errors for base table selections

Discuss histograms v.s. samples

Single Table Estimation

- 1d Histograms: accurate for selection on a single equality or range predicate; poor for multiple predicates; useless for LIKE
- Samples: great for correlations, or predicates like LIKE; poor for low selectivity predicates: estimate is 0, then use ”magic constants”

[How good are they]

Joins (0 to 6)

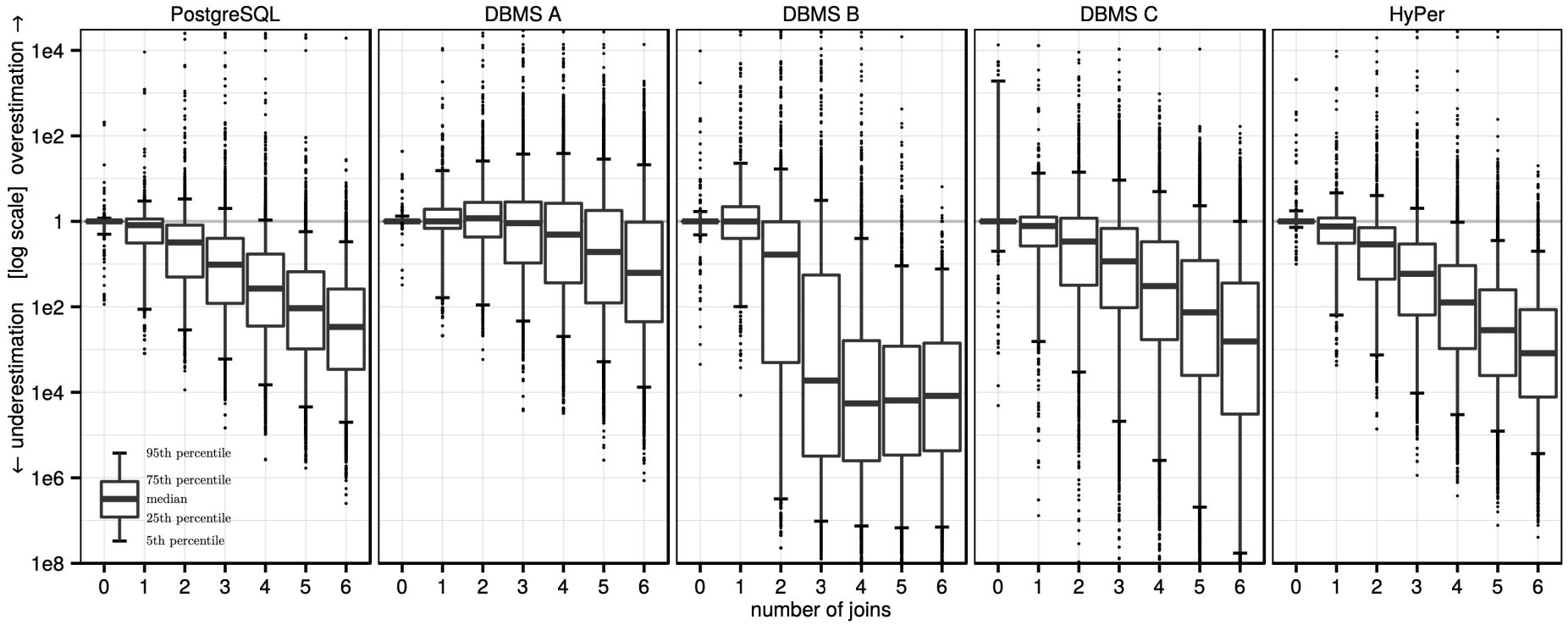

Figure 3: Quality of cardinality estimates for multi-join queries in comparison with the true cardinalities. Each boxplot summarizes the error distribution of all subexpressions with a particular size (over all queries in the workload)

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Joins (0 to 6)

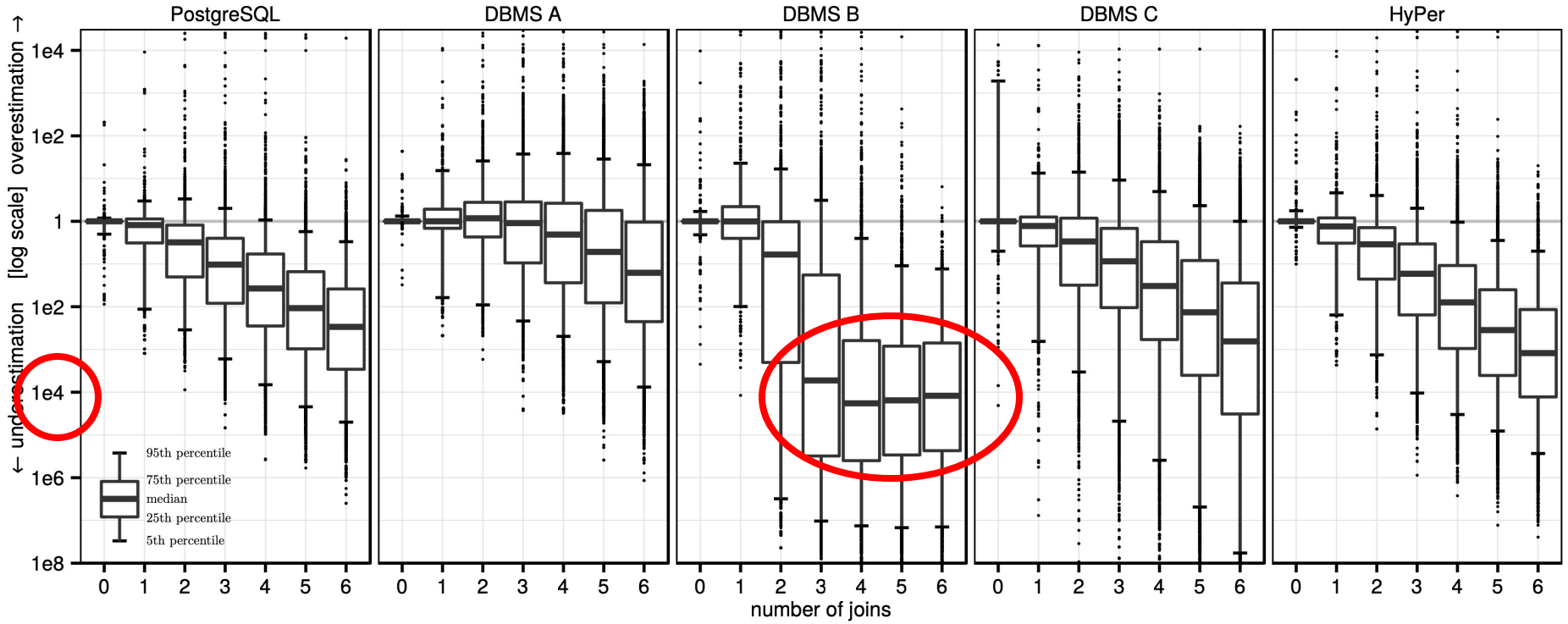
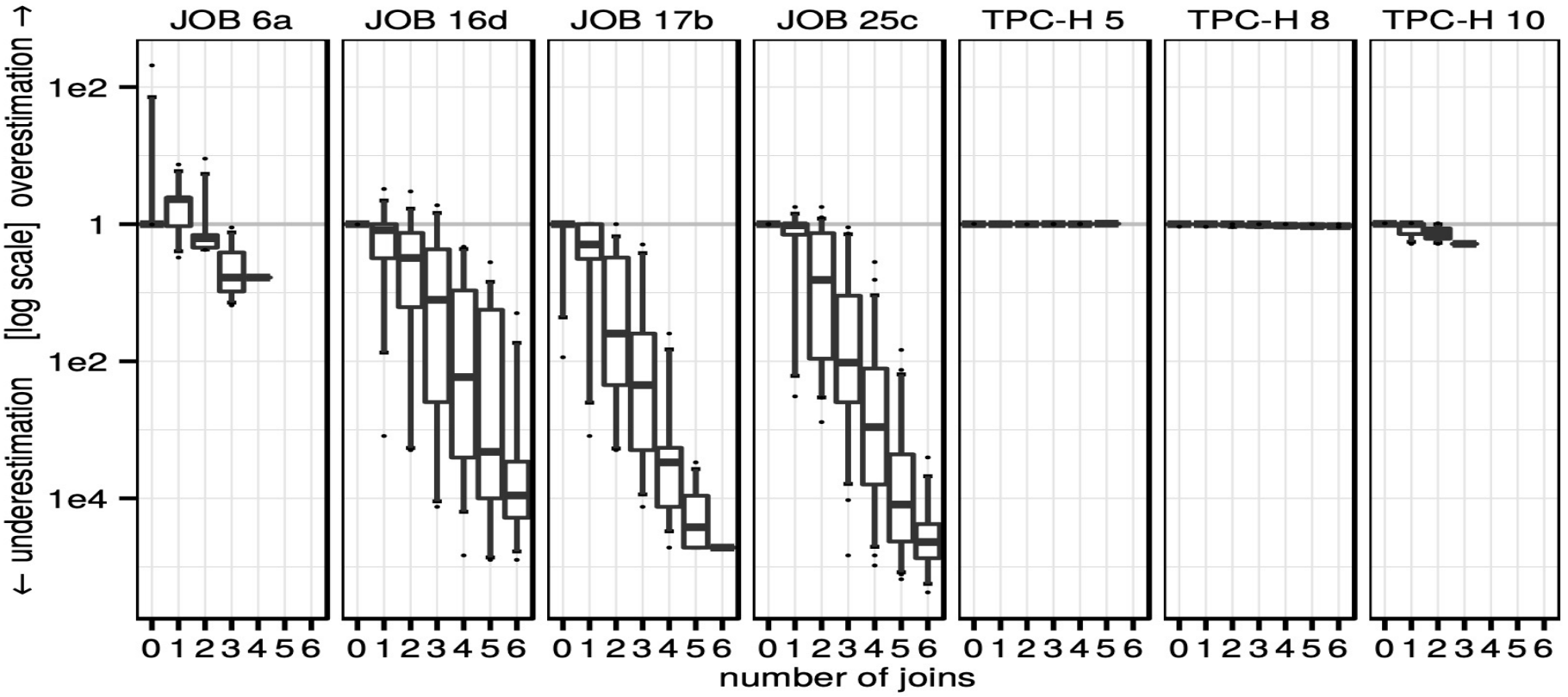


Figure 3: Quality of cardinality estimates for multi-join queries in comparison with the true cardinalities. Each boxplot summarizes the error distribution of all subexpressions with a particular size (over all queries in the workload)

[How good are they]

TPC-H v.s. Real Data (IMDB)



[How good are they]

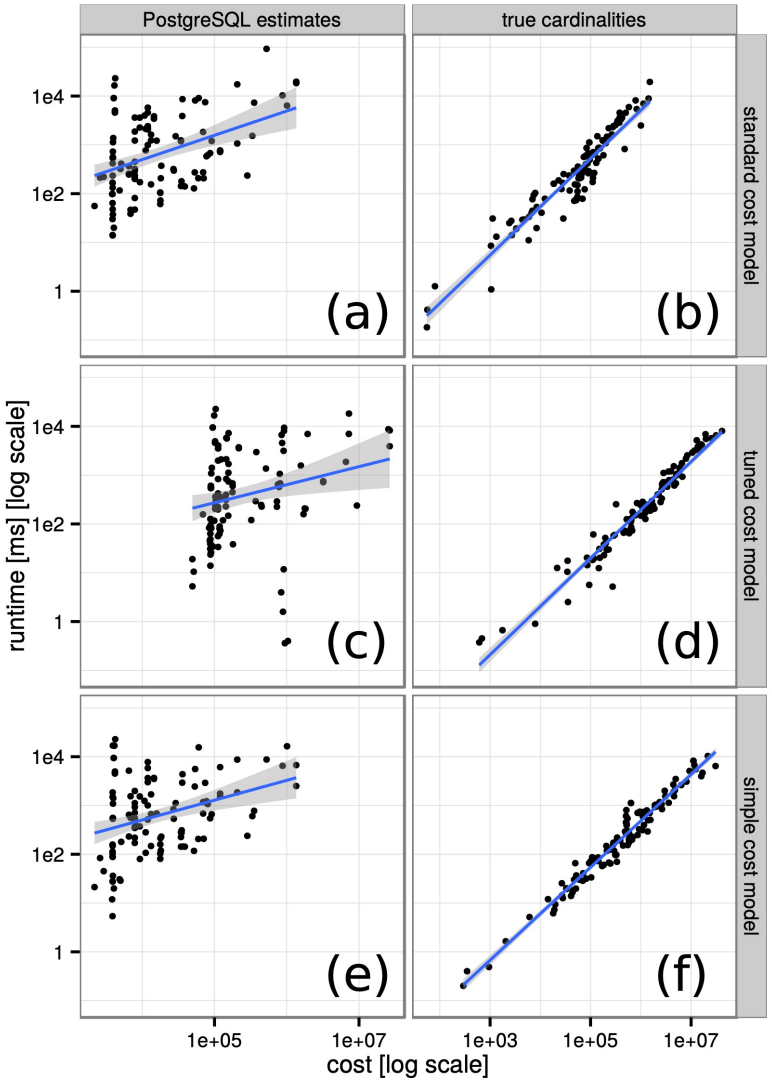
Cardinalities to Cost

- Cardinality estimation creates largest errors
- Complex or simple cost models don't differ much

