

DATA516/CSED516

Scalable Data Systems and Algorithms

Lecture 5 Advanced Query Processing

Announcements

- Project proposals were due last week
- HW2 was due yesterday
- HW3 will be posted soon, due on 11/16
- Next paper review due on 11/17

- Next two weeks we have guest lecturers
 - 11/10 Shan Shan Huang on Cloud Databases
 - 11/17 Mingxi Wu on Graph Databases

Today's Lecture

- Brief overview of last week's papers:
 - Snowflake
 - Dremel
- Brief review of query processing
- Begin advanced query processing
 - Today: single server
 - Next week (depending on the guest lecture): distributed processing

Snowflake – Discussion

- "The Snowflake Elastic Data Warehouse",
Dageville et al., SIGMOD'2016

Snowflake

- It is an SaaS – what is this? Give other examples of types of cloud services...

Snowflake

- It is an SaaS – what is this? Give other examples of types of cloud services...
- SaaS = software as a service
- Other examples:
 - Platform as a service (PaaS):
e.g. Amazon's EC
 - Infrastructure as a service (virtual machines)
 - Software as a Service
 - Function as a Service: Amazon's Lambda

Snowflake

- Describe Snowflake's Data Storage

Snowflake

- Describe Snowflake's Data Storage

In class:

- S3:PUT/GET/DELETE
- Table → horizontal partition in files
- Blobs+PAX
- Temp storage → S3

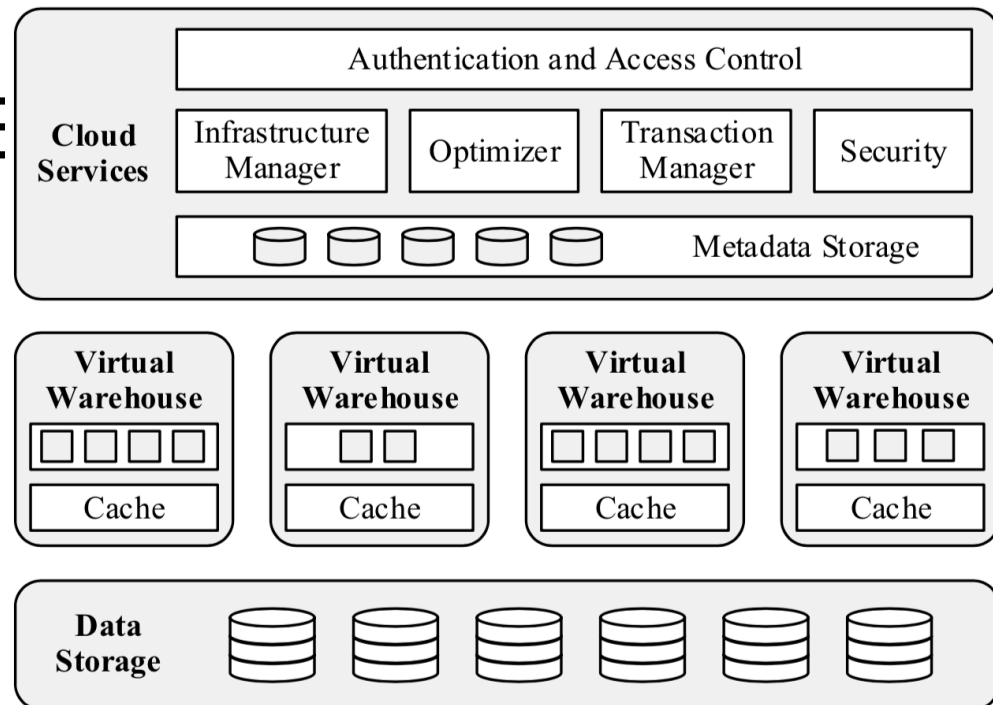


Figure 1: Multi-Cluster, Shared Data Architecture

Snowflake

- Describe Elasticity in Snowflake
- Describe failure handling in Snowflake

Snowflake

- Describe Elasticity in Snowflake
 - Virtual Warehouse (VW) serves one user
 - T-Shirt sizes: X-Small ... XX-Large
 - Small query may run on subset of VW
- Describe failure handling in Snowflake

Snowflake

- Describe Elasticity in Snowflake
 - Virtual Warehouse (VW) serves one user
 - T-Shirt sizes: X-Small ... XX-Large
 - Small query may run on subset of VW
- Describe failure handling in Snowflake
 - Restart the query
 - No partial retries (like MapReduce or Spark)

Snowflake

- Describe its execution engine

Snowflake

- Describe its execution engine
- Column-oriented (in class)
- Vectorized (“tuple batches” – in class)
- Push-based (in class)

Snowflake

- What does Snowflake use instead of indexes?

Snowflake

- What does Snowflake use instead of indexes?
- “Pruning”: for each file (recall: this is a horizontal partition of a table) and each attribute, it stores the min/max values in that column in that file; may skip files when not needed.

Dremel

- Melnik et al., “Dremel: A Decade of Interactive SQL Analysis at Web Scale”, VLDB’2020
- This is the “ten years best paper award companion paper”; the original Dremel paper was in 2010

Dremel

- Dremel = internal name for Google's BigQuery
- A fully managed, serverless data warehouse for scalable data analytics
- Google's internal history:
 - MapReduce: “databases are bad”
 - BigTable: “tables are OK, but SQL is bad”
 - Dremel: “we love SQL”
 - Spanner: “we love SQL and transactions”

Dremel: Data Storage

- Initially data was stored on local disks
- Migration to Borg meant that the disks were no longer owned by Dremel, but shared among many applications
- Solution: move data to GFS
- But performance degraded: lots work was need to regain performance; but little details given in Sec. 7

Dremel: Disaggregated Shuffle

Standard Shuffle: $O(n^2)$ behavior
E.g. to reshuffle data from 1000 servers,
need 10^6 pairwise communications

Disaggregated Shuffle:
add intermediate servers.
E.g. 10 intermediate servers,
hence $2 \cdot 10 \cdot 1000 = 2 \cdot 10^4$ pairwise comm.

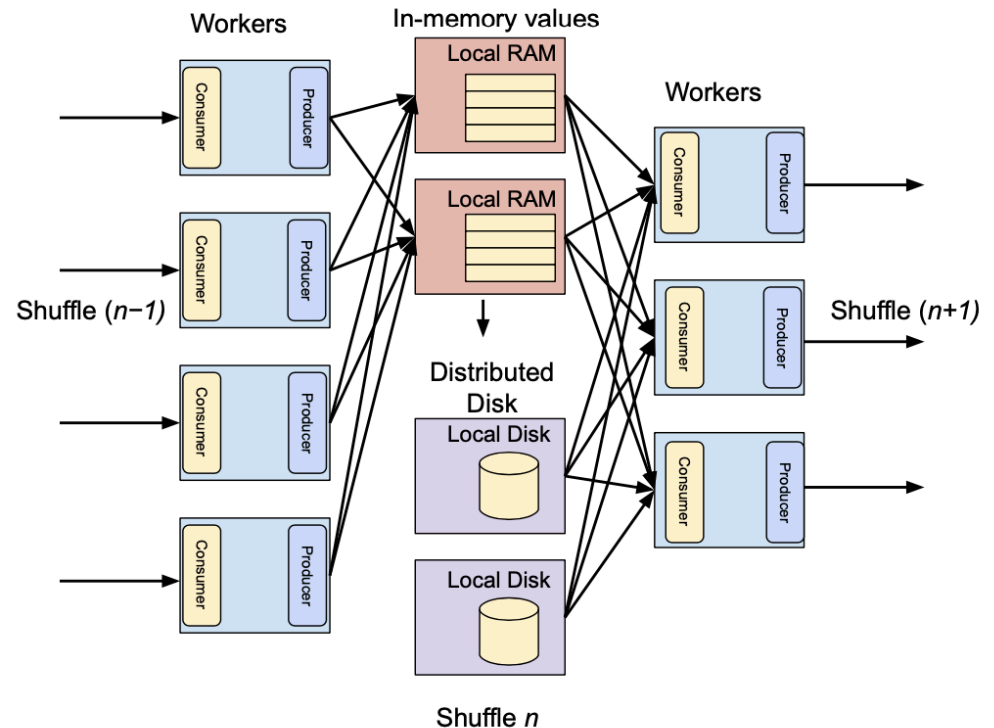
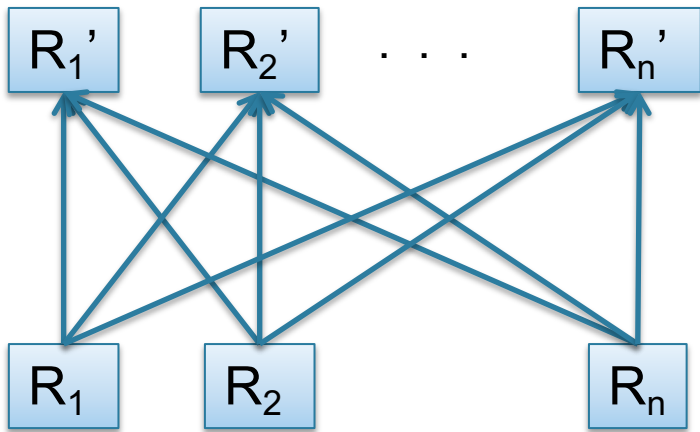


Figure 2: Disaggregated in-memory shuffle

Dremel: Columnar Storage

- We have seen that Snowflake uses PAX-like storage
- Dremel is fully column oriented
- The major novelty is that it stores nested data (Json, or Protobuf) also in column storage
- The original method in 2010 was complicated
- New method is much simpler (next)

Dremel: Columnar Storage

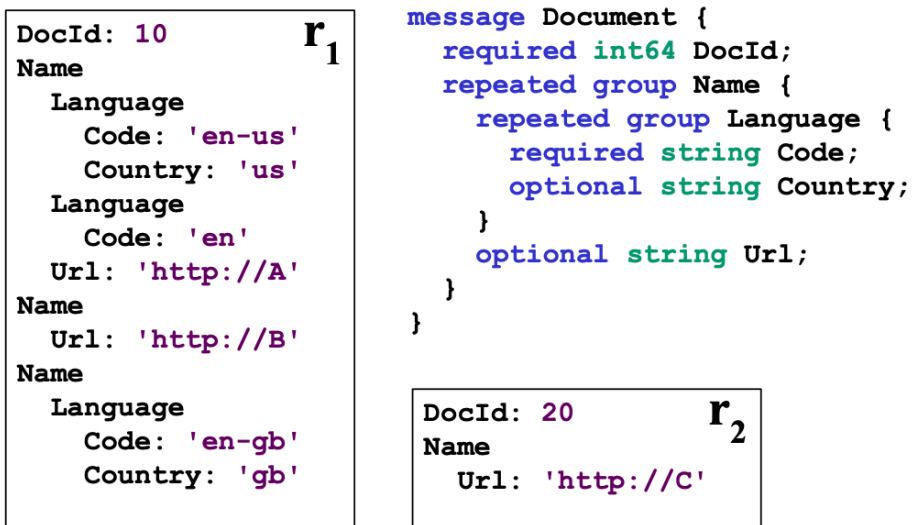


Figure 5: Two sample nested records and their schema (based on Figure 2 in [32])

Need to have the schema!

