CSE544
Data Management

Lecture 12

Annoucements

- No lecture Monday, 2/19
- No lecture Wednesday, 2/21
- Makeup lecture Friday, 2/23 – Gates371
- Also Friday 2/23: HW3 is due
- Project milestone due Monday, 2/26

Query Optimization

Three major components:

1. Search space — last week
2. Cardinality and cost estimation — last lecture
3. Plan enumeration algorithms — today

Paper Discussion

- How Good Are Query Optimizers, Really? VLDB’2015

Questions in the paper

- How good are cardinality estimators?
- How important are they for the optimizer?
- How large does the plan space need to be?

Cardinality Estimators

- Standard database benchmark: TPC-H
- They designed a new benchmark. Why?

Cardinality Estimators

- Standard database benchmark: TPC-H
- They designed a new benchmark. Why?
- Because TPC-H is synthetically generated, unrealistically uniform

Cardinality Estimators

What type of queries are in IMDB/JOB?

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- For CE: select * multijoin queries
- For runtime: replace * with min   Why?

Cardinality Estimators

What type of queries are in IMDB/JOB?

- For CE: select * multijoin queries
- For runtime: replace * with min Why?

- Materializing * is expensive…
- …and postgres does not push min down the plan

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

Single Table Estimation

What technique helped here? (conjectured)

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Table 1: Q-errors f[illegible]elections

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Sampling. E.g. Hyper: 1000 rows

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Table 1: Q-errors for b tions

Low selectivity:
$10^{-5} – 10^{-6}$

Single Table Estimation

- 1d Histograms:
  - Good for single equality or range predicate
  - Poor for multiple predicates
  - Useless for LIKE
- Samples:
  - Good for multiple predicates, LIKE
  - Poor for low selectivity predicates

Joins (0 to 6)

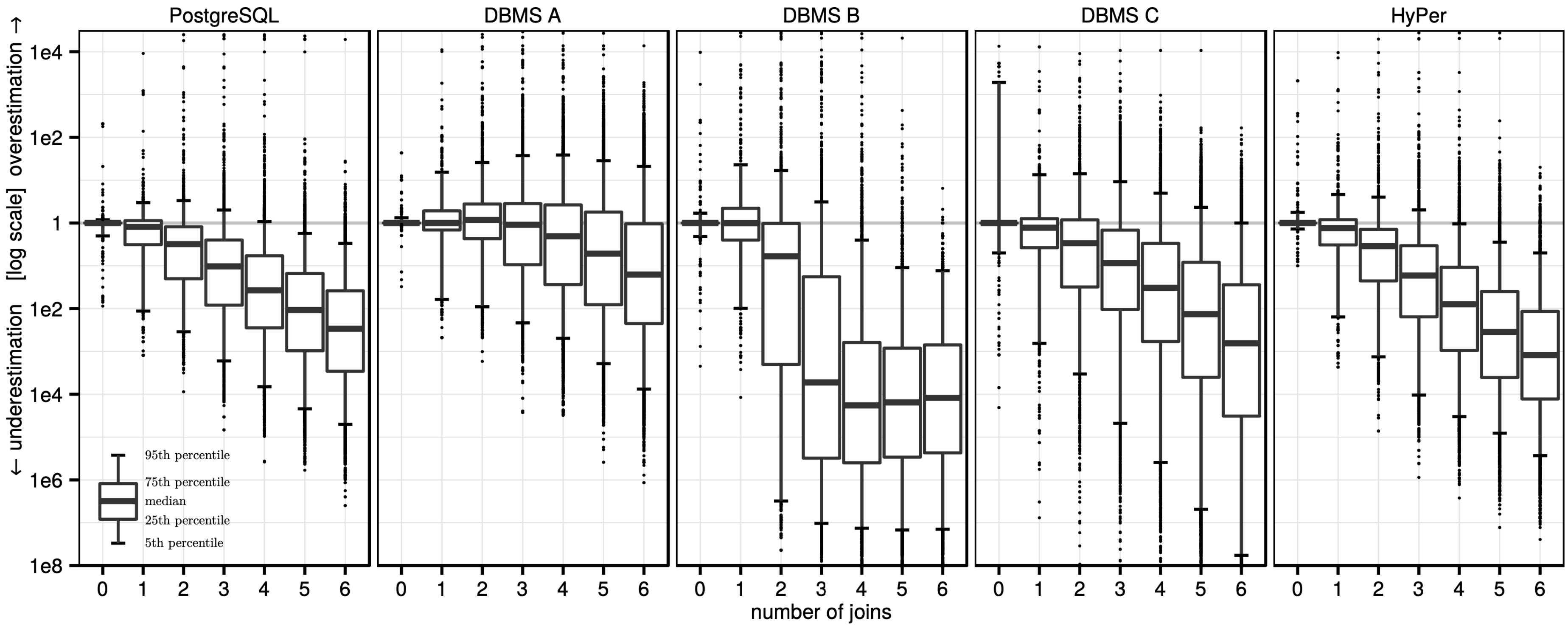

Figure 3: Quality of cardinality estimates for multi-join queries in comparison with the true cardinalities. Each boxplot summarizes the error distribution of all subexpressions with a particular size (over all queries in the workload)

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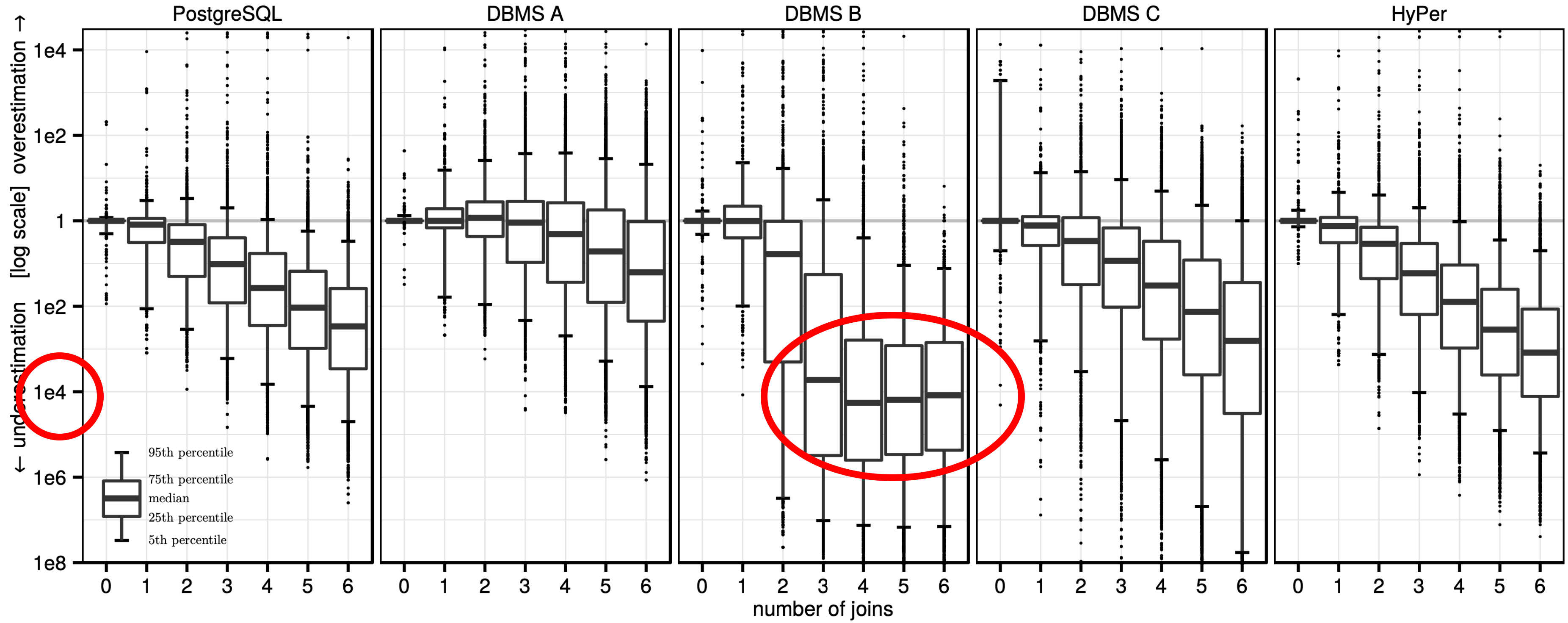

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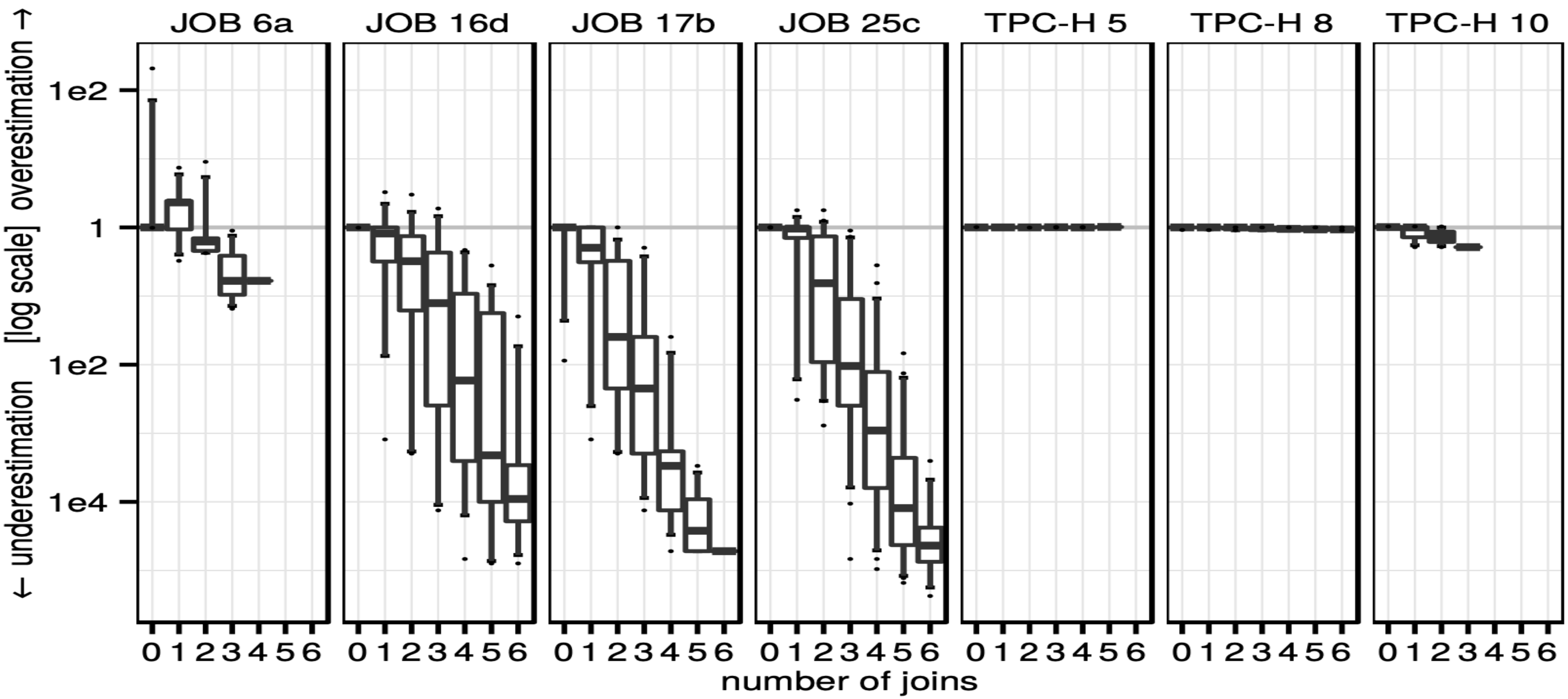
Estimation of Joins