Postgres cost

No I/O, keep only CPU

Their own simple formula



Yet Another Difficulties

SQL Queries issued from applications:

- Query is optimized once: *prepare*
- Then, executed repeatedly

Query constants are unknow until execution: optimized plan is suboptimal

```
select
  o_year, sum(case when nation = 'BRAZIL' then volume else 0 end) / sum(volume)
from
 (select YEAR(o_orderdate) as o_year,
            l_extendedprice * (1 - l_discount) as volume,
                  n2.n_name as nation
  from part, supplier, lineitem, orders,
       customer, nation n1, nation n2, region
  where p_partkey = l_partkey and s_suppkey = l_suppkey
    and l_orderkey = o_orderkey and o_custkey = c_custkey
    and c_nationkey = n1.n_nationkey
    and n1.n_regionkey = r_regionkey
    and r_name = 'AMERICA'
    and s_nationkey = n2.n_nationkey
    and o_orderdate between '1995-01-01'
    and '1996-12-31'
    and p_type = 'ECONOMY ANODIZED STEEL'
   and s_acctbal ≤ C1 and l_extendedprice ≤ C2 ) as all_nations
group by o_year order by o_year
```

```
select
  o_year, sum(case when nation = 'BRAZIL' then volume else 0 end) / sum(volume)
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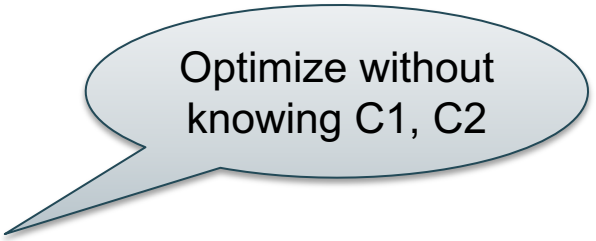

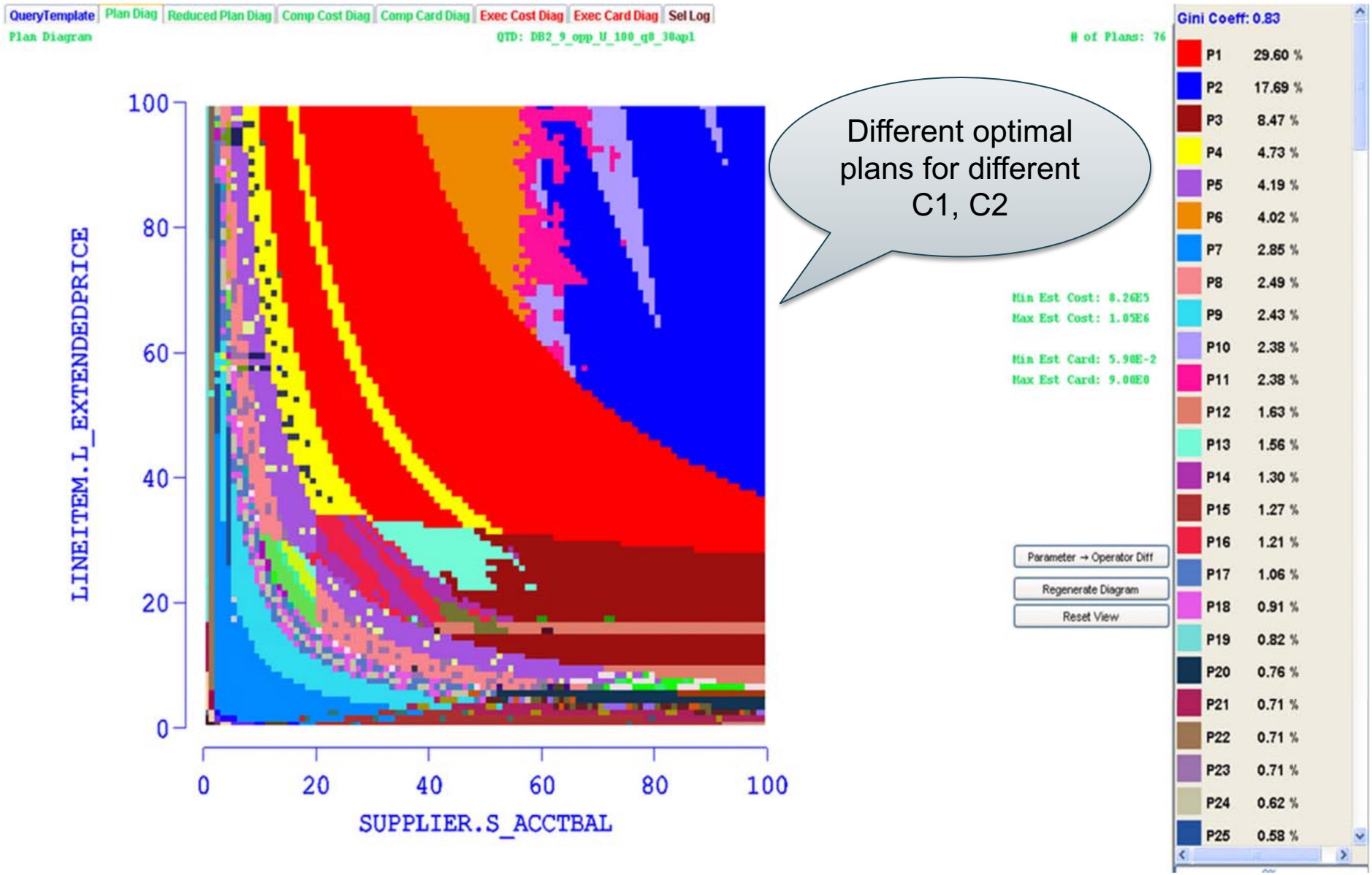
QueryTemplate
Plan Diag
Reduced Plan Diag
Comp Cost Diag
Comp Card Diag
Exec Cost Diag
Exec Card Diag
Sel Log
Plan Diagram
QTD: DB2_9_opp_U_100_q8_30apl
# of Plans: 76
Different optimal plans for different C1, C2
LINEITEM.L_EXTENDEDPRICE
SUPPLIER.S_ACCTBAL
0
20
40
60
80
100
Min Est Cost: 8.26E5
Max Est Cost: 1.05E6
Min Est Card: 5.90E-2
Max Est Card: 9.00E0
Parameter → Operator Diff
Regenerate Diagram
Reset View
Gini Coeff: 0.83
P1 29.60 %
P2 17.69 %
P3 8.47 %
P4 4.73 %
P5 4.19 %
P6 4.02 %
P7 2.85 %
P8 2.49 %
P9 2.43 %
P10 2.38 %
P11 2.38 %
P12 1.63 %
P13 1.56 %
P14 1.30 %
P15 1.27 %
P16 1.21 %
P17 1.06 %
P18 0.91 %
P19 0.82 %
P20 0.76 %
P21 0.71 %
P22 0.71 %
P23 0.71 %
P24 0.62 %
P25 0.58 %

Query Optimization

Three major components:

1. Cardinality and cost estimation
2. Search space
3. Plan enumeration algorithms

Search Space

Refers to the set of all possible alternate plans that the optimizers may explore

- **Access Path Selection**: how to use indices
- **Rewrite Rules**: what identities the optimizer applies

Access Path

Access path: implements a selection $\sigma_P(R)$

(P is sometimes called *search argument* SARG)

- A file scan, or
- An index *plus* a matching selection condition

Supplier(sid,sname,scity,sstate)

Access Path Selection

```
SELECT * FROM Supplier
WHERE sid > 300 ∧ scity='Seattle'
```

B(Supplier) = 100
T(Supplier) = 1000
V(Supplier,scity) = 20
Max(Supplier, sid) = 1000
Min(Supplier,sid) =1

Indices:

B+-tree on sid; clustered

B+-tree on scity; unclustered

Which access path should we use?

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Which access path should we use?

1. Sequential scan: cost = 100
2. Index scan on sid: cost = 7/10 * 100 = 70

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Which access path should we use?

1. Sequential scan: cost = 100
2. Index scan on sid: cost = 7/10 * 100 = 70
3. Index scan on scity: cost = 1000/20 = 50

Rewrite Rules

Search space is defined by the set of rewrite rules that the optimizer implements

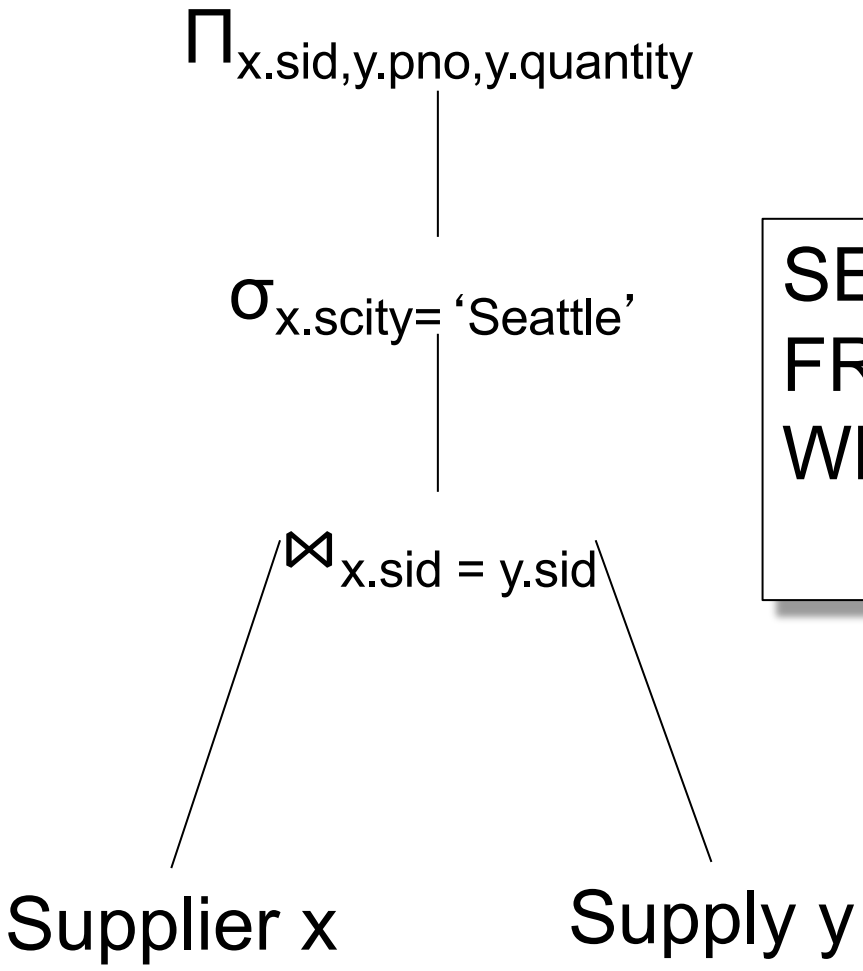
Supplier(sid, sname, scity, sstate)
Supply(sid, pno, quantity)

Example Optimization