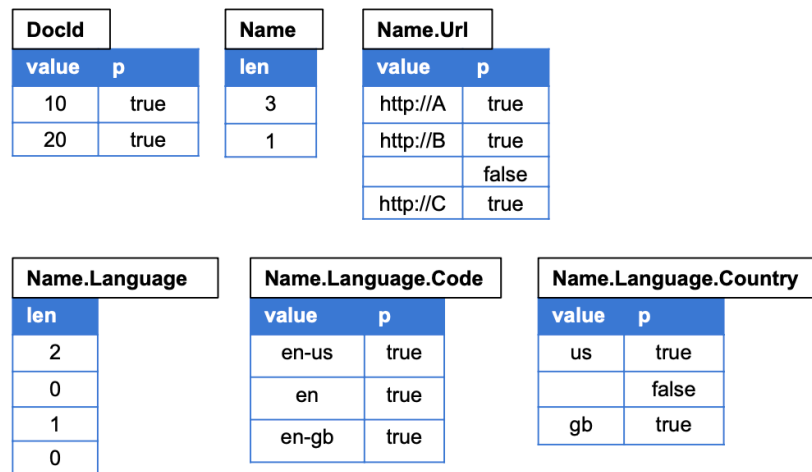


Figure 7: Columnar representation of the data in Figure 5 showing length (len) and presence (p)

Need to decode all ancestors!

Discussion

Alternative: normalize the data!

DocId: 10	r₁
Name	
Language	
Code: 'en-us'	
Country: 'us'	
Language	
Code: 'en'	
Url: 'http://A'	
Name	
Url: 'http://B'	
Name	
Language	
Code: 'en-gb'	
Country: 'gb'	

```
message Document {
  required int64 DocId;
  repeated group Name {
    repeated group Language {
      required string Code;
      optional string Country;
    }
    optional string Url;
  }
}
```

DocId: 20	r₂
Name	
Url: 'http://C'	

DocID	Name		
DocID	NameID	DocIDRef	URL
10	1	10	http://A
20	2	10	http://B
	3	10	NULL
	4	20	http://C

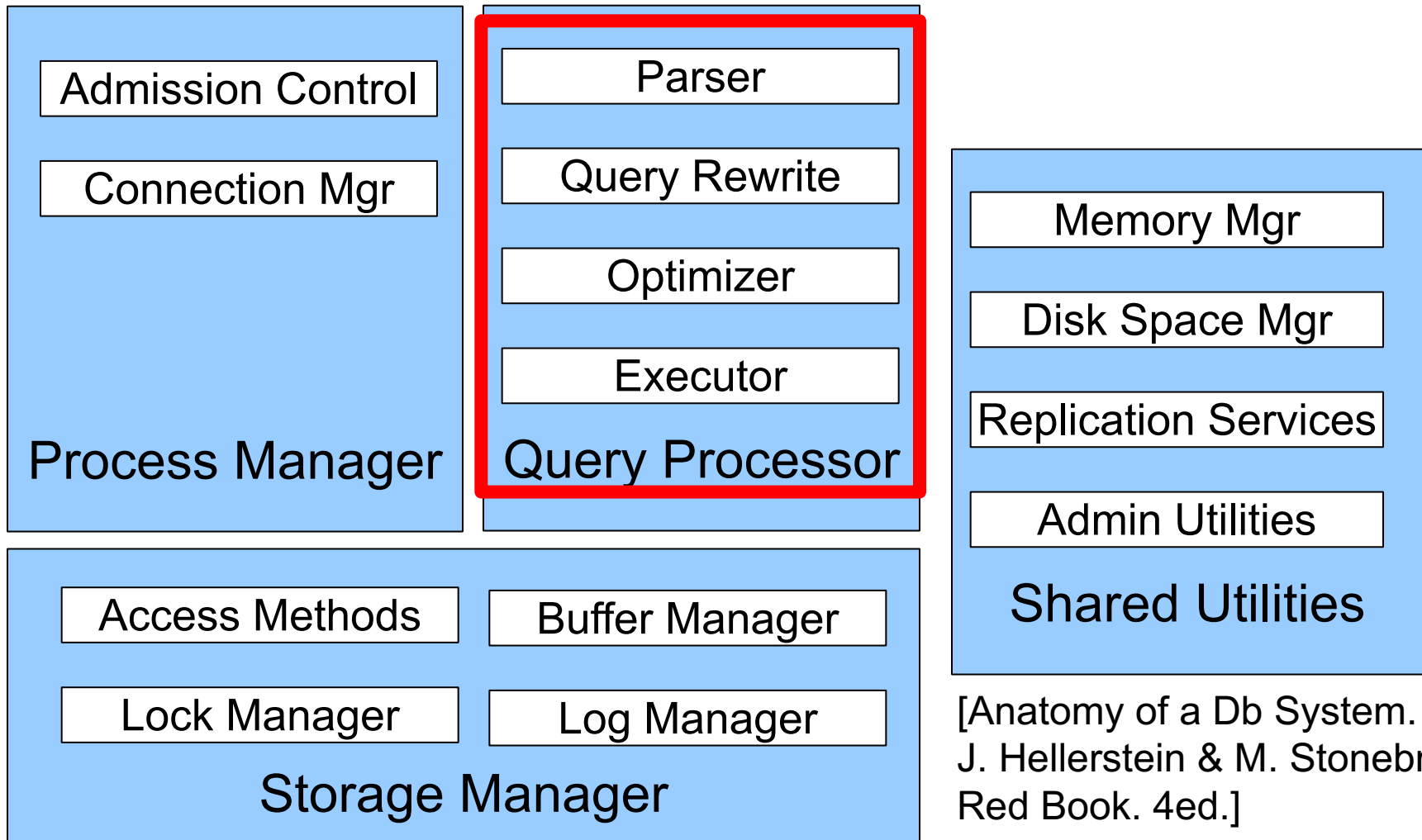
Language		
NameIDRef	Code	Country
1	en-us	us
1	en	NULL
3	en-gb	gb

Figure 5: Two sample nested records and their schema (based on Figure 2 in [32])

Snowflake maps Json automatically to relations.
How? (I don't know, but you can try to figure it out!)

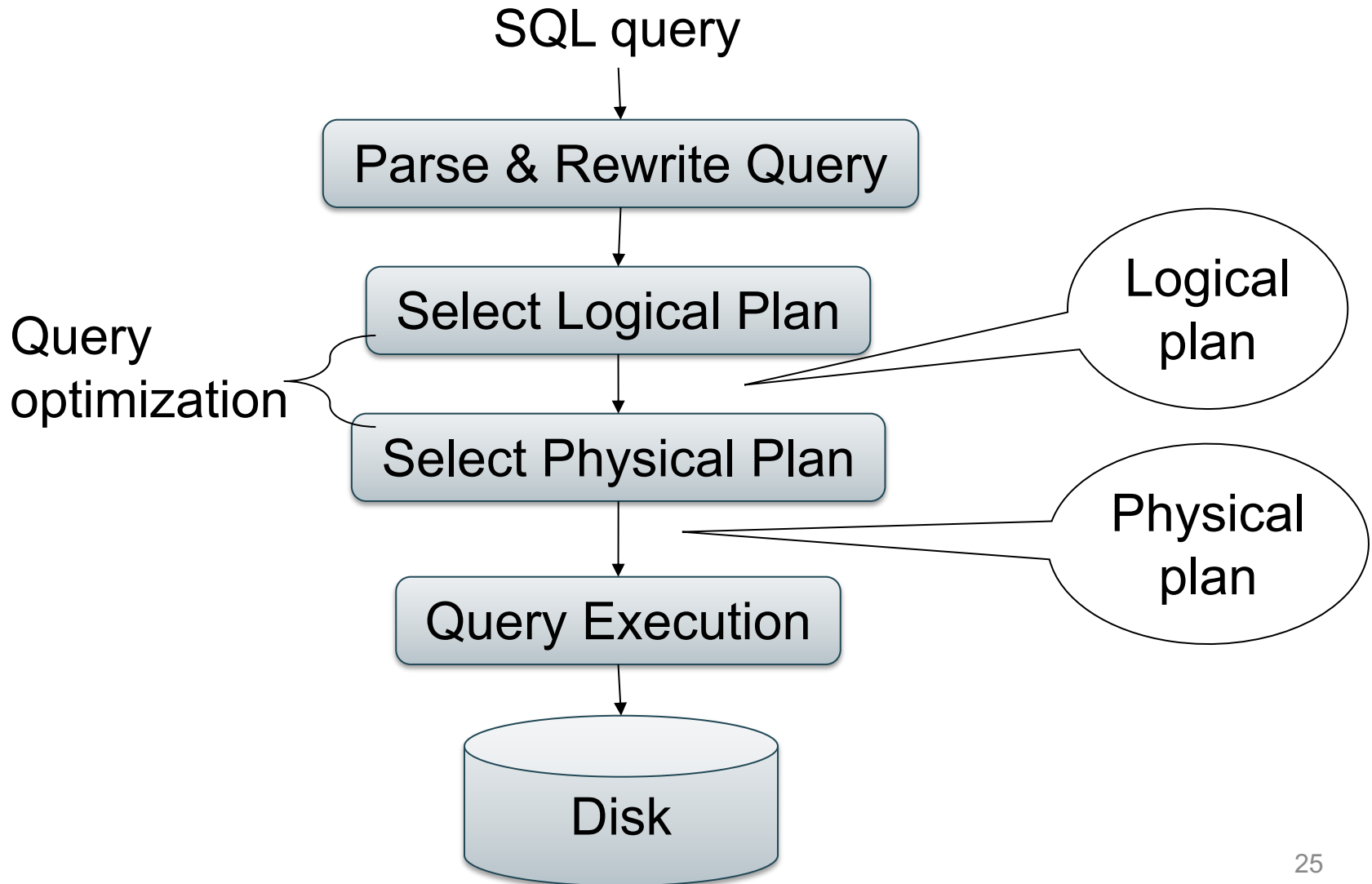
Review of Query Processing

DBMS Architecture



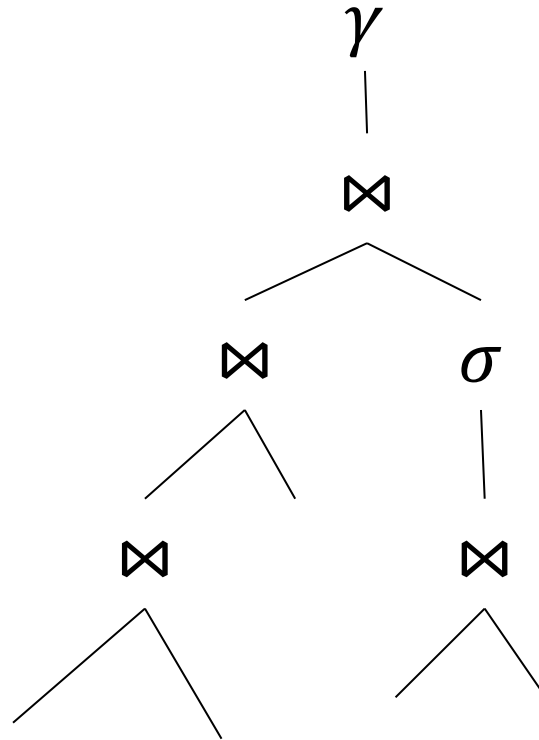
[Anatomy of a Db System.
J. Hellerstein & M. Stonebraker.
Red Book. 4ed.]

