DATA516/CSED516
Scalable Data Systems and Algorithms

Lecture 3

Query Optimization, Spark

Announcements

- HW2 is posted and due on Nov. 2nd
- Project proposals due on Oct. 29th
- Review was due today (*How good…?*)
- Review of three (!) papers due next week

Quick Recap

- What is data independence?
- What are the ops in the relational algebra?
- What is a logical query plan?
- What is a physical query plan?
- Describe briefly 3 join algorithms

Outline for Today

- Query Optimization
  - *How good are they?*
- Spark
  - May run out of time, please come to section!

Recap

- Optimizer has three components:
  - Search space
  - Cardinality and cost estimation
  - Plan enumeration algorithms

Recap

- Optimizer has three components:
  - Search space
  - Cardinality and cost estimation
  - Plan enumeration algorithms
- Paper addresses three questions:
  - How good are the cardinality estimators?
  - How important is the cost model?
  - How large does the search space need to be?

Paper Outline

- How good are the cardinality estimators?
- How important is the cost model?
- How large does the search space need to be?

The Job Benchmark

- Why do they use the IMDB database instead of TPC-H?

- IMDB – popular data on the web, can be imported into any RDBMS with moderate effort

Lesson: you can always import your dataset into RDBMS!

The Job Benchmark

JOB Benchmark: 33 templates, 113 queries

Discuss the difference in class:

- SQL query
- SQL query template (or structure)

Group-by Queries

- None in JOB!
- Important in DS; we'll discuss them later

Review: Cardinality Estimation

Problem: given statistics on base tables and a query, estimate size of the answer

What are the statistics on base tables?

Review: Cardinality Estimation

Problem: given statistics on base tables and a query, estimate size of the answer

What are the statistics on base tables?

- Number of tuples (cardinality) T(R)
- Number of values in R.a: V(R,a)
- Histograms (later today)

Review: Cardinality Estimation

What are the four assumptions that database systems do?

Review: Cardinality Estimation

What are the four assumptions that database systems do?

- Uniformity
- Independence
- Containment of values
- Preservation of values

Single Table Estimation

$\sigma_{A=c}(R) = T(R)/V(R,A)$

What assumption does this make?

Single Table Estimation

$\sigma_{A=c}(R) = T(R)/V(R,A)$

What assumption does this make?

Uniformity

Single Table Estimation

$\sigma_{A=c}(R) = T(R)/V(R,A)$

What assumption does this make?

Uniformity

	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
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HyPer	1.02	4.47	8.00	2084

Table 1: Q-errors for base table selections

Histograms

- T(R), V(R,A) too coarse
- Histogram: separate stats per bucket

- In each bucket store:
  - T(bucket)
  - V(bucket,A)

Employee(ssn, name, age)

Histograms

T(Employee) = 25000, V(Empolyee, age) = 50

Estimate $\sigma_{age=48}$(Empolyee) = ?

Employee(ssn, name, age)

Histograms

T(Employee) = 25000, V(Empolyee, age) = 50

Estimate $\sigma_{age=48}$(Empolyee) = ? = 25000/50 = 500

Employee(ssn, name, age)

Histograms

T(Employee) = 25000, V(Empolyee, age) = 50

Estimate $\sigma_{age=48}$(Empolyee) = ? = 25000/50 = 500

Age:	0..20	20..29	30-39	40-49	50-59	> 60
T =	200	800	5000	12000	6500	500
V =	3	10	7	6	5	4

Estimate $\sigma_{age=48}$(Empolyee) = ?

Employee(ssn, name, age)

Histograms

T(Employee) = 25000, V(Empolyee, age) = 50

Estimate $\sigma_{age=48}$(Empolyee) = ? = 25000/50 = 500

Age:	0..20	20..29	30-39	40-49	50-59	> 60
T =	200	800	5000	**12000**	6500	500
V =	3	10	7	**6**	5	4

Estimate $\sigma_{age=48}$(Empolyee) = ? = 12000/6 = 2000

Types of Histograms

- Eq-Width

- Eq-Depth

- Compressed: store outliers separately

- V-Optimal histograms

Employee(ssn, name, age)

Histograms

Eq-width:

Age:	0..20	20..29	30-39	40-49	50-59	> 60
T	200	800	5000	12000	6500	500
V	2	8	10	10	8	3

Employee(ssn, name, age)

Histograms

Eq-width:

Age:	0..20	20..29	30-39	40-49	50-59	> 60
T	200	800	5000	12000	6500	500
V	2	8	10	10	8	3

Eq-depth:

Age:	0..32	33..41	42-46	47-52	53-58	> 60
T	1800	2000	2100	2200	1900	1800
V	8	10	9	10	8	6

Employee(ssn, name, age)

Histograms

Eq-width:

Age:	0..20	20..29	30-39	40-49	50-59	> 60
T	200	800	5000	12000	6500	500
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Eq-depth:

Age:	0..32	33..41	42-46	47-52	53-58	> 60
T	1800	2000	2100	2200	1900	1800
V	8	10	9	10	8	6

Compressed: store separately highly frequent values: (48,1900)

V-Optimal Histograms

- Error:

$$\sum_{v \in Domain(A)} \left(|\sigma_{A=v}(R)| - est_{Hist}\left(\sigma_{A=v}(R)\right) \right)^2$$

- Bucket boundaries = $\text{argmin}_{\text{Hist}}$(Error)
- Dynamic programming
- Modern databases systems use V-optimal histograms or some variations

Multiple Predicates

- Independence assumption:
  - Simple
  - But often leads to major underestimates

- Modeling correlations:
  - Solution 1: 2d Histograms
  - Solution 2: use sample from the data

Supplier(sid, sname, scity, sstate)

Independence Assumption

T(Supplier) = 250,000

scity:	A..E	F..I	J..M	N..Q	R..U	V..Z
T	2000	8000	50000	120000	65000	5000
V	50	40	250	300	130	100

