

CSE544

Data Management

Lectures 12

Advanced Query Processing

Announcements

- Project Milestone due on Friday
- Homework 4 posted; due next Friday
- There will be a short Homework 5, on transactions

Quick Recap

- Name 3 join processing algorithms

Outline

Algorithms for multi-joins

- AGM formula for maximum output size
- Generic-join algorithm matching that formula

Multi-join

- `select * from R, S, T, ... where ...`
- Standard approach:
 - Compute one join at a time
 - Optimizer chooses an “optimal” join order
- Issues:
 - Cardinality estimation is hard
 - Even “optimal” plan may be suboptimal

Plans Are Suboptimal

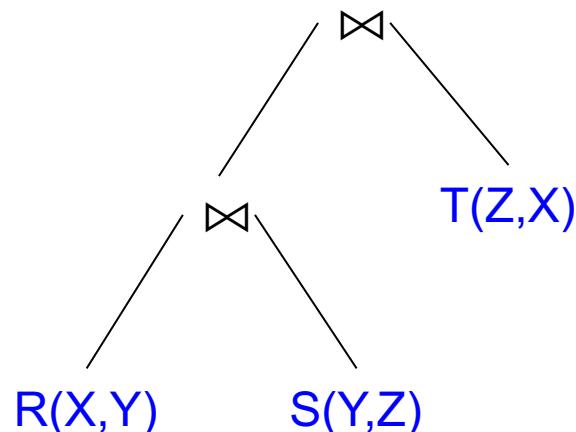
Because intermediate results are much larger than the final query answer

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

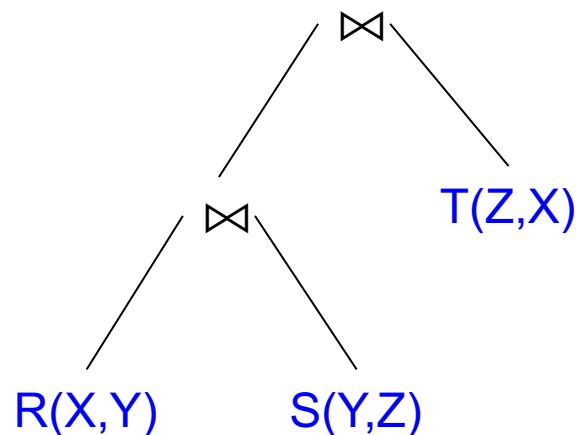


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where R.Y = S.Y and S.Z = T.Z and T.X = R.X
```

Query plan



R:

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

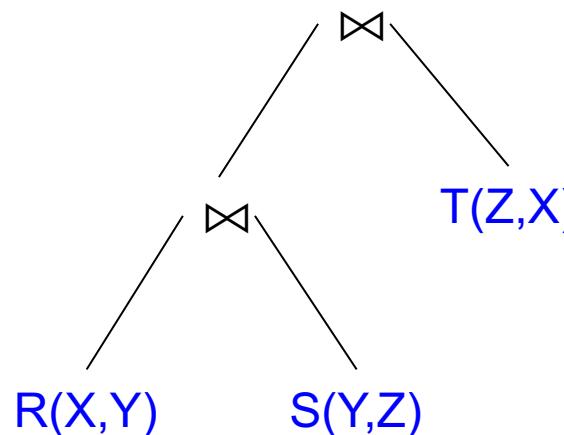
N

Example

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

Query plan



N

R:	
X	Y
0	1
0	2
0	3
...	...
0	$N/2$
1	0
2	0
...	...
$N/2$	0

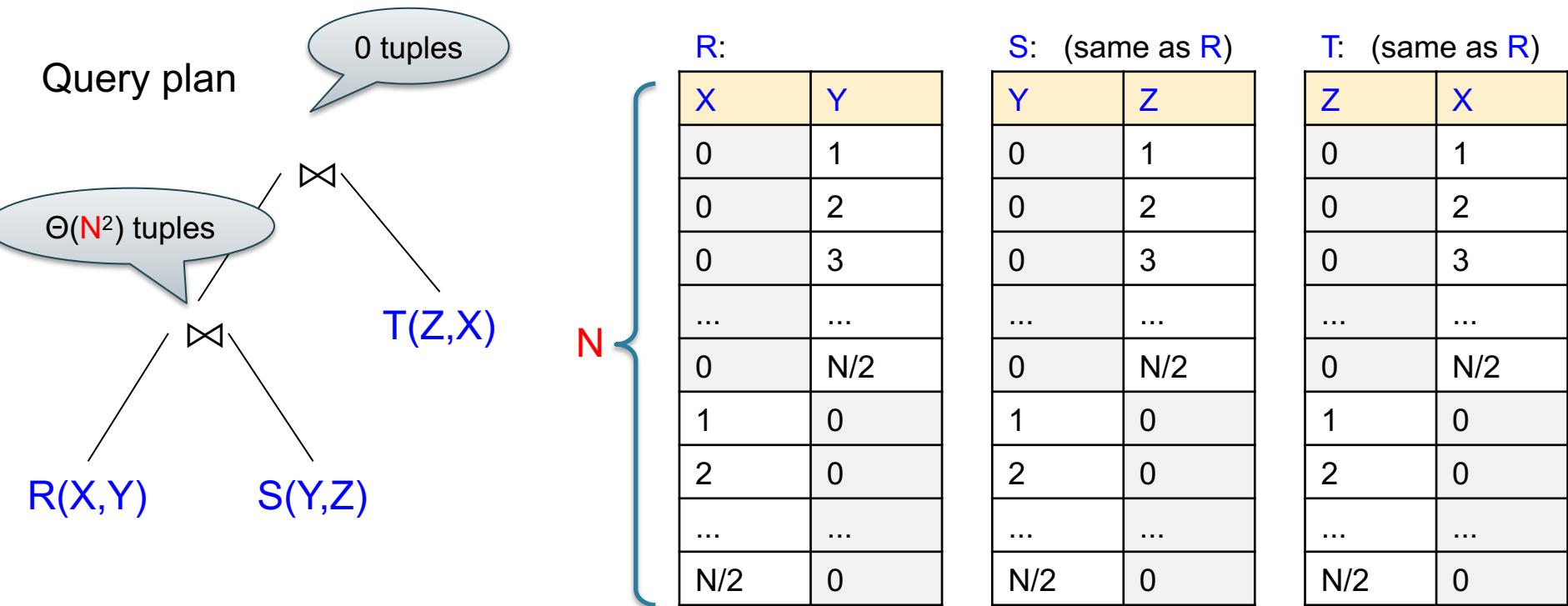
S: (same as R)	
Y	Z
0	1
0	2
0	3
...	...
0	$N/2$
1	0
2	0
...	...
$N/2$	0

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

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
```



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?

Worst-Case Optimality

Fix input statistics for D

- Runtime = $O(\max_{D \text{ satisfies stats}}(|Q(D)|))$

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E.g. $R(X,Y) \wedge S(Y,Z)$, $|R|, |S| \leq N$

Worst-Case Optimality

Fix input statistics for D

- Runtime = $O(\max_{D \text{ satisfies stats}}(|Q(D)|))$

E.g. $R(X,Y) \wedge S(Y,Z)$, $|R|, |S| \leq N$

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

Worst-Case Optimality

Fix input statistics for D

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- $S.Y$ is a key:

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- $S.Y$ is a key: $|Q(D)| \leq N$
- $S.Y$ has degree $\leq d$:

Worst-Case Optimality

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E.g. $R(X,Y) \wedge S(Y,Z)$, $|R|, |S| \leq N$

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

Worst-Case Optimality

Fix input statistics for D

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E.g. $R(X,Y) \wedge S(Y,Z)$, $|R|, |S| \leq N$

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E.g. $R(X, Y) \wedge S(Y, Z) \wedge T(Z, X)$

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

The Two Questions

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

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

Simple Fact #1

- Consider any query:

$$Q(X_1, \dots, X_k) = R_1(\text{Vars}_1) \wedge \dots \wedge R_m(\text{Vars}_m)$$

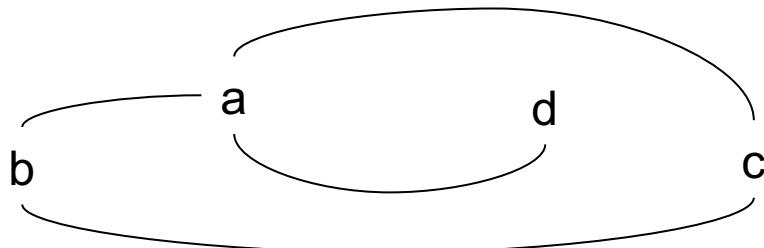
- Its output size is no larger than the product of all cardinalities:

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

Why?

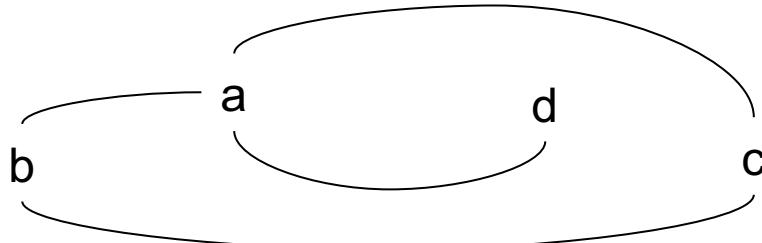
Graphs and Hypergraphs

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

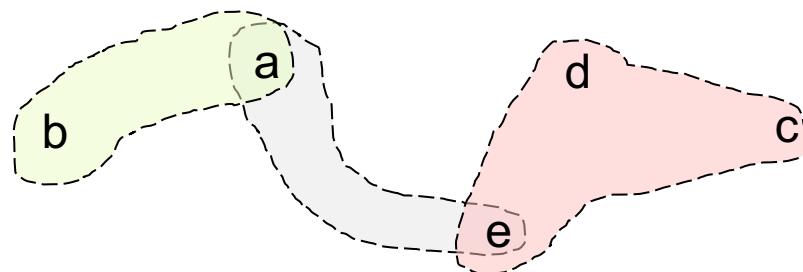


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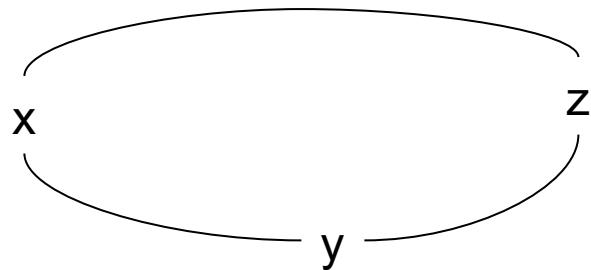


- A hypergraph is $G = (V, E)$ where each edge is some set (of 1 or 2 or >2 nodes)

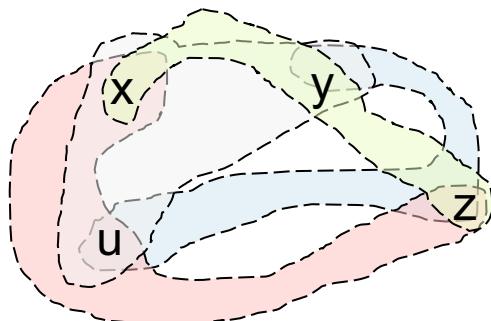


Conjunctive Queries are Hypergraphs

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

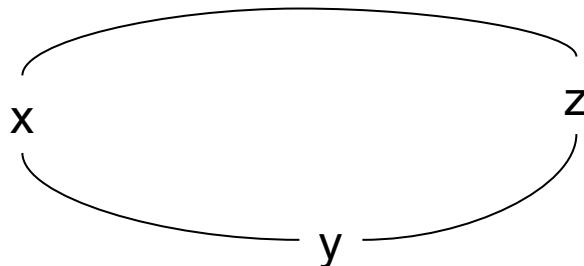


$$Q(x,y,z) = A(x,y,z) \wedge B(x,y,u) \wedge C(x,z,u) \wedge D(y,z,u)$$



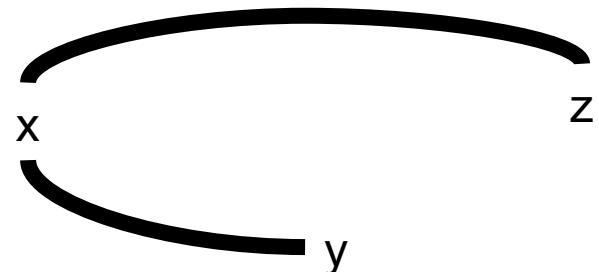
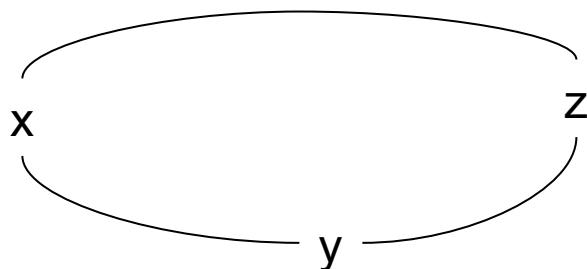
Edge Cover

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



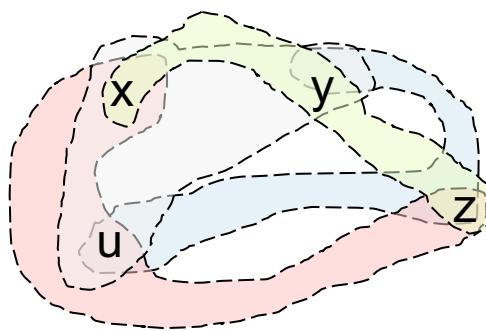
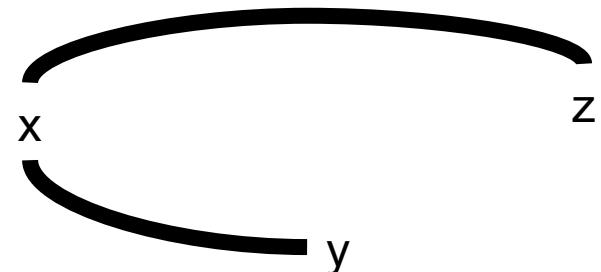
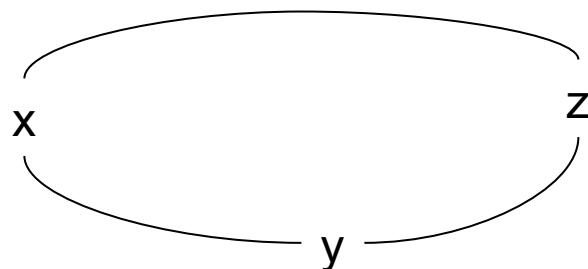
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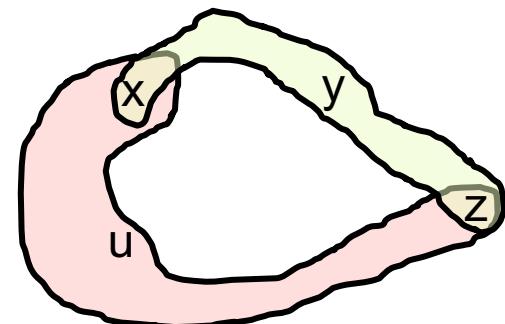
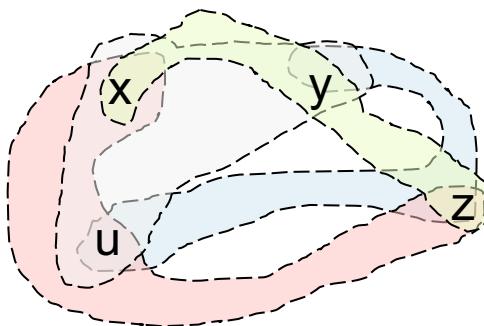
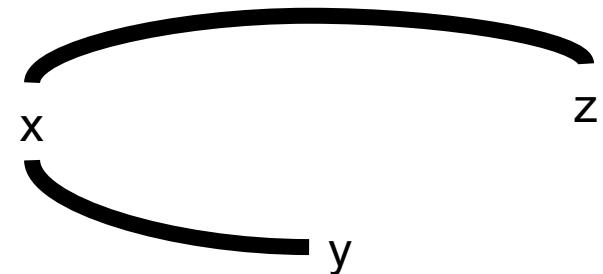
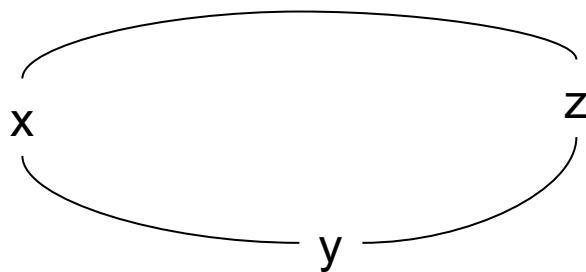
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Edge Cover

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Simple Fact #2

- Consider any query:

$$Q(X_1, \dots, X_k) = R_1(\text{Vars}_1) \wedge \dots \wedge R_m(\text{Vars}_m)$$

- 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

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

Examples

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- Edge covers:

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

Examples

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

- Edge covers:

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

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

Examples

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

- Edge covers:

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

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

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

Examples

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

- Edge covers:

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

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

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

- Edge covers:

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

Examples

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

- Edge covers:

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

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

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

- Edge covers:

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

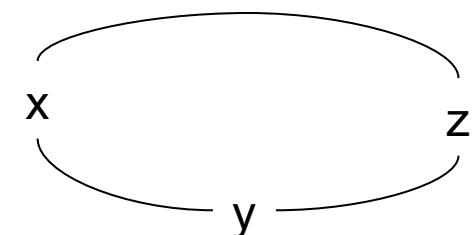
$$|Q| \leq \min(|A| \times |B|, |A| \times |C|, \dots)$$

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 : $\sum_{e: v \in e} w_e \geq 1$

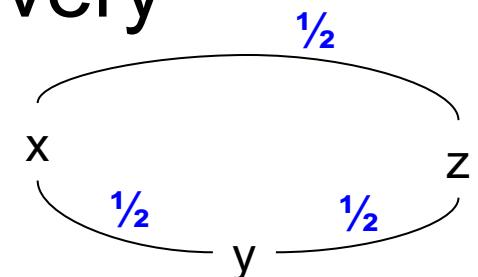
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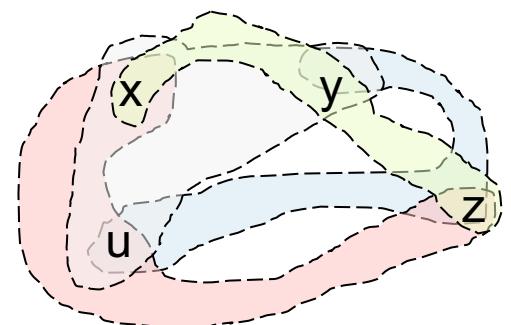
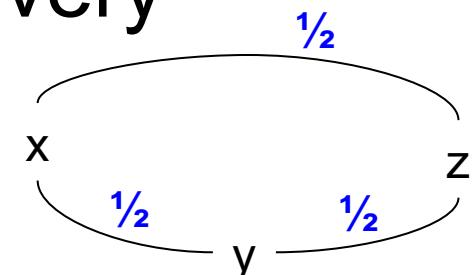
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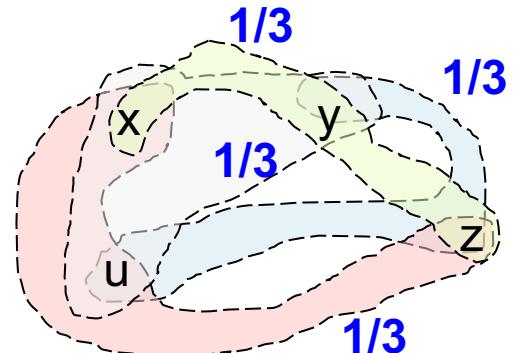
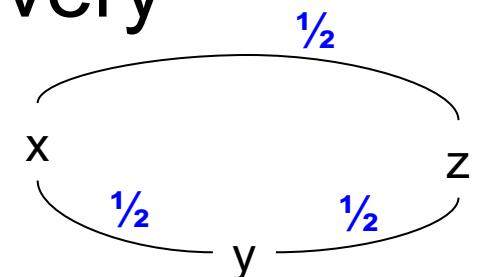
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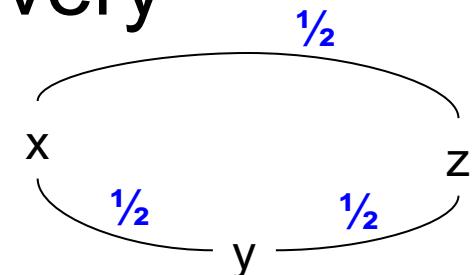
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