- Error increases exponentially with the number of joins
  - This was known from [Ioannidis'91]

- Underestimate, because of positive correlations

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



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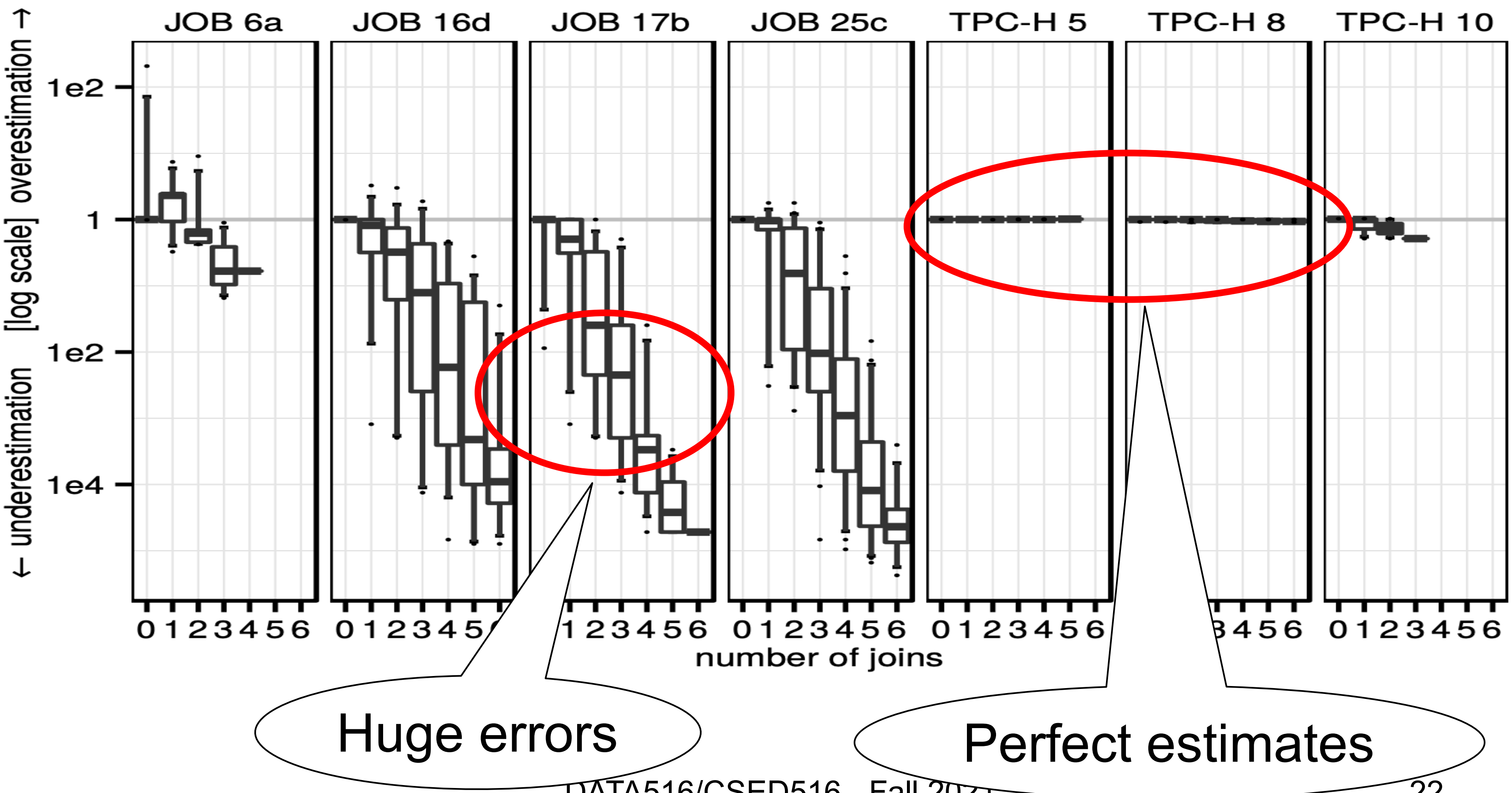

Impact of Mis-estimates

- Question: how much does a good/poor CE matter for the quality of a query plan
- How did they measure that?

Impact of Mis-estimates

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- How did they measure that?
  - Inject into postgres other systems' estimates – won't discuss this
  - Inject into postgres true cardinalities; call it optimal plan, compare with regular plan
- Two configs of indexes: PK and PK+FK

Impact of Mis-estimates

PK indexes

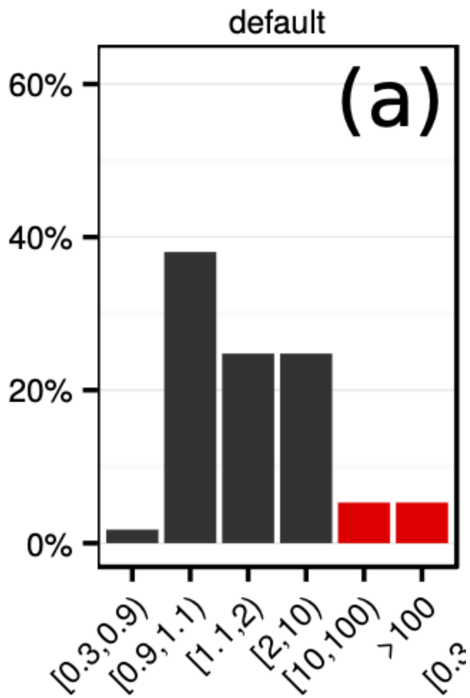
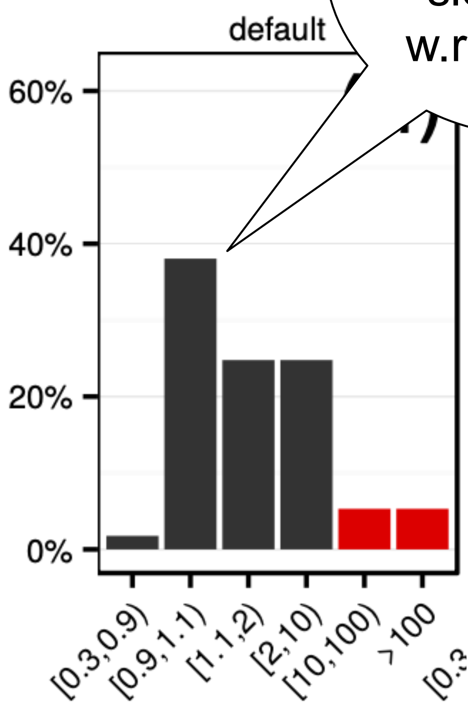


Figure 6: Slowdown of queries using PostgreSQL estimates w.r.t. using true cardinalities (primary key indexes only)

Impact of Mis-estimates

PK indexes

Most queries: no slowdown w.r.t optimal



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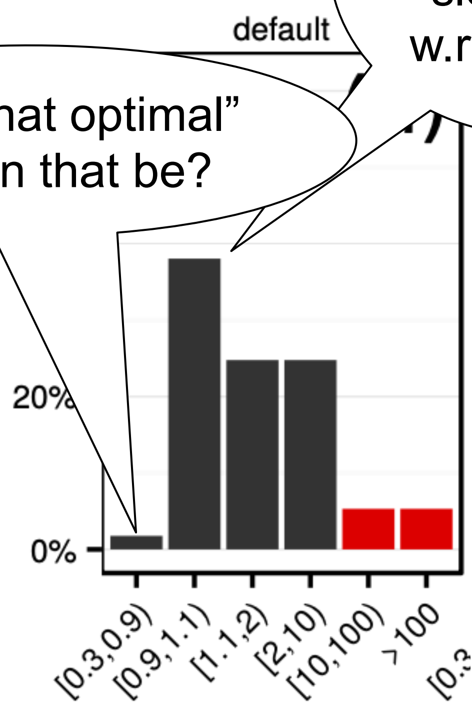
"Better that optimal" how can that be?



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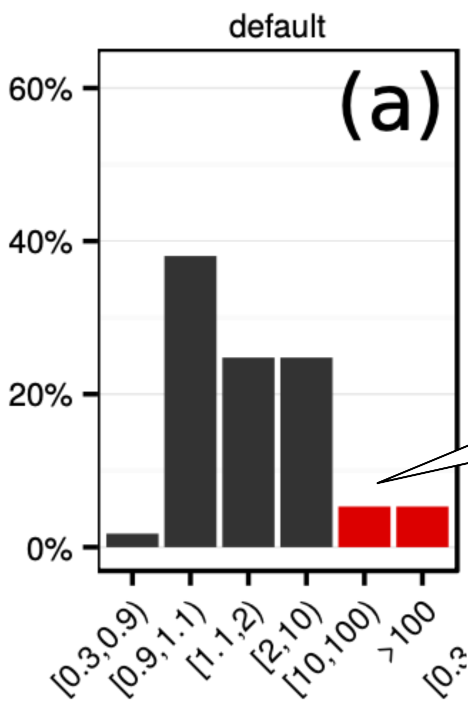

Which queries
had major slowdown?