```
SELECT x.sid, y.pno, y.quantity
FROM.   Supplier x, Supply y
WHERE x.sid = y.sid
        and x.scity = 'Seattle'
```

Supplier(sid, sname, scity, sstate)
Supply(sid, pno, quantity)

Example Optimization

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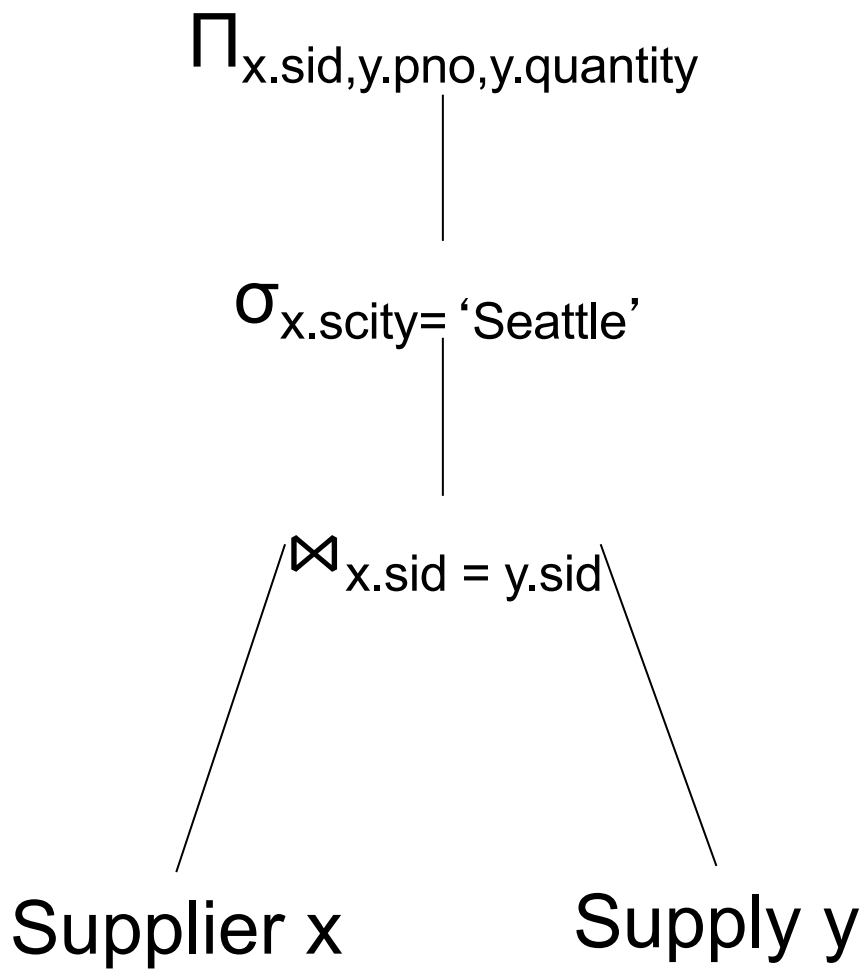
```

Supplier(sid, sname, scity, sstate)
Supply(sid, pno, quantity)

Push Selections Down



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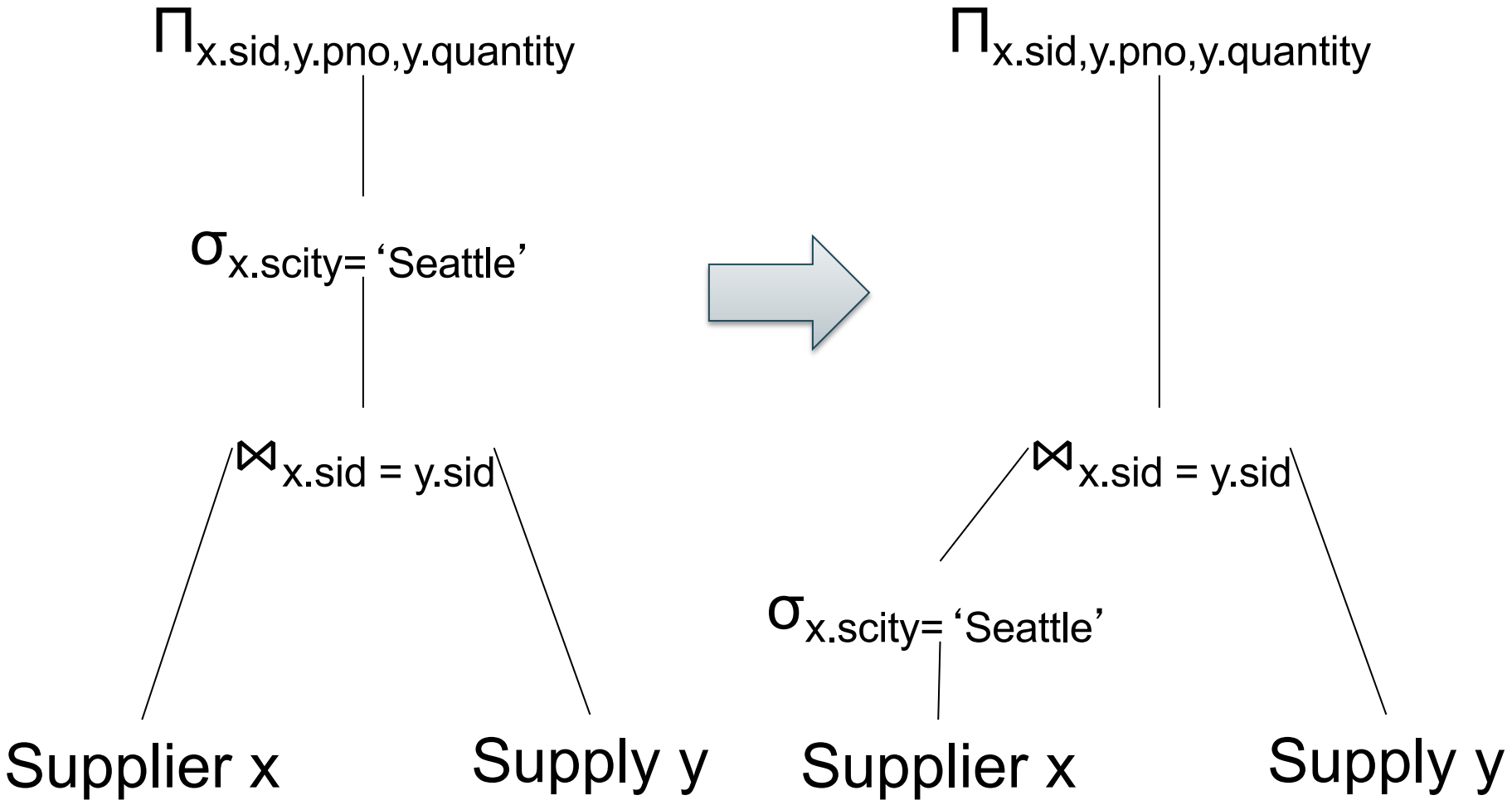

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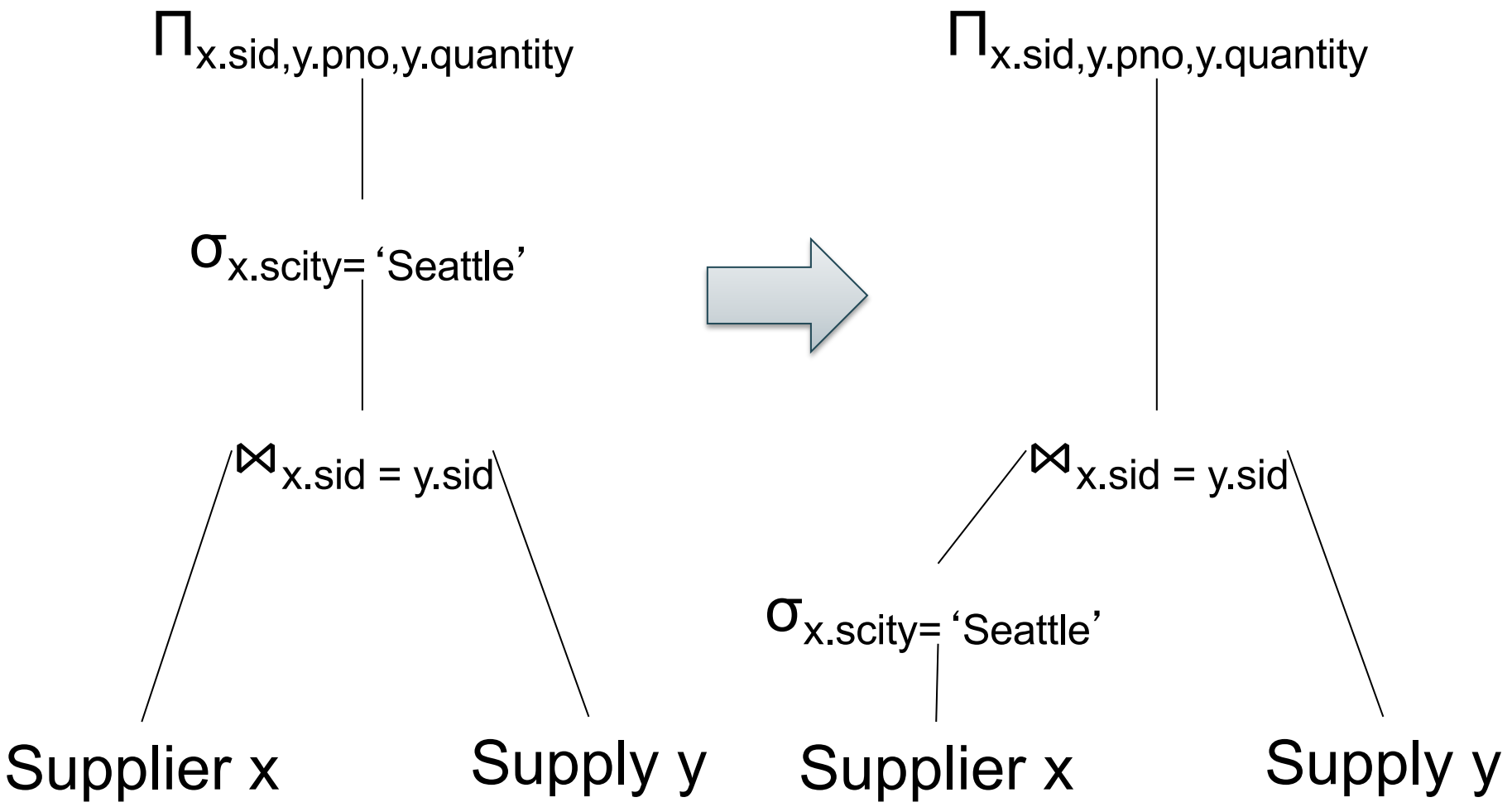
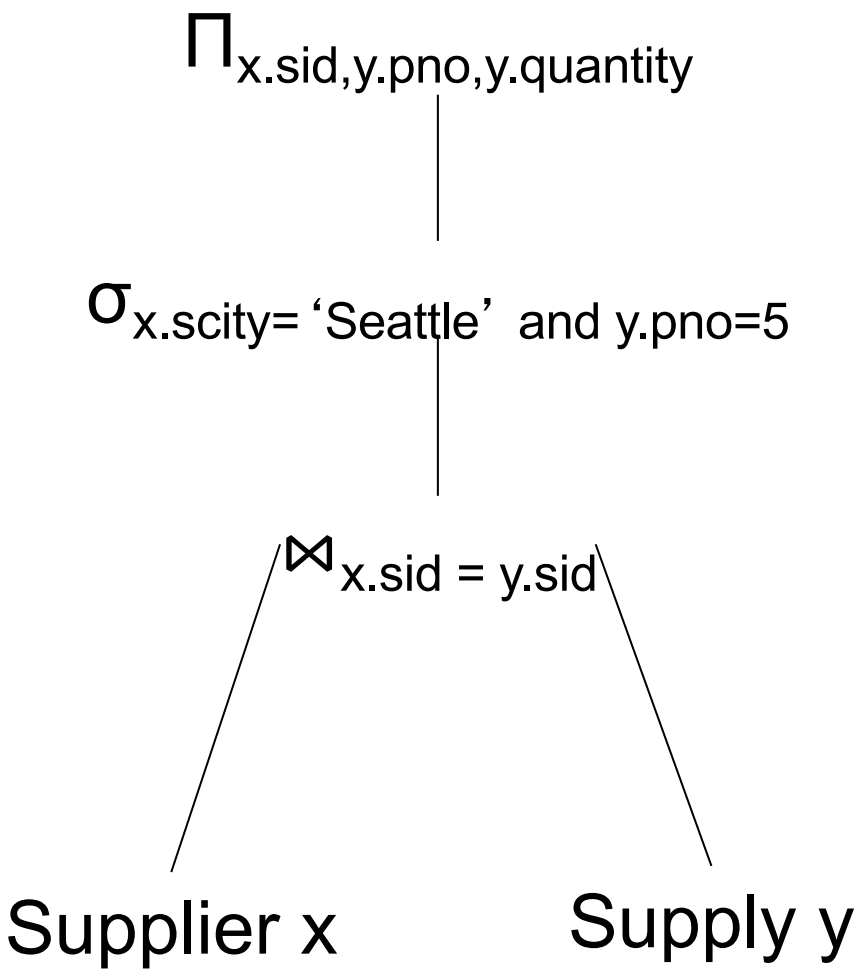