sstate:	A..J	K..S	T..Z
T	125000	80000	45000
V	20	10	20

```
select * from Supplier
where scity = 'Mountainview'
   and sstate = 'CA'
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Estimate $\sigma_{sscity=\text{'Mtv'} \wedge sstate=\text{'CA'}}$(Supplier) = ?

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Select random tuple in Supplier, with probability 1/T

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Select random tuple in Supplier, with probability 1/T

Pr(scity = 'Mtv') = Pr(scity = 'Mtv' | scity ∊ J..M) * P(scity ∊ J..M)

Supplier(sid, sname, scity, sstate)

Independence Assumption

T(Supplier) = 250,000

scity:	A..E	F..I	J..M	N..Q	R..U	V..Z
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$\Pr(\text{scity} = \text{'Mtv'}) = \Pr(\text{scity} = \text{'Mtv'} \mid \text{scity} \in \text{J..M}) * P(\text{scity} \in \text{J..M}) = 1/V_{J..M} * T_{J..M}/T$

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Independence Assumption

T(Supplier) = 250,000

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Supplier(sid, sname, scity, sstate)

Independence Assumption

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select * from Supplier
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Estimate $\sigma_{sscity=\text{‘Mtv’} \wedge sstate=\text{‘CA’}}(\text{Supplier}) = ?$

Select random tuple in Supplier, with probability 1/T

$\Pr(scity = \text{‘Mtv’}) = \Pr(scity = \text{‘Mtv’} \mid scity \in J..M) * P(scity \in J..M) = 1/V_{J..M} * T_{J..M}/T$

$\Pr(sstate = \text{‘CA’}) = \Pr(sstate = \text{‘CA’} \mid sstate \in A..J) * P(sstate \in A..J)$

Supplier(sid, sname, scity, sstate)

Independence Assumption

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Pr(sstate = 'CA') = Pr(sstate = 'CA' | sstate ∈ A..J) * P(sstate ∈ A..J) = $1/V_{A..J} * T_{A..J}/T$

Supplier(sid, sname, scity, sstate)

Independence Assumption

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scity:	A..E	F..I	J..M	N..Q	R..U	V..Z
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select * from Supplier
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Estimate $\sigma_{\text{sscity='Mtv'} \wedge \text{sstate='CA'}}(\text{Supplier}) = ?$

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Pr(sstate = 'CA') = Pr(sstate = 'CA' | sstate ∈ A..J) * P(sstate ∈ A..J) = $1/V_{A..J} * T_{A..J}/T$

Pr(scity = 'Mtv' ∧ sstate = 'CA') =

Supplier(sid, sname, scity, sstate)

Independence Assumption

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scity:	A..E	F..I	J..M	N..Q	R..U	V..Z
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Pr(sstate = 'CA') = Pr(sstate = 'CA' | sstate ∈ A..J) * P(sstate ∈ A..J) = $1/V_{A..J} * T_{A..J}/T$

Pr(scity = 'Mtv' ∧ sstate = 'CA') = $(1/V_{J..M} * T_{J..M}/T) * (1/V_{A..J} * T_{A..J}/T)$

Independence

Supplier(sid, sname, scity, sstate)

Independence Assumption

T(Supplier) = 250,000

scity:	A..E	F..I	J..M	N..Q	R..U	V..Z
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select * from Supplier
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```

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Select random tuple in Supplier, with probability 1/T

$Pr(scity = 'Mtv') = Pr(scity = 'Mtv' \mid scity \in J..M) * P(scity \in J..M) = 1/V_{J..M} * T_{J..M}/T$

$Pr(sstate = 'CA') = Pr(sstate = 'CA' \mid sstate \in A..J) * P(sstate \in A..J) = 1/V_{A..J} * T_{A..J}/T$

$Pr(scity = 'Mtv' \wedge sstate = 'CA') = (1/V_{J..M} * T_{J..M}/T) * (1/V_{A..J} * T_{A..J}/T)$

Answer: $(1/V_{J..M} * T_{J..M}/T) * (1/V_{A..J} * T_{A..J}/T) * T = 1/1250 * 1/40 * 250000 = 5$

Supplier(sid, sname, scity, sstate)

Independence Assumption

T(Supplier) = 250,000

scity:	A..E	F..I	J..M	N..Q	R..U	V..Z
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Estimate $\sigma_{\text{sscity='Mtv'} \wedge \text{sstate='CA'}}(\text{Supplier}) = ?$

This is likely an underestimate. Why?

Select random tuple in Supplier, with probability 1/T

Pr(scity = 'Mtv') = Pr(scity = 'Mtv' | scity ∈ J..M) * P(scity ∈ J..M) = $1/V_{J..M} * T_{J..M}/T$

Pr(sstate = 'CA') = Pr(sstate = 'CA' | sstate ∈ A..J) * P(sstate ∈ A..J) = $1/V_{A..J} * T_{A..J}/T$

Pr(scity = 'Mtv' ∧ sstate = 'CA') = $(1/V_{J..M} * T_{J..M}/T) * (1/V_{A..J} * T_{A..J}/T)$

Answer: $(1/V_{J..M} * T_{J..M}/T) * (1/V_{A..J} * T_{A..J}/T) * T = 1/1250 * 1/40 * 250000 = 5$

Modeling Correlations

1. Multi-dimensional histograms
   – Also called column-group statitics

2. Sample from the data

Supplier(sid, sname, scity, sstate)

2d-Histogram

T(Supplier) = 250,000

1d Histograms

scity:	A..E	F..I	J..M	N..Q	R..U	V..Z
T	2000	8000	50000	120000	65000	5000
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Estimate $\sigma_{\text{sscity='Mtv'} \wedge \text{sstate='CA'}}$(Supplier) = ?

2d Histogram

Sstate \ scity	A..E	F..I	J..M	N..Q	R..U	V..Z
A..J	…		T,V=…			
K..S						
T..Z						

Supplier(sid, sname, scity, sstate)

2d-Histogram

T(Supplier) = 250,000

1d Histograms

scity:	A..E	F..I	J..M	N..Q	R..U	V..Z
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Estimate $\sigma_{\text{sscity='Mtv'} \wedge \text{sstate='CA'}}$(Supplier) = ?

2d Histogram

Sstate \ scity	A..E	F..I	J..M	N..Q	R..U	V..Z
A..J	…		T,V=…			
K..S						
T..Z						

Answer: $T_{\text{histogram}} / V_{\text{histogram}}$

Supplier(sid, sname, scity, sstate)