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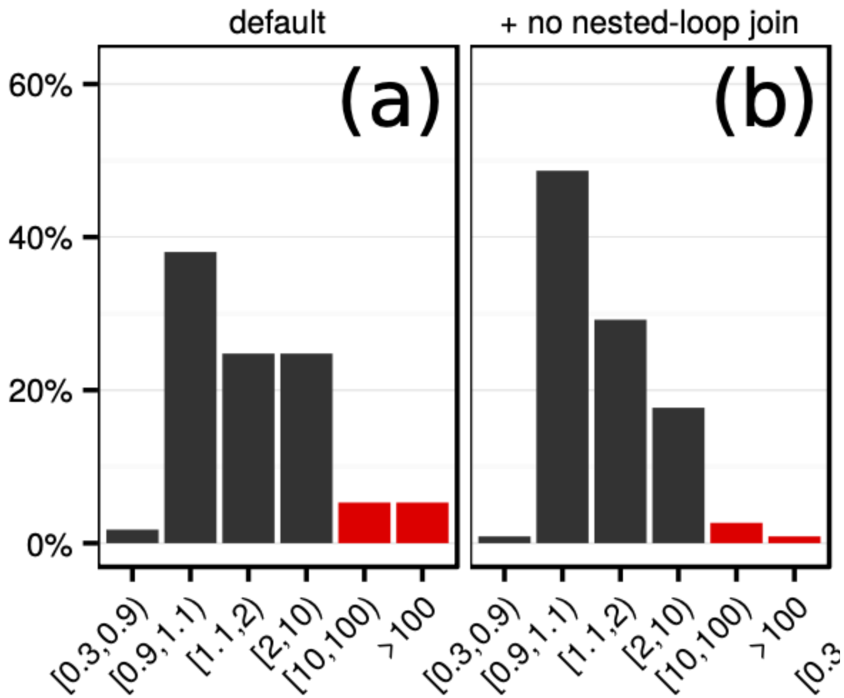
Impact of Mis-estimates

PK indexes



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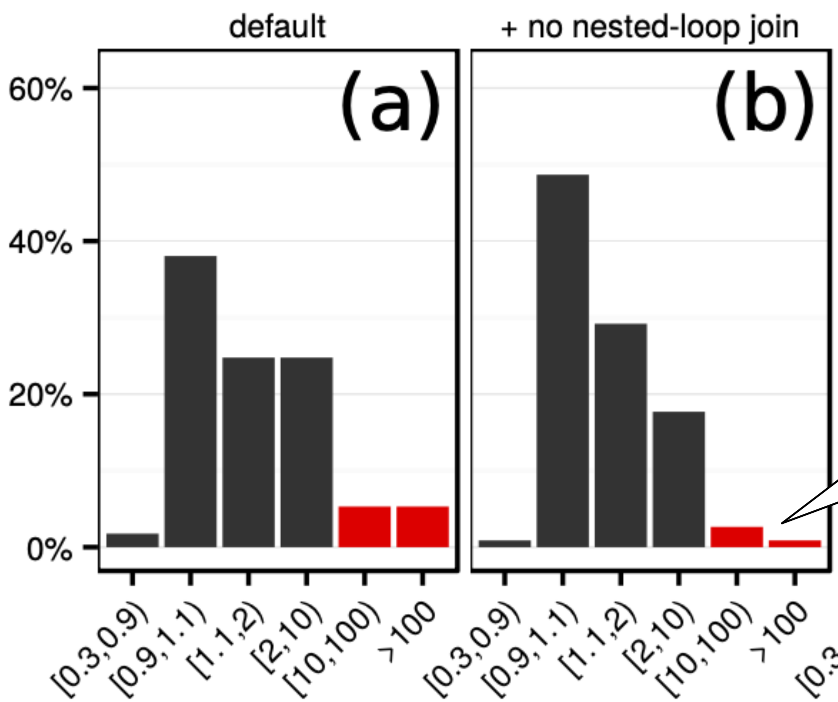

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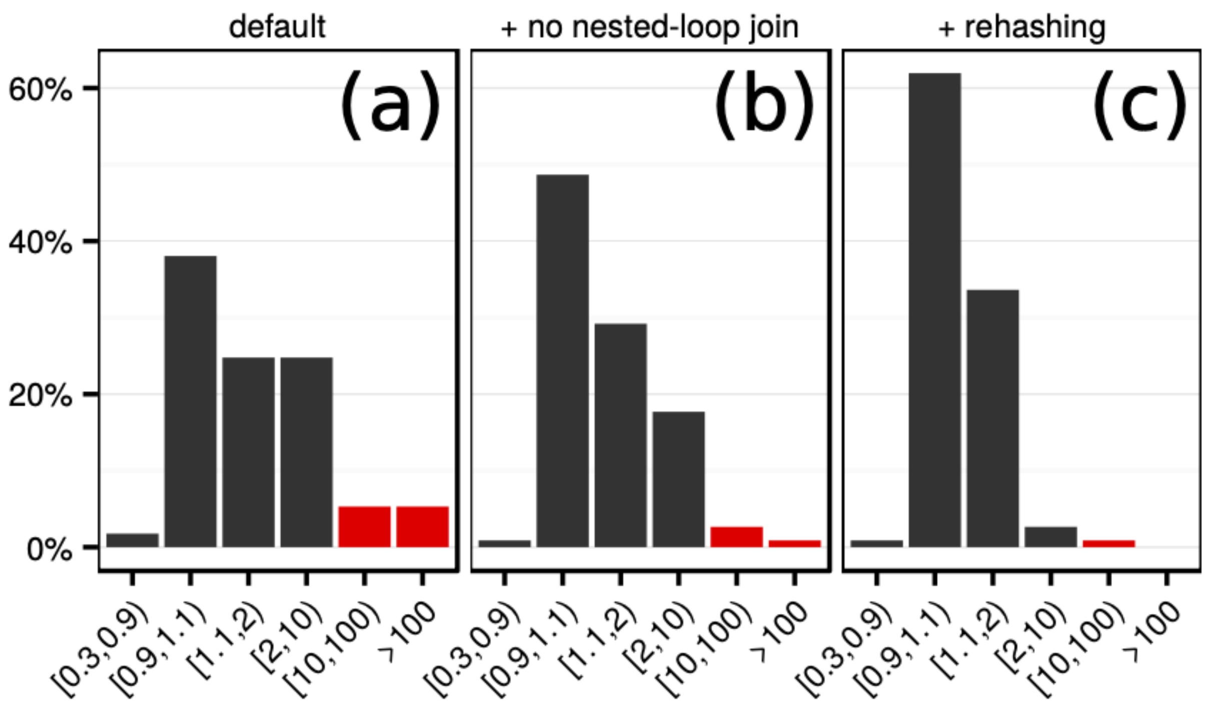
Still some queries significantly slower.
Why?

Impact of Mis-estimates

PK indexes



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Impact of Mis-estimates

Indexes on PK only

- Low sensitivity to CE, because the “fact” table needs to be scanned anyway
- Plans most sensitive to CE errors:
  - Plans with nested-loop joins
  - Hash-table preallocation
- Discuss “robust query optimization”

Impact of Mis-estimates

FK/PK indexes

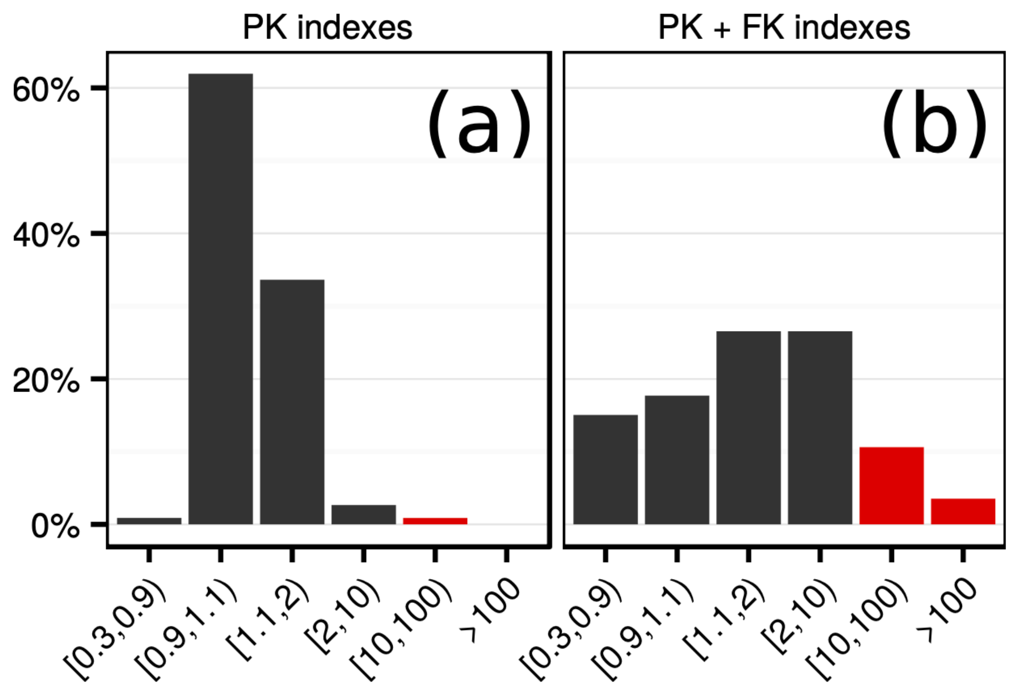
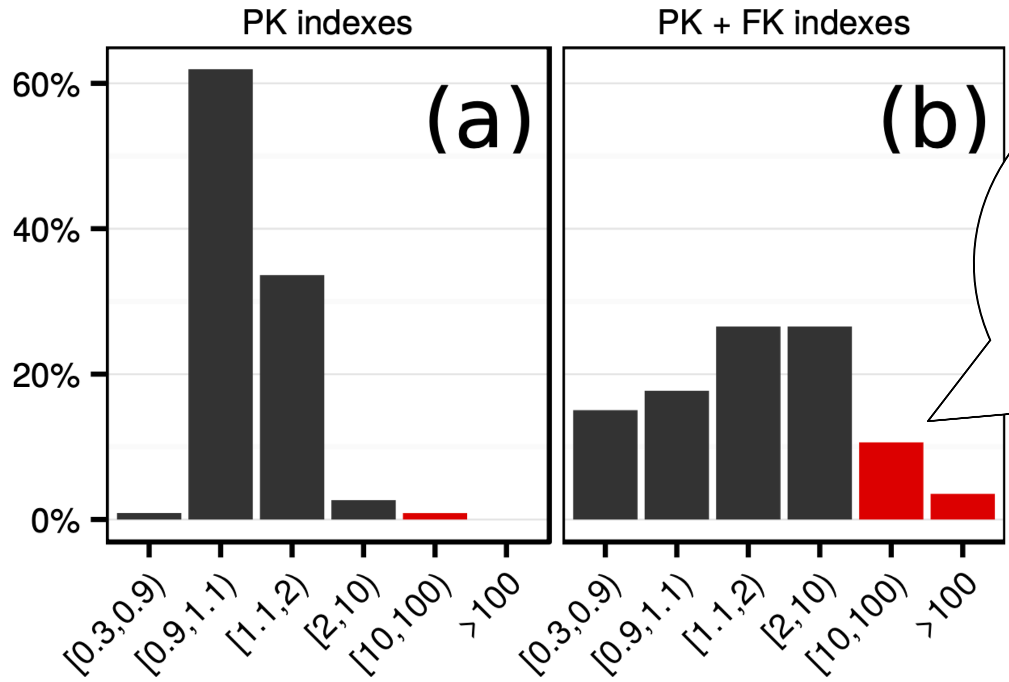