$\sigma_C(R \bowtie S) = \sigma_C(R) \bowtie S$ when C refers only to R

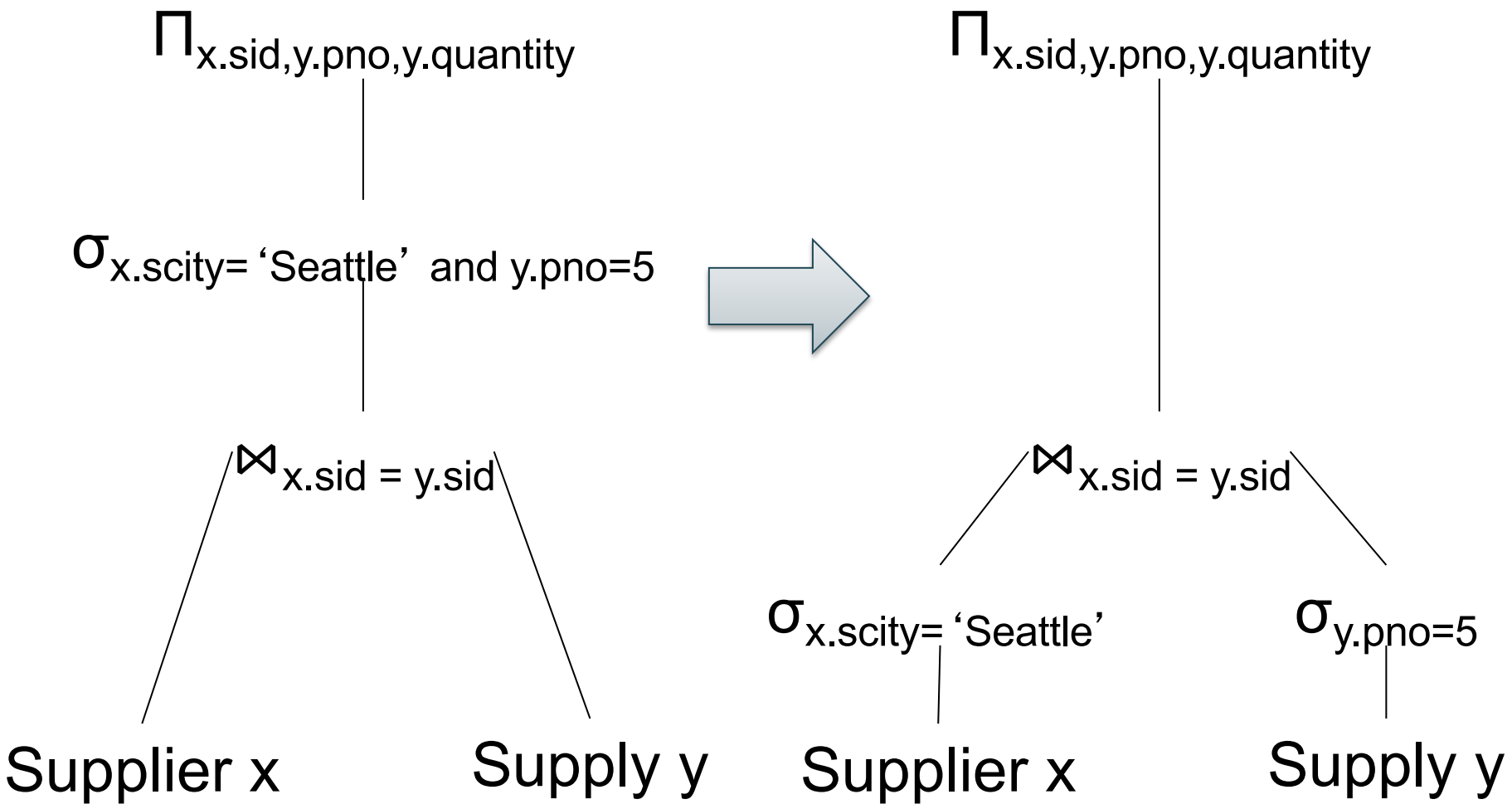
Supplier(sid, sname, scity, sstate)
Supply(sid, pno, quantity)

Push Selections Down



Supplier(sid, sname, scity, sstate)
Supply(sid, pno, quantity)

Push Selections Down



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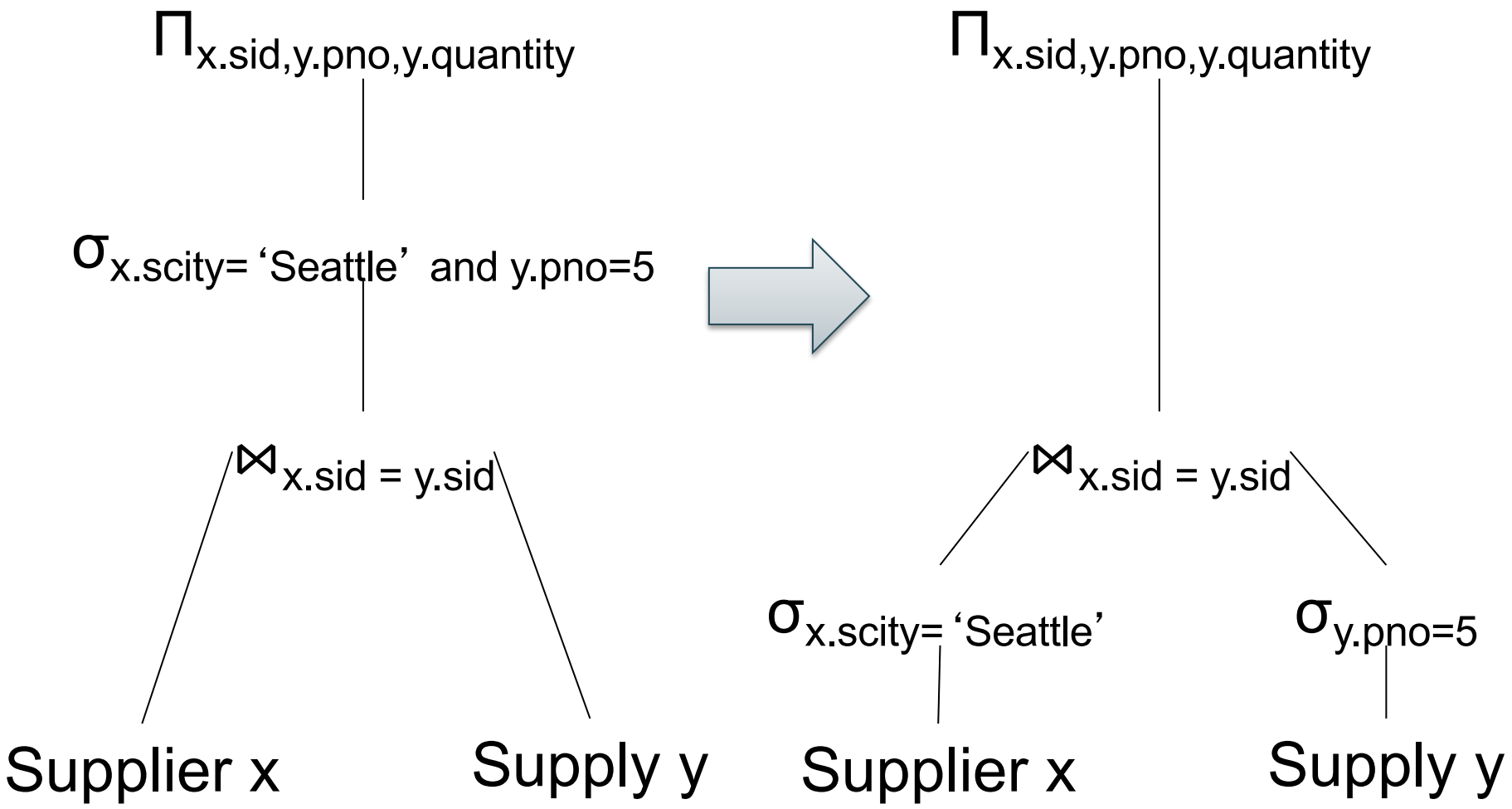
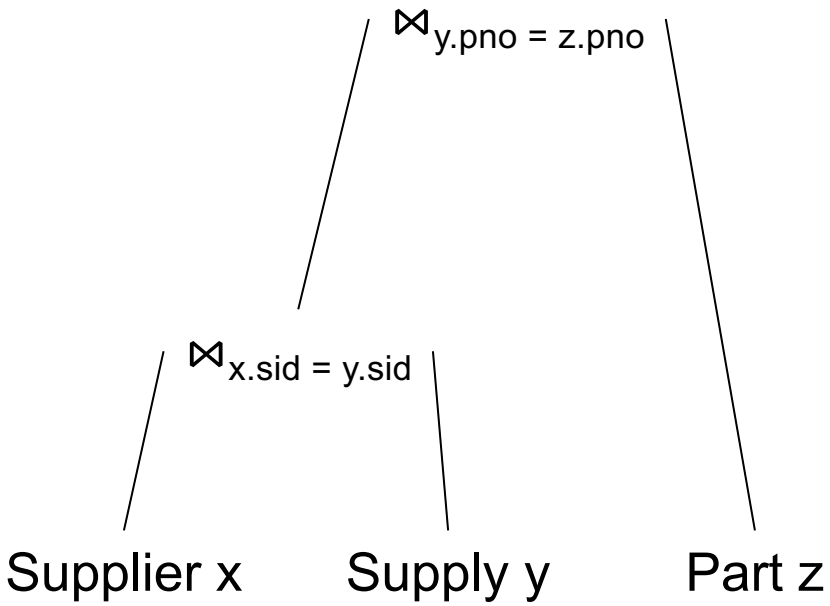


$$\sigma_{C1 \text{ and } C2}(R \bowtie S) = \sigma_{C1}(\sigma_{C2}(R \bowtie S)) = \sigma_{C1}(R \bowtie \sigma_{C2}(S)) = \sigma_{C1}(R) \bowtie \sigma_{C2}(S)$$

Supplier(sid, sname, scity, sstate)
Supply(sid, pno, quantity)
Part(pno, pname, pprice)

Join Reorder



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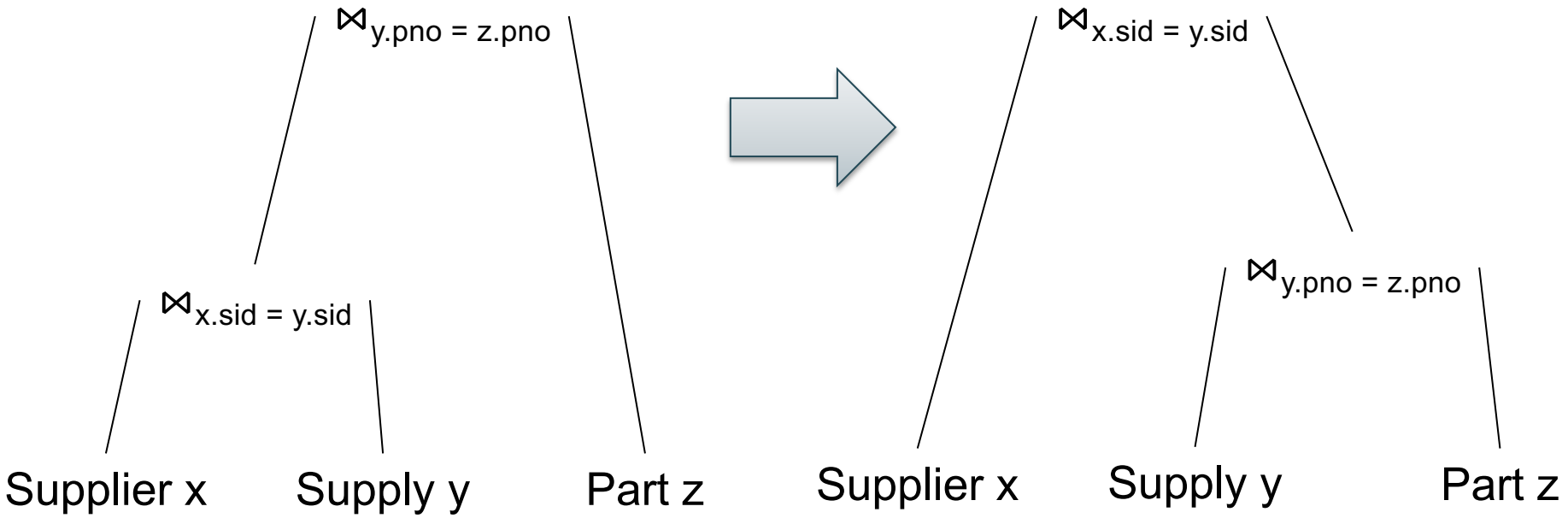