Sample

- Compute a small, uniform sample from Supplier

Estimate $\sigma_{\text{sscity='Mtv'} \land \text{sstate='CA'}}(\text{Supplier}) = ?$

Supplier(sid, sname, scity, sstate)

Sample

- Compute a small, uniform sample from Supplier
- Use Thomson's estimator:

Estimate $\sigma_{\text{sscity='Mtv'} \wedge \text{sstate='CA'}}(\text{Supplier})$ = ?

Supplier(sid, sname, scity, sstate)

Sample

- Compute a small, uniform sample from Supplier

Estimate $\sigma_{\text{sscity='Mtv'} \wedge \text{sstate='CA'}}(\text{Supplier}) = ?$

- Use Thomson's estimator:

Answer: $\sigma_{\text{sscity='Mtv'} \wedge \text{sstate='CA'}}(\text{Sample}) * T(\text{Supplier}) / T(\text{Sample})$

Correlations

- Solution 1: 2d histograms
  - Plus: can be accurate for 2 predicates
  - Minus: unclear how to use for 3 or more preds
  - Minus: limited number of buckets (why?)
  - Minus: too many 2d histogram candidates
- Solution 2: sampling
  - Plus: can be accurate for >2 predicates
  - Plus: work for complex preds, e.g. “like”
  - Minus: fail for low selectivity predicates

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Recap: Single Table Estimation

$\sigma_{A=c}(R) = T(R)/V(R,A)$

Assumes uniformity

	median	90th	95th	max
PostgreSQL	1.00	2.08	6.10	207
DBMS A	1.01	1.33	1.98	43.4
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Table 1: Q-errors for base table selections

Review: Estimate Join Size

Estimate: $T(R \bowtie_{A=B} S) = ??$

Review: Estimate Join Size

Estimate: $T(R \bowtie_{A=B} S) = ??$

Answer: $T(R \bowtie_{A=B} S) = T(R)\ T(S) / \max(V(R,A),V(S,B))$

What assumptions do we make?

Review: Estimate Join Size

Estimate: $T(R \bowtie_{A=B} S) = ??$

Answer: $T(R \bowtie_{A=B} S) = T(R)\ T(S) / \max(V(R,A),V(S,B))$

What assumptions do we make?

- Uniformity
- Containment of values
- Independence:
  - less obvious
  - reason is that both T(R),T(S) are estimated too

Joins (0 to 6)

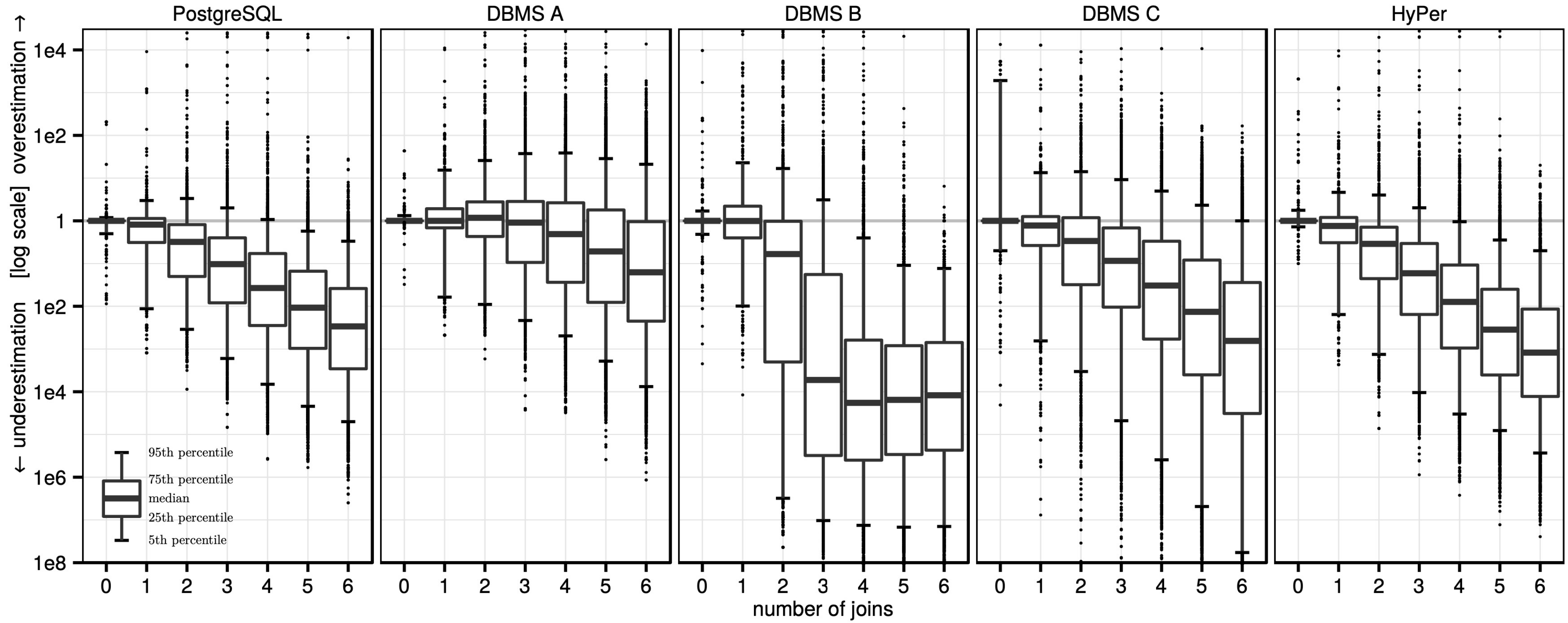


Figure 3: Quality of cardinality estimates for multi-join queries in comparison with the true cardinalities. Each boxplot summarizes the error distribution of all subexpressions with a particular size (over all queries in the workload)

Joins (0 to 6)

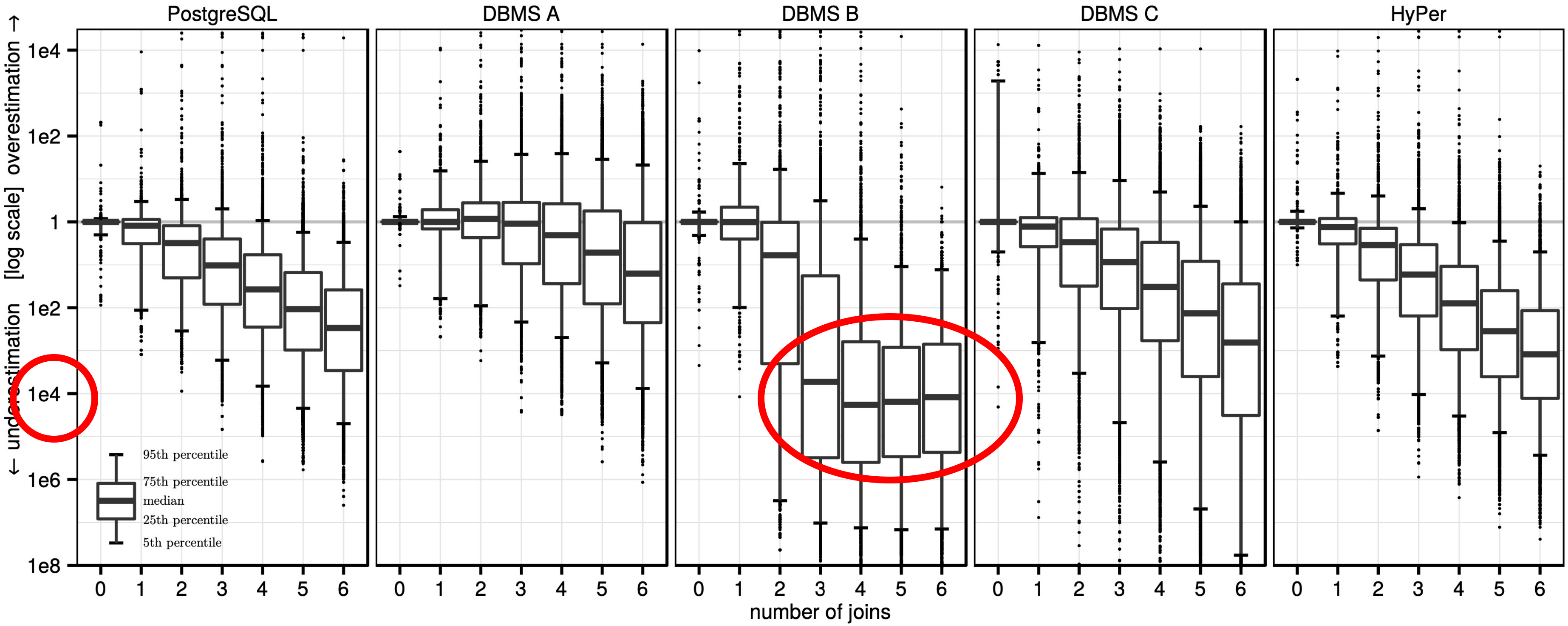


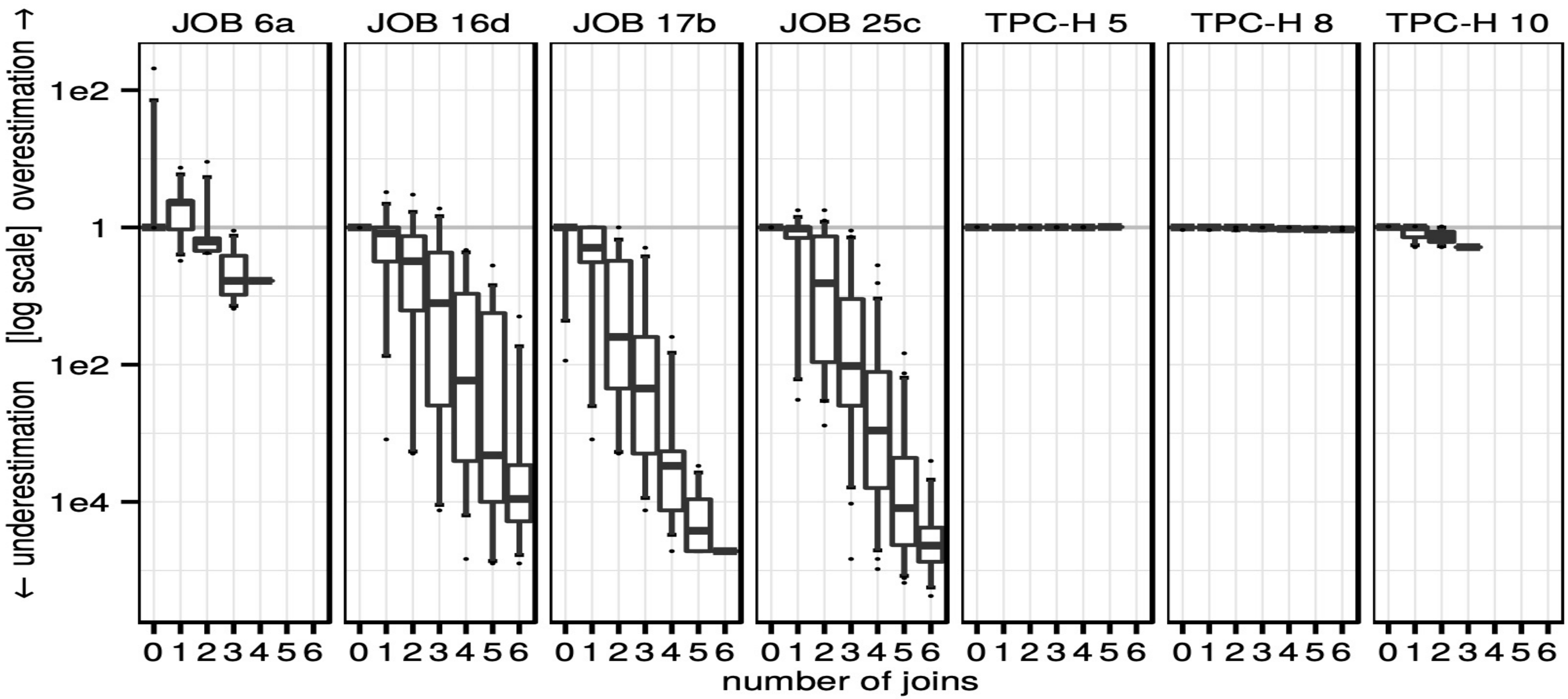
Figure 3: Quality of cardinality estimates for multi-join queries in comparison with the true cardinalities. Each boxplot summarizes the error distribution of all subexpressions with a particular size (over all queries in the workload)

Discussion

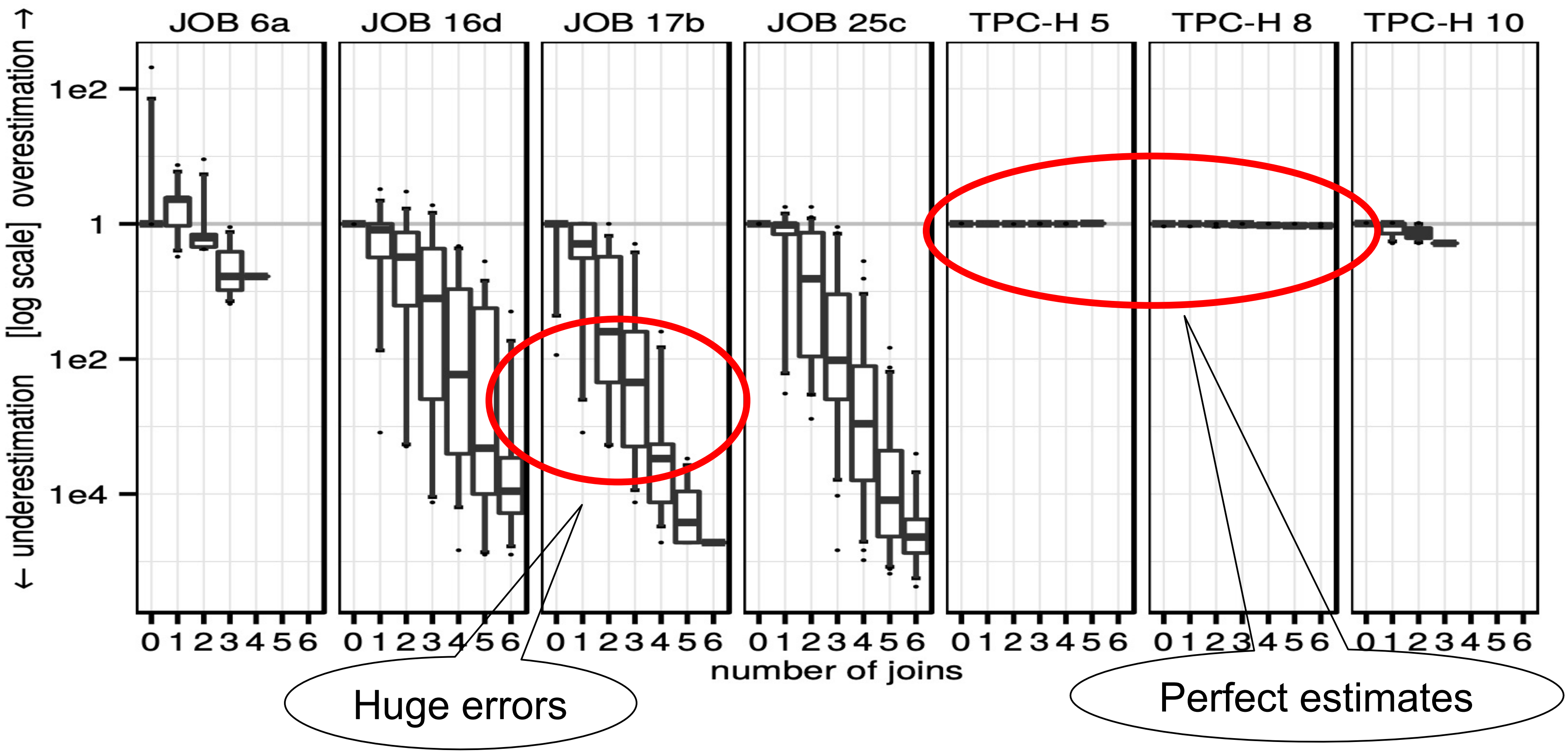
- Paper explains the need for real data

- Synthetic data used in benchmarks is often generated using uniform, independent distributions; formulas for cardinality estimation are perfect

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



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



Impact of Mis-estimates

- Sec.4 (probably more than you want to know)
- Simple configuration (key index only):
  - Minor performance impact, because the big, “fact” table needs to be scanned anyway
  - Most come from nested-loop joins (why?)
  - Most of the rest come from hash-join (why?)
  - Briefly discuss re-hashing
- More complex configuration
  - Higher perf. Impact

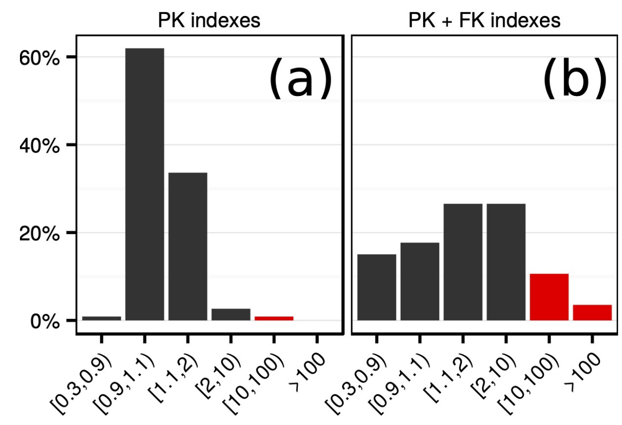


Figure 7: Slowdown of queries using PostgreSQL estimates w.r.t. using true cardinalities (different index configurations)

Paper Outline

- How good are the cardinality estimators?

- How important is the cost model?

- How large does the search space need to be?

Review: Cost Model

Cost model: for each physical operator we use a formula to convert cardinality to cost

- Example: nested loop join $R \bowtie S$
  - Cost = $c_1 * T(R) + c_2 * T(R) * T(S)$

Review: Cost Model

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- Example: nested loop join $R \bowtie S$
  - Cost = $c_1 * T(R) + c_2 * T(R) * T(S)$
- Example: hash-join $R \bowtie S$
  - Cost = $c_3 * T(R) + c_4 * T(S)$ // $c_3 \neq c_4$

Review: Cost Model

Cost model: for each physical operator we use a formula to convert cardinality to cost

- Example: nested loop join $R \bowtie S$
  - Cost = c_1*T(R) + c_2*T(R)*T(S)
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  - Cost = c_3*T(R) + c_4*T(S) // $c_3 \neq c_4$
- Difficult to choose the right constants!

Review: Cost Model

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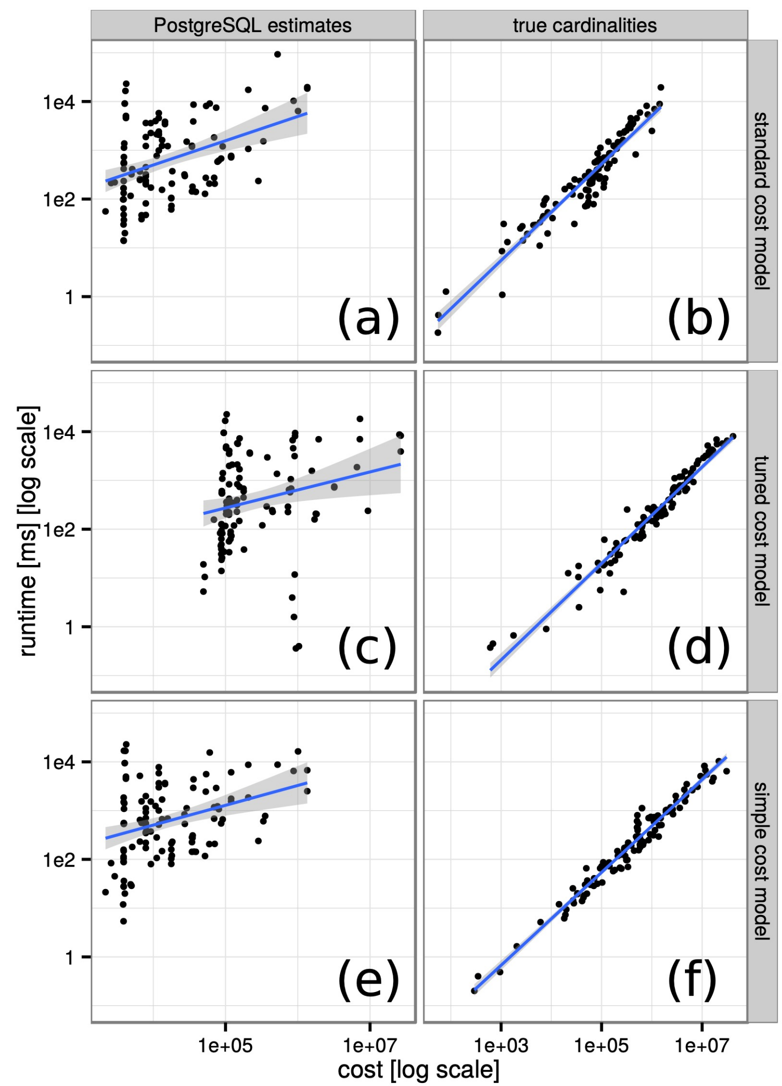
How important is the cost model?

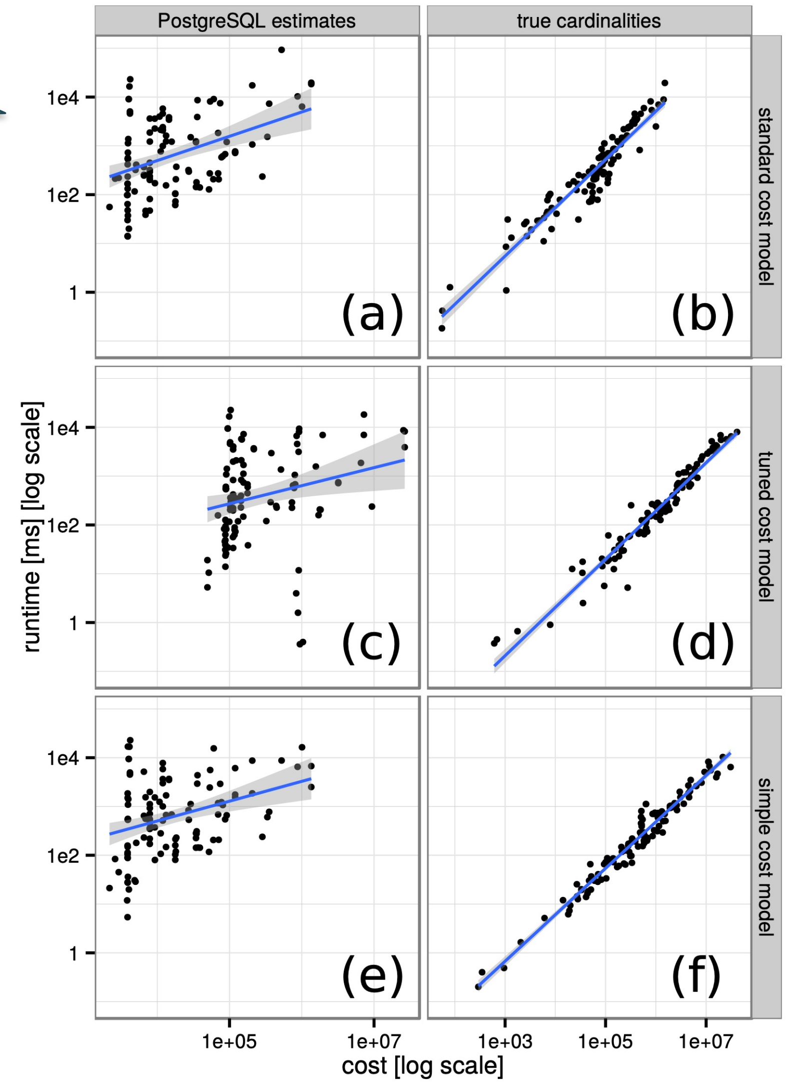
[How good are they]

Cardinalities to Cost



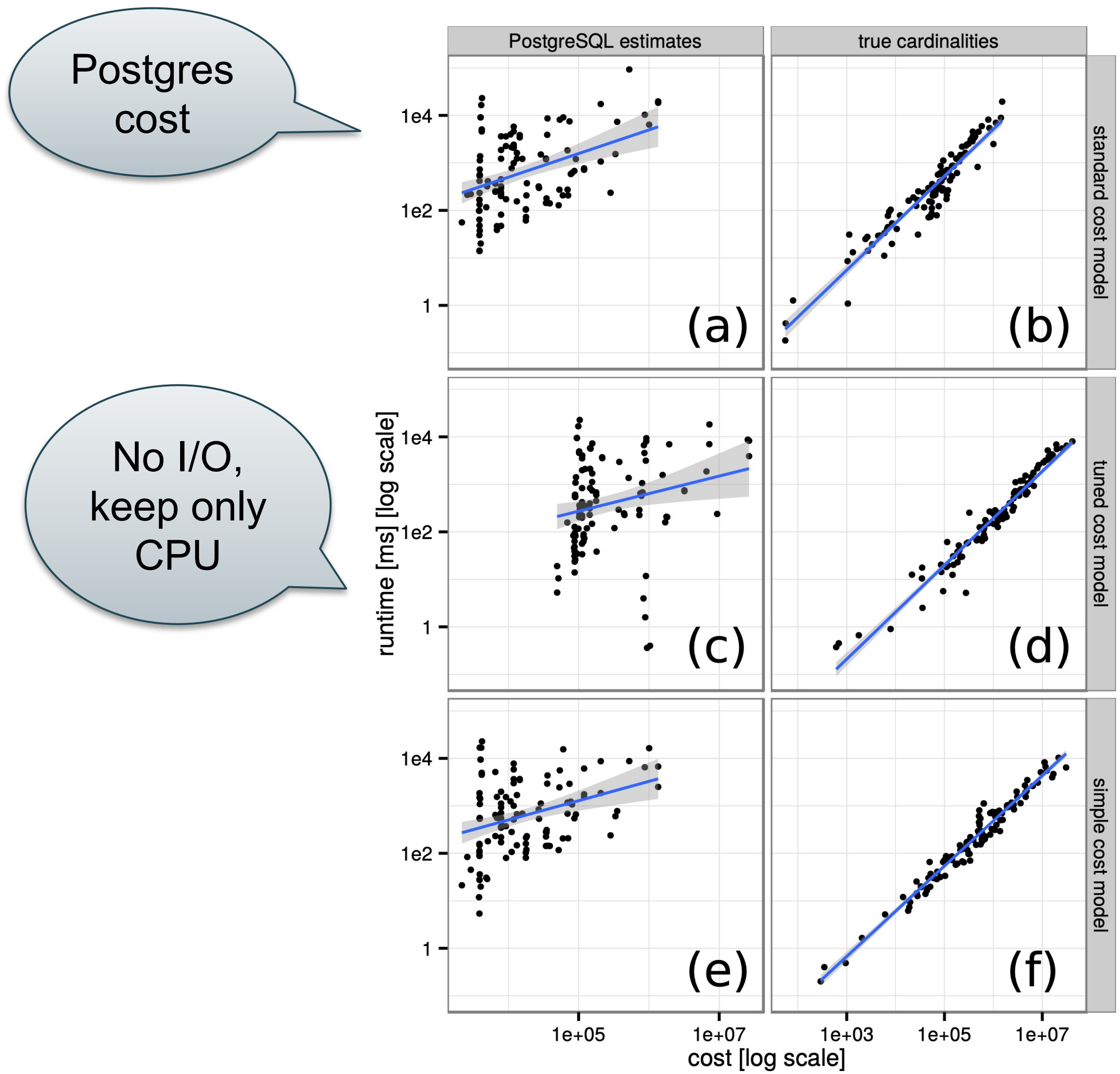
Cardinalities to Cost

Postgres cost



[How good are they]

Cardinalities to Cost



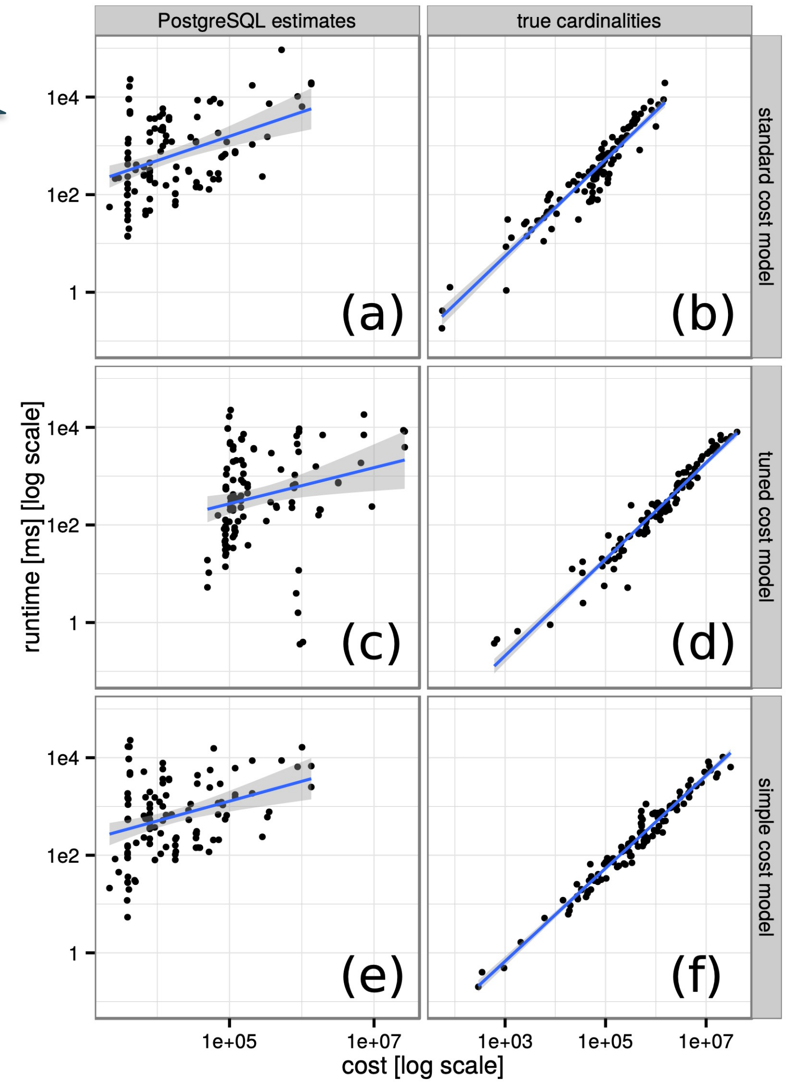
[How good are they]

Cardinalities to Cost

Postgres cost

No I/O, keep only CPU

Their own simple formula



[How good are they]

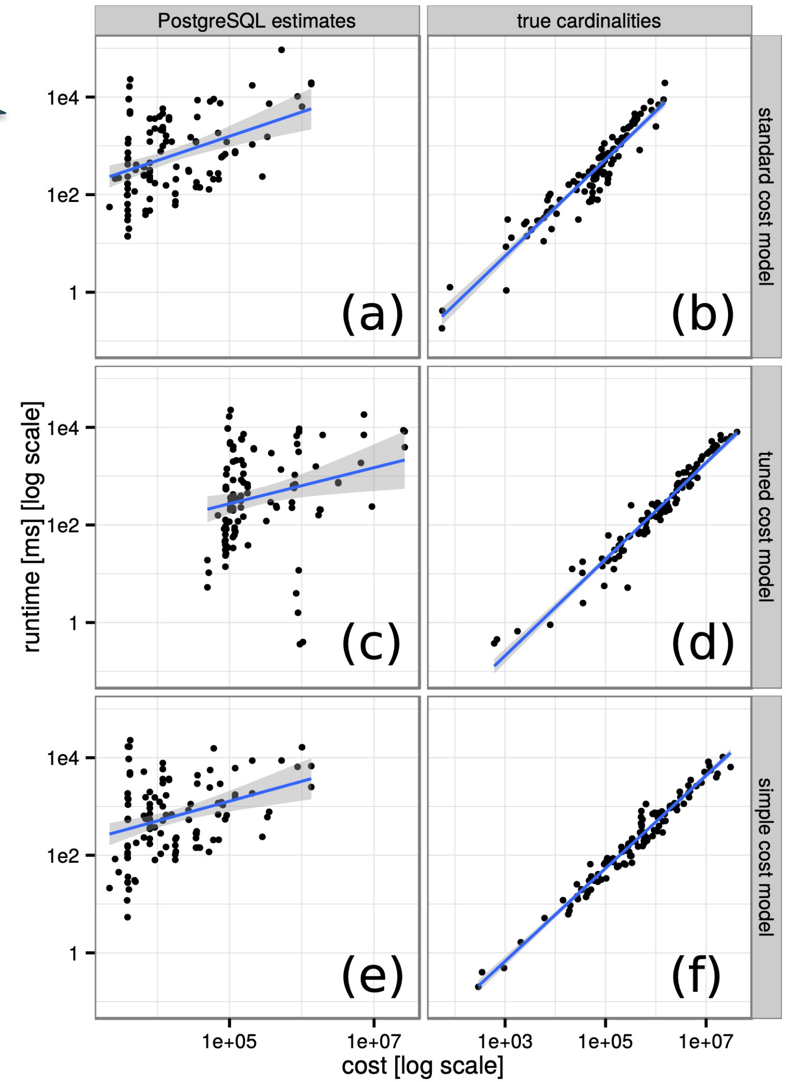
Cardinalities to Cost

- 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



Not in the paper!

Digression: Yet Another Difficulty

SQL Queries issued from applications:

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

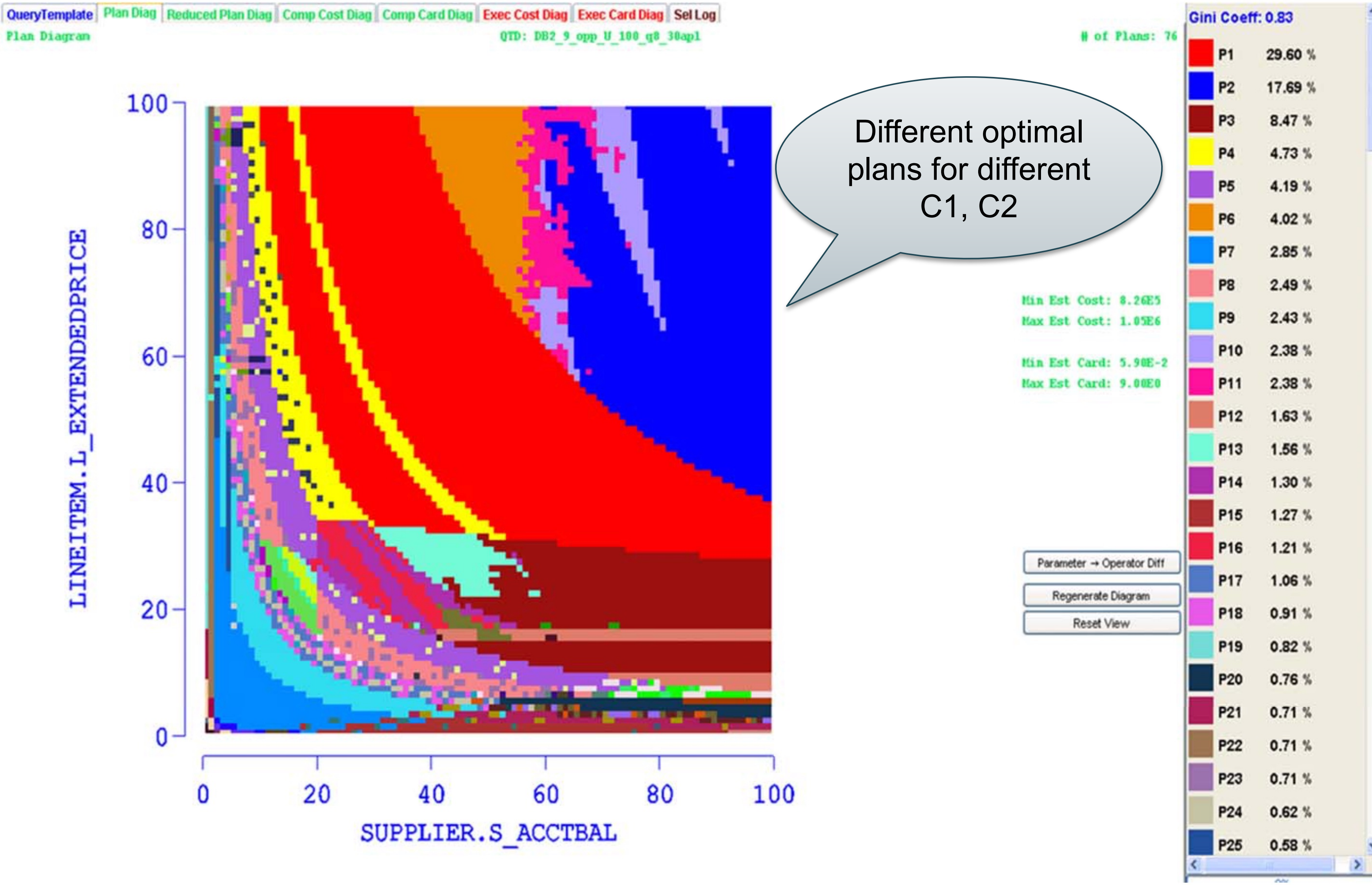
Query constants are unknow until execution: optimized plan is suboptimal