Figure 7: Slowdown of queries using PostgreSQL estimates w.r.t. using true cardinalities (different index configurations)

Impact of Mis-estimates

FK/PK indexes



Better runtime, but more plans available: more sensitive to CE errors

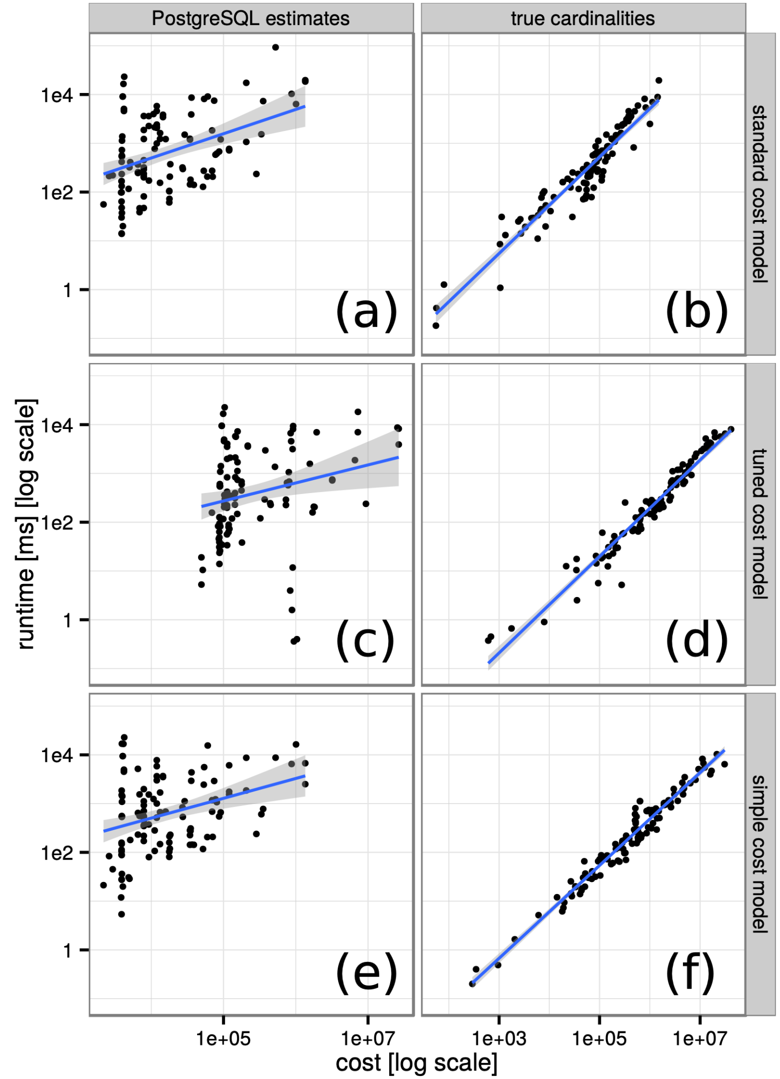
Figure 7: Slowdown of queries using PostgreSQL estimates w.r.t. using true cardinalities (different index configurations)

Discussion

- When PK indexes only, optimizer chooses a good plan anyway; impact of CE is limited; confirmed by others too

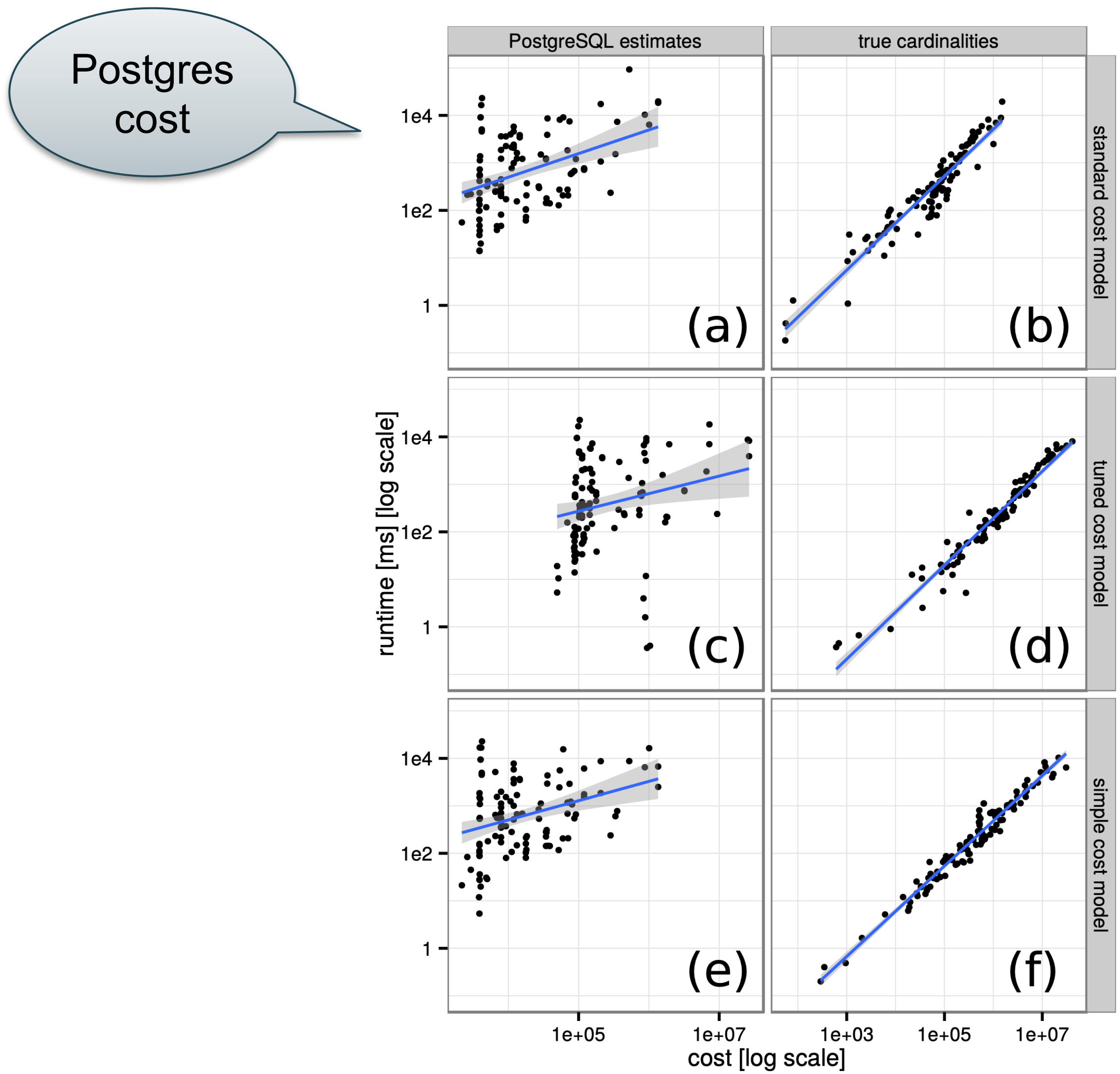
- When indexes on PK+FK, performance improves, but sensitivity to CE higher

Cardinalities to Cost



[How good are they]

Cardinalities to Cost



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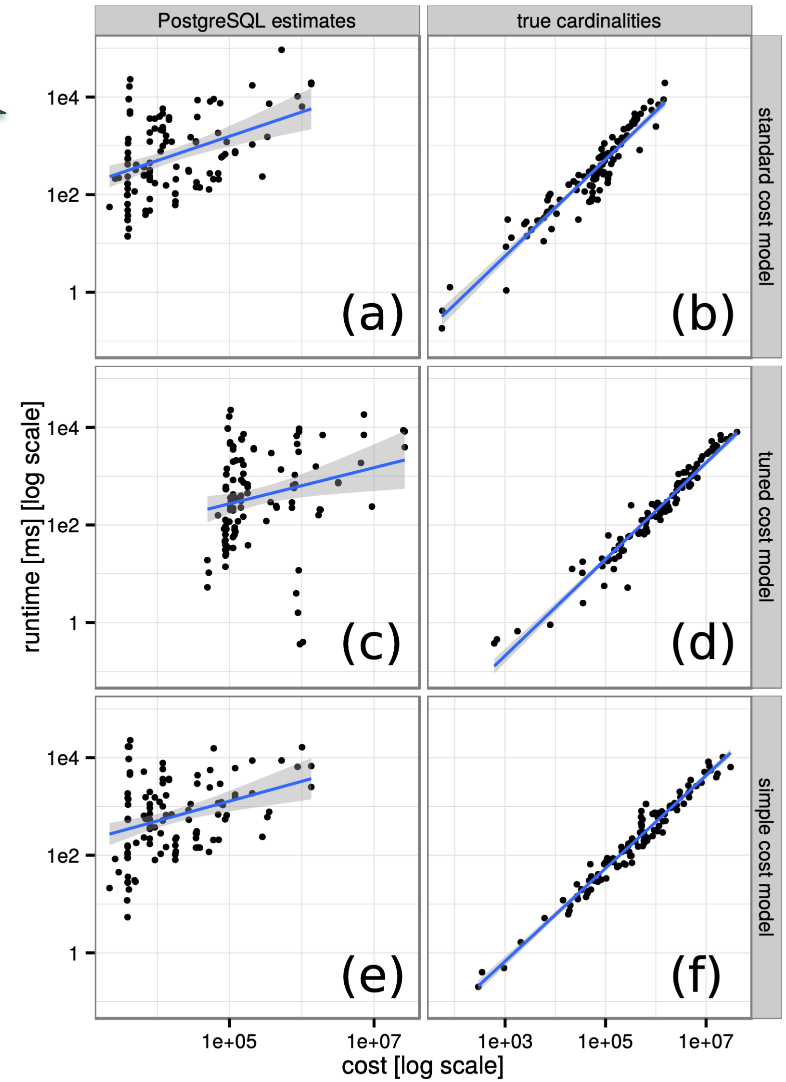
Cardinalities to Cost