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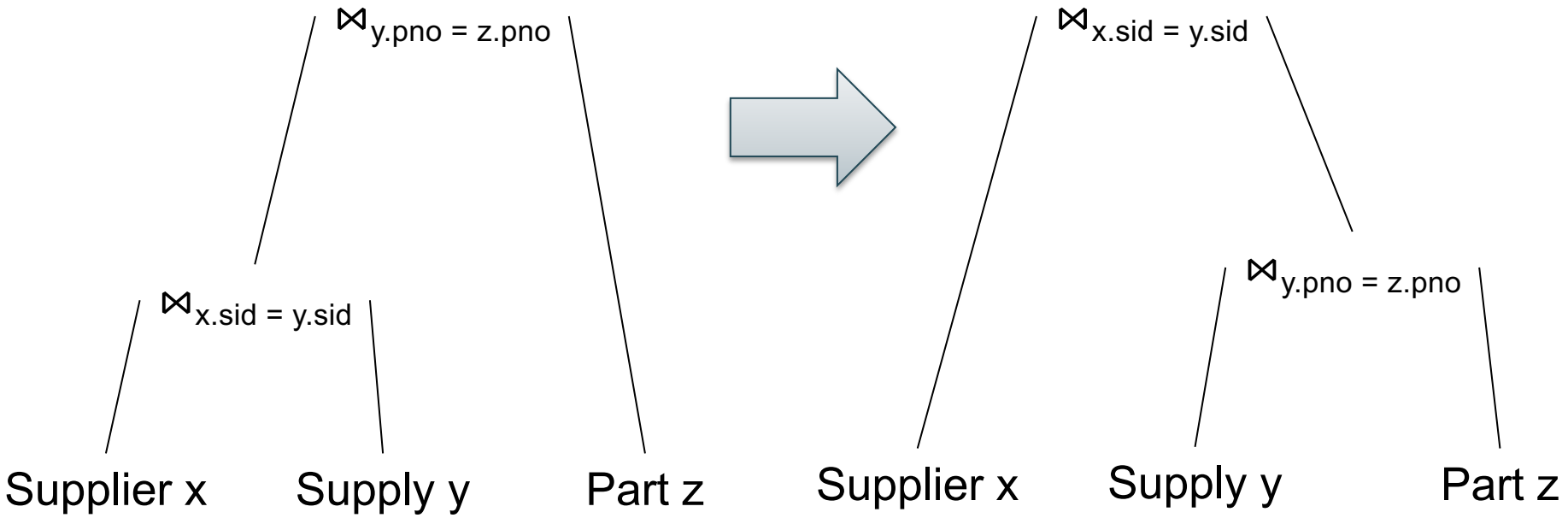
Join Reorder



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

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

Supplier(sid, sname, scity, sstate)
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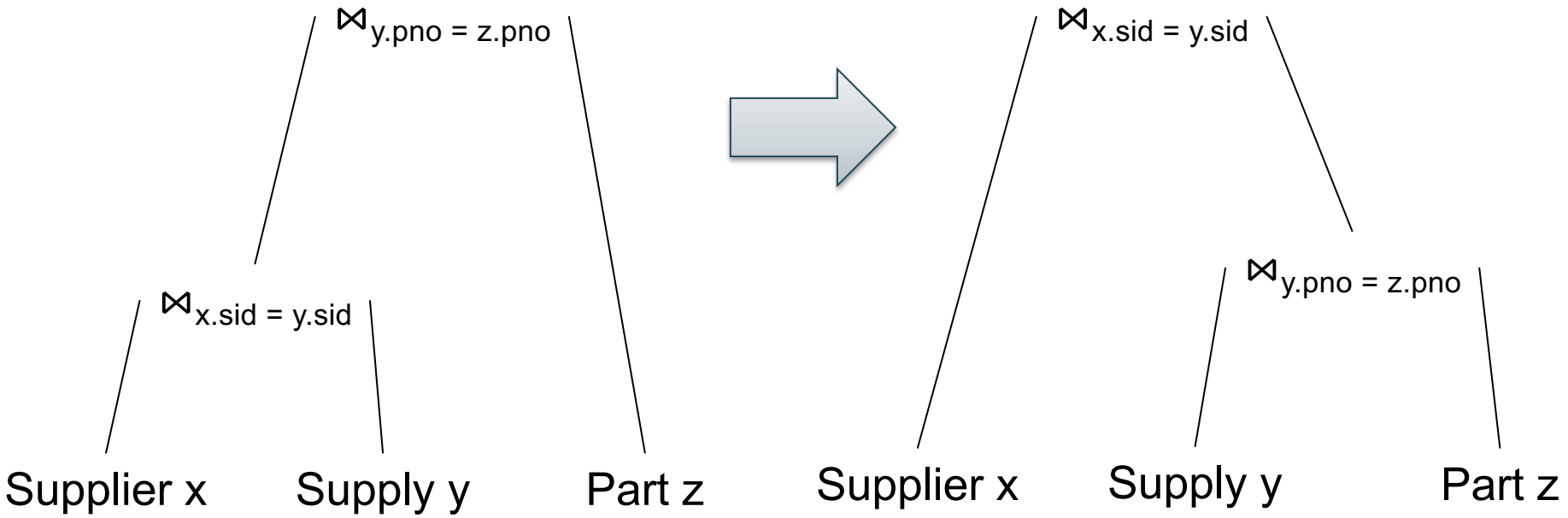
Join Reorder

Which plan is better?



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

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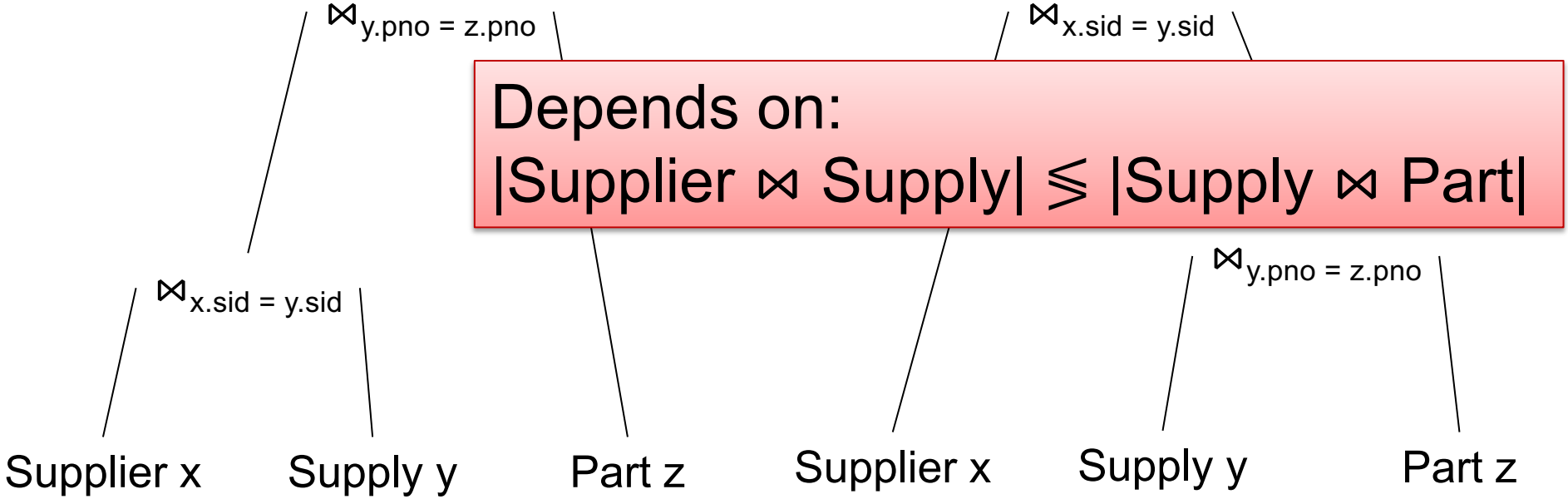

Depends on:
|Supplier ⋈ Supply| ⩽ |Supply ⋈ Part|

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

$R \bowtie S = S \bowtie R$

Supplier(sid, sname, scity, sstate)
Supply(sid, pno, quantity)
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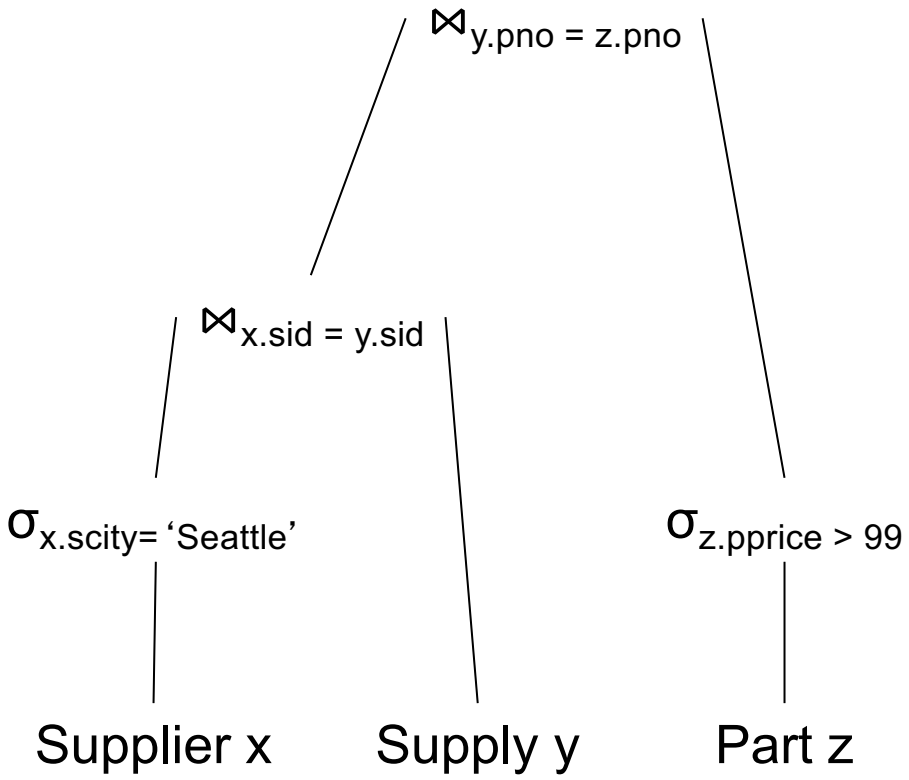
Join Reorder



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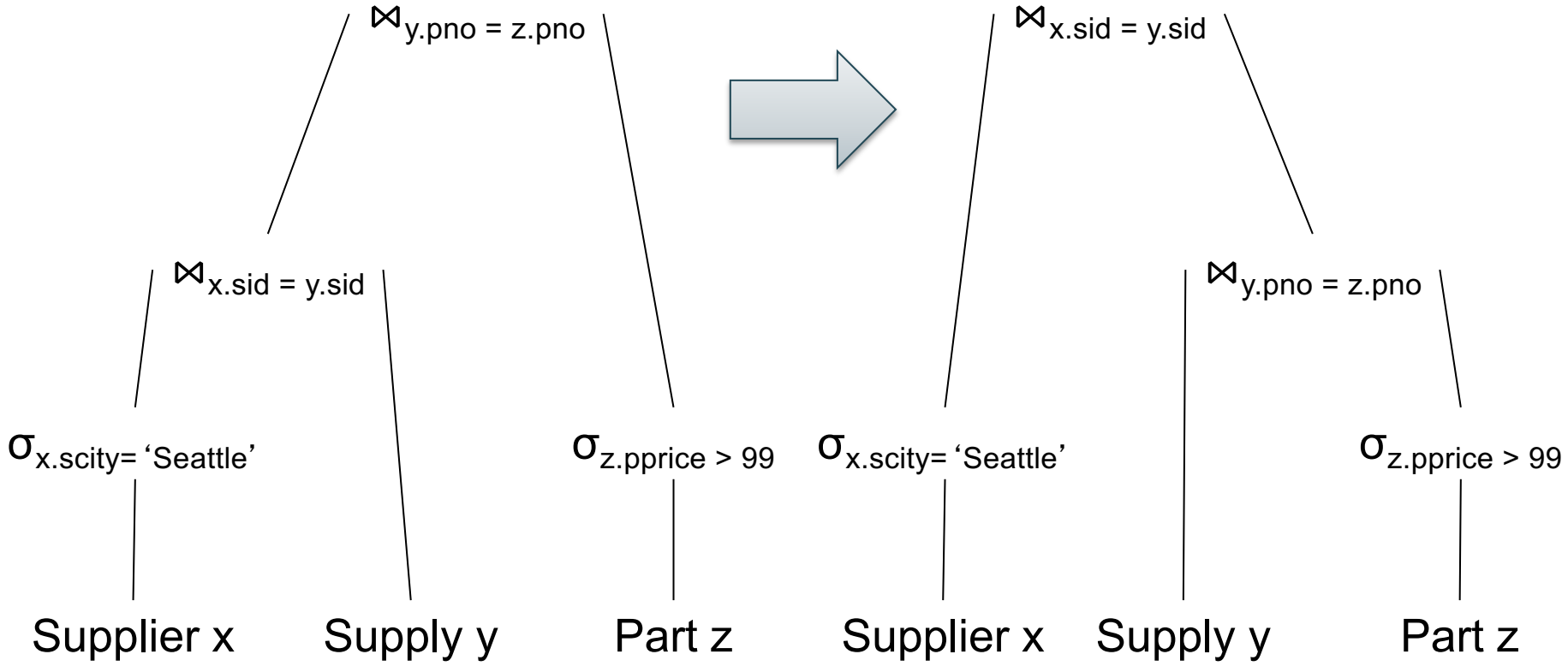