```
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
```

Jayant Haritsa, ICDE'2019 tutorial

```
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
```

Optimize without knowing C1, C2


QueryTemplate
Plan Diag
Reduced Plan Diag
Comp Cost Diag
Comp Card Diag
Exec Cost Diag
Exec Card Diag
Sel Log
Plan Diagram
# 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 %

Paper Outline

- How good are the cardinality estimators?
- How important is the cost model?
- How large does the search space need to be?

Search Space

- The set of alternative plans
- Rewrite rules; examples:
  - Push selections down: $\sigma_C(R \bowtie S) = \sigma_C(R) \bowtie S$
  - Join reorder: $(R \bowtie S) \bowtie T = R \bowtie (S \bowtie T)$
  - Push aggregates down (later today)
- Types of join trees (next)

[How good are they]

The need for a rich search space

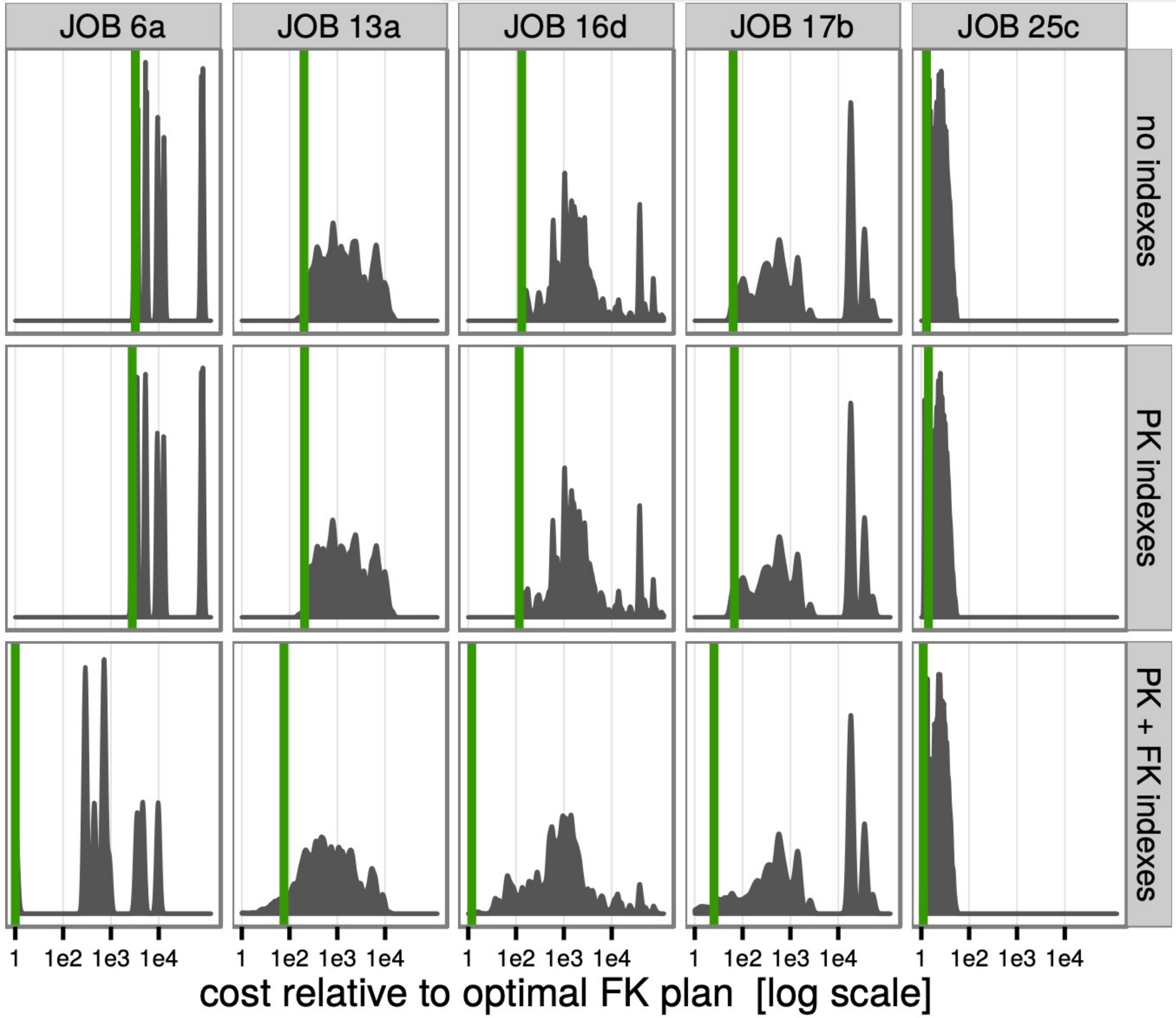


Figure 9: Cost distributions for 5 queries and different index configurations. The vertical green lines represent the cost of the optimal plan

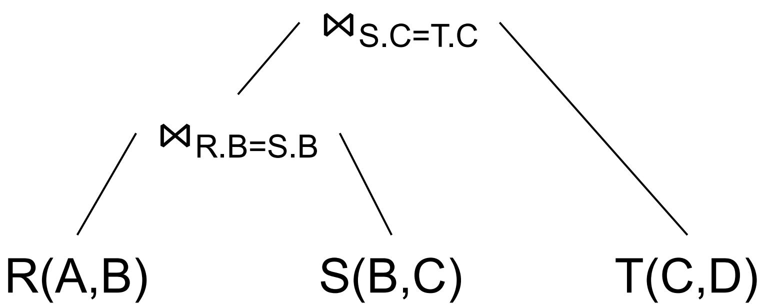
Types of Join Trees

- Based on the join condition:
  - With cartesian products
  - Without cartesian products

- Based on the shape:
  - Left deep
  - Right deep
  - Zig-zag
  - Bushy

Cartesian Product: with or without

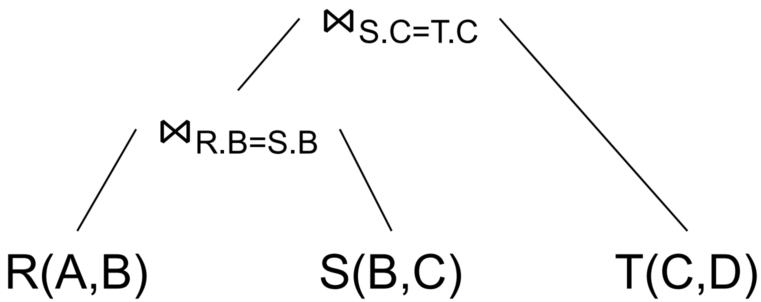
R(A,B) $\bowtie_{R.B=S.B}$ S(B,C) $\bowtie_{S.C=T.C}$ T(C,D)



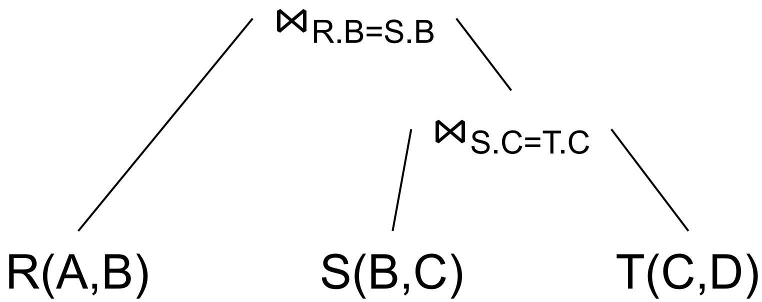
Without cartesian product

Cartesian Product: with or without

R(A,B) $\bowtie_{R.B=S.B}$ S(B,C) $\bowtie_{S.C=T.C}$ T(C,D)

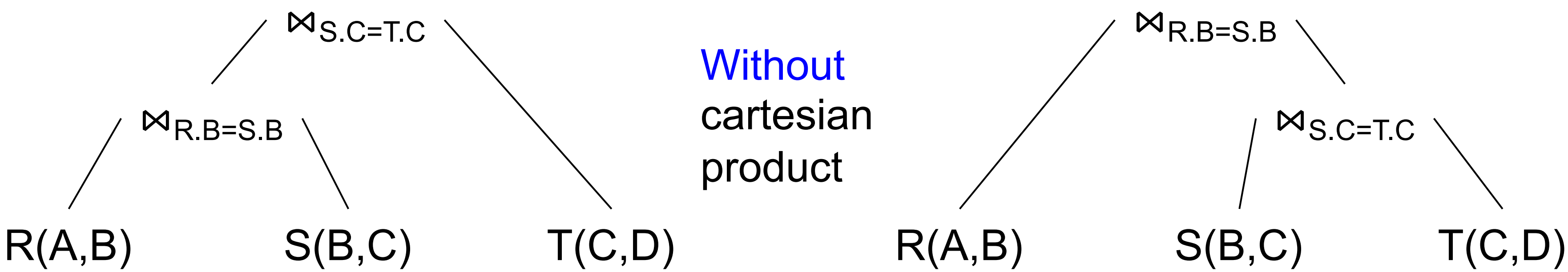


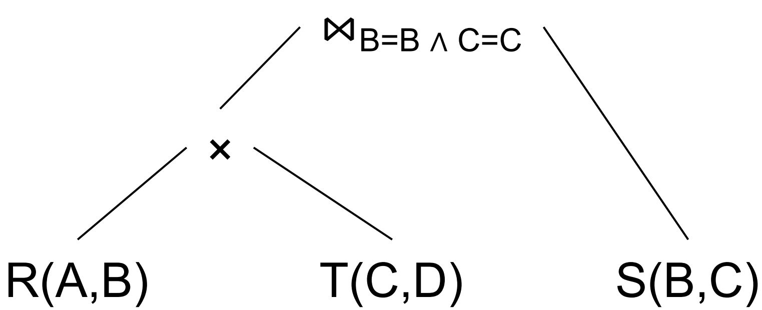
Without cartesian product



Cartesian Product: with or without

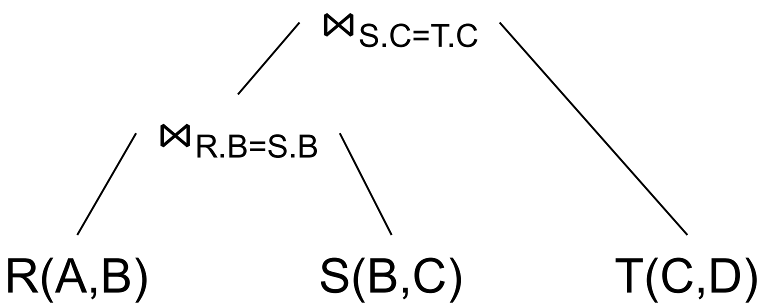
$R(A,B) \bowtie_{R.B=S.B} S(B,C) \bowtie_{S.C=T.C} T(C,D)$



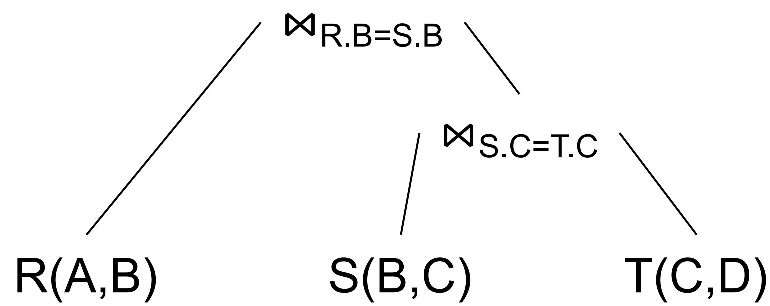


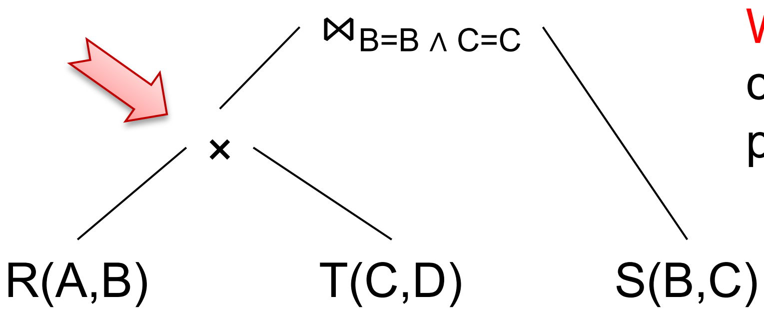
Cartesian Product: with or without

$R(A,B) \bowtie_{R.B=S.B} S(B,C) \bowtie_{S.C=T.C} T(C,D)$



Without
cartesian
product

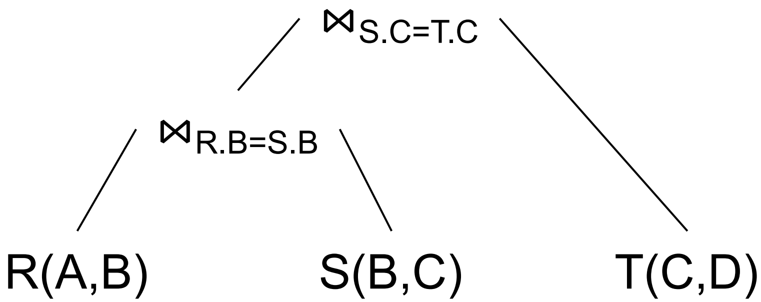




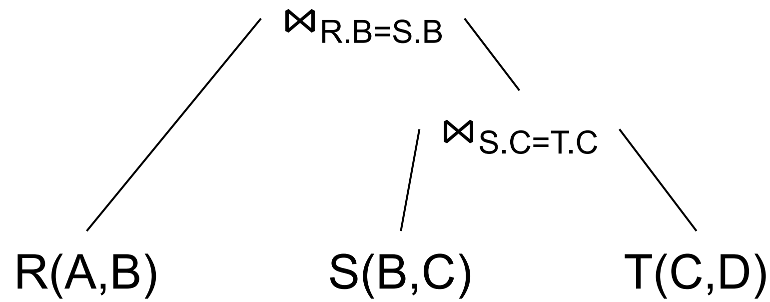
With
cartesian
product

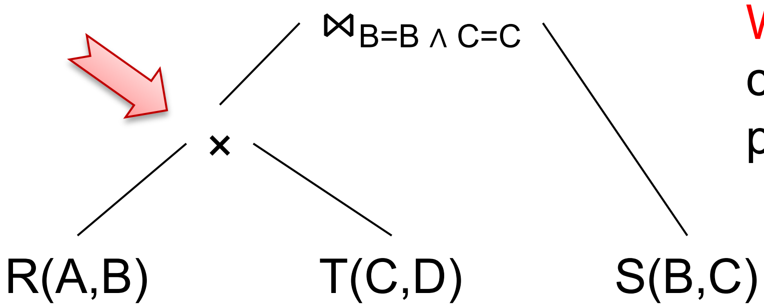
Cartesian Product: with or without

R(A,B) $\bowtie_{R.B=S.B}$ S(B,C) $\bowtie_{S.C=T.C}$ T(C,D)



Without cartesian product



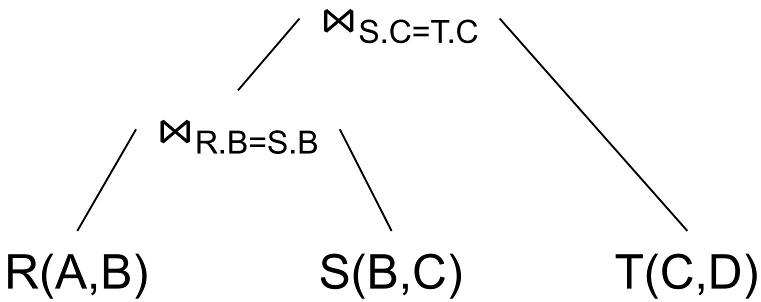


With cartesian product

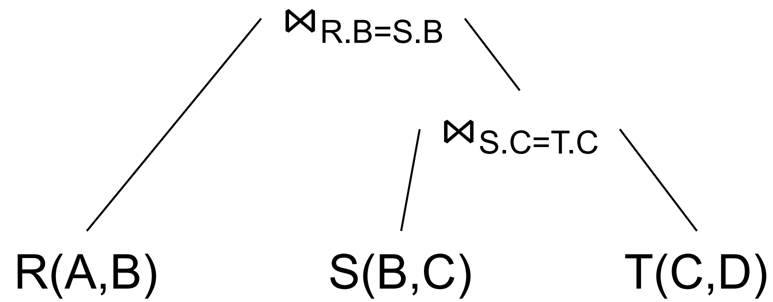
When could this plan be better?

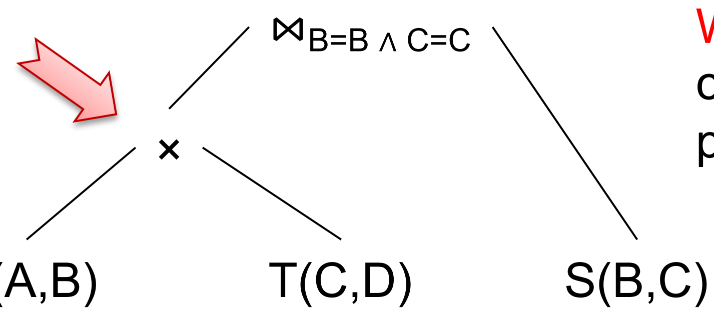
Cartesian Product: with or without

$R(A,B) \bowtie_{R.B=S.B} S(B,C) \bowtie_{S.C=T.C} T(C,D)$



Without cartesian product



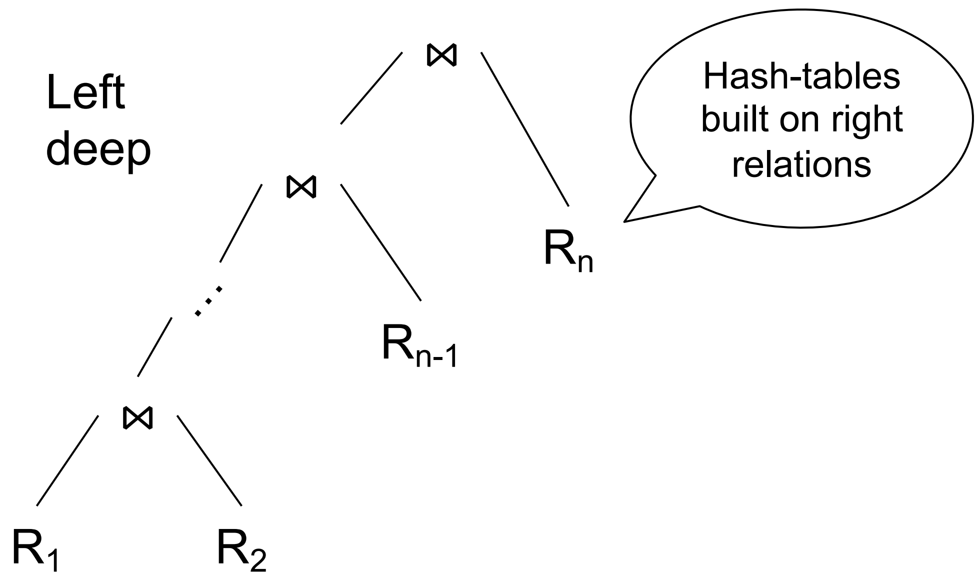


With cartesian product

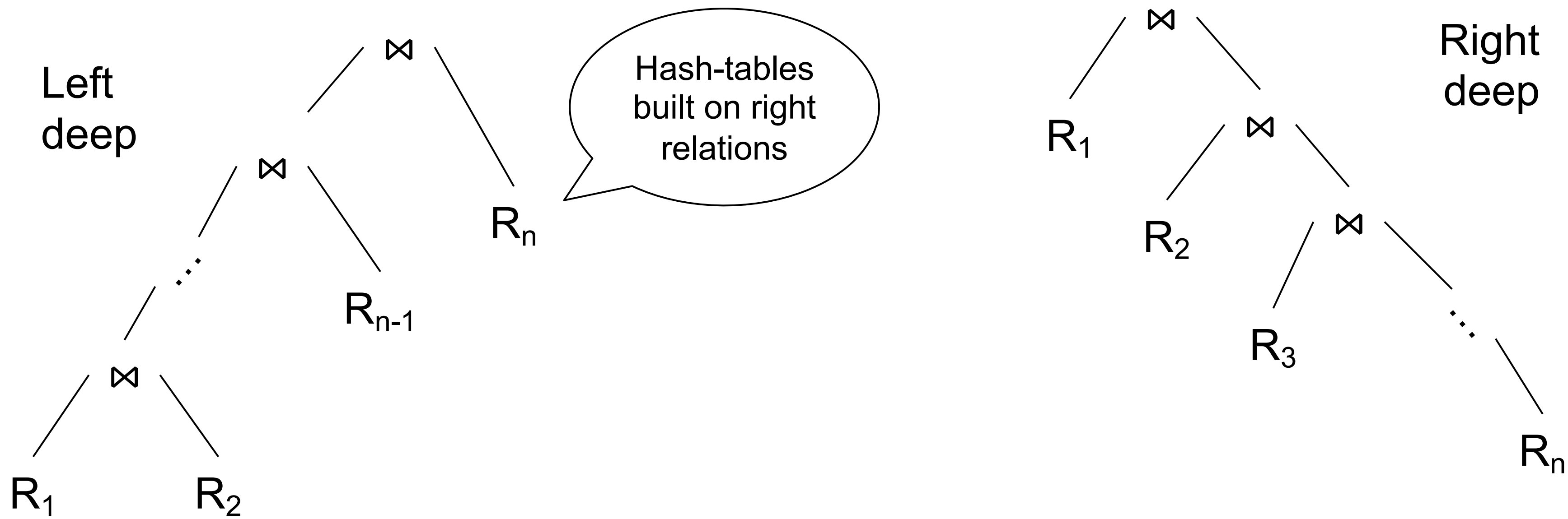
When could this plan be better?

When R, T are very small, and S is very large

Shapes of Join Trees

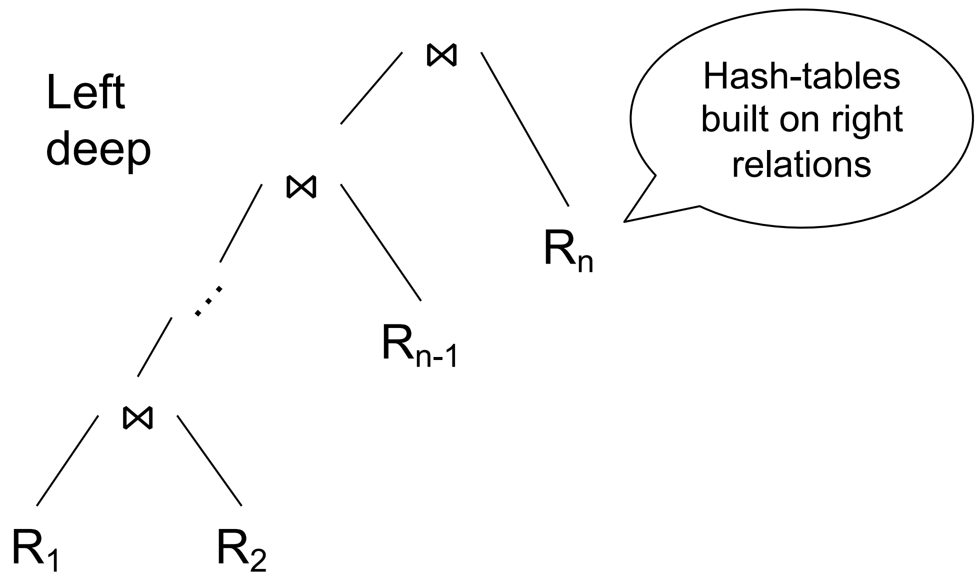


Shapes of Join Trees

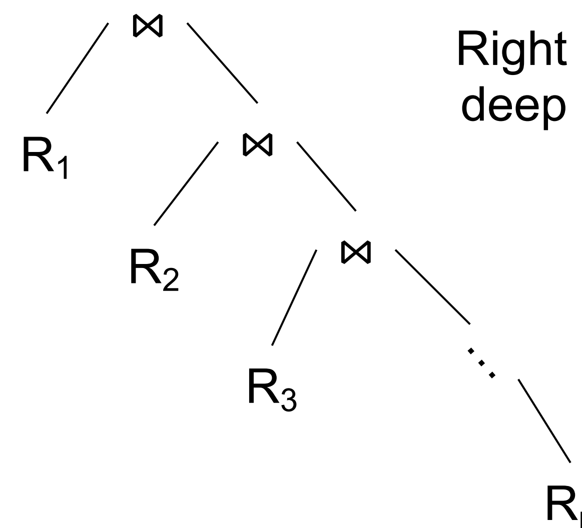


Shapes of Join Trees

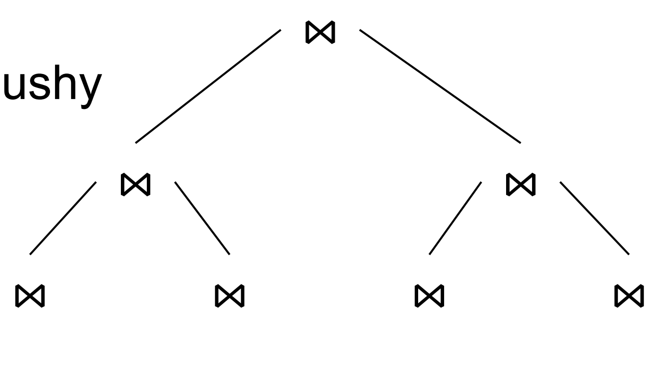
Left deep



Right deep

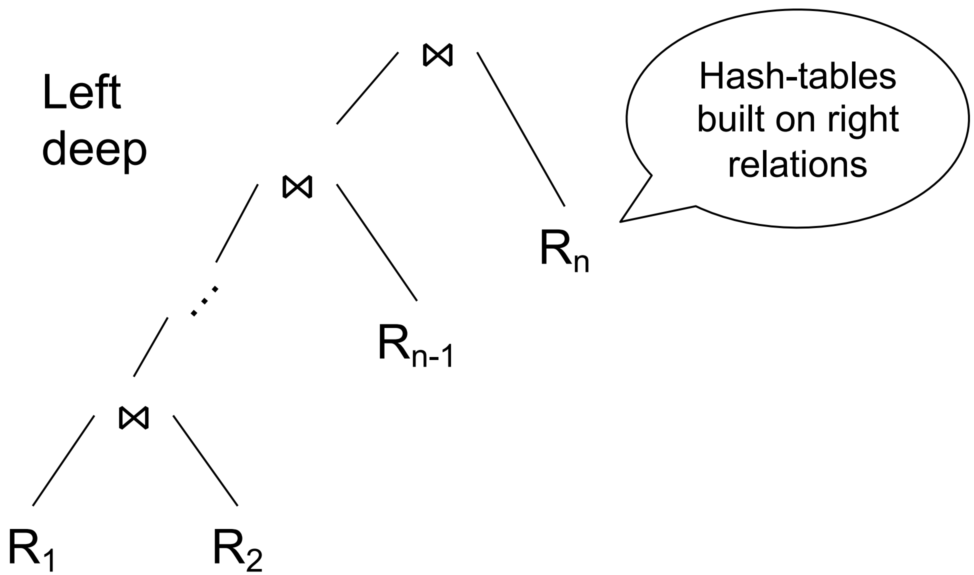


Bushy

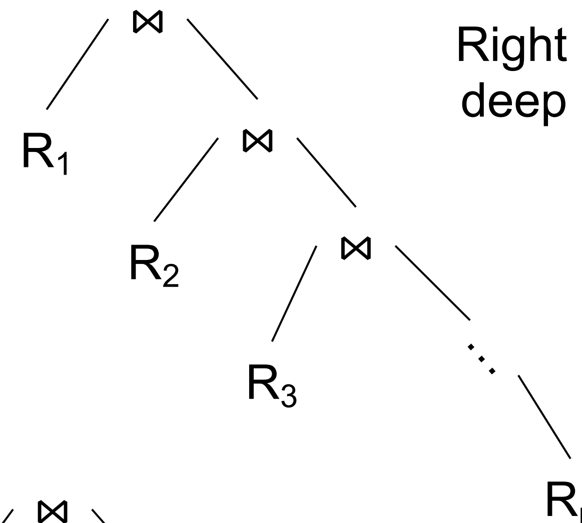


Shapes of Join Trees

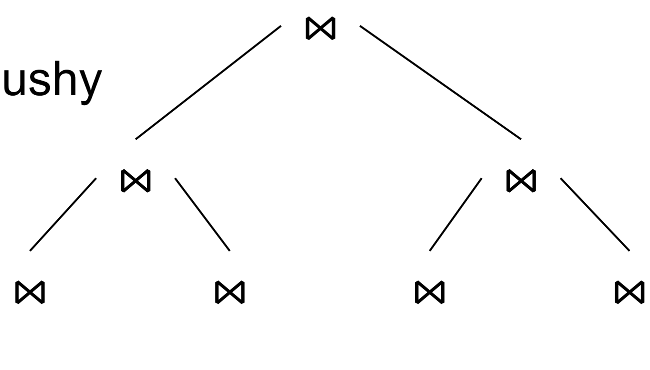
Left deep



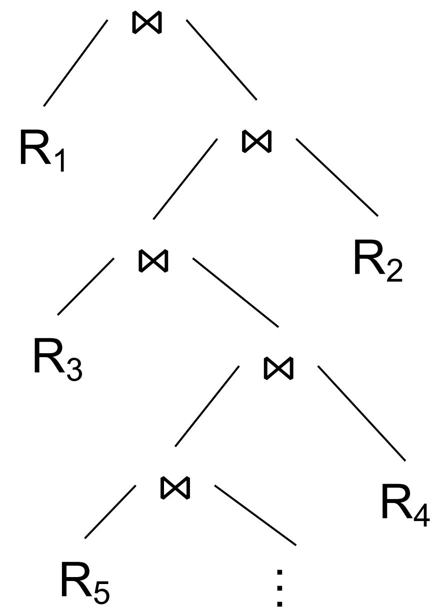
Right deep



Bushy



Zig-zag



[How good are they]

The effect of restricting the search space

Left/right
convention switched:
Right-deep build
all hash tables first.
Unclear to me
why they are worst.

	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)

Search Space: Discussion

- Search space can be huge
- Database systems often reduce it by applying heuristics:
  - No cartesian products
  - Restrict to left-deep trees (or other restriction)

Rewrite Rules

- We have seen last time:
  - Push selection down: $\sigma_C(R \bowtie S) = \sigma_C(R) \bowtie S$
  - AND: $\sigma_{C1 \text{ and } C2}(R \bowtie S) = \sigma_{C1}(\sigma_{C2}(R \bowtie S))$
  - Join associativity: $(R \bowtie S) \bowtie T = R \bowtie (S \bowtie T)$
  - Join commutativity: $R \bowtie S = S \bowtie R$
- Two more rules
  - Push aggregates down
  - Remove redundant joins

Very important
for Data Science!

Motivation

- Try this in Redshift

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

Answer: 1500000
Time: 2 s

Motivation

- Try this in Redshift

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

Answer: 1500000
Time: 2 s

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

Answer: 59986052
Time: 1 s

Motivation

- Try this in Redshift

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select count(*) from customer;
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Answer: 1500000
Time: 2 s