Lifecycle of a Query

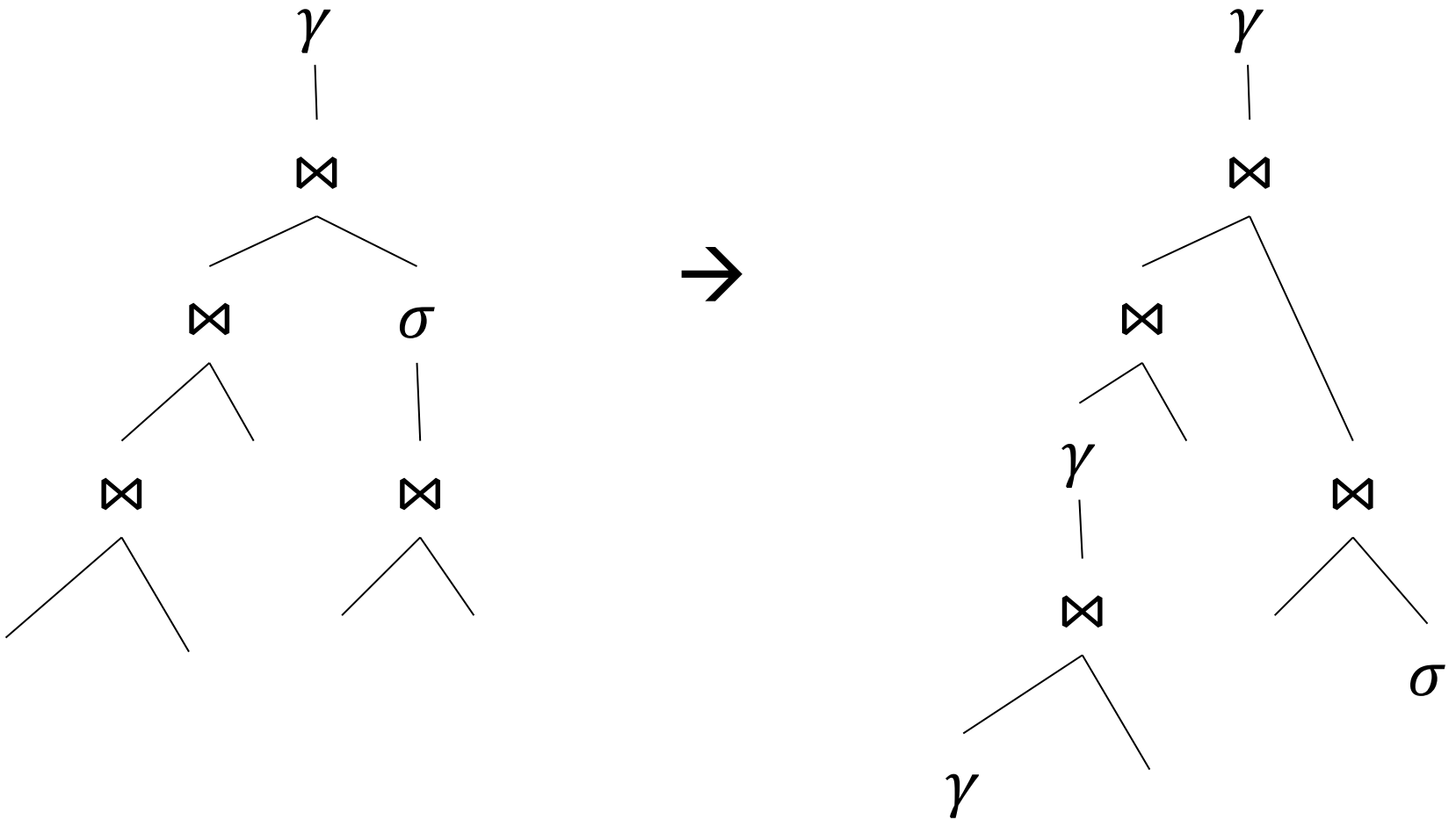


SQL \rightarrow Query Plan

SELECT ...
FROM ...
WHERE ...
GROUP BY ...
HAVING ...



Optimizer: Plan \rightarrow Plan



Quick Recap

- Name 3 join processing algorithms
- Speedup, scaleup
- Shared-memory v.s. shared-nothing
- Parallel hash join algorithm
- Discuss skew

Cost Estimator → Large Errors ☹️

[Neumann et al., VLDB'2015]

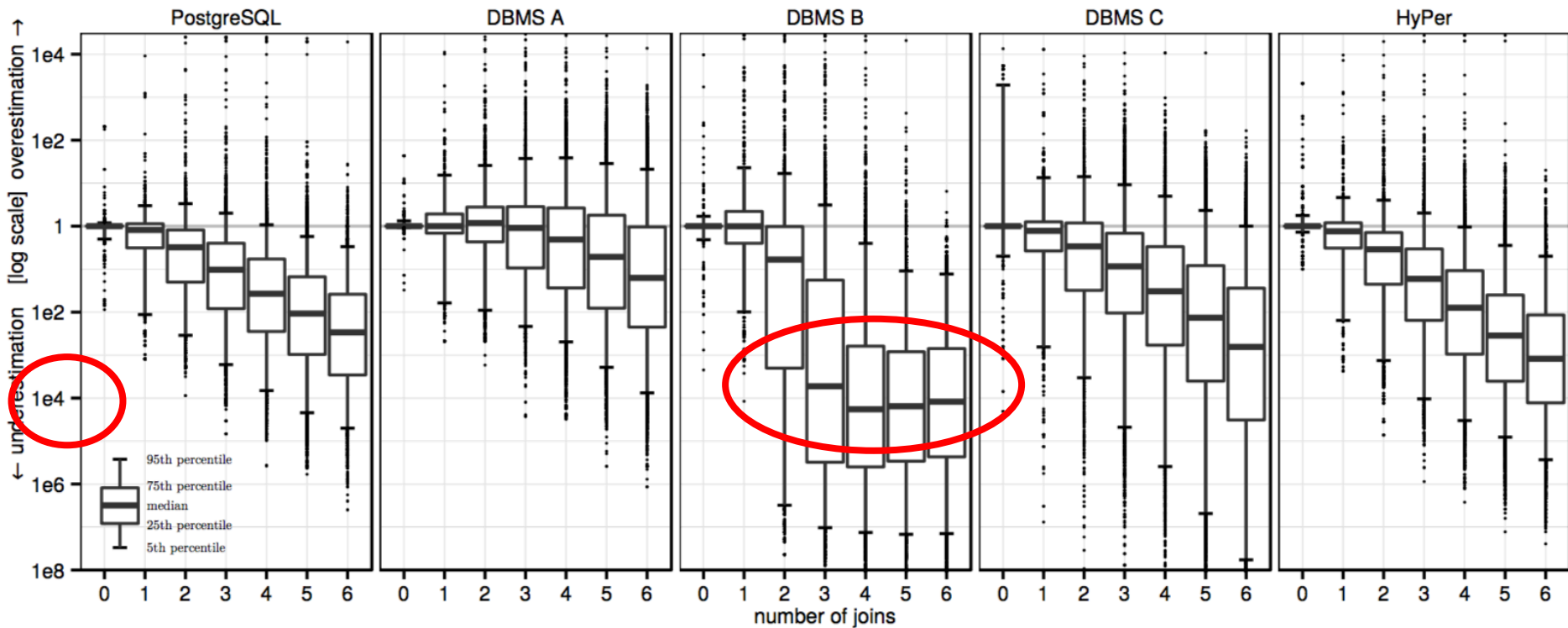


Figure 3: Quality of cardinality estimates for multi-join queries in comparison with the true cardinalities. Each boxplot summarizes the error distribution of all subexpressions with a particular size (over all queries in the workload)

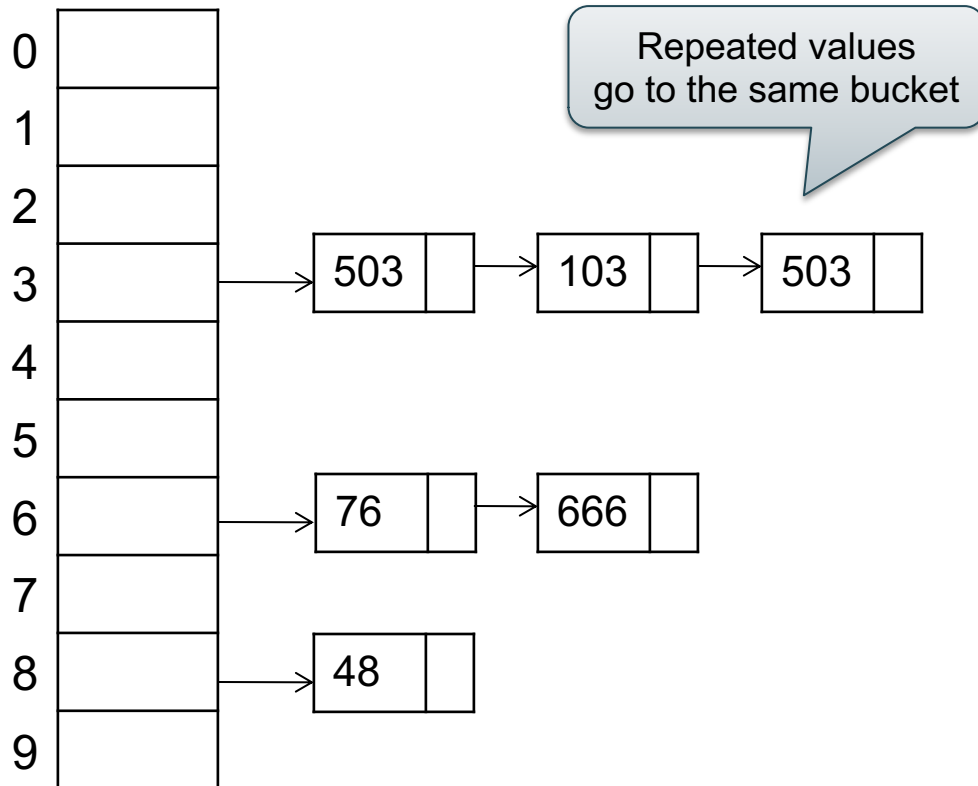
Query Execution

- Nested loop join: $O(N^2)$
- Merge join: $O(N \cdot \log(N))$
- Hash join: $O(N)$ (maybe)

Distributed Query Processing

- Optimizer is the same
- Cost estimator is the same, just harder (why?)
- New operator: shuffle
 - Hash partition → skew is an issue
 - Broadcast → skew no problem, but size is

Skew: Affects any Hash Table



Rule of thumbs:

1. Ideal size of a bucket = N/p
2. When a data value occurs many more times than N/p , we call it "heavy hitter", and there will be skew
3. If all data values occur much fewer times than N/p , then there is no skew
4. Last statement is probabilistic; exact calculation uses Chernoff bounds, and is complex

Limitations of Query Processing

- Biggest limitation is the quality of the cardinality estimator
- Another limitation: if the query is cyclic, then any plan is bad
- Today's topic: advanced techniques
 - Handle cyclic queries well
 - Are more robust to cardinality estimators.

Motivation

- When the joins are “cyclic” then standard query plan are severely suboptimal
- Where we find cyclic queries:
 - Rare events: find actor X who acted in movie Y who was directed by director Z who was married to X
 - Social network analysis: count the number of triangles; the number of 5-cliques, etc
 - “Motif analysis”: finding occurrences of certain small subgraphs (“motifs”)

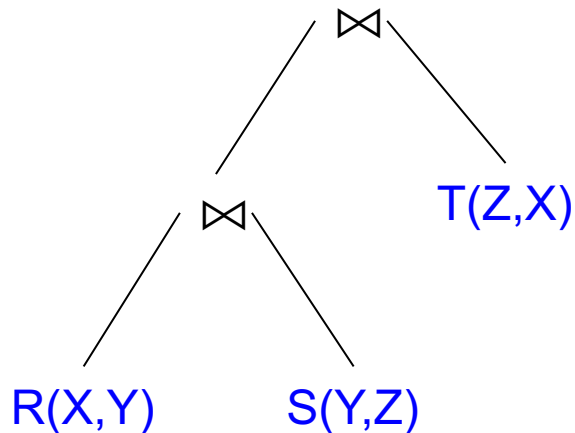
A query plans produces large intermediate results; answer is small

Example

$Q(X,Y,Z) = R(X,Y) \wedge S(Y,Z) \wedge T(Z,X)$

```
select *           -- natural join
from R, S, T
where R.Y = S.Y and S.Z = T.Z and T.X = R.X
```

Query plan



Example

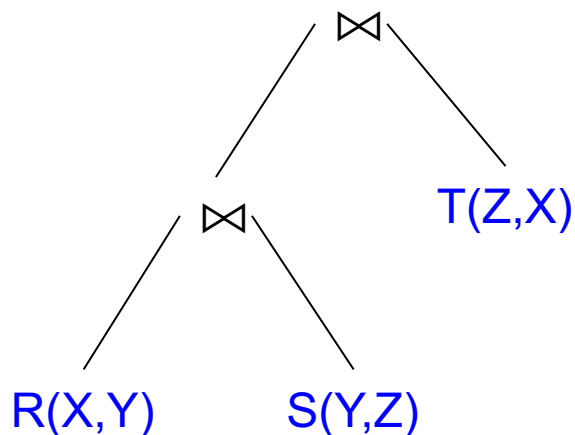
$$Q(X,Y,Z) = R(X,Y) \wedge S(Y,Z) \wedge T(Z,X)$$

```

select *
from R, S, T
where R.Y = S.Y and S.Z = T.Z and T.X = R.X
  
```

-- natural join

Query plan



R:

X	Y
0	1
0	2
0	3
...	...
0	N/2
1	0
2	0
...	...
N/2	0

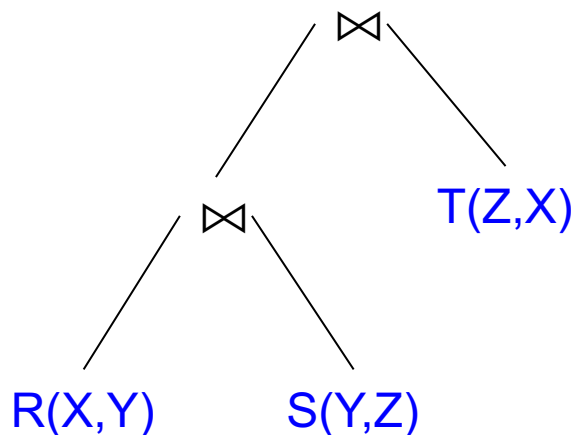
N

Example

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Query plan



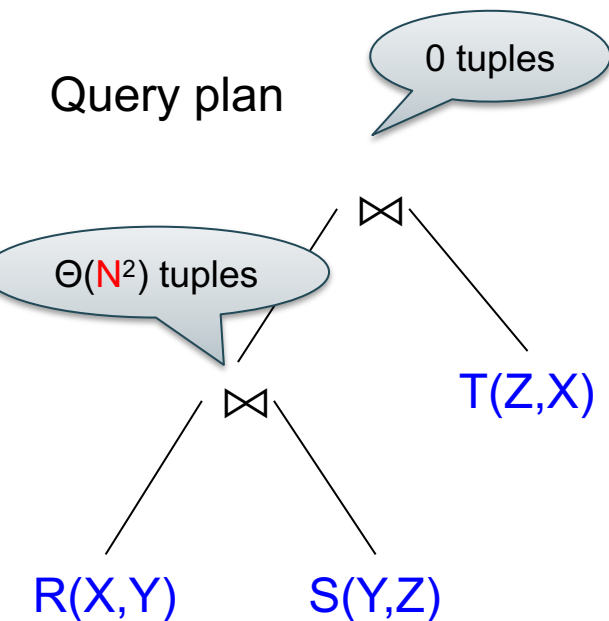
N

R:		S: (same as R)		T: (same as R)	
X	Y	Y	Z	Z	X
0	1	0	1	0	1
0	2	0	2	0	2
0	3	0	3	0	3
...
0	N/2	0	N/2	0	N/2
1	0	1	0	1	0
2	0	2	0	2	0
...
N/2	0	N/2	0	N/2	0

Example

$$Q(X,Y,Z) = R(X,Y) \wedge S(Y,Z) \wedge T(Z,X)$$

select * -- natural join
 from R, S, T
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N

R:		S: (same as R)		T: (same as R)	
X	Y	Y	Z	Z	X
0	1	0	1	0	1
0	2	0	2	0	2
0	3	0	3	0	3
...
0	N/2	0	N/2	0	N/2
1	0	1	0	1	0
2	0	2	0	2	0
...
N/2	0	N/2	0	N/2	0

Optimal Algorithm

To define “optimal” we need to answer two questions:

Q1: How large is the output of a query?

Q2: How can we compute it in time no larger than the largest output?

Full Conjunctive Query

- Full CQ = all variables occur in the head

$$Q(X_1, \dots, X_k) = R_1(Vars_1) \wedge \dots \wedge R_m(Vars_m)$$

- Equivalent SQL:

```
select   *  
from    R1, R2, ...  
where   [join and selection conditions]
```


Worst-Case Optimality

Fix input statistics for D

- $|R|, |S| \leq N$
- How large are the answers to these queries?

$$Q(X, Y, Z) = R(X, Y) \wedge S(Y, Z)$$

No other info: $|Q(D)| \leq N^2$

Worst-Case Optimality

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$$Q(X, Y, Z) = R(X, Y) \wedge S(Y, Z) \wedge T(Z, X)$$

No other info:

Worst-Case Optimality

Fix input statistics for D

- $|R|, |S| \leq N$
- How large are the answers to these queries?

$$Q(X, Y, Z) = R(X, Y) \wedge S(Y, Z)$$

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$$Q(X, Y, Z) = R(X, Y) \wedge S(Y, Z) \wedge T(Z, X)$$

No other info: $|Q(D)| \leq N^{3/2}$

Worst-Case Optimality

Fix input statistics for D

- $|R|, |S| \leq N$
- How large are the answers to these queries?

$$Q(X, Y, Z) = R(X, Y) \wedge S(Y, Z)$$

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$$Q(X, Y, Z) = R(X, Y) \wedge S(Y, Z) \wedge T(Z, X)$$

No other info: $|Q(D)| \leq N^{3/2}$



WOW!

The Two Questions

Q1: Given statistics, what is $\max(|Q(D)|)$?

Q2: How can we compute Q in time $O(\max(|Q(D)|))$?

Simple Fact #1

- Consider any query:

$$Q(X_1, \dots, X_k) = R_1(Vars_1) \wedge \dots \wedge R_m(Vars_m)$$

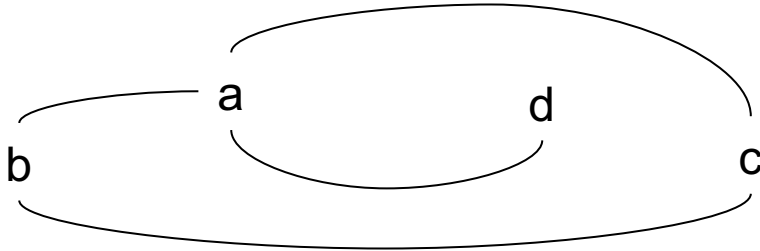
- Its output size is no larger than the product of all cardinalities:

$$|Q| \leq |R_1| \times \dots \times |R_m|$$

Why?

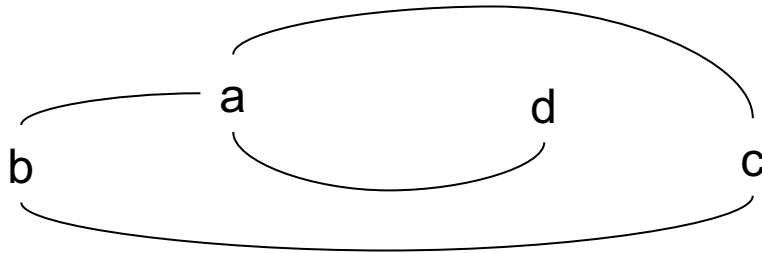
Graphs and Hypergraphs

- An undirected graph $G = (V, E)$ where each edge $e \in E$ is a set of two nodes

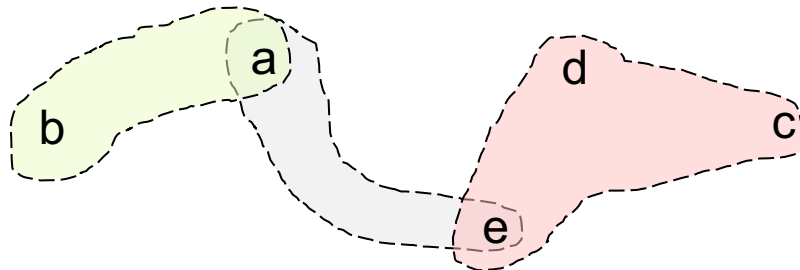


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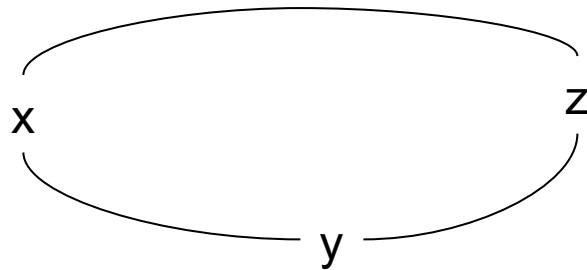


- A hypergraph is $G = (V, E)$ where each edge is some set (of 1 or 2 or >2 nodes)

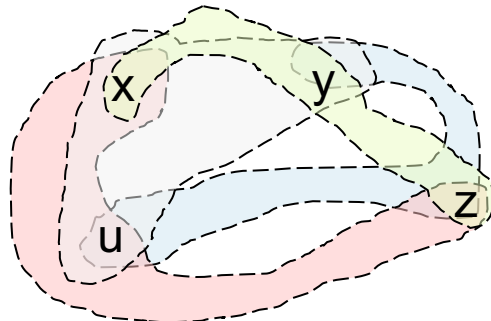


Conjunctive Queries are Hypergraphs

$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x)$$

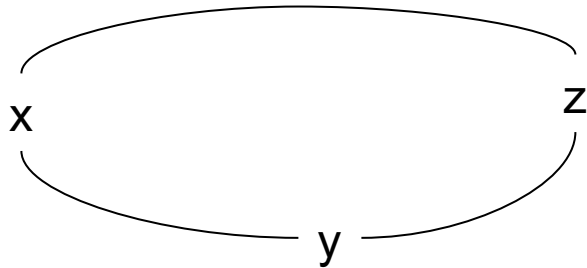


$$Q(x, y, z) = A(x, y, z) \wedge B(x, y, u) \wedge C(x, z, u) \wedge D(y, z, u)$$



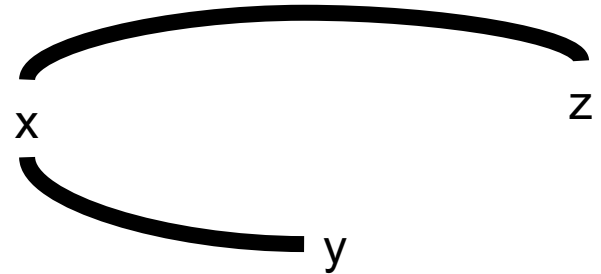
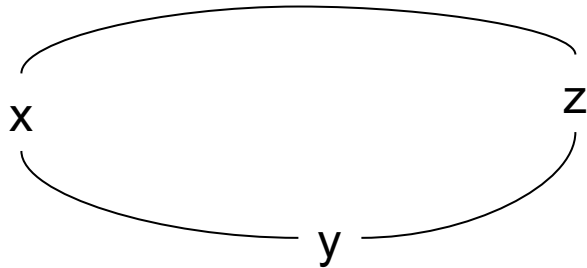
Edge Cover

- An edge cover of a (hyper)graph is a subset of edges that contain all the vertices



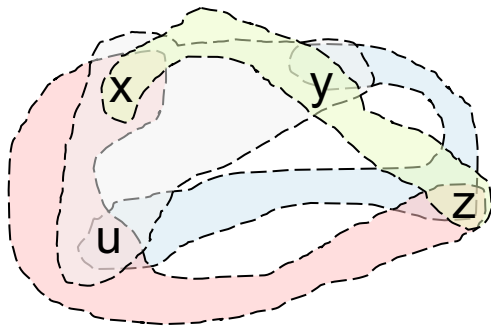
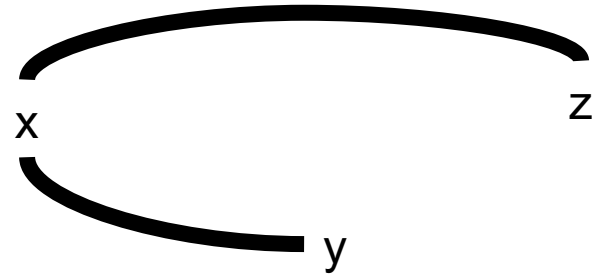
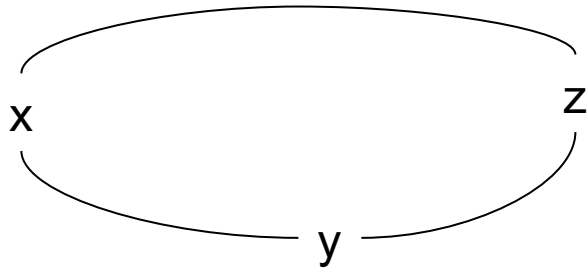
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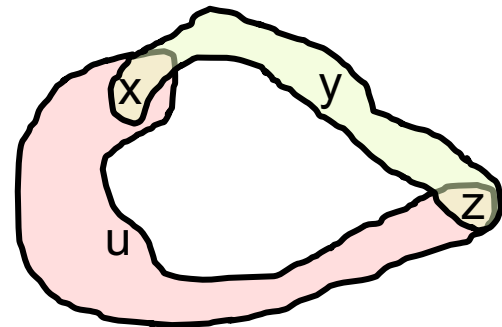
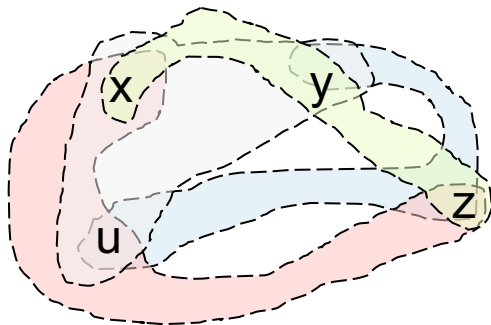
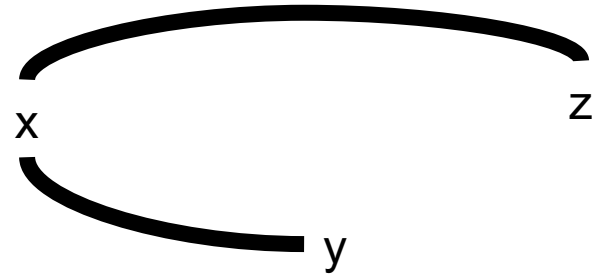
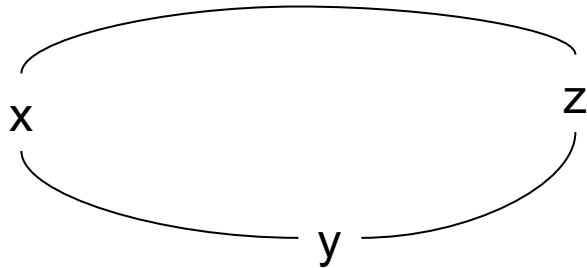
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Edge Cover

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Simple Fact #2

- Consider any query:

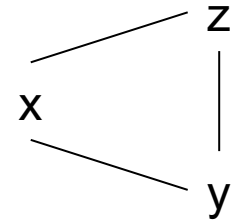
$$Q(X_1, \dots, X_k) = R_1(Vars_1) \wedge \dots \wedge R_m(Vars_m)$$

- Let $R_{i_1}, R_{i_2}, \dots, R_{i_n}$ be an edge cover. Then the output size is no larger than their product:

$$|Q| \leq |R_{i_1}| \times \dots \times |R_{i_n}|$$

Why?

Examples

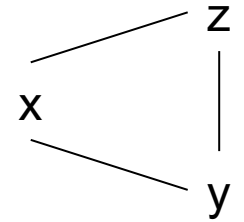


$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x)$$

- Edge covers:

$$R(x, y) \wedge S(y, z)$$

Examples



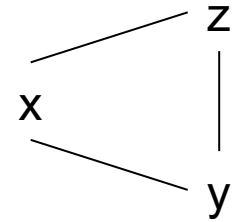
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Examples



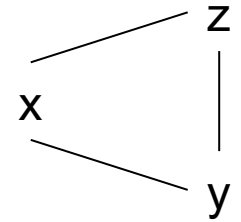
$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x)$$

- Edge covers:

$$R(x, y) \wedge S(y, z) \text{ or } R(x, y) \wedge T(z, x)$$

$$|Q| \leq |R| \times |S|$$

Examples



$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x)$$

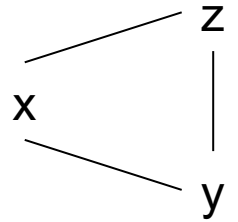
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$$R(x, y) \wedge S(y, z) \text{ or } R(x, y) \wedge T(z, x)$$

$$|Q| \leq |R| \times |S|$$

$$|Q| \leq |R| \times |T|$$

Examples

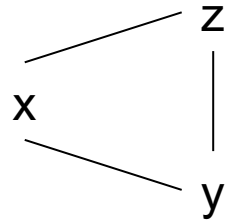


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Examples



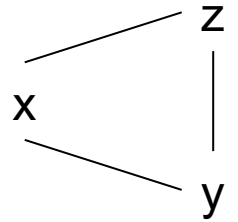
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- Edge covers:

$$R(x, y) \wedge S(y, z) \text{ or } R(x, y) \wedge T(z, x) \text{ or } S(y, z) \wedge T(z, x)$$

$$|Q| \leq \min(|R| \times |S|, |R| \times |T|, |S| \times |T|)$$

Examples



$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x)$$

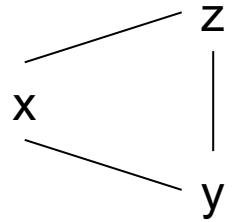
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Examples



$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x)$$

- Edge covers:

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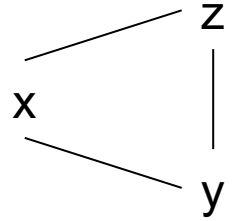
$$|Q| \leq \min(|R| \times |S|, |R| \times |T|, |S| \times |T|)$$

$$Q(x, y, z, u) = A(x, y, z) \wedge B(x, y, u) \wedge C(x, z, u) \wedge D(y, z, u)$$

- Edge covers:

$$A(x, y, z) \wedge B(x, y, u) \text{ or } A(x, y, z) \wedge C(x, z, u) \text{ or } \dots$$

Examples



$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x)$$

- Edge covers:

$$R(x, y) \wedge S(y, z) \text{ or } R(x, y) \wedge T(z, x) \text{ or } S(y, z) \wedge T(z, x)$$

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$$Q(x, y, z, u) = A(x, y, z) \wedge B(x, y, u) \wedge C(x, z, u) \wedge D(y, z, u)$$

- Edge covers:

$$A(x, y, z) \wedge B(x, y, u) \text{ or } A(x, y, z) \wedge C(x, z, u) \text{ or } \dots$$

$$|Q| \leq \min(|A| \times |B|, |A| \times |C|, \dots)$$

More examples

Assume all relations have size **N**.

What are the maximum output sizes?

- $Q(x, y, z, u, v) = R(x, y) \wedge S(y, z) \wedge T(z, u) \wedge K(u, v)$



More examples

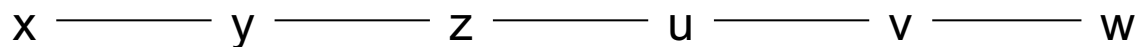
Assume all relations have size **N**.

What are the maximum output sizes?

- $Q(x, y, z, u, v) = R(x, y) \wedge S(y, z) \wedge T(z, u) \wedge K(u, v)$



- $Q(x, y, z, u, v, w) =$
 $R(x, y) \wedge S(y, z) \wedge T(z, u) \wedge K(u, v) \wedge L(v, w)$



More examples

Assume all relations have size N .

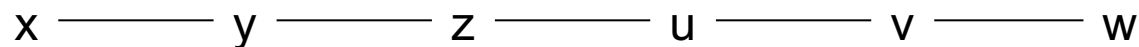
What are the maximum output sizes?

- $Q(x, y, z, u, v) = R(x, y) \wedge S(y, z) \wedge T(z, u) \wedge K(u, v)$



Answer: N^3
in both cases

- $Q(x, y, z, u, v, w) =$
 $R(x, y) \wedge S(y, z) \wedge T(z, u) \wedge K(u, v) \wedge L(v, w)$

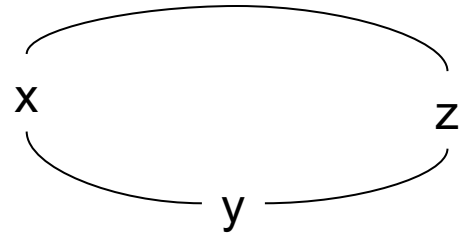


Fractional Edge Cover

- A fractional edge cover of a (hyper)graph is a set of non-negative numbers w_e , one for each edge e , such that, for every vertex v :
$$\sum_{e:v \in e} w_e \geq 1$$

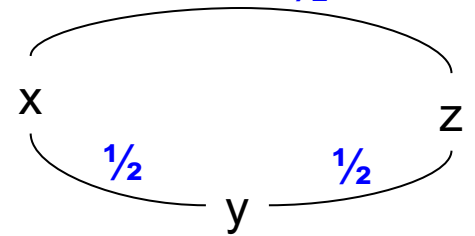
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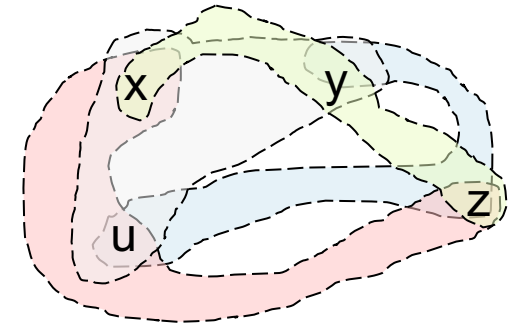
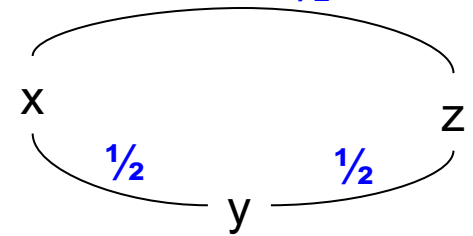
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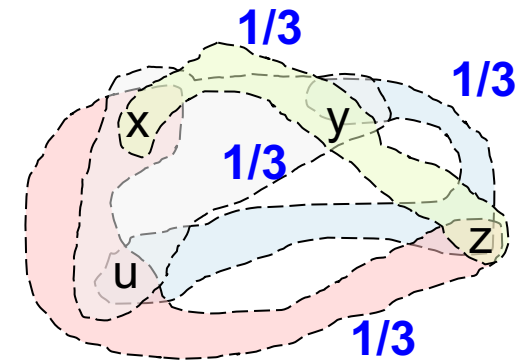
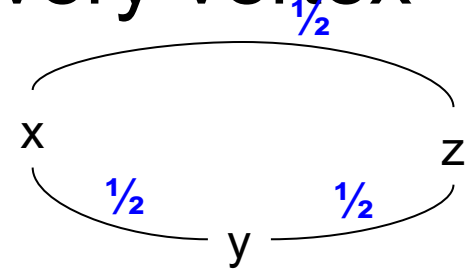
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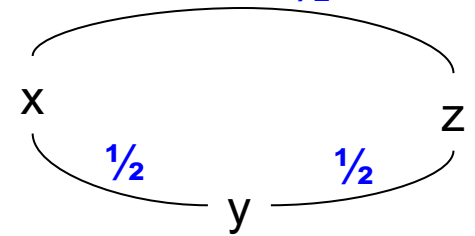
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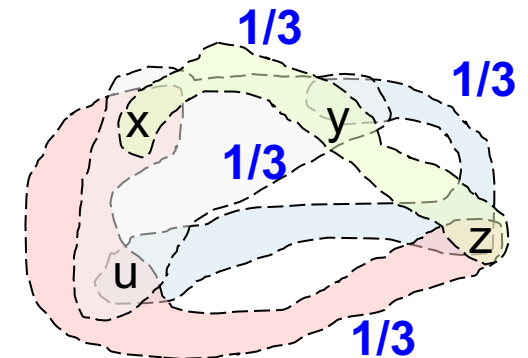


Fractional Edge Cover

- A fractional edge cover of a (hyper)graph is a set of non-negative numbers w_e , one for each edge e , such that, for every vertex v : $\sum_{e:v \in e} w_e \geq 1$



- **Fact:** every edge cover is also a fractional edge cover. Why?



Not so Simple Fact #3

- Consider any query:

$$Q(X_1, \dots, X_k) = R_1(Vars_1) \wedge \dots \wedge R_m(Vars_m)$$

- Let w_1, w_2, \dots, w_m be a fractional edge cover. Then the output size is no larger than:

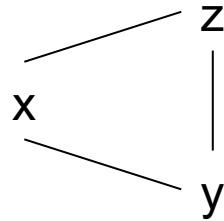
$$|Q| \leq |R_1|^{w_1} \times \dots \times |R_m|^{w_m}$$

Examples

Assume all relations have size **N**

What are the maximum sizes?

- $Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x)$



- $Q(x, y, z, u, v) = R(x, y) \wedge S(y, z) \wedge T(z, u) \wedge K(u, v)$

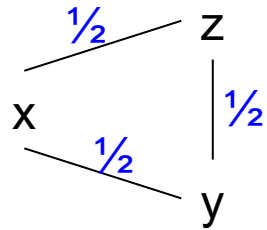


Examples

Assume all relations have size N

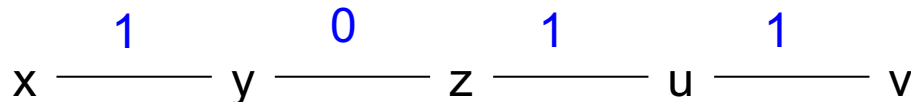
What are the maximum sizes?

- $Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x)$



Answer: $|Q| \leq N^{3/2}$

- $Q(x, y, z, u, v) = R(x, y) \wedge S(y, z) \wedge T(z, u) \wedge K(u, v)$



Answer: $|Q| \leq N^3$

Discussion

- When all relations have the same cardinality N :
 - Choose the fractional edge cover w_1, w_2, \dots, w_m with the smallest sum.
 - This sum is denoted ρ^* , hence $|Q| \leq N^{\rho^*}$
- When relations have different cardinalities, try all edge covers, use minimum bound

Examples

Query	w_1, w_2, \dots, w_m	$ R_1 ^{w_1} \times \dots \times R_m ^{w_m}$	$ Q \leq \dots$
$R(x, y) \wedge S(y, z)$	1, 1	$ R \times S $	$\leq R \times S $
$R(x, y) \wedge S(y, z) \wedge T(z, x)$	$\frac{1}{2}, \frac{1}{2}, \frac{1}{2}$		
	1, 1, 0		
	1, 0, 1		
	0, 1, 1		

Examples

Query	w_1, w_2, \dots, w_m	$ R_1 ^{w_1} \times \dots \times R_m ^{w_m}$	$ Q \leq \dots$
$R(x, y) \wedge S(y, z)$	1, 1	$ R \times S $	$\leq R \times S $
$R(x, y) \wedge S(y, z) \wedge T(z, x)$	$\frac{1}{2}, \frac{1}{2}, \frac{1}{2}$	$(R \times S \times T)^{\frac{1}{2}}$	
	1, 1, 0	$ R \times S $	
	1, 0, 1	$ R \times T $	
	0, 1, 1	$ S \times T $	

Examples

Query	w_1, w_2, \dots, w_m	$ R_1 ^{w_1} \times \dots \times R_m ^{w_m}$	$ Q \leq \dots$
$R(x, y) \wedge S(y, z)$	1, 1	$ R \times S $	$\leq R \times S $
$R(x, y) \wedge S(y, z) \wedge T(z, x)$	$\frac{1}{2}, \frac{1}{2}, \frac{1}{2}$	$(R \times S \times T)^{\frac{1}{2}}$	$\leq \min($ $(R \times S \times T)^{\frac{1}{2}},$ $ R \times S ,$ $ R \times T ,$ $ S \times T)$
	1, 1, 0	$ R \times S $	
	1, 0, 1	$ R \times T $	
	0, 1, 1	$ S \times T $	

Examples

Query	w_1, w_2, \dots, w_m	$ R_1 ^{w_1} \times \dots \times R_m ^{w_m}$	$ Q \leq \dots$
$R(x, y) \wedge S(y, z)$	1, 1	$ R \times S $	$\leq R \times S $
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	1, 1, 0	$ R \times S $	
	1, 0, 1	$ R \times T $	
	0, 1, 1	$ S \times T $	
$A(x, y, z) \wedge B(x, y, u)$ $\wedge C(x, z, u) \wedge D(y, z, u)$			

Examples

Query	w_1, w_2, \dots, w_m	$ R_1 ^{w_1} \times \dots \times R_m ^{w_m}$	$ Q \leq \dots$
$R(x, y) \wedge S(y, z)$	1, 1	$ R \times S $	$\leq R \times S $
$R(x, y) \wedge S(y, z) \wedge T(z, x)$	$\frac{1}{2}, \frac{1}{2}, \frac{1}{2}$	$(R \times S \times T)^{\frac{1}{2}}$	$\leq \min($ $(R \times S \times T)^{\frac{1}{2}},$ $ R \times S ,$ $ R \times T ,$ $ S \times T)$
	1, 1, 0	$ R \times S $	
	1, 0, 1	$ R \times T $	
	0, 1, 1	$ S \times T $	
$A(x, y, z) \wedge B(x, y, u)$ $\wedge C(x, z, u) \wedge D(y, z, u)$	$\frac{1}{3}, \frac{1}{3}, \frac{1}{3}, \frac{1}{3}$		
	1, 1, 0, 0		
	1, 0, 1, 0		
	...		

Examples

Query	w_1, w_2, \dots, w_m	$ R_1 ^{w_1} \times \dots \times R_m ^{w_m}$	$ Q \leq \dots$
$R(x, y) \wedge S(y, z)$	1, 1	$ R \times S $	$\leq R \times S $
$R(x, y) \wedge S(y, z) \wedge T(z, x)$	$\frac{1}{2}, \frac{1}{2}, \frac{1}{2}$	$(R \times S \times T)^{\frac{1}{2}}$	$\leq \min($ $(R \times S \times T)^{\frac{1}{2}},$ $ R \times S ,$ $ R \times T ,$ $ S \times T)$
	1, 1, 0	$ R \times S $	
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	0, 1, 1	$ S \times T $	
$A(x, y, z) \wedge B(x, y, u)$ $\wedge C(x, z, u) \wedge D(y, z, u)$	$\frac{1}{3}, \frac{1}{3}, \frac{1}{3}, \frac{1}{3}$	$(A \times B \times C \times D)^{\frac{1}{3}}$	$\min(\dots)$
	1, 1, 0, 0	$ A \times B $	
	1, 0, 1, 0	$ A \times C $	
	

Examples

Query	w_1, w_2, \dots, w_m	$ R_1 ^{w_1} \times \dots \times R_m ^{w_m}$	$ Q \leq \dots$
$R(x, y) \wedge S(y, z)$	1, 1	$ R \times S $	$\leq R \times S $
$R(x, y) \wedge S(y, z) \wedge T(z, x)$	$\frac{1}{2}, \frac{1}{2}, \frac{1}{2}$	$(R \times S \times T)^{\frac{1}{2}}$	$\leq \min($ $(R \times S \times T)^{\frac{1}{2}},$ $ R \times S ,$ $ R \times T ,$ $ S \times T)$
	1, 1, 0	$ R \times S $	
	1, 0, 1	$ R \times T $	
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$A(x, y, z) \wedge B(x, y, u)$ $\wedge C(x, z, u) \wedge D(y, z, u)$	$\frac{1}{3}, \frac{1}{3}, \frac{1}{3}, \frac{1}{3}$	$(A \times B \times C \times D)^{\frac{1}{3}}$	$\min(\dots)$
	1, 1, 0, 0	$ A \times B $	
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$R(x, y) \wedge S(y, z) \wedge T(z, u)$ $\wedge K(u, v)$			

Examples

Query	w_1, w_2, \dots, w_m	$ R_1 ^{w_1} \times \dots \times R_m ^{w_m}$	$ Q \leq \dots$
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$R(x, y) \wedge S(y, z) \wedge T(z, x)$	$\frac{1}{2}, \frac{1}{2}, \frac{1}{2}$	$(R \times S \times T)^{\frac{1}{2}}$	$\leq \min($ $(R \times S \times T)^{\frac{1}{2}},$ $ R \times S ,$ $ R \times T ,$ $ S \times T)$
	1, 1, 0	$ R \times S $	
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$A(x, y, z) \wedge B(x, y, u)$ $\wedge C(x, z, u) \wedge D(y, z, u)$	$\frac{1}{3}, \frac{1}{3}, \frac{1}{3}, \frac{1}{3}$	$(A \times B \times C \times D)^{\frac{1}{3}}$	$\min(\dots)$
	1, 1, 0, 0	$ A \times B $	
	1, 0, 1, 0	$ A \times C $	
	
$R(x, y) \wedge S(y, z) \wedge T(z, u)$ $\wedge K(u, v)$	1, 0, 1, 1	$ R \times T \times K $	
	1, 1, 0, 1	$ R \times S \times K $	
	1, $\frac{1}{2}, \frac{1}{2}, 1$		

Examples

Query	w_1, w_2, \dots, w_m	$ R_1 ^{w_1} \times \dots \times R_m ^{w_m}$	$ Q \leq \dots$
$R(x, y) \wedge S(y, z)$	1, 1	$ R \times S $	$\leq R \times S $
$R(x, y) \wedge S(y, z) \wedge T(z, x)$	$\frac{1}{2}, \frac{1}{2}, \frac{1}{2}$	$(R \times S \times T)^{\frac{1}{2}}$	$\leq \min($ $(R \times S \times T)^{\frac{1}{2}},$ $ R \times S ,$ $ R \times T ,$ $ S \times T)$
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	1, 0, 1	$ R \times T $	
	0, 1, 1	$ S \times T $	
$A(x, y, z) \wedge B(x, y, u)$ $\wedge C(x, z, u) \wedge D(y, z, u)$	$\frac{1}{3}, \frac{1}{3}, \frac{1}{3}, \frac{1}{3}$	$(A \times B \times C \times D)^{\frac{1}{3}}$	$\min(\dots)$
	1, 1, 0, 0	$ A \times B $	
	1, 0, 1, 0	$ A \times C $	
	
$R(x, y) \wedge S(y, z) \wedge T(z, u)$ $\wedge K(u, v)$	1, 0, 1, 1	$ R \times T \times K $	
	1, 1, 0, 1	$ R \times S \times K $	
	1, $\frac{1}{2}, \frac{1}{2}, 1$	(no need; why?)	

Examples

Query	w_1, w_2, \dots, w_m	$ R_1 ^{w_1} \times \dots \times R_m ^{w_m}$	$ Q \leq \dots$
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$R(x, y) \wedge S(y, z) \wedge T(z, x)$	$\frac{1}{2}, \frac{1}{2}, \frac{1}{2}$	$(R \times S \times T)^{\frac{1}{2}}$	$\leq \min($ $(R \times S \times T)^{\frac{1}{2}},$ $ R \times S ,$ $ R \times T ,$ $ S \times T)$
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	1, 1, 0, 0	$ A \times B $	
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$R(x, y) \wedge S(y, z) \wedge T(z, u)$ $\wedge K(u, v)$	1, 0, 1, 1	$ R \times T \times K $	$\min(R \times T $ $\times K ,$ $ R \times S \times K)$
	1, 1, 0, 1	$ R \times S \times K $	
	1, $\frac{1}{2}, \frac{1}{2}, 1$	(no need; why?)	

Upper Bound of a Query

Theorem $|Q| \leq \min_{w_1, \dots, w_m} |R_1|^{w_1} \times \dots \times |R_m|^{w_m}$

This is called the AGM bound* of Q. It is tight.

Note: it suffices to consider only those fractional edge covers w_1, \dots, w_m that are not convex combinations of others

We will prove tightness on a special case.

But first, let's discuss an algorithm for computing Q with this runtime

*Atserias, Grohe, Marx introduced this bound

$$\text{AGM}(Q) = \min_{w_1, \dots, w_m} |R_1|^{w_1} \times \dots \times |R_m|^{w_m}$$

Generic Join – Overview

- Choose a variable order
- Sort every relation R_i according to this order:
time is $O(|R_i| \log |R_i|) = \tilde{O}(|R_i|)$
- Generic join assumes relations are sorted;
it computes Q in time $\tilde{O}(\text{AGM}(Q))$
- “Worst case optimal”

Generic Join – The Intersection

Intersection is the main building block of G.J.

$$Q(x) = R(x) \wedge S(x)$$

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Generic Join – The Intersection

Intersection is the main building block of G.J.

$$Q(x) = R(x) \wedge S(x)$$

- Discuss merge-join in class – what is runtime?
- Edge covers of Q: 1,0 and 0,1; $|Q| \leq \min(|R|, |S|)$
- Discuss improved merge-join in class
Runtime: $\tilde{O}(\min(|R|, |S|))$

Generic Join Algorithm

Let x be the first variable

Let R_{i_1}, R_{i_2}, \dots be all relations containing x

Compute $D = \Pi_x(R_{i_1}) \cap \Pi_x(R_{i_2}) \cap \dots$

for every value $v \in D$ do:

 Compute Q ,

 where R_{i_1}, R_{i_2}, \dots are restricted to $x = v$

needs to
be done in time
 $\tilde{O}(\min_j \Pi_x(R_j))$

Generic Join Example

$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x),$$

Generic Join Example

$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x),$$

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Generic Join Example

$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x),$$

$$A = \Pi_x(R(x, y)) \cap \Pi_x(T(z, x))$$

for a **in** A **do**

/* compute $Q(a, y, z) = R(a, y) \wedge S(y, z) \wedge T(z, a)$ */

$$B = \Pi_y(R(a, y)) \cap \Pi_y(S(y, z))$$

Generic Join Example

$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x),$$

$$A = \Pi_x(R(x, y)) \cap \Pi_x(T(z, x))$$

for a in A do

/ compute $Q(a, y, z) = R(a, y) \wedge S(y, z) \wedge T(z, a)$ */*

$$B = \Pi_y(R(a, y)) \cap \Pi_y(S(y, z))$$

for b in B do

/ compute $Q(a, b, z) = R(a, b) \wedge S(b, z) \wedge T(z, a)$ */*

Generic Join Example

$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x),$$

$$A = \Pi_x(R(x, y)) \cap \Pi_x(T(z, x))$$

for a in A do

/ compute $Q(a, y, z) = R(a, y) \wedge S(y, z) \wedge T(z, a)$ */*

$$B = \Pi_y(R(a, y)) \cap \Pi_y(S(y, z))$$

for b in B do

/ compute $Q(a, b, z) = R(a, b) \wedge S(b, z) \wedge T(z, a)$ */*

$$C = \Pi_z(S(b, z)) \cap \Pi_z(T(z, a))$$

for c in C do

output (a,b,c)

Generic Join Example

$$Q(x, y, z) = R(x, y) \wedge S(y, z) \wedge T(z, x),$$

$$A = \Pi_x(R(x, y)) \cap \Pi_x(T(z, x))$$

for a in A do

/ compute $Q(a, y, z) = R(a, y) \wedge S(y, z) \wedge T(z, a)$ */*

$$B = \Pi_y(R(a, y)) \cap \Pi_y(S(y, z))$$

for b in B do

/ compute $Q(a, b, z) = R(a, b) \wedge S(b, z) \wedge T(z, a)$ */*

$$C = \Pi_z(S(b, z)) \cap \Pi_z(T(z, a))$$

for c in C do

output (a,b,c)

Runs in time
 $\tilde{O}(AGM(Q))$

Discussion

- All relations need to be presorted, or indexed
- Runtime is guaranteed to be worst-case optimal, no matter what variable order we choose
- In practice, the variable order does matter, in class: discuss $R(x,y) \wedge S(y,z)$

Comparison to Naïve Nested Loop

Naïve nested loop:

// tuple at a time:

For t1 in R1 do

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```
// value at a time:  
For x in Domain do  
  For y in Domain do  
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```

Generic-join

```
A =  $\cap$  domains for x  
For x in A do  
  B =  $\cap$  domains for y  
  For y in B do  
    C =  $\cap$  domains for z  
    For z in C do  
      ...
```

Tightness

- There exists instances R_1, R_2, \dots such that the size of the query's output is $AGM(Q)$
- Proof is simple and instructive; we will show for special case $|R_1| = \dots = |R_m| = N$
- In this case $AGM(Q) = N^{\rho^*}$

Fractional Edge Covering Number

- The fractional edge covering number of a hypergraph is $\rho^* = \min \sum_e w_e$, where the minimum is over all fractional edge covers of the hypergraph.

Fact Assume $|R_1| = \dots = |R_m| = N$. Then $\text{AGM}(Q) = N\rho^*$

Fractional Vertex Packing

- A fractional vertex packing of a (hyper)graph is a set of non-negative numbers v_x , one for each node x , such that, for every edge e : $\sum_{x: x \in e} v_x \leq 1$

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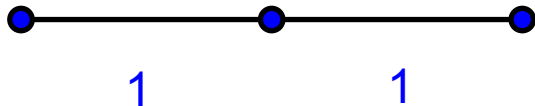
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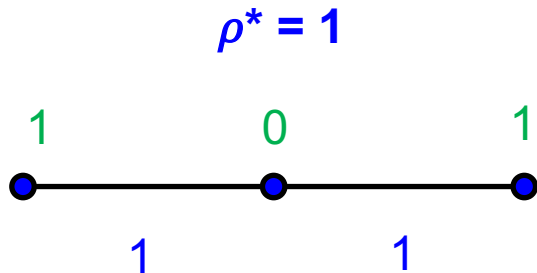


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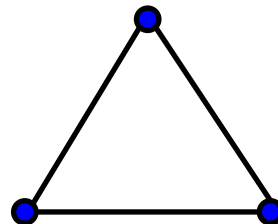
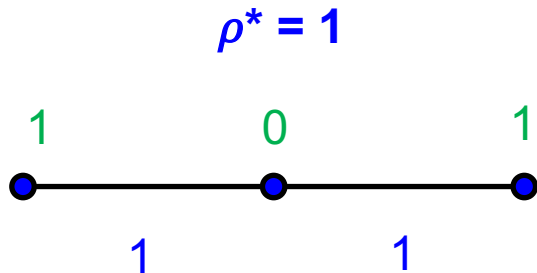


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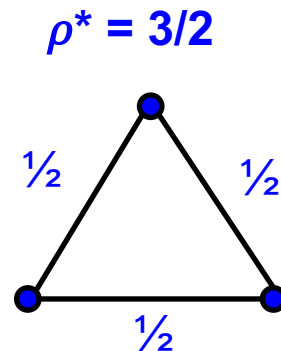
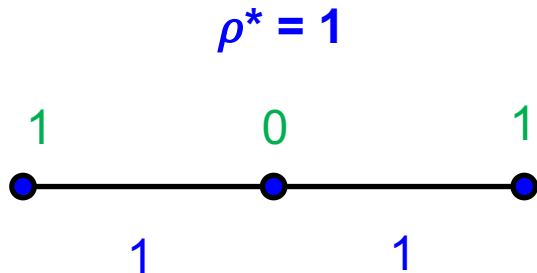


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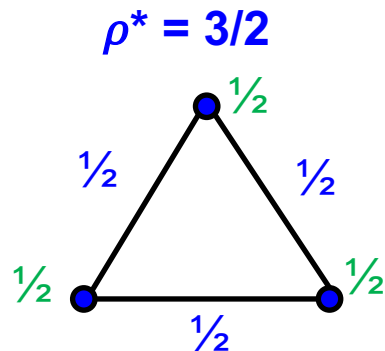
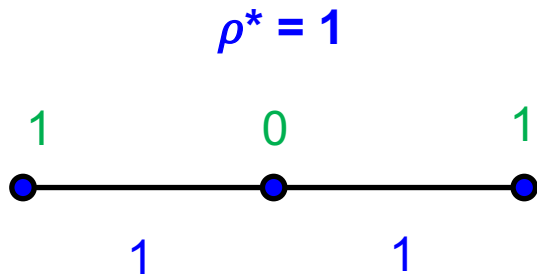


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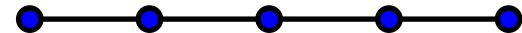
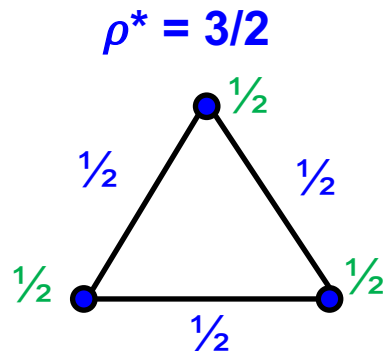
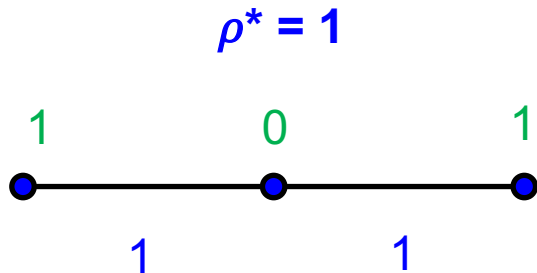


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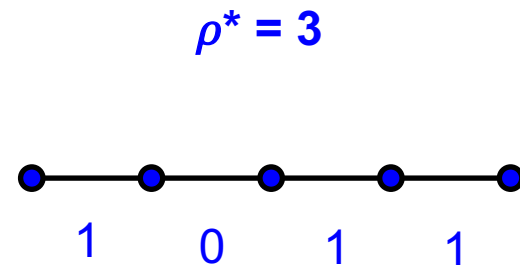
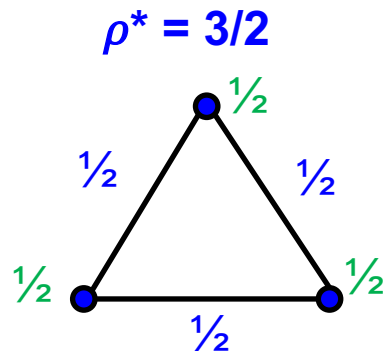
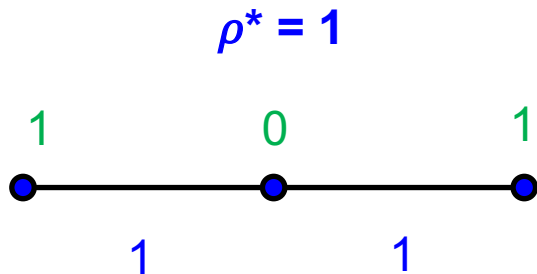


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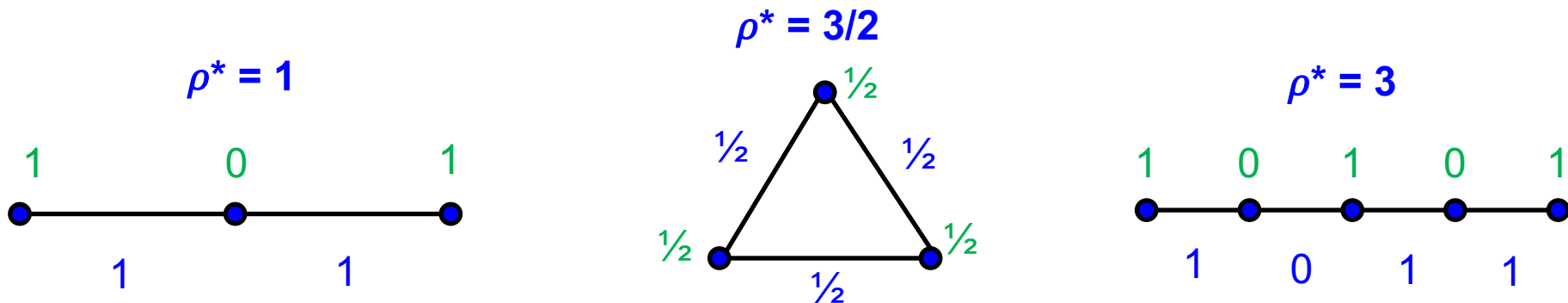


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Fact Fix a fractional vertex packing $v = (v_x)_{x \in \text{Nodes}}$.
Then there exists a database such that
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Proof. For every relation R_j with variables x_{i_1}, x_{i_2}, \dots
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(a) $|R_j| = N^{v_{i_1} + v_{i_2} + \dots} \leq N$ (why?)

(b) $|Q| = N^{\sum_x v_x}$ (why?)

Example

$$Q(x,y,z) = R(x,y) \wedge S(y,z) \wedge T(z,x),$$

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- Define $R = D_x \times D_y$, $S = D_y \times D_z$, $T = D_z \times D_x$.
- Then $|R| = |S| = |T| = N$,
 $Q = D_x \times D_y \times D_z$ and $|Q| = N^{3/2}$

Keys

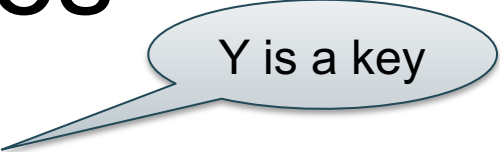
$R(X,Y) \wedge S(Y,Z), \quad |R|, |S| \leq N$

- No other info: $|Q(D)| \leq N^2$
- $S.Y$ is a key: $|Q(D)| \leq N$

The Query Expansion method:

- If Y is a key in some relation S , then add all attributes of S relations containing Y
- Compute $AGM(Q^{\text{expanded}})$

Examples



Y is a key

$$Q(X, Y, Z) = R(X, Y) \wedge S(Y, Z)$$

Examples

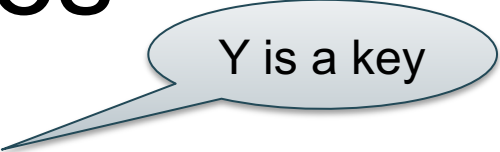


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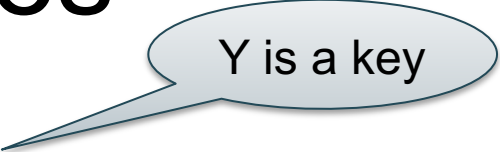


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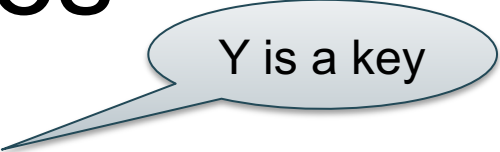
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- $Q^{exp}(X, Y, Z) = R(X, Y, Z) \wedge S(Y, Z) \wedge T(Z, X)$
- Edge covers: 1,0,0 or 0,1,1
- $AGM(Q^{exp}) = \min(|R|, |S| \times |T|)$

Summary

Given cardinalities of all input tables:

- AGM bound gives upper bound on query size
- GJ computes the query in this time

Generic Join:

- A nested loop algorithm
- No longer one-join-at-a-time
- Theoretical optimality means it will be efficient for very expensive queries; less so for cheaper queries