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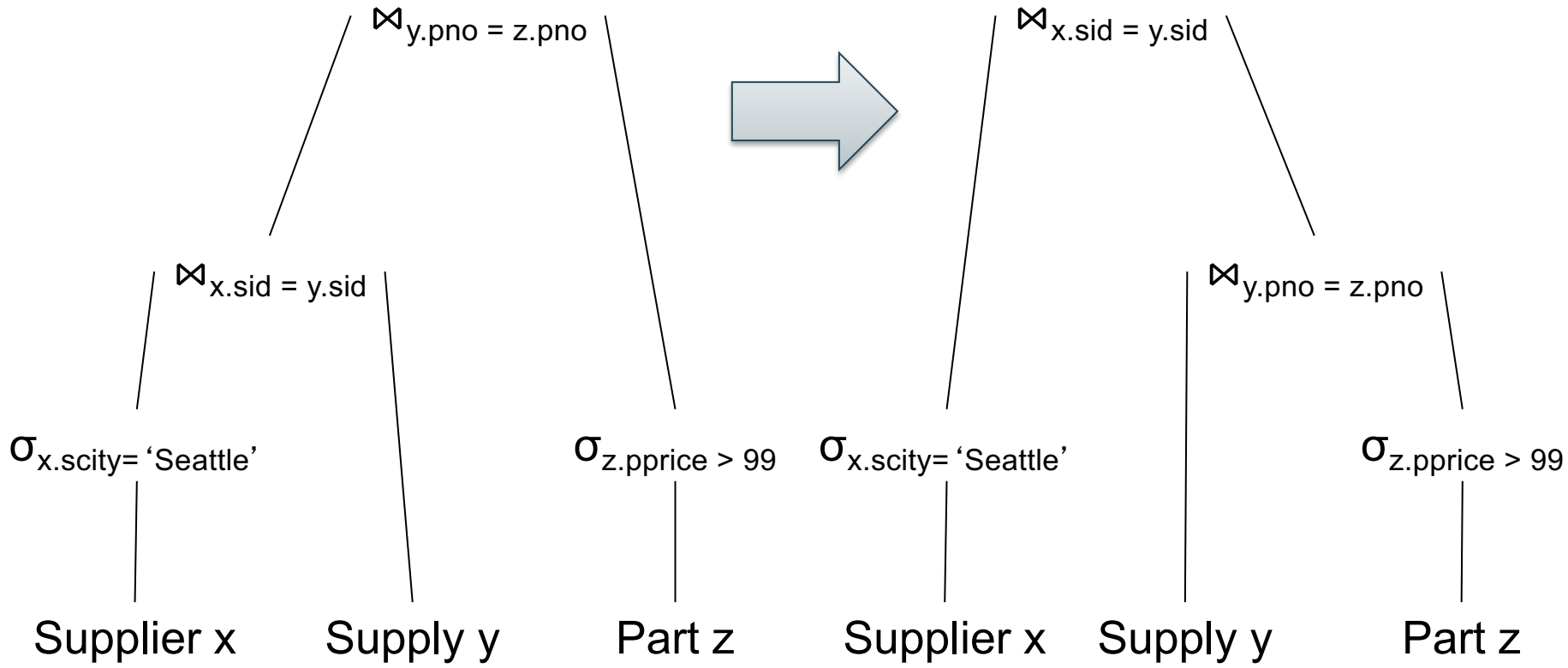

Lesson: need sizes of $\sigma_{x.scity= \text{'Seattle'}}$(Supplier), $\sigma_{z.pprice > 99}$(Part)

Discussion

- Both rewrite rules **and** cardinality estimations are needed for optimization
- They can be developed independently

- Next: a powerful optimization rule: aggregate pushdown or better known as generalized distributivity law

Motivation

- Try this in postgres

```
select count(*) from author;
```

Answer: 2652053
Time: 0.058 s

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select count(*) from publication;
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Answer: 5120896
Time: 0.062 s

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```
select count(*) from author, publication;
```

Timeout!!!

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Answer: 5120896
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select count(*) from author, publication;
```

Timeout!!!

But 3rd query is simply the **product** of the first two!

Supplier(sid, sname, scity, sstate)
Supply(sid, pno, quantity)
Part(pno, pname, pprice)

Aggregate Push-down

```
SELECT x.sstate, sum(y.quanity*z.price)
FROM Supplier x, Supply y, Part z
WHERE x.sid = y.sid and y.pno = z.pno
GROUP BY x.sstate
```

Supplier(sid, sname, scity, sstate)
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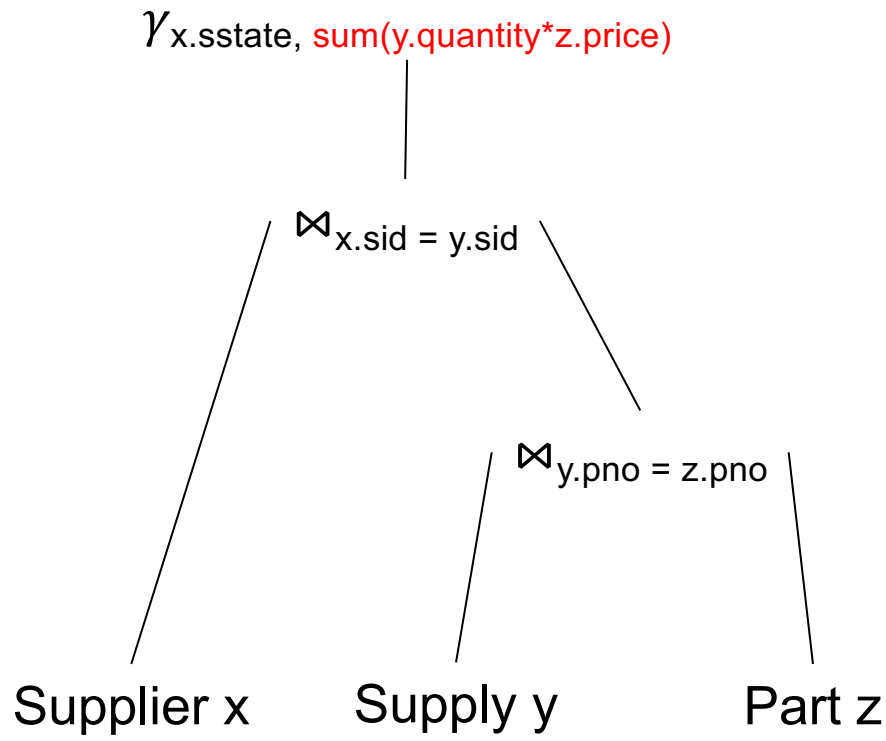
Aggregate Push-down

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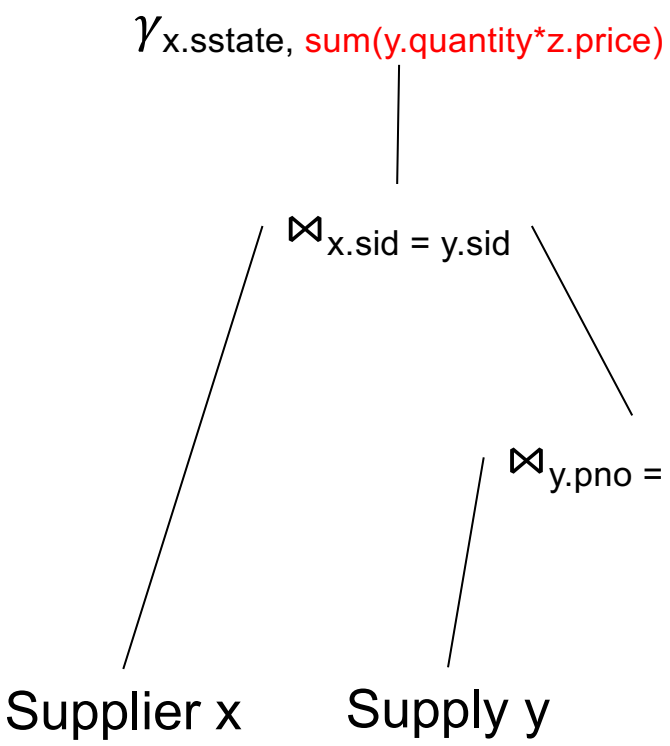

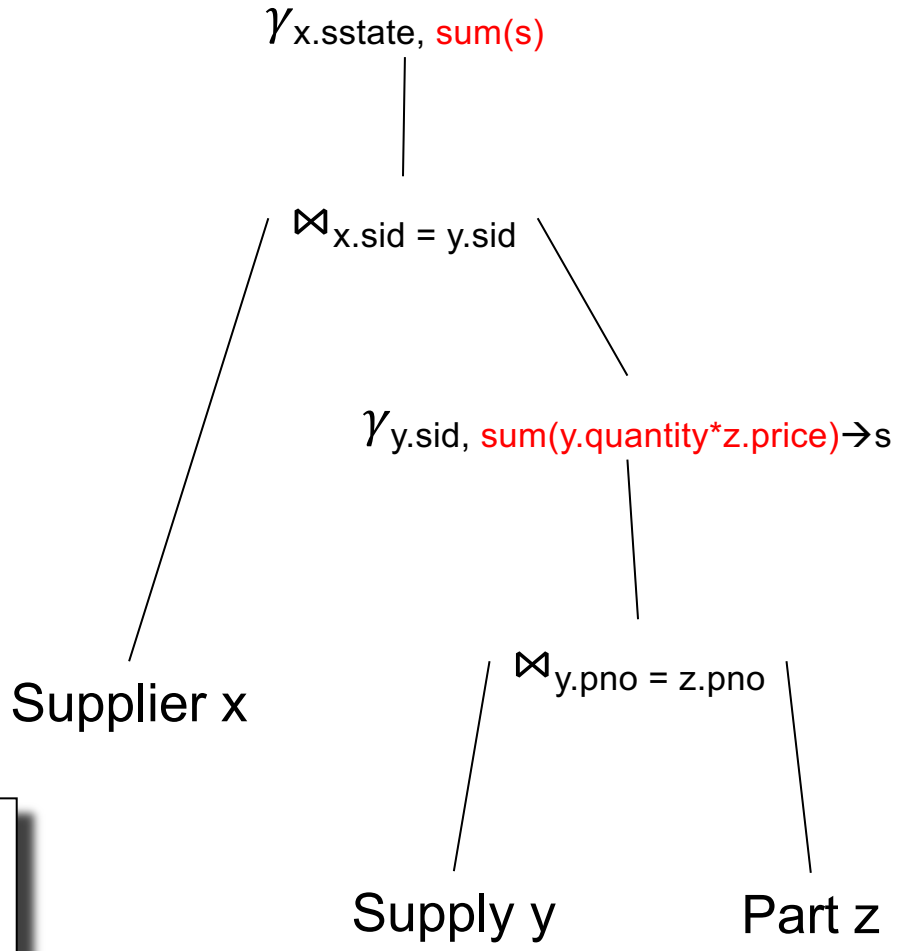


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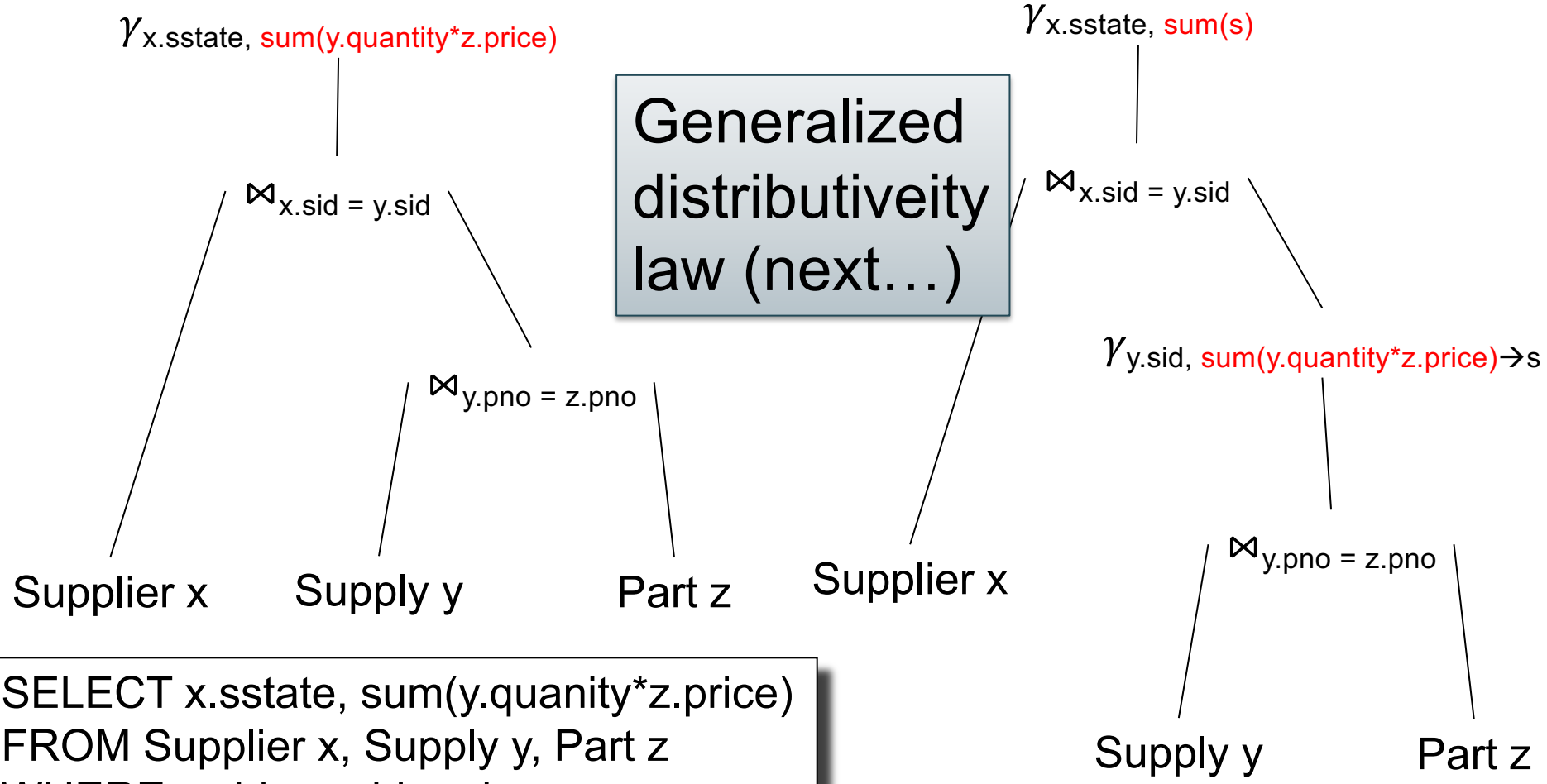