Postgres cost

No I/O, keep only CPU



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Cardinalities to Cost

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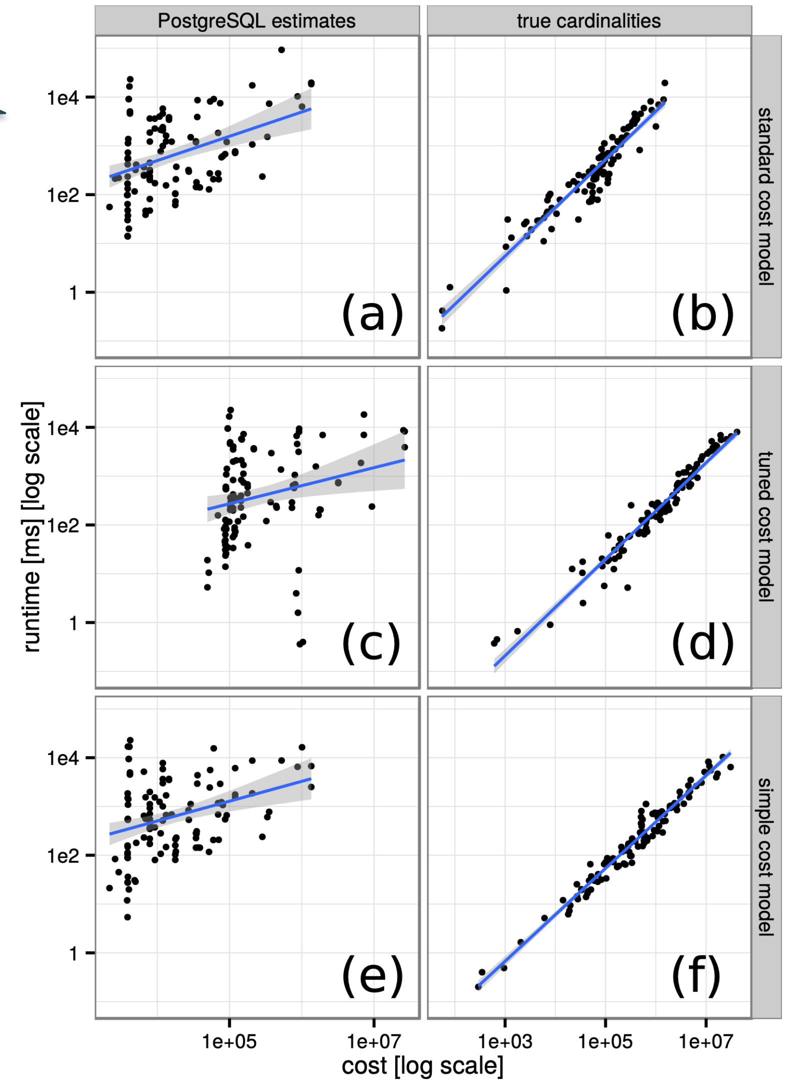
Their own simple formula



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Cardinalities to Cost

- CE accounts for largest errors

Postgres cost

- Cost models: both simple or complex are fine

No I/O, keep only CPU

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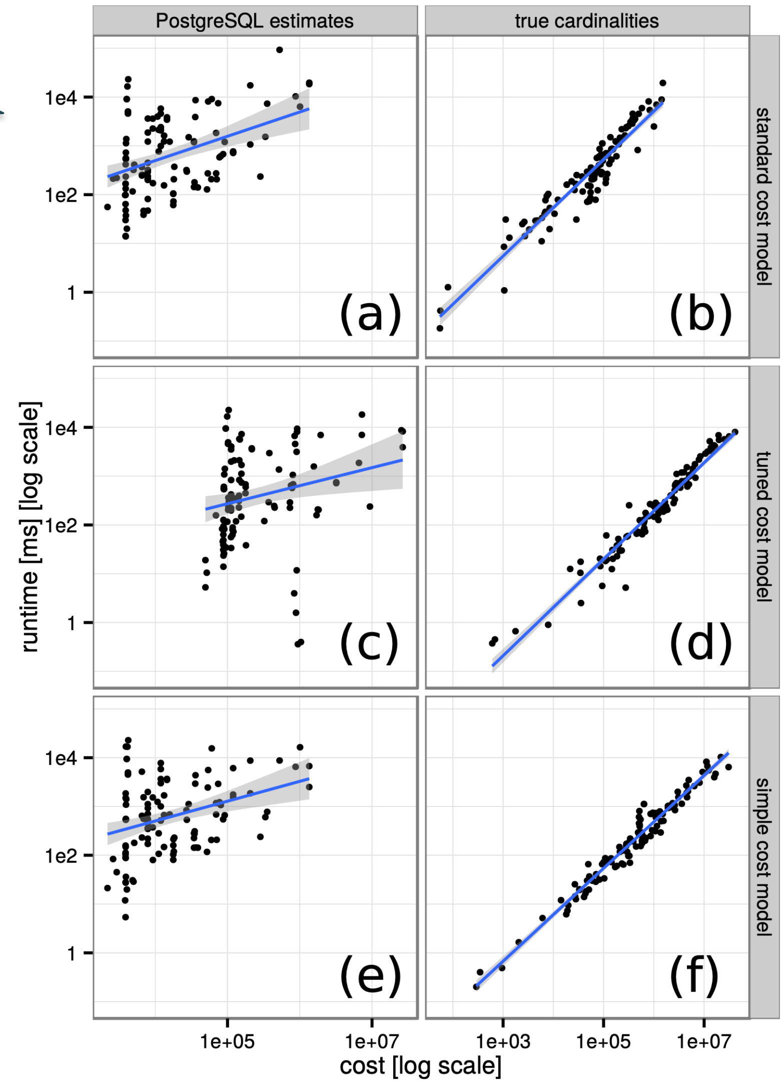

Query Optimization

Three major components:

1. Search space — last week
2. Cardinality and cost estimation — last lecture
3. Plan enumeration algorithms — today

Two Types of Optimizers

- Heuristic-based optimizers
  - Limited, used only by the simplest DBMS
- Cost-based optimizers (next)
  - Enumerate query plans, return the cheapest

Two Types of Plan Enumeration Algorithms

- Dynamic programming
  - Based on System R [Selinger 1979]
  - *Join reordering algorithm*

- Cascades optimizer

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:
  - Consider all plans of the form $P = P_1 \bowtie P_2$
  - $Cost(P) = Cost(\bowtie) + Cost(P_1) + Cost(P_2)$
  - Keep the cheapest plan, or
  - Keep multiple plans, for “interesting orders”

Runtime: exponential in n.
Mitigated by: no cartesian products, restricted plan shapes

Importance of the Plan Space

- Do we need to explore a large space, or should we pick a plan at random?
- Do we need bushy trees, or are left-, or right-, or zigzag-trees enough?
- Do we need dynamic programming, or is greedy enough?

[How good are they]

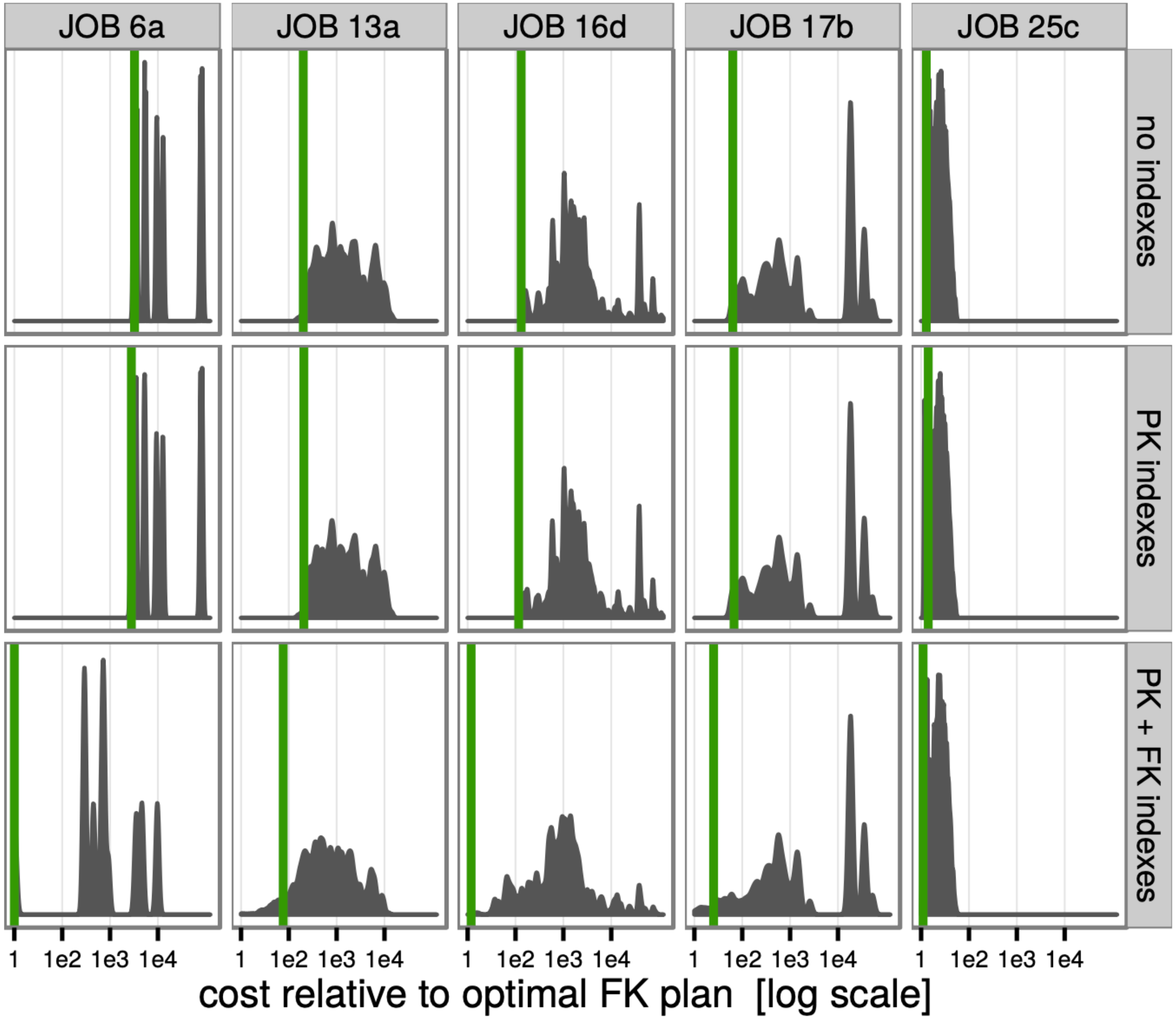

Figure 9: Cost distributions for 5 queries and different index configurations. The vertical green lines represent the cost of the optimal plan