```
select count(*) from lineitem;
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Answer: 59986052
Time: 1 s

```
select count(*) from customer, lineitem;
```

Motivation

- Try this in Redshift

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select count(*) from customer;
```

Answer: 1500000
Time: 2 s

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select count(*) from lineitem;
```

Answer: 59986052
Time: 1 s

```
select count(*) from customer, lineitem;
```

Timeout!!!

Motivation

- Try this in Redshift

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

Answer: 1500000
Time: 2 s

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

Answer: 59986052
Time: 1 s

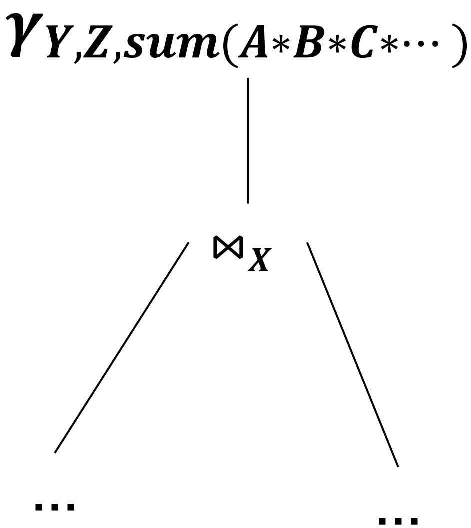
```
select count(*) from customer, lineitem;
```

Timeout!!!

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

Pushing Aggregates Down

select Y,Z, sum(A*B*C*…) from…where…
group by Y, Z



Pushing Aggregates Down

select Y,Z, sum(A*B*C*…) from…where…
group by Y, Z

$$\gamma_{Y,Z,sum(A*B*C*\cdots)}$$

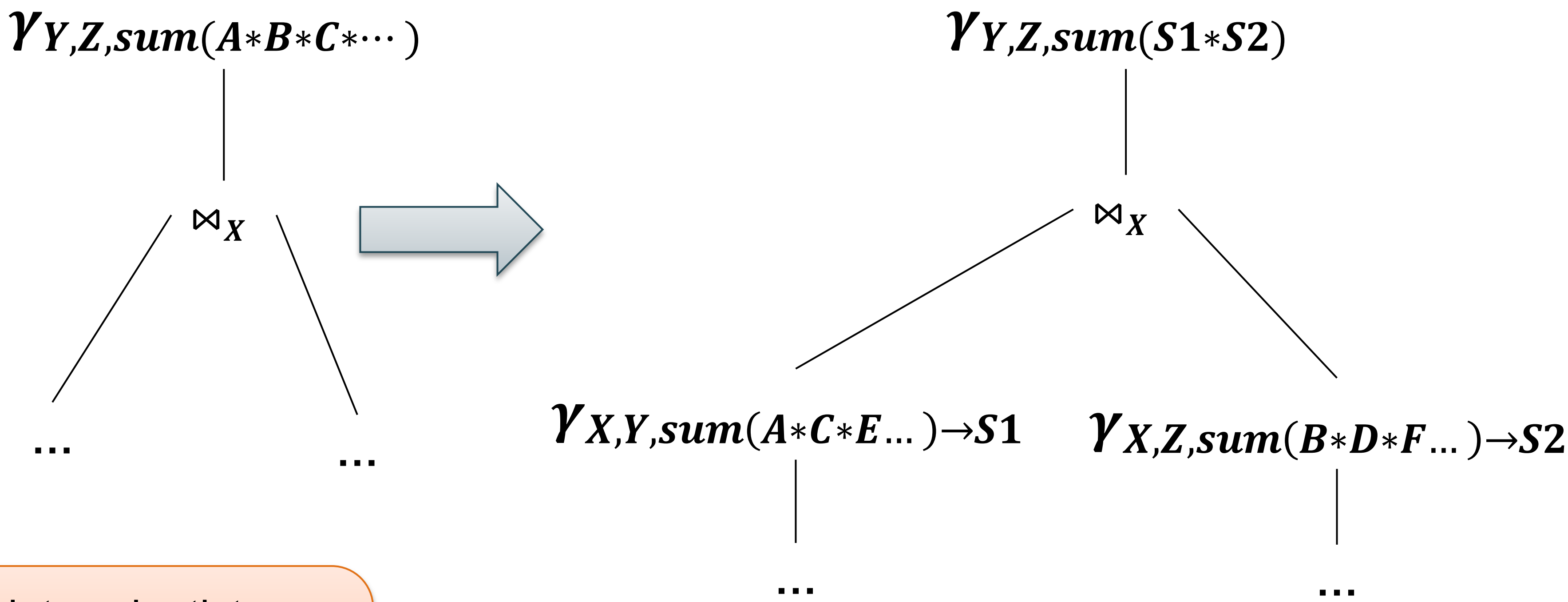
$$\bowtie_X$$

… …

As data scientists, you may really need this optimization; do it manually, if needed!

Pushing Aggregates Down

select Y,Z, sum(A*B*C*…) from…where…
group by Y, Z



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Pushing Aggregates Down

select Y,Z, sum(A*B*C*…) from…where…
group by Y, Z

$$\gamma_{Y,Z,sum(A*B*C*\cdots)}$$

$$\bowtie_X$$

… …

$$\gamma_{Y,Z,sum(S1*S2)}$$

$$\bowtie_X$$

$$\gamma_{X,Y,sum(A*C*E\ldots)\rightarrow S1} \qquad \gamma_{X,Z,sum(B*D*F\ldots)\rightarrow S2}$$

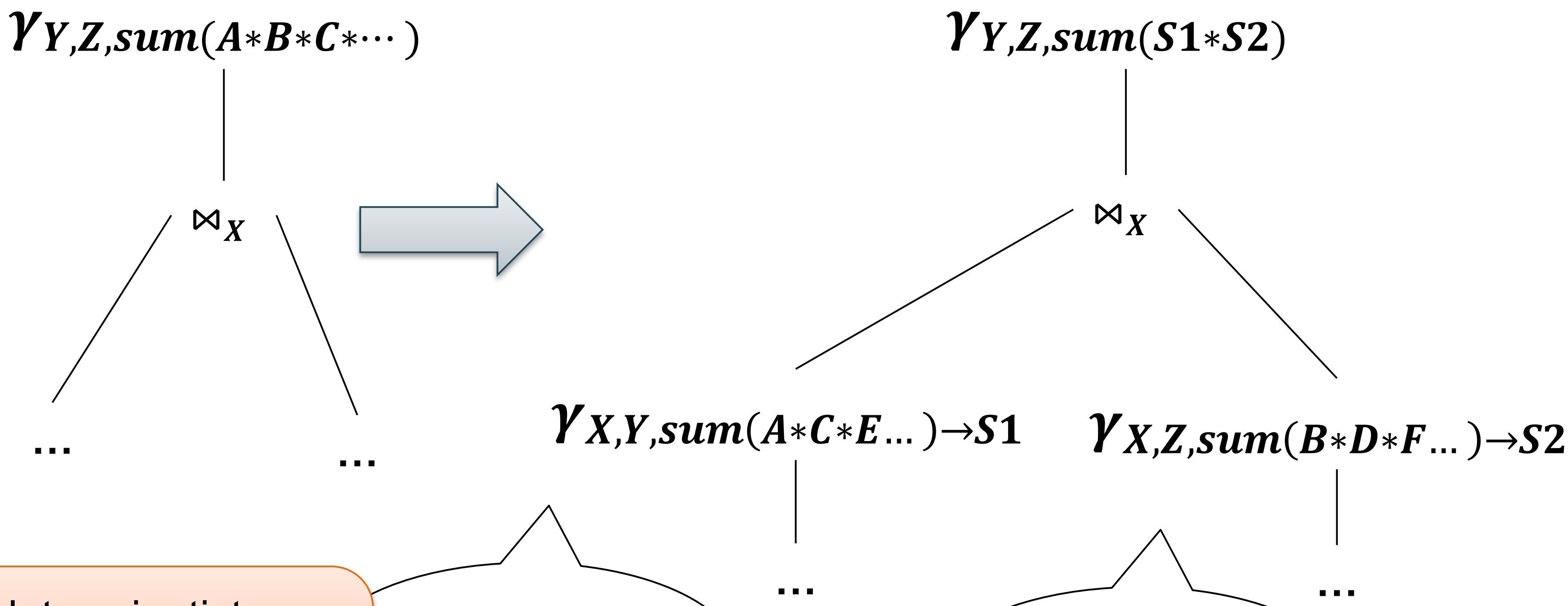
… …

Group by the attrs
from the left Y,
plus join attrs X

As data scientists,
you may really need
this optimization; do it
manually, if needed!

Pushing Aggregates Down

```
select Y,Z, sum(A*B*C*…) from…where…
group by Y, Z
```



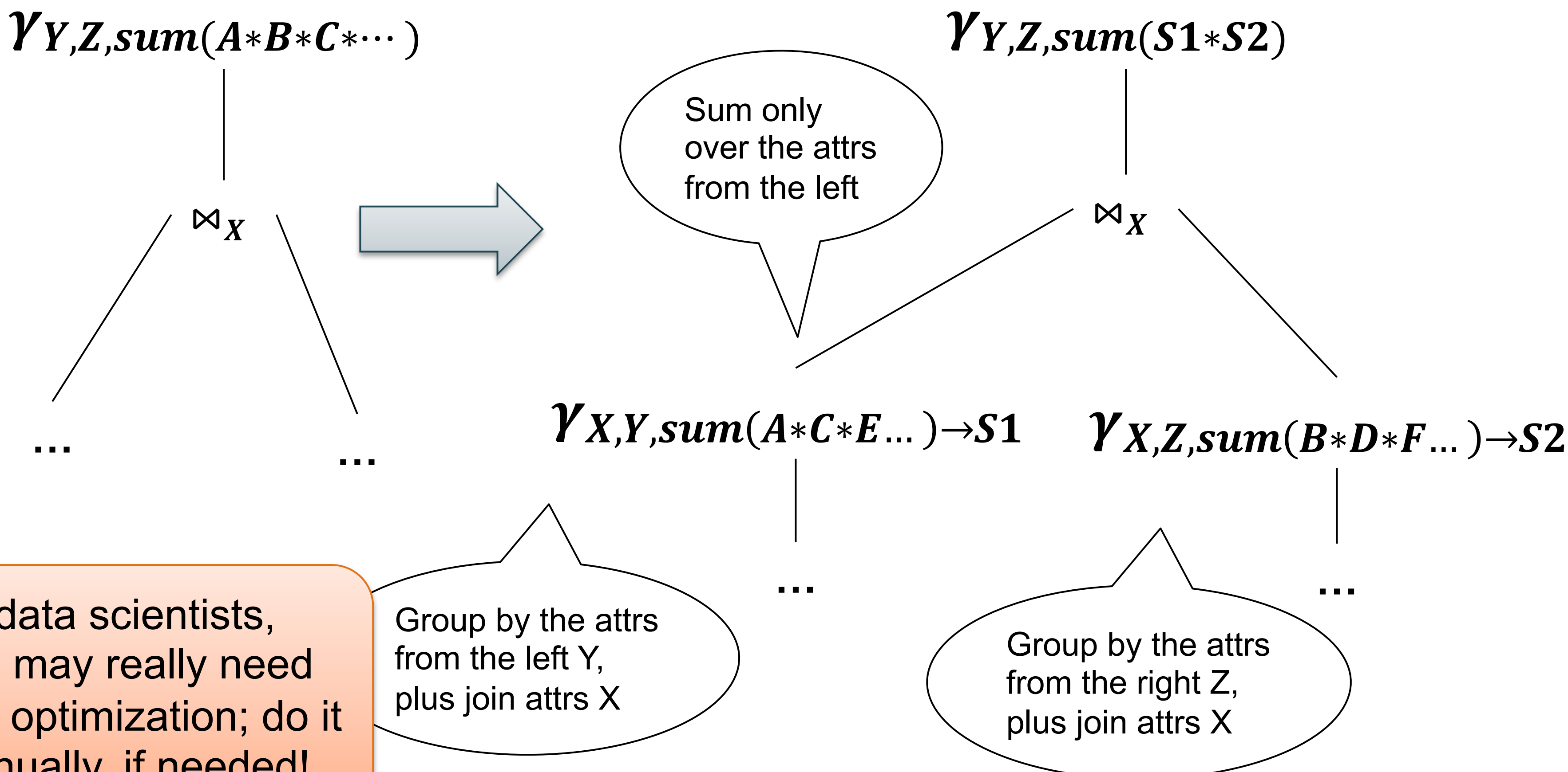
Group by the attrs from the left Y, plus join attrs X

Group by the attrs from the right Z, plus join attrs X

As data scientists, you may really need this optimization; do it manually, if needed!

Pushing Aggregates Down

select Y,Z, sum(A*B*C*…) from…where…
group by Y, Z



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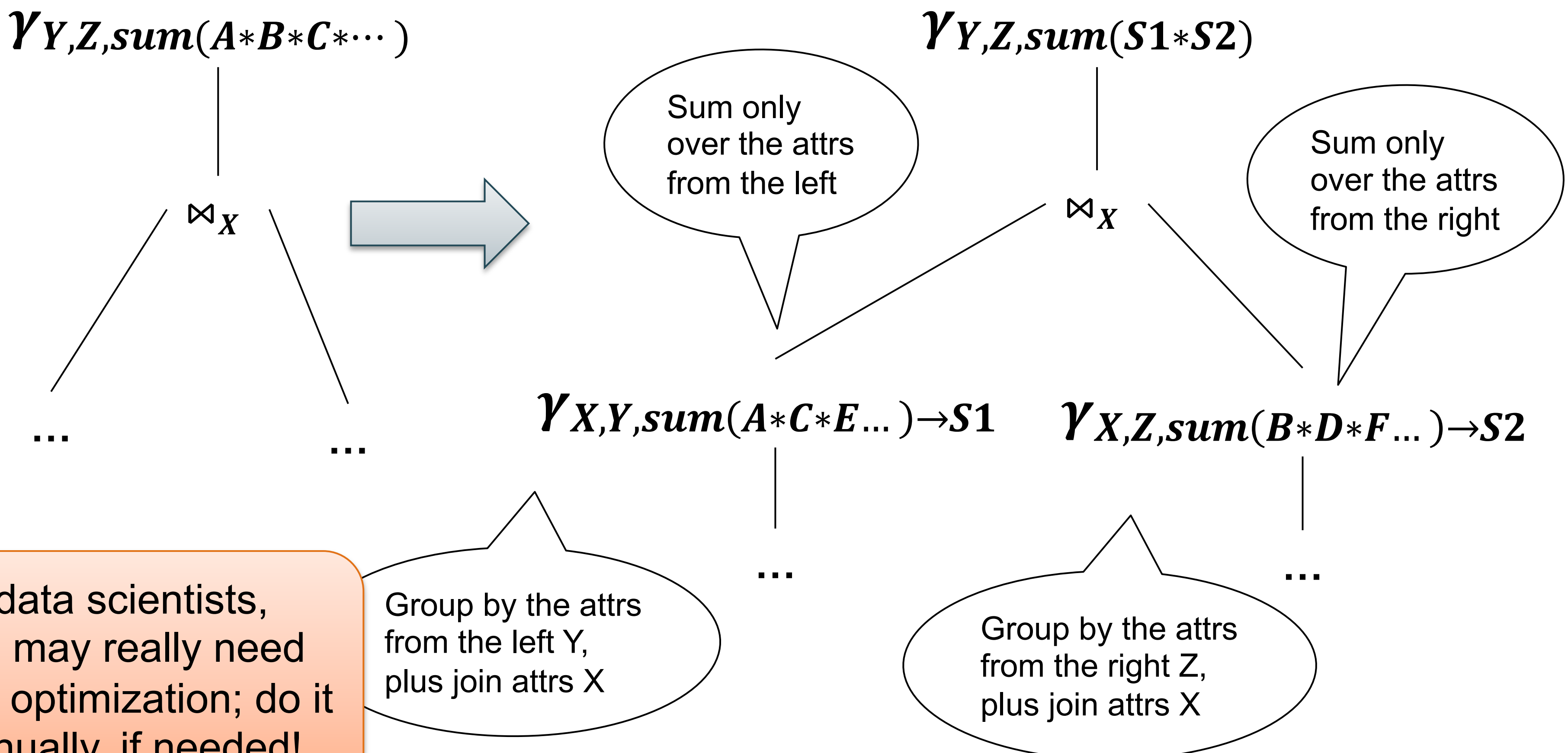
Pushing Aggregates Down

select Y,Z, sum(A*B*C*…) from…where…
group by Y, Z



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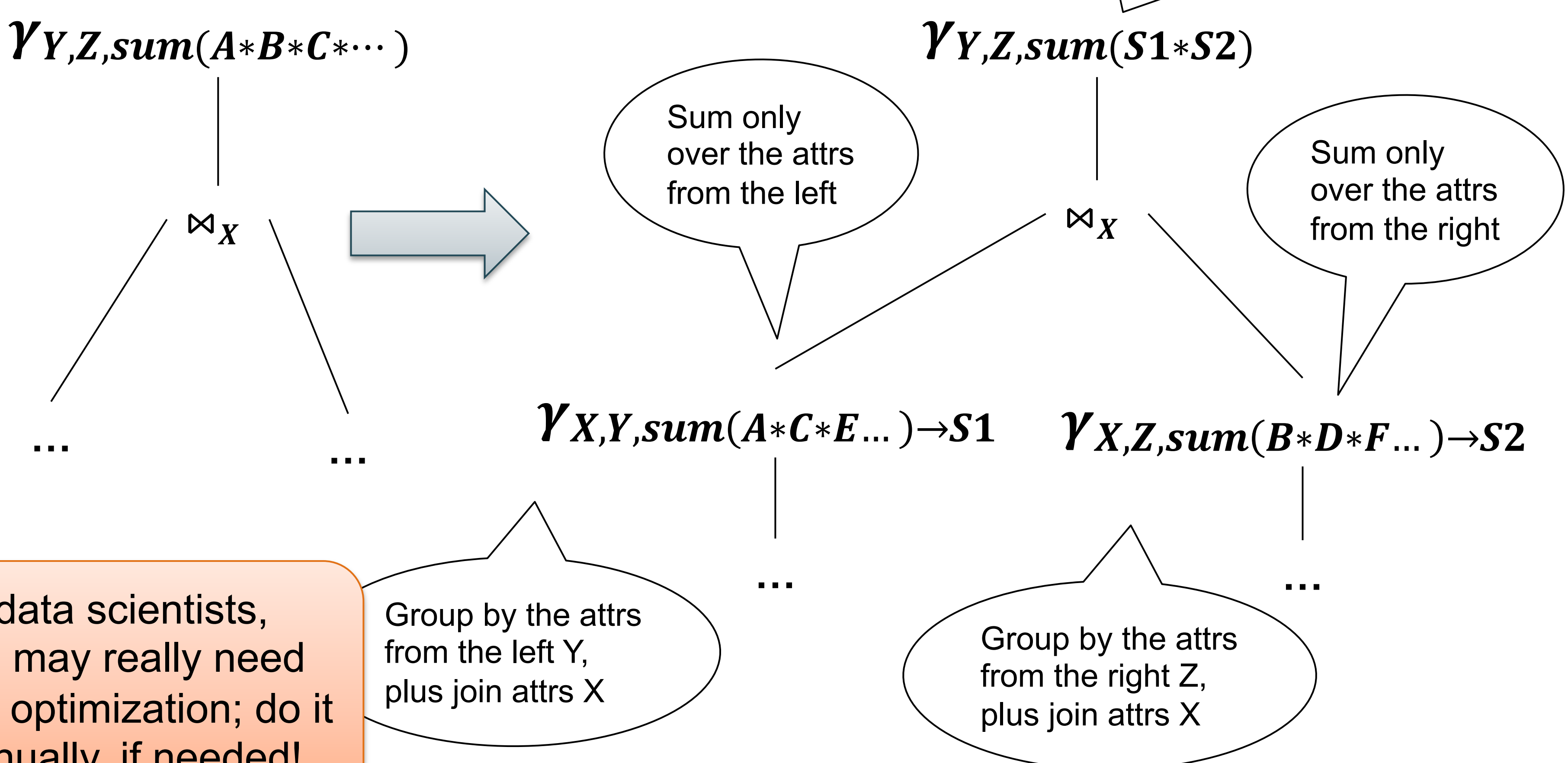
Pushing Aggregates Down

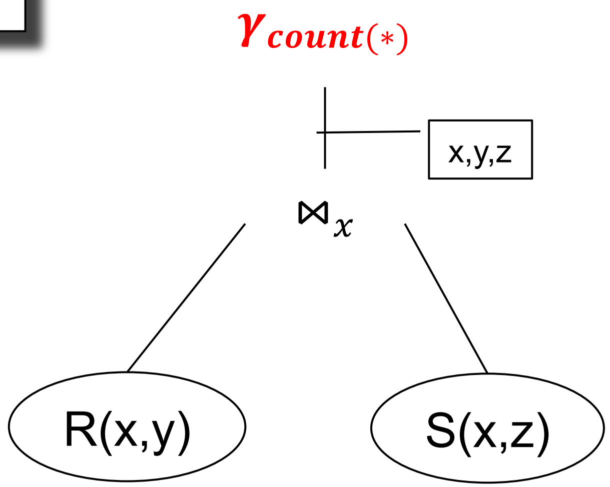
select Y,Z, sum(A*B*C*…) from…where…
group by Y, Z



As data scientists, you may really need this optimization; do it manually, if needed!

Example 1

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



Example 1

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

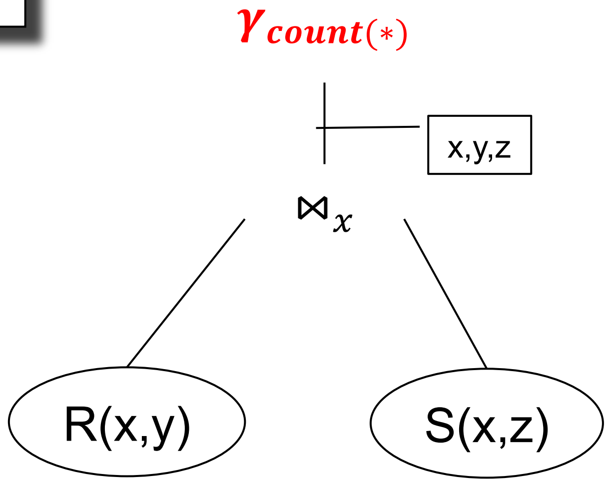
R:

x	y
b	a
b	c
f	d
h	g

S:

x	z
b	g
b	k
h	m

Answer = ????