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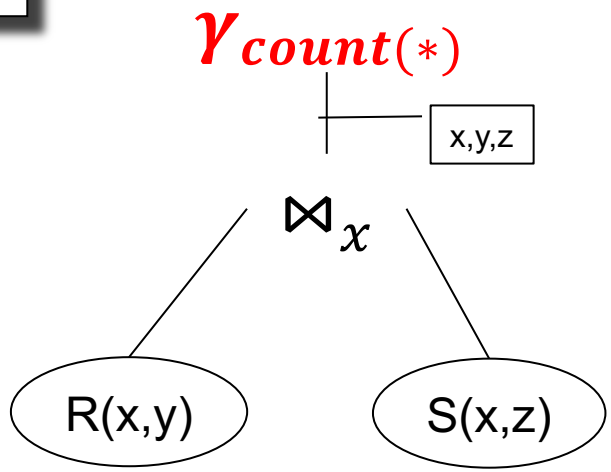
Generalized Distributivity Law

SELECT count(*) from R, S where R.x=S.x



Generalized Distributivity Law

SELECT count(*) from R, S where R.x=S.x

R:

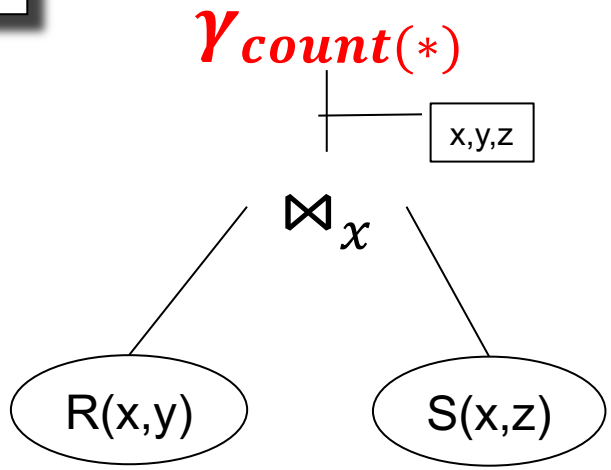
x	y
b	a
b	c
f	d
h	g

S:

x	z
b	g
b	k
h	m

Answer = 5

Runtime = $O(N^2)$



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R:

x	y
b	a
b	c
f	d
h	g

S:

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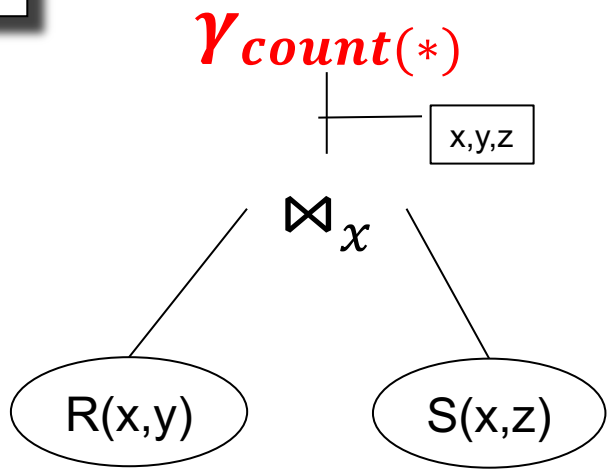
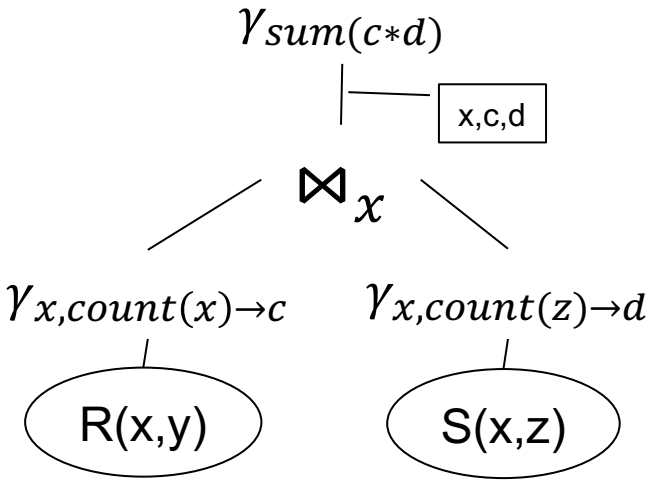
b	g
b	k
h	m

Answer = 5

Runtime = $O(N^2)$





Generalized Distributivity Law

SELECT count(*) from R, S where R.x=S.x

R:

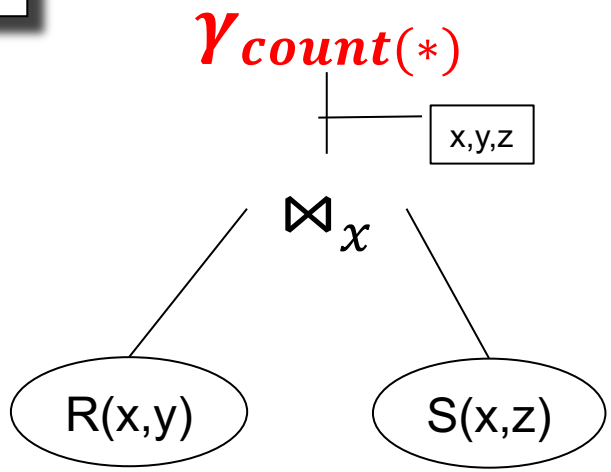
x	y
b	a
b	c
f	d
h	g

S:

x	z
b	g
b	k
h	m

Answer = 5

Runtime = $O(N^2)$



A:

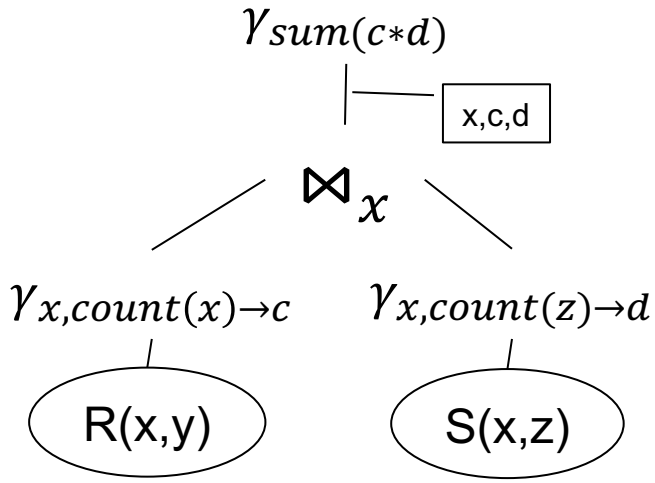
x	c
b	2
f	1
h	1

B:

x	d
b	2
h	1

A⋈B

x	c	d
b	2	2
h	1	1



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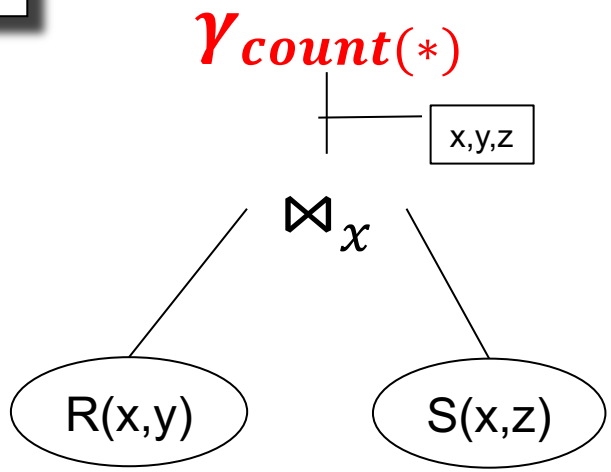

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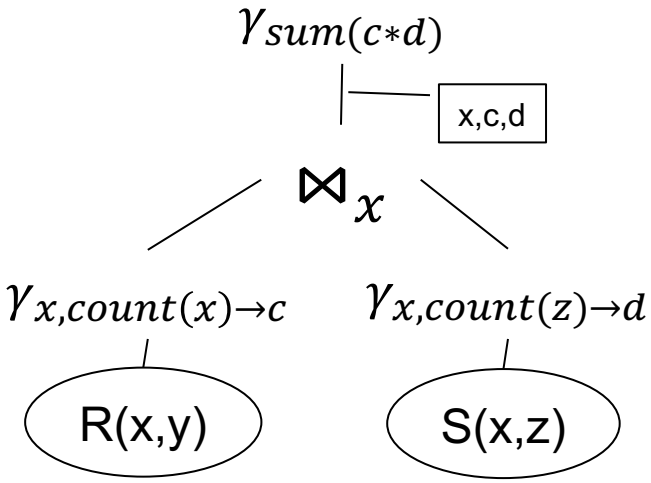
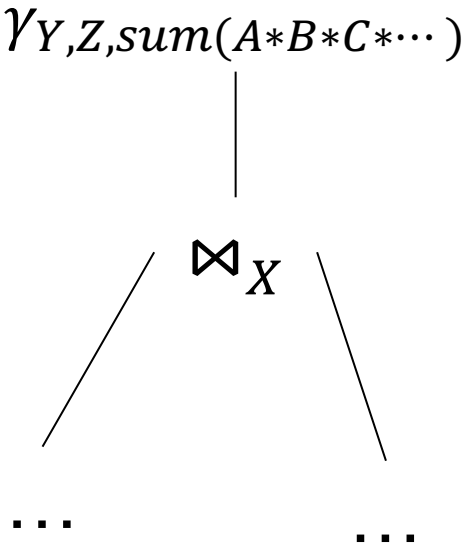
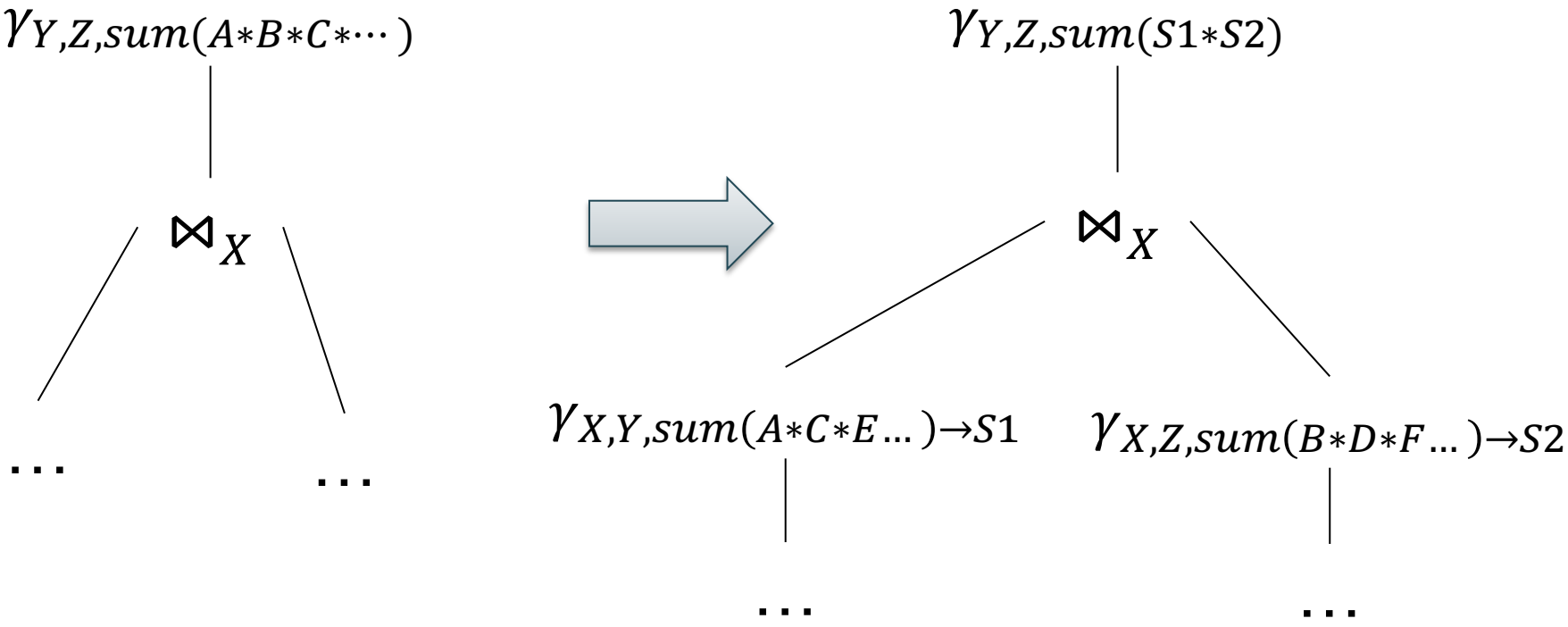