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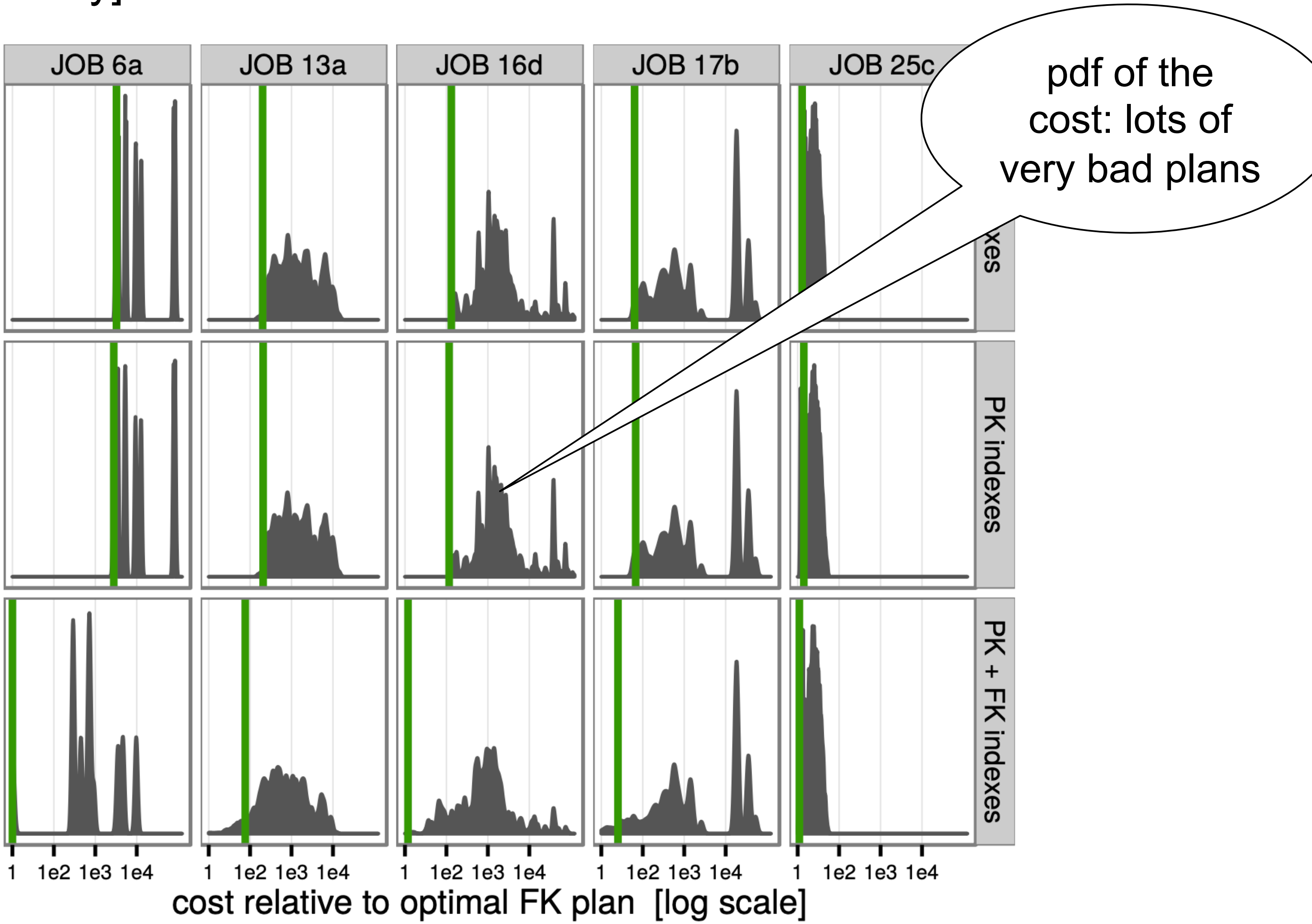

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[How good are they]

	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)

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Generally, not much worse than optimal…

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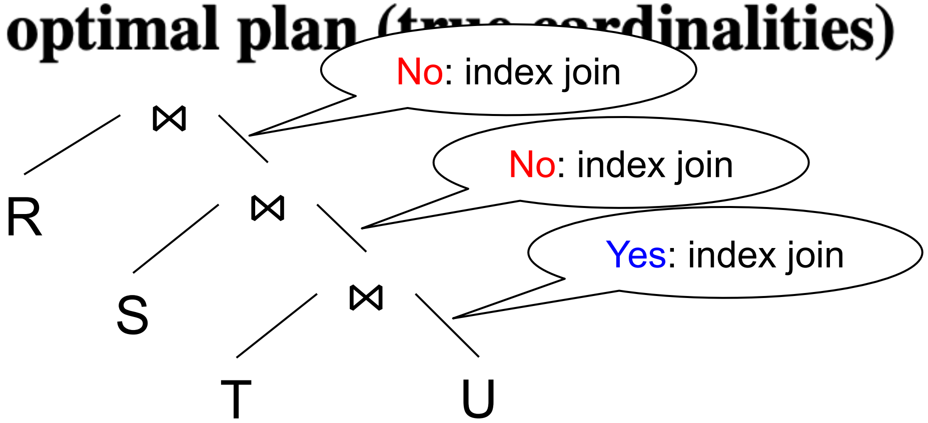


…except here. Right-deep plans prevent index joins.

[How good are they]

	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

Cascades Optimizer

- Extends join ordering to full rewrite
- Supported by some of the most advanced DBMS today: SQL Server, Cocroach Lab; (not sure about DuckDB)
- Mostly “insider knowledge”

Cascades Optimizer

- Main idea: apply optimization rules:

  Q → Q'

- But keep both Q and Q'

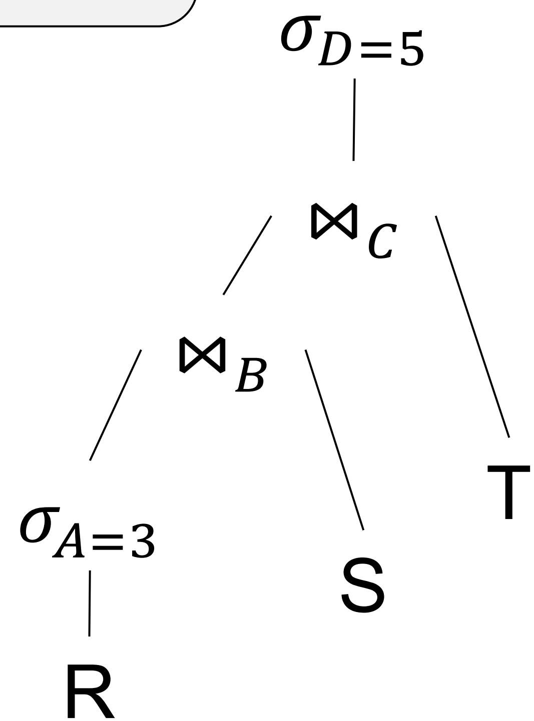
- "Memo" data structure: reuses subplans

R(A,B), S(B,C), T(C,D)

```
select *
from R, S, T
where R.B=S.B
    and S.C=T.C
    and R.A = 3
    and T.D = 5
```

The Memo

Initialize Memo w/ one (naïve) plan



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1 Scan R

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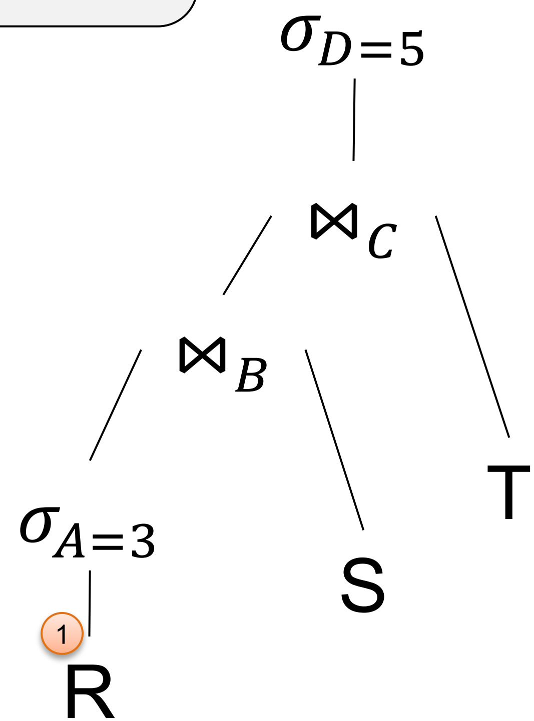

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1	Scan R
2	Select[A=3] 1

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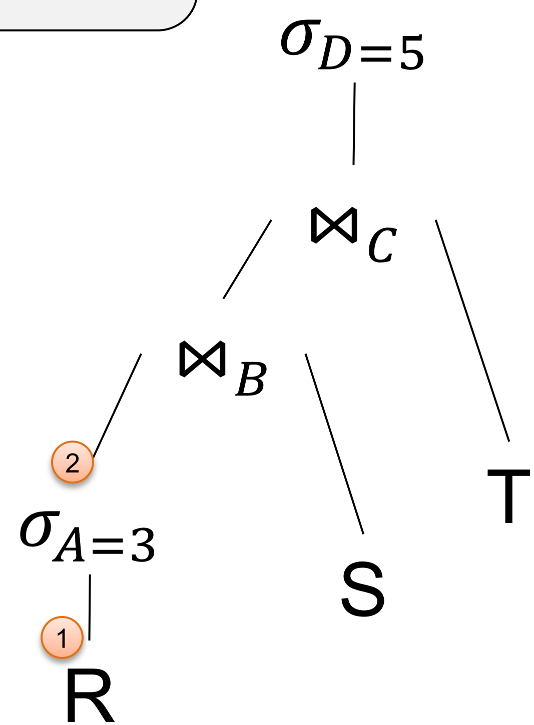

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1	Scan R
2	Select[A=3] 1
3	Scan S
4	Join[B=B] 2, 3
5	Scan T
6	Join[C=C] 4,5
7	Select[D=5] 6

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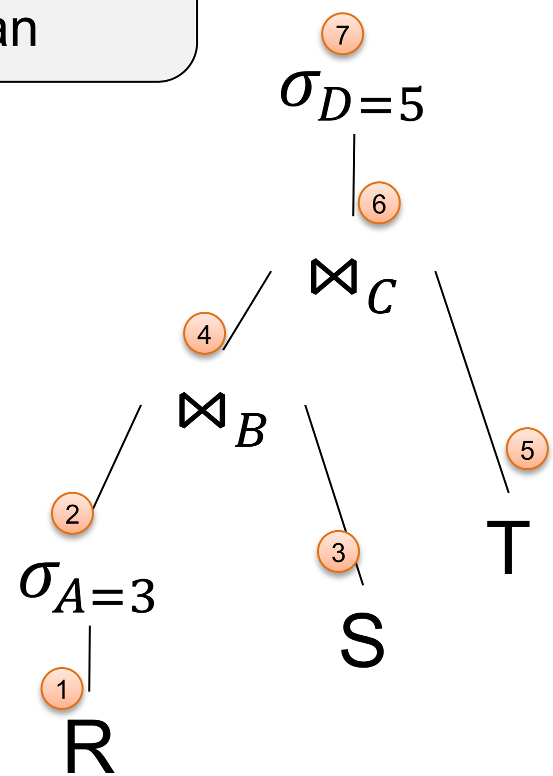

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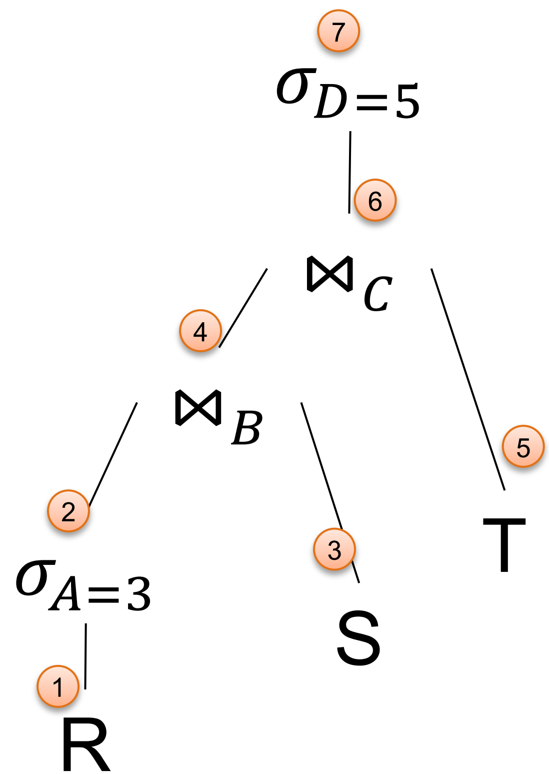

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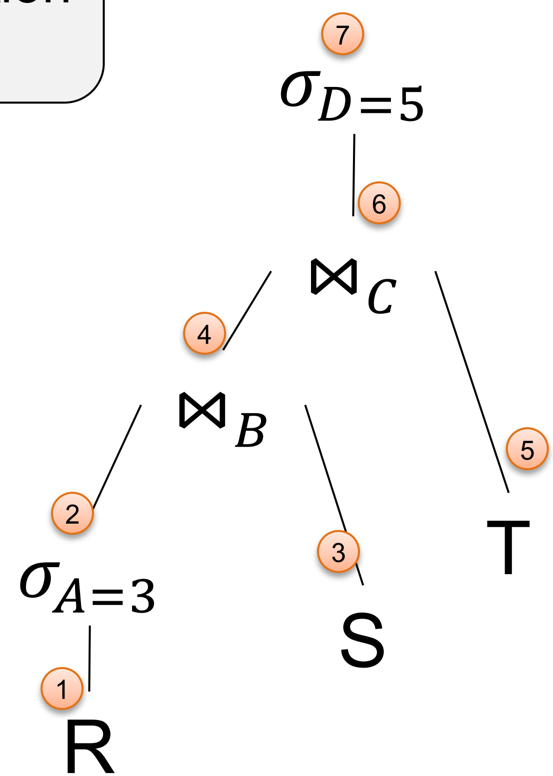
Apply an optimization rule



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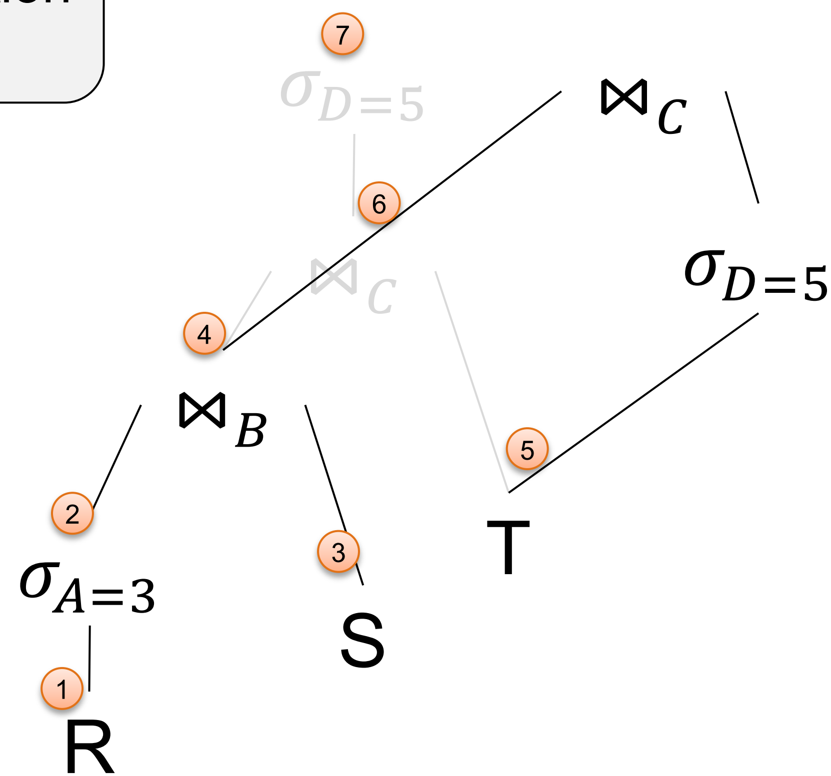

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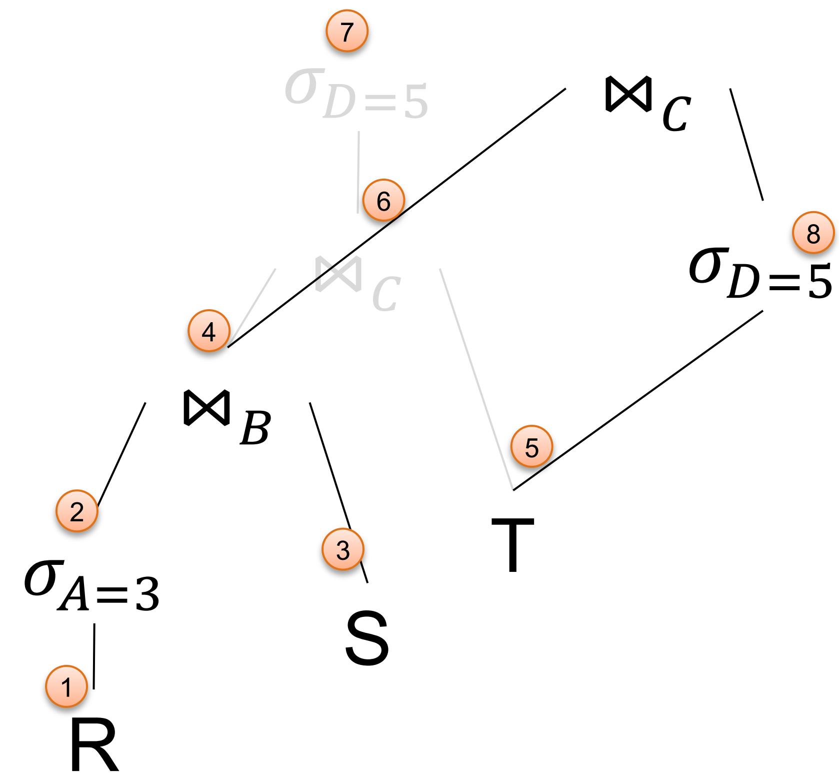

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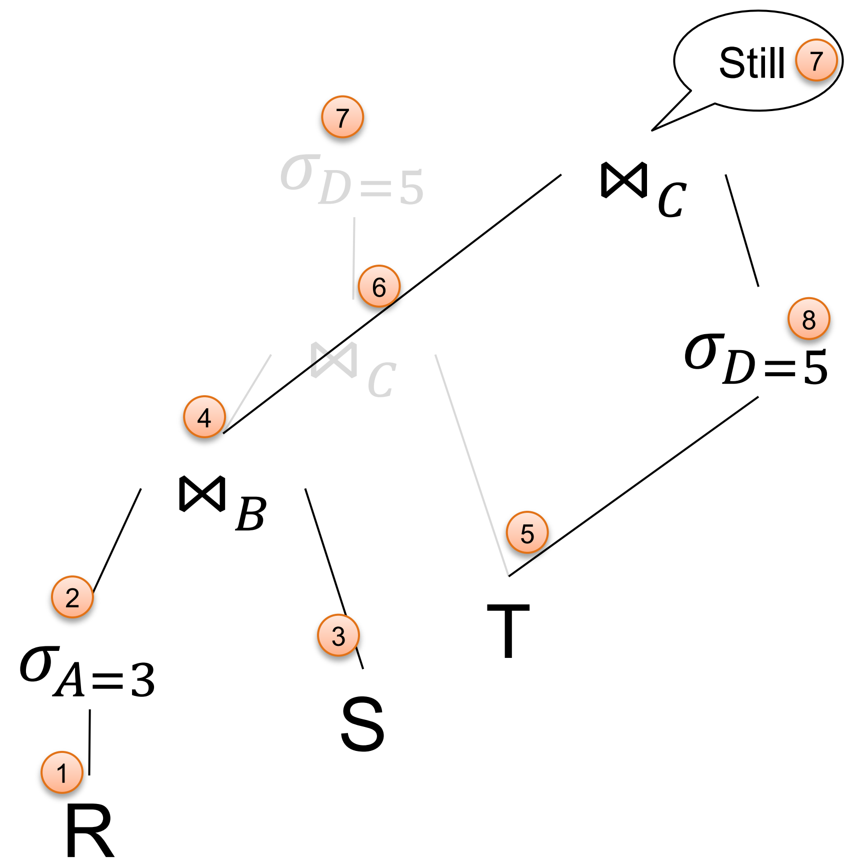
7	Select[D=5] 6	Join[C=C] 4,8
8	Select[D=5] 5	

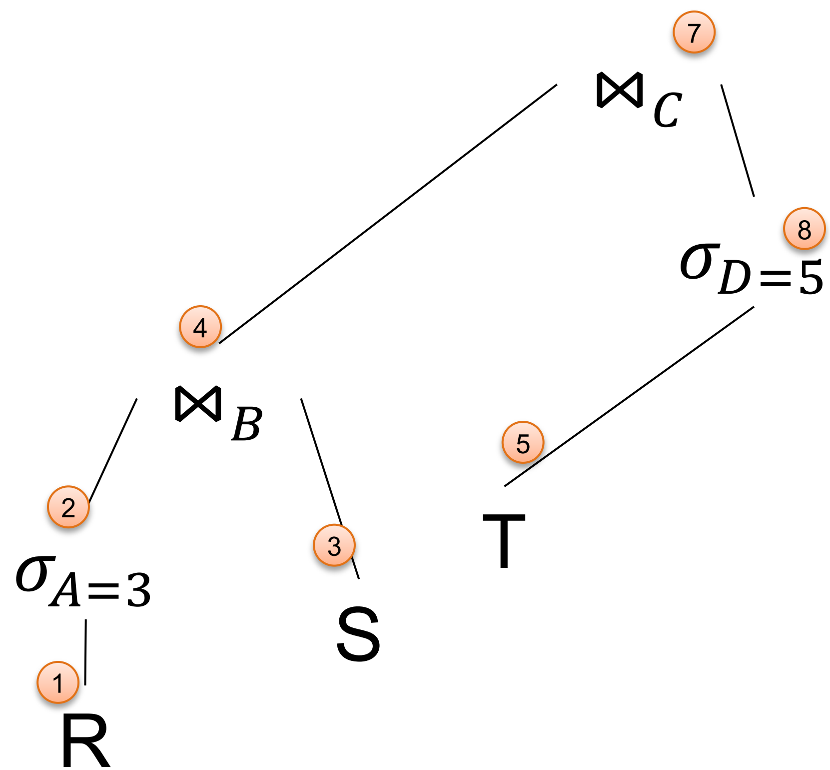


R(A,B), S(B,C), T(C,D)

```
select *
from R, S, T
where R.B=S.B
   and S.C=T.C
   and R.A = 3
   and T.D = 5
```

The Memo

1	Scan R	
2	Select[A=3] 1	
3	Scan S	
4	Join[B=B] 2, 3	
5	Scan T	
6	Join[C=C] 4,5	
7	Select[D=5] 6	Join[C=C] 4,8
8	Select[D=5] 5	

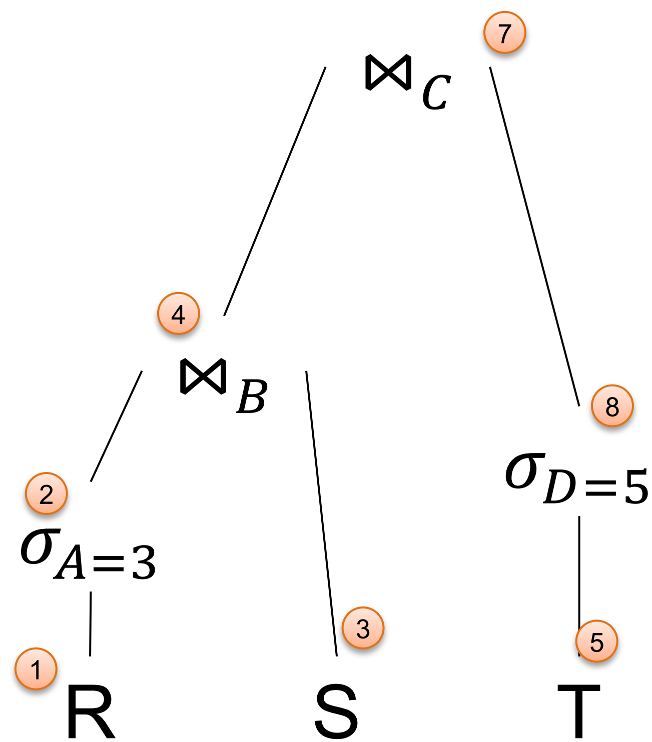


R(A,B), S(B,C), T(C,D)

The Memo

```
select *
from R, S, T
where R.B=S.B
   and S.C=T.C
   and R.A = 3
   and T.D = 5
```

1	Scan R	
2	Select[A=3] 1	
3	Scan S	
4	Join[B=B] 2, 3	
5	Scan T	
6	Join[C=C] 4,5	
7	Select[D=5] 6	Join[C=C] 4,8
8	Select[D=5] 5	



R(A,B), S(B,C), T(C,D)

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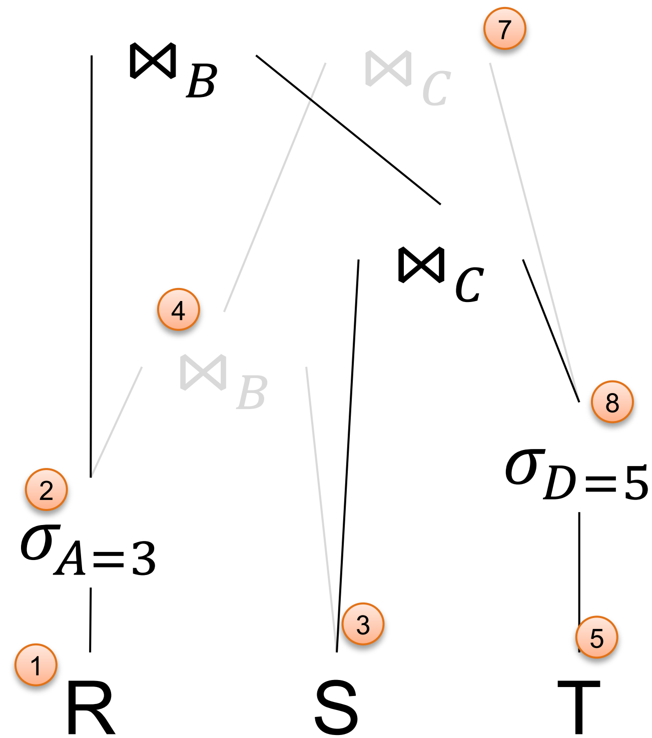
select *
from R, S, T
where R.B=S.B
    and S.C=T.C
    and R.A = 3
    and T.D = 5
```

The Memo

1	Scan R	
2	Select[A=3] 1	
3	Scan S	
4	Join[B=B] 2, 3	
5	Scan T	
6	Join[C=C] 4,5	
7	Select[D=5] 6	Join[C=C] 4,8
8	Select[D=5] 5	

Apply another rule

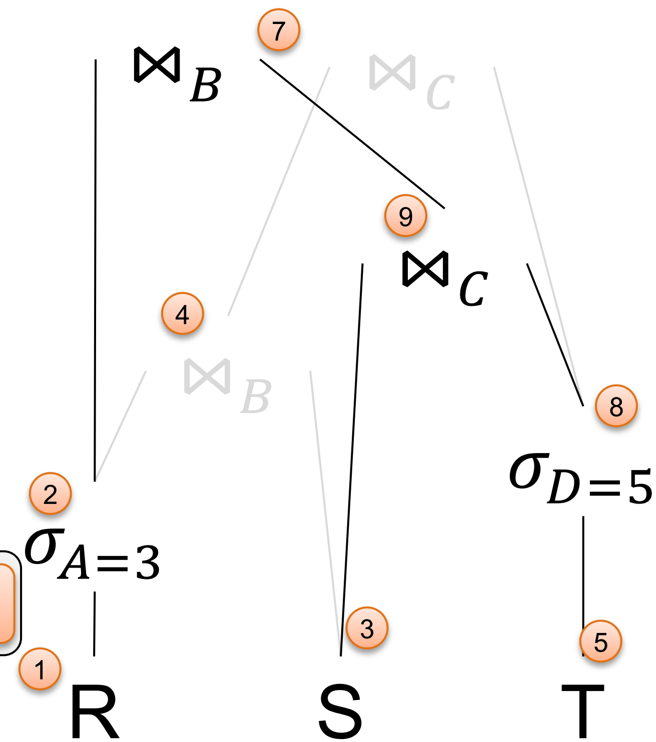


R(A,B), S(B,C), T(C,D)

```
select *
from R, S, T
where R.B=S.B
   and S.C=T.C
   and R.A = 3
   and T.D = 5
```

The Memo

1	Scan R
2	Select[A=3] 1
3	Scan S
4	Join[B=B] 2, 3
5	Scan T
6	Join[C=C] 4,5
7	Select[D=5] 6 · Join[C=C] 4,8 · Join[B=B] 2,9
8	Select[D=5] 5
9	Join[C=C] 3, 8



Conclusions

- Query optimizers: some of the most complex systems in use today

> Query optimization is not rocket science.
>
> If you fail at query optimization, they send you to build rockets.
>
> Anonymous