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R:

x	y
b	a
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f	d
h	g

S:

x	z
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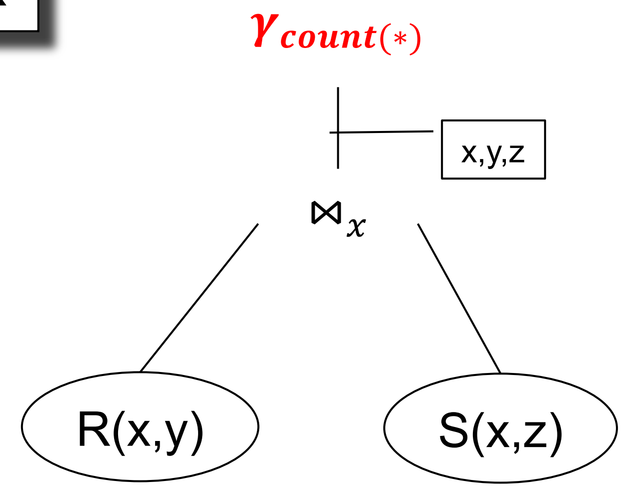
Answer = 5

Runtime = O(N^2)



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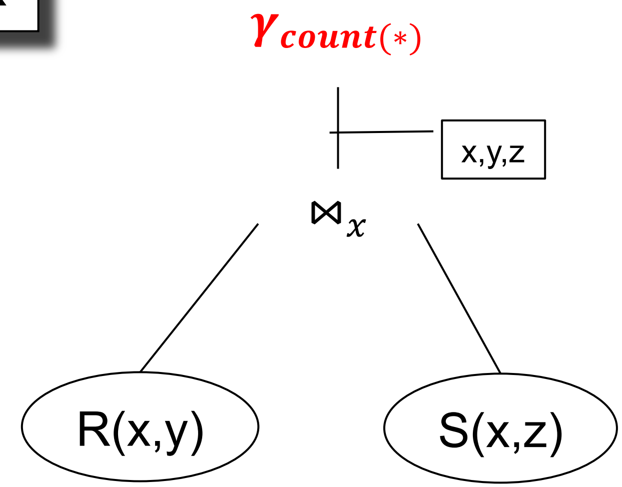
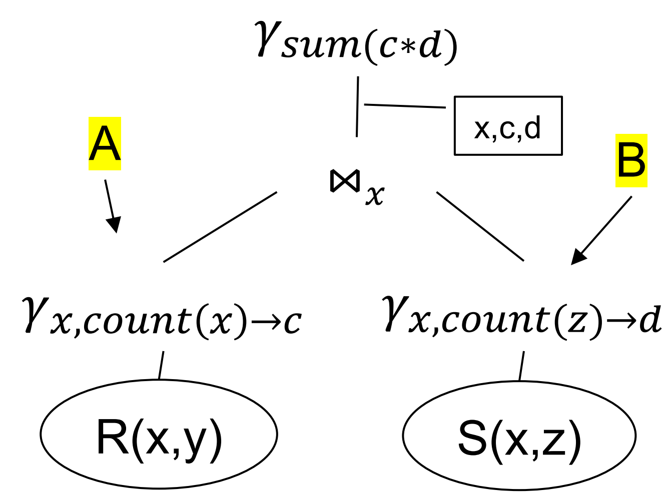
Runtime = $O(N^2)$





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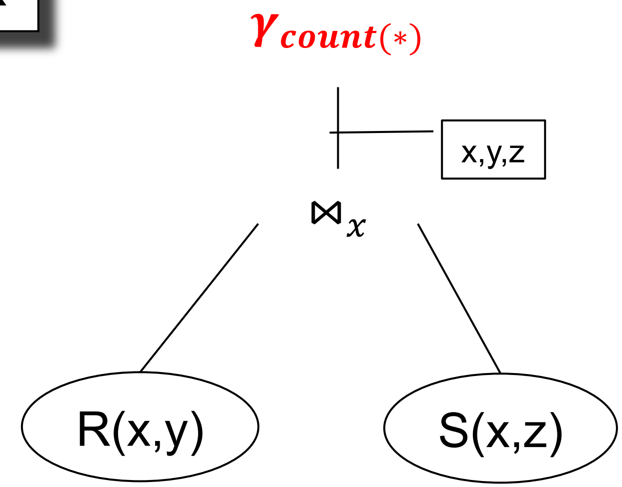


A:

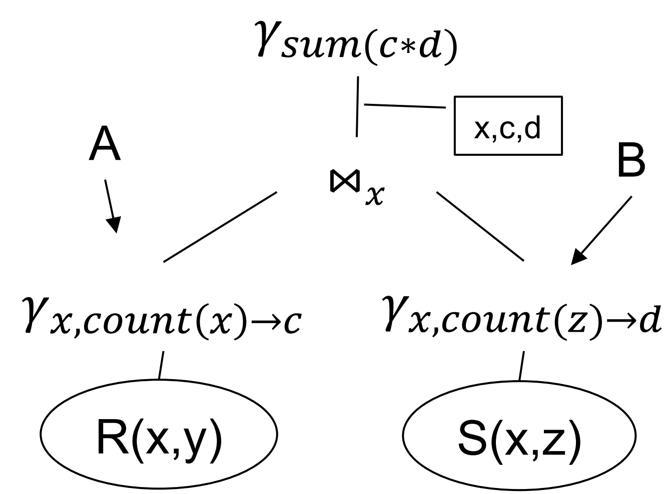
x	c
b	2
f	1
h	1

B:

x	d
b	2
h	1

A⋈B

x	c	d
b	2	2
h	1	1



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S:

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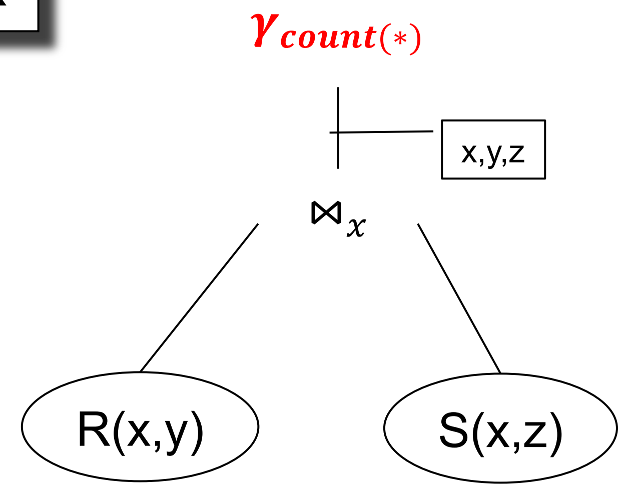
Answer = 5

Runtime = $O(N^2)$



Answer = 5

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A⋈B

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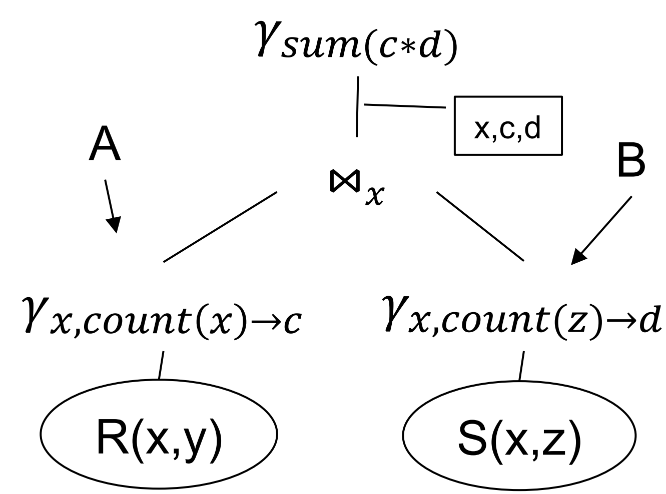


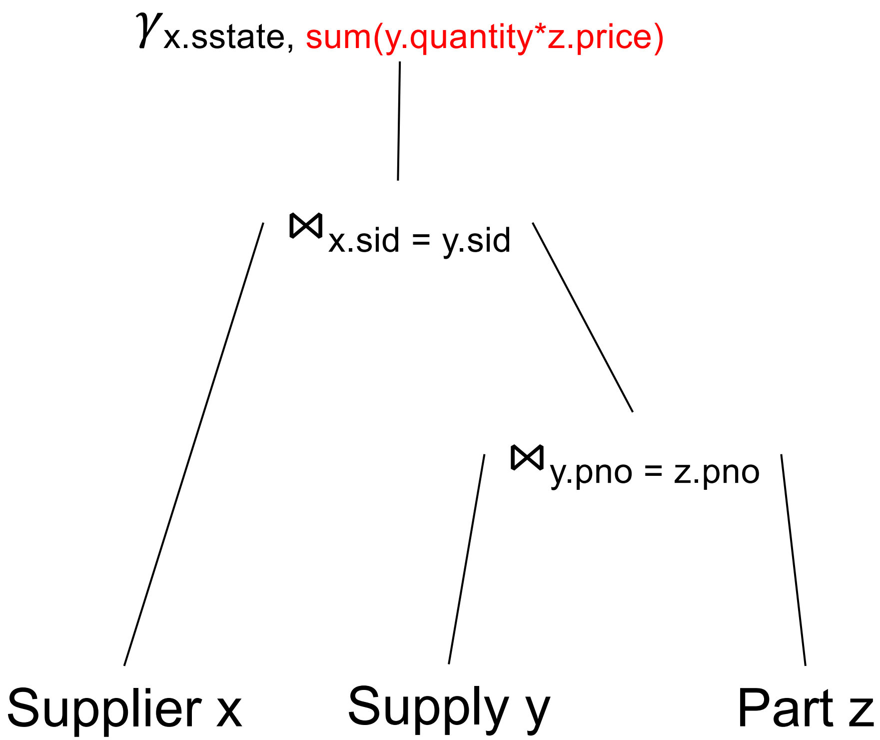
```
Supplier(sid, sname, scity, sstate)
Supply(sid, pno, quantity)
Part(pno, pname, pprice)
```

Example 2

```
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
```

Example 2

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




```
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FROM Supplier x, Supply y, Part z
WHERE x.sid = y.sid and y.pno = z.pno
GROUP BY x.sstate
```

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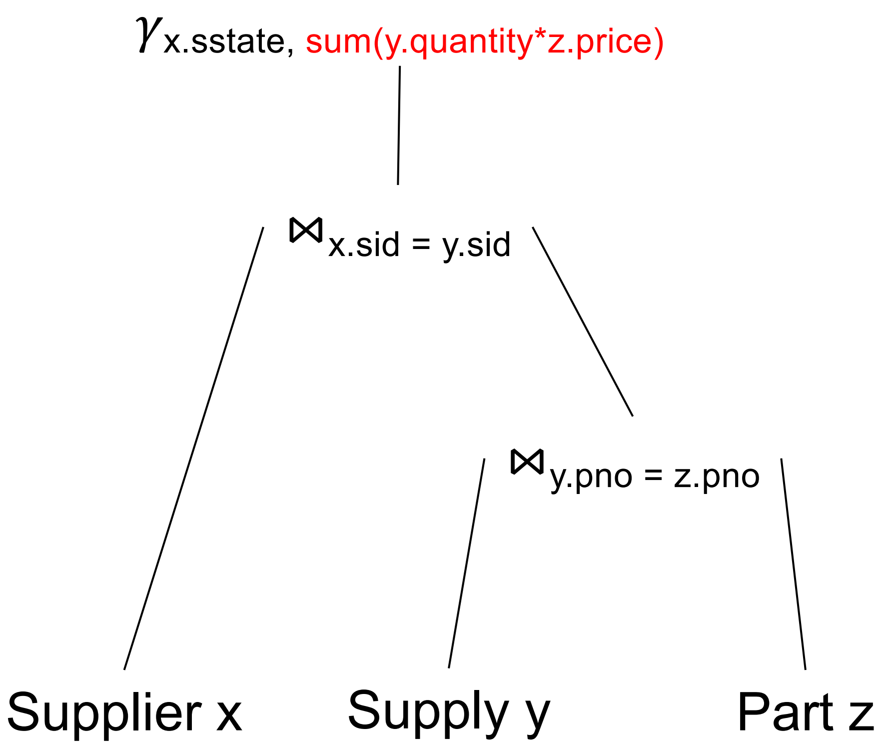
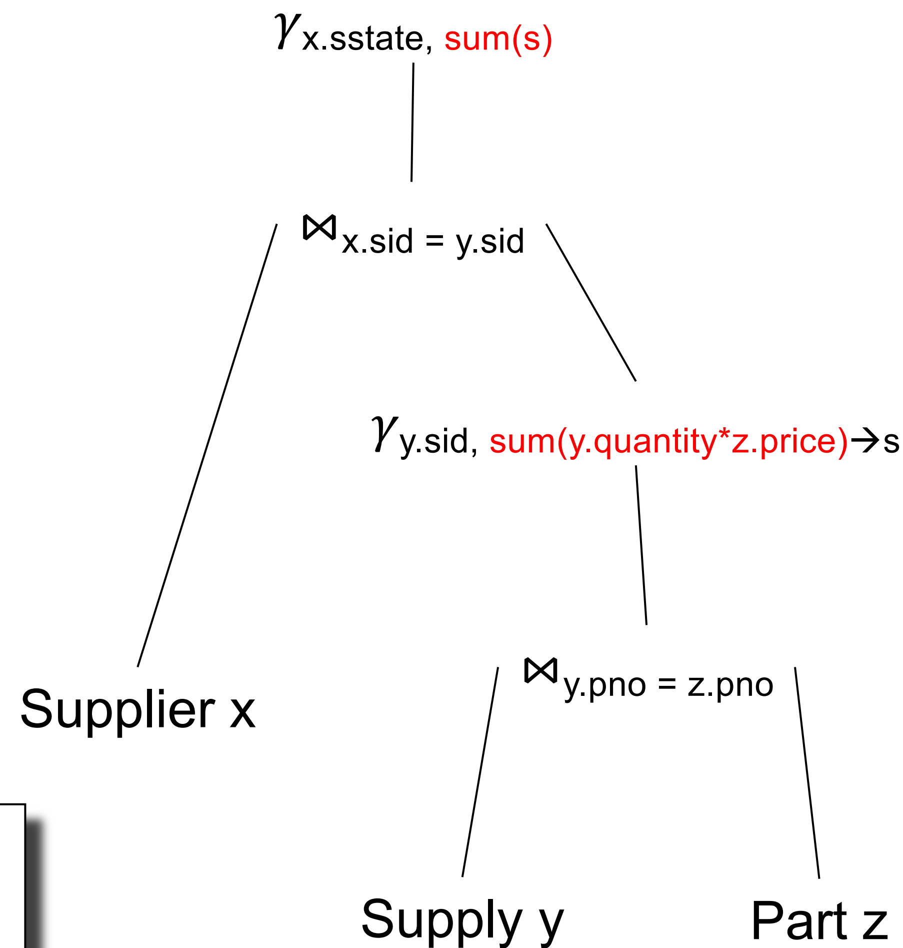





```
SELECT x.sstate, sum(y.quanity*z.price)
FROM Supplier x, Supply y, Part z
WHERE x.sid = y.sid and y.pno = z.pno
GROUP BY x.sstate
```

Discussion

- Join-aggregates: common in data science
- Implementation in RDBMS seems spotty:
  – Postgres: NO (someone started, abandoned)
  – Redshift: NO (I don't know the status)
  – SQL Server: YES (at least a few years back)
  – Snowflake: ??
- You may have to force this manually, by writing nested SQL queries
- Let's make sure we understand it (next)

Redundant Foreign-key / key Joins

- Simple, highly effective
- Almost all engines implement this

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

Foreign-Key / Key

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

?

Supplier(<u>sid</u>, sname, scity, sstate)
Supply(<u>sid, pno</u>, quantity)

Foreign-Key / Key

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

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

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

Foreign-Key / Key

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

```
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

Summary of Rules

- Database optimizers typically have a database of rewrite rules

- E.g. SQL Server: 400+ rules

- Rules become complex as they need to serve specialized types of queries

Query Optimization

1. Search space
2. Cardinality and cost estimation

Discussed already

3. Plan enumeration algorithms

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

- Today's systems combine both

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: $Q = \{R_1, \ldots, R_n\}$

Avoid cartesian products; possibly restrict tree shapes

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)

Details

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

- Size = $T(R_i)$
- Best plan: scan(R_i)
- Cost = $c*T(R_i)$ // c=the cost to read one tuple

Details

Step k = 2…n:
For each $Q = \{R_{i_1}, \ldots, R_{i_k}\}$ // w/o cartesian product

- Size = estimate the size of Q

- For each j=1,…,k:
  - Let: $Q' = Q - \{R_{i_j}\}$
  - Let: $\mathrm{Plan}(Q') \bowtie R_{i_j}$ $\quad \mathrm{Cost}(Q') + \mathrm{CostOf}(\bowtie)$

- $\mathrm{Plan}(Q), \mathrm{Cost}(Q) =$ cheapest of the above

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

- Optimizer has three components:
  - Search space
  - Cardinality and cost estimation
  - Plan enumeration algorithms
- Optimizer realizes *physical data independence*
- Weakest link: cardinality estimation
  - Poor plans are almost always due to that

Spark

Motivation

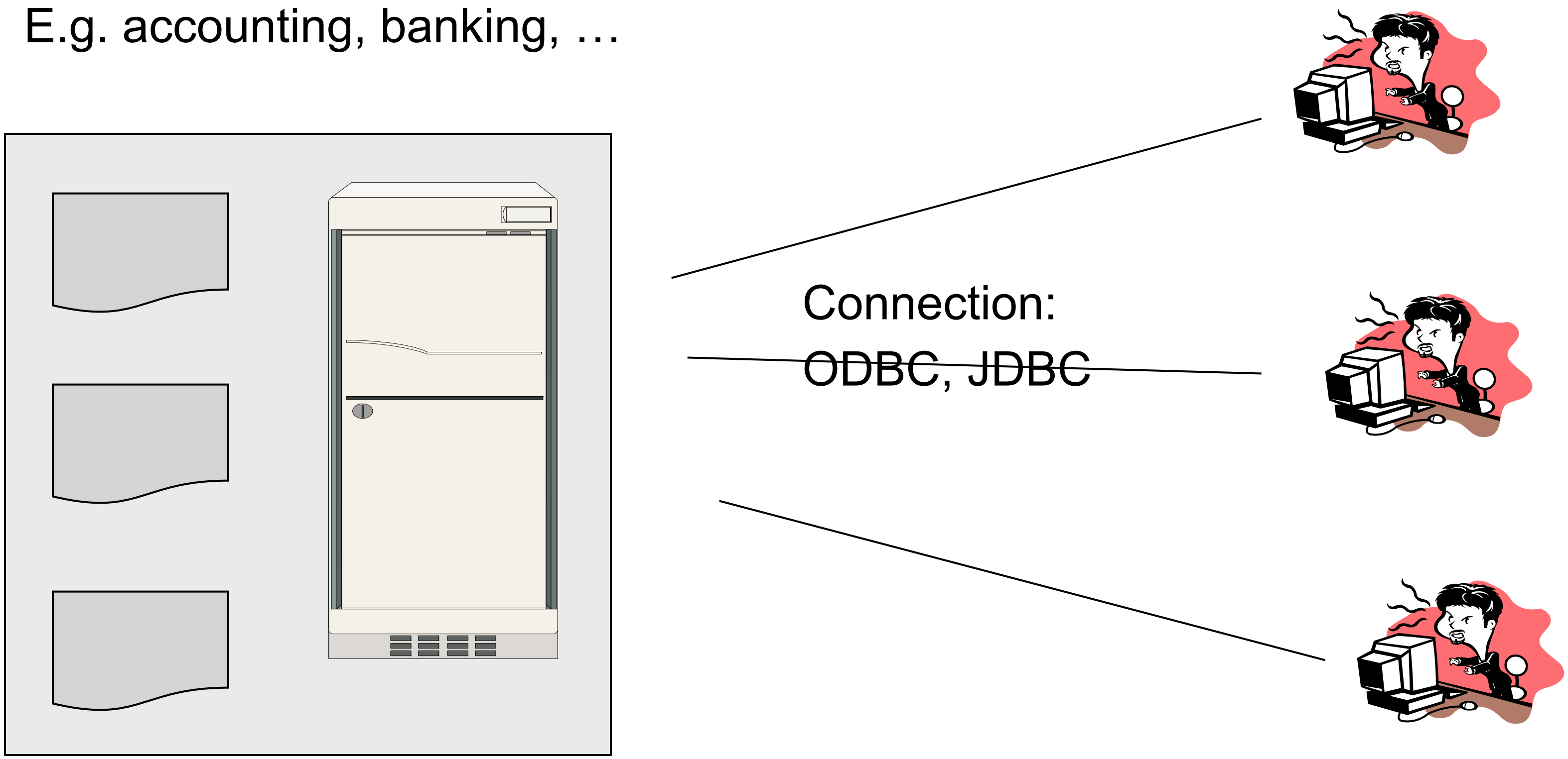
- Limitations of relational database systems:
  - Single server (at least traditionally)
  - SQL is a limited language (eg no iteration)
- Spark:
  - Distributed system
  - Functional language (Java/Scala) good for ML
- Implementation:
  - Extension of MapReduce
  - Distributed physical operators

Review: Single Client

E.g. data analytics

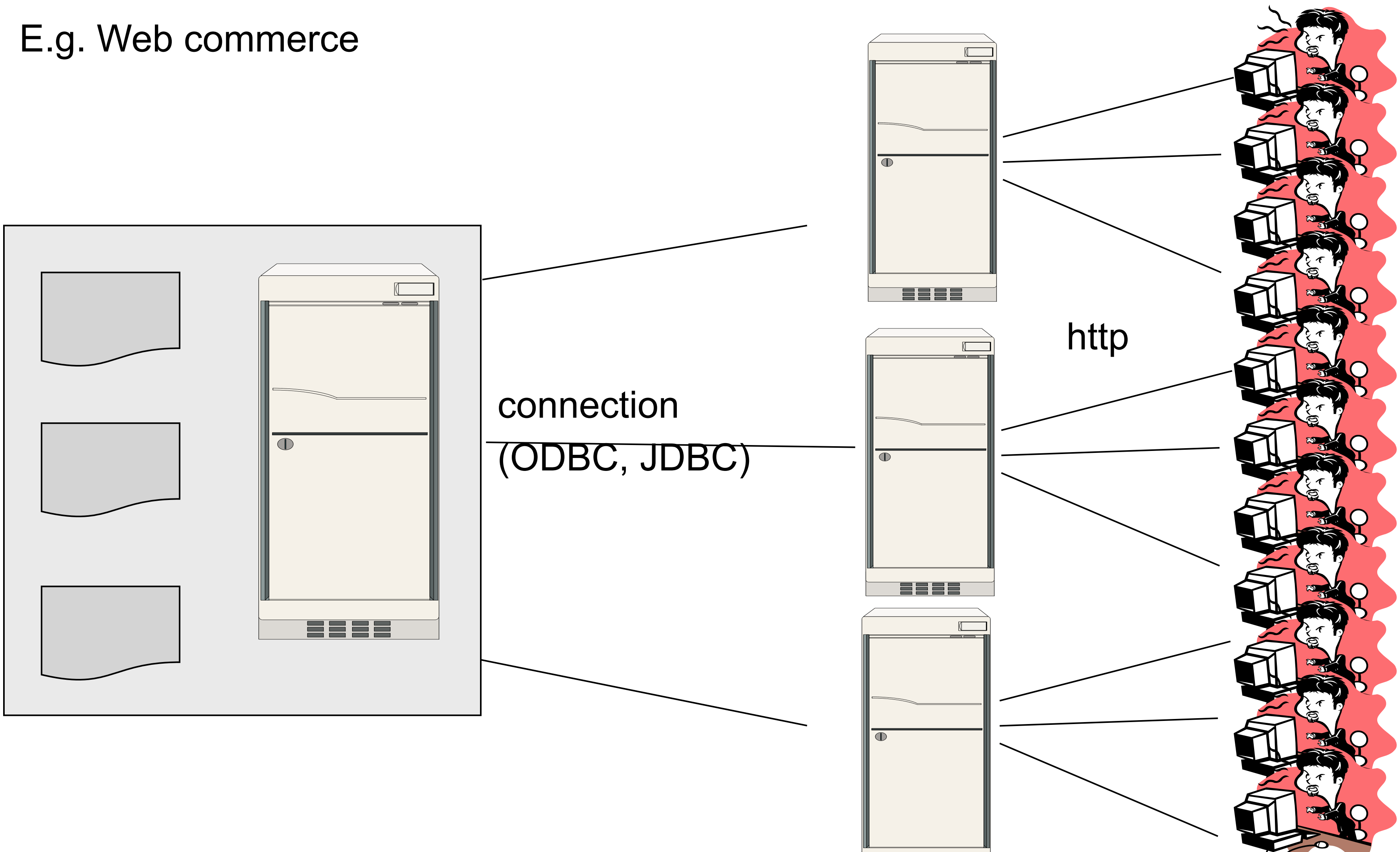
Review: Client-Server

E.g. accounting, banking, …

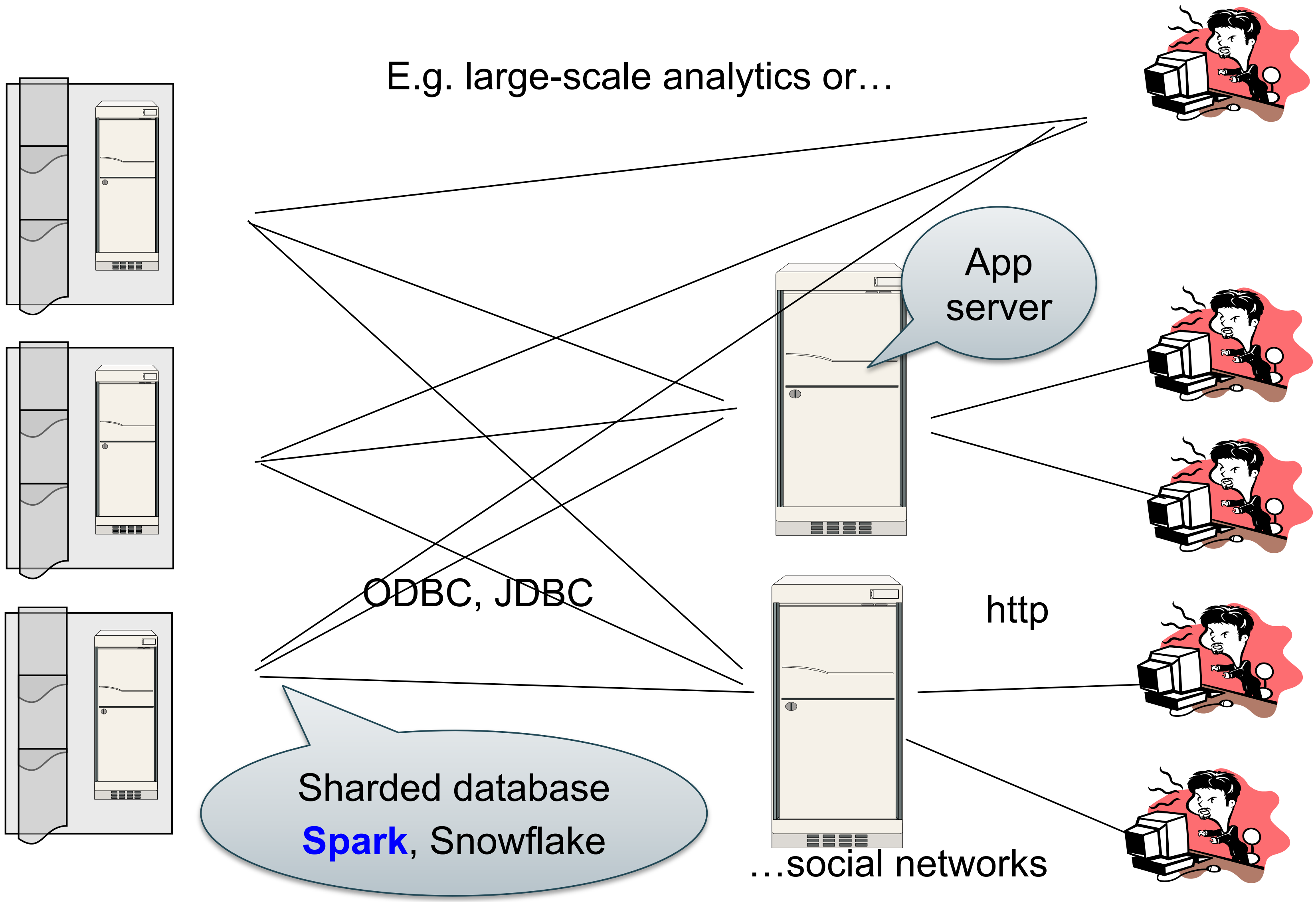


Review: Three-tier

E.g. Web commerce



Review: Distributed Database



Programming in Spark

- A Spark program consists of:
  - Transformations (map, reduce, join…). Lazy
  - Actions (count, reduce, save...). Eager

- Eager: operators are executed immediately

- Lazy: operators are not executed immediately
  - A *operator tree* is constructed in memory instead
  - Similar to a relational algebra tree

Collections in Spark

RDD<T> = an RDD collection of type T

- Distributed on many servers, not nested
- Operations are done in parallel
- Recoverable via lineage; more later

Seq<T> = a sequence

- Local to one server, may be nested
- Operations are done sequentially

Example from paper, new syntax

Search logs stored in HDFS

```
// First line defines RDD backed by an HDFS file
lines = spark.textFile(“hdfs://…”)

// Now we create a new RDD from the first one
errors = lines.filter(x -> x.startsWith(“Error”))

// Persist the RDD in memory for reuse later
errors.persist()
errors.collect()
errors.filter(x -> x.contains(“MySQL”)).count()
```

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Transformation: Not executed yet…

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// Persist the RDD in memory for reuse later
errors.persist()
errors.collect()
errors.filter(x -> x.contains("MySQL")).count()
```

Transformation: Not executed yet…

Action: triggers execution of entire program

Anonymous Functions

A.k.a. lambda expressions, starting in Java 8

```
errors = lines.filter(x -> x.startsWith("Error"))
```

Chaining Style

```
sqlerrors = spark.textFile("hdfs://…")
            .filter(x -> x.startsWith("ERROR"))
            .filter(x -> x.contains("sqlite"))
            .collect();
```

Example

The RDD s:

Error…	Warning…	Warning…	Error…	Abort…	Abort…	Error…	Error…	Warning…	Error…

```
sqlerrors = spark.textFile("hdfs://…")
             .filter(x -> x.startsWith("ERROR"))
             .filter(x -> x.contains("sqlite"))
             .collect();
```

Example

Parallel step 1

The RDD s:

Error…	Warning…	Warning…	Error…	Abort…	Abort…	Error…	Error…	Warning…	Error…
filter("ERROR")	filter("ERROR")	filter("ERROR")	filter("ERROR")	filter("ERROR")	filter("ERROR")	filter("ERROR")	filter("ERROR")	filter("ERROR")	filter("ERROR")

```
sqlerrors = spark.textFile("hdfs://…")
            .filter(x -> x.startsWith("ERROR"))
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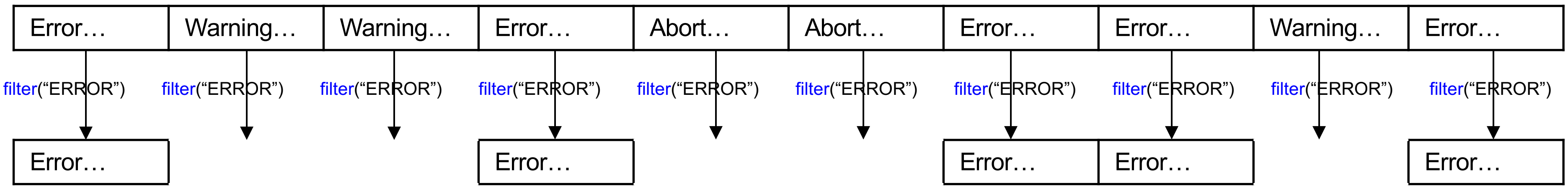
            .collect();
```

Example

Parallel step 1

The RDD s:

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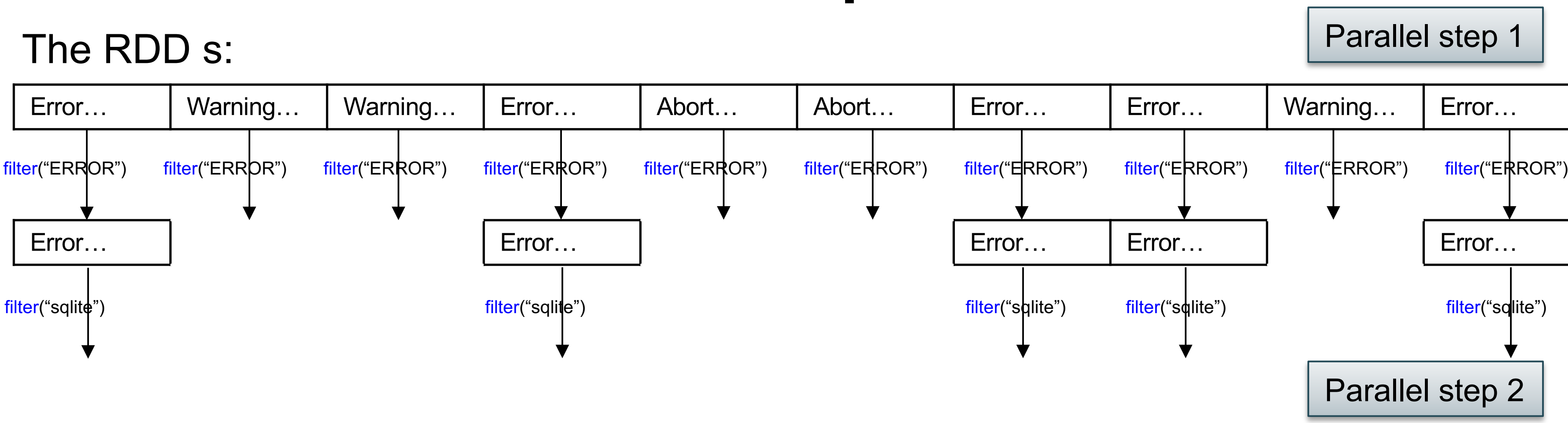


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```

More on Programming Interface

Large set of pre-defined transformations:

- Map, filter, flatMap, sample, groupByKey, reduceByKey, union, join, cogroup, crossProduct, …

Small set of pre-defined actions:

- Count, collect, reduce, lookup, and save

Programming interface includes **iterations**

Transformations:	
`map(f : T -> U):`	`RDD<T> -> RDD<U>`
`flatMap(f: T -> Seq(U)):`	`RDD<T> -> RDD<U>`
`filter(f:T->Bool):`	`RDD<T> -> RDD<T>`
`groupByKey():`	`RDD<(K,V)> -> RDD<(K,Seq[V])>`
`reduceByKey(F:(V,V)-> V):`	`RDD<(K,V)> -> RDD<(K,V)>`
`union():`	`(RDD<T>,RDD<T>) -> RDD<T>`
`join():`	`(RDD<(K,V)>,RDD<(K,W)>) -> RDD<(K,(V,W))>`
`cogroup():`	`(RDD<(K,V)>,RDD<(K,W)>)-> RDD<(K,(Seq<V>,Seq<W>))>`
`crossProduct():`	`(RDD<T>,RDD<U>) -> RDD<(T,U)>`

Actions:	
`count():`	`RDD<T> -> Long`
`collect():`	`RDD<T> -> Seq<T>`
`reduce(f:(T,T)->T):`	`RDD<T> -> T`
`save(path:String):`	Outputs RDD to a storage system e.g., HDFS

More Complex Example

```
val points = spark.textFile(...)
                  .map(parsePoint).persist()
var w = // random initial vector
for (i <- 1 to ITERATIONS) {
  val gradient = points.map{ p =>
    p.x * (1/(1+exp(-p.y*(w dot p.x)))-1)*p.y
  }.reduce((a,b) => a+b)
  w -= gradient
}
```

[From Zaharia12]