Generalized Distributivity Law



Generalized Distributivity Law



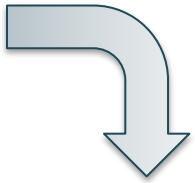
Discussion

- Most DBMS support only some subset of the generalized distributivity law
- Fun activity: check if your favorite DBMS supports it
- Next: a rewrite rule that most DBMS support

Supplier(sid, sname, scity, sstate)
Supply(sid, pno, quantity)

Key / Foreign-Key

```
Select x.pno, x.quantity
From Supply x, Supplier y
Where x.sid = y.sid
```



?

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Supply(sid, pno, quantity)

Key / Foreign-Key

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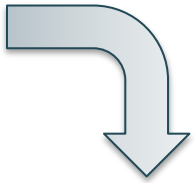

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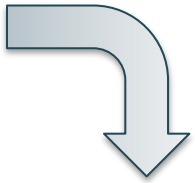


```
Select x.pno, x.quantity
From Supply x
```

Only if these constraints hold:

1. Supplier.sid = key
2. Supply.sid = foreign key
3. Supply.sid NOT NULL

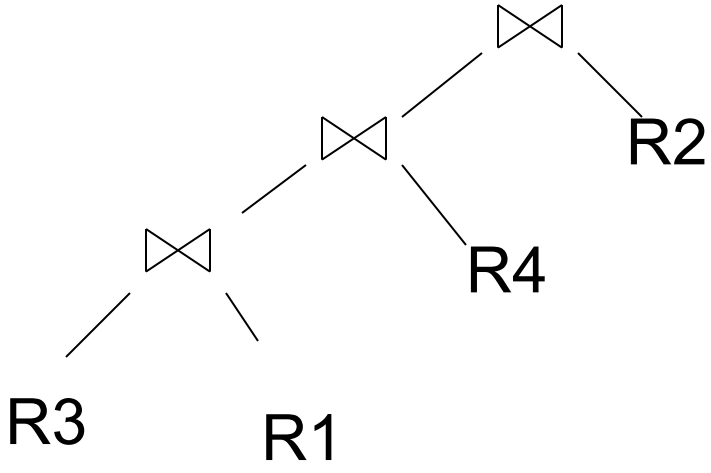
Practice

- Database optimizers typically have a database of rewrite rules
- E.g. SQL Server: about 500 rules
- Rules become complex as they need to serve specialized types of queries

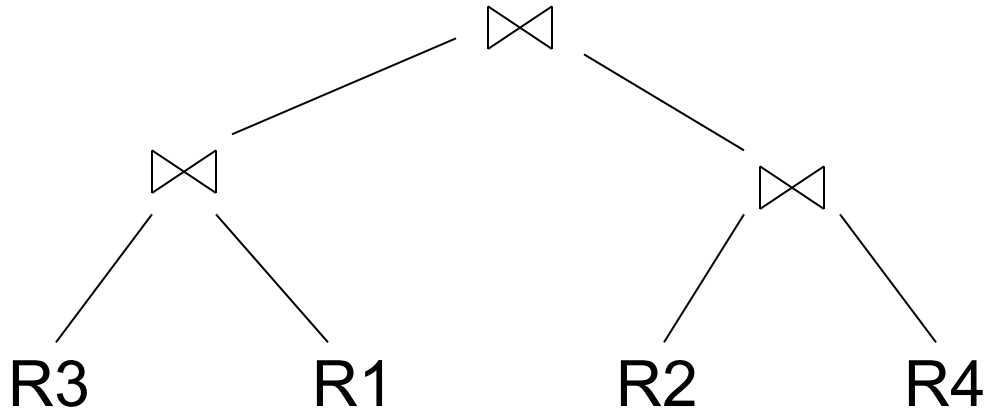
Search Space Challenges

- Search space is huge
- Typical compromises:
  - Left-deep plans
  - Plans without cartesian products

Left-Deep Plans and Bushy Plans



Left-deep plan



Bushy plan

[How good are they]

The need for a rich search space

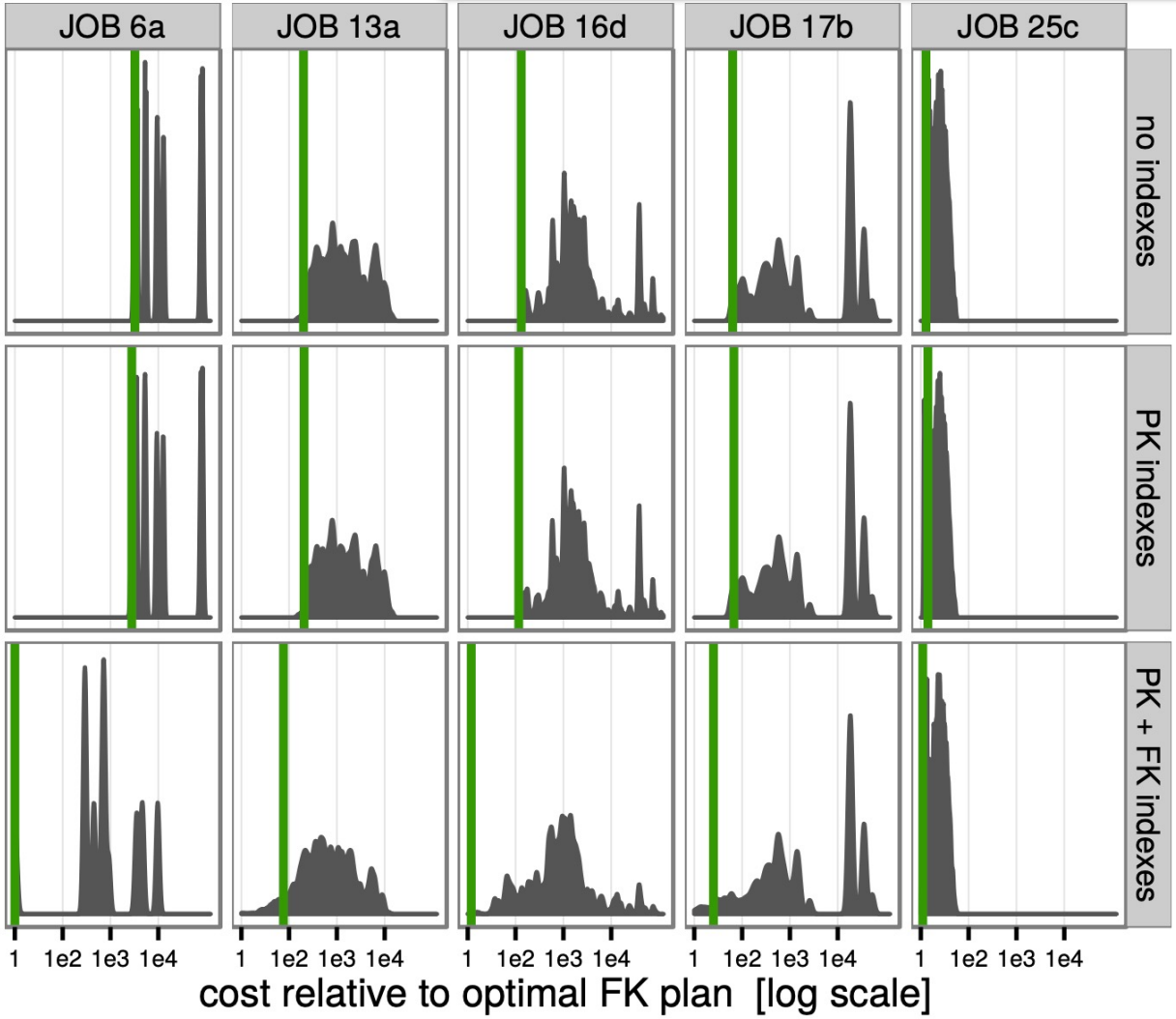


Figure 9: Cost distributions for 5 queries and different index configurations. The vertical green lines represent the cost of the optimal plan

[How good are they]

The effect of restricting the search space

	PK indexes			PK + FK indexes		
	median	95%	max	median	95%	max
zig-zag	1.00	1.06	1.33	1.00	1.60	2.54
left-deep	1.00	1.14	1.63	1.06	2.49	4.50
right-deep	1.87	4.97	6.80	47.2	30931	738349

Table 2: Slowdown for restricted tree shapes in comparison to the optimal plan (true cardinalities)

Query Optimization

Three major components:

1. Cardinality and cost estimation
2. Search space
3. Plan enumeration algorithms

Two Types of Optimizers

- Heuristic-based optimizers
- Cost-based optimizers (next)

Two Types of Plan Enumeration Algorithms

- Dynamic programming (in class)
  - Based on System R [Selinger 1979]
  - *Join reordering algorithm*

- Rule-based algorithm (will not discuss)
  - Database of rules (=algebraic laws)
  - Usually: dynamic programming

System R Optimizer

For each subquery $Q \subseteq \{R_1, \ldots, R_n\}$, compute best plan:

- Step 1: $Q = \{R_1\}, \{R_2\}, \ldots, \{R_n\}$
- Step 2: $Q = \{R_1,R_2\}, \{R_1,R_3\}, \ldots, \{R_{n-1}, R_n\}$
- …
- Step n: $Q = \{R_1, \ldots, R_n\}$

Details

For each subquery $Q \subseteq \{R_1, \ldots, R_n\}$ store:

- Estimated Size(Q)
- A best plan for Q: Plan(Q)
- The cost of that plan: Cost(Q)

One plan for each "interesting order"

Details

Step 1: single relations $\{R_1\}$, $\{R_2\}$, …, $\{R_n\}$

- Consider all possible access paths:
  - Sequential scan, or
  - Index 1, or
  - Index 2, or
  - …
- Keep optimal plan for each "interesting order"

Details

Step k = 2…n:

For each $Q = \{R_{i_1}, \ldots, R_{i_k}\}$

- For each j=1,…,k:
  - Let: $Q' = Q - \{R_{i_j}\}$
  - Let: $Plan(Q') \bowtie R_{i_j}$ $Cost(Q') + CostOf(\bowtie)$
- $Plan(Q), Cost(Q) =$ cheapest of the above
  - Keep separate optimal for “interesting orders”

[How good are they]

Is Dynamic Programming needed?

	PK indexes						PK + FK indexes					
	PostgreSQL estimates			true cardinalities			PostgreSQL estimates			true cardinalities		
	median	95%	max	median	95%	max	median	95%	max	median	95%	max
Dynamic Programming	1.03	1.85	4.79	1.00	1.00	1.00	1.66	169	186367	1.00	1.00	1.00
Quickpick-1000	1.05	2.19	7.29	1.00	1.07	1.14	2.52	365	186367	1.02	4.72	32.3
Greedy Operator Ordering	1.19	2.29	2.36	1.19	1.64	1.97	2.35	169	186367	1.20	5.77	21.0

Table 3: Comparison of exhaustive dynamic programming with the Quickpick-1000 (best of 1000 random plans) and the Greedy Operator Ordering heuristics. All costs are normalized by the optimal plan of that index configuration

Discussion

- All database systems implement Selinger's algorithm for join reorder
- For other operators (group-by, aggregates, difference): rule-based
- Many search strategies beyond dynamic programming

Final Discussion

- Query optimizer realizes the *physical data independence* principle:
  - SQL = what we want to get
  - Optimized plan = how to get it

- Optimizer =
  Search space + Size est + Algorithm
- Typically, good at avoiding “worst plans”, less so at finding “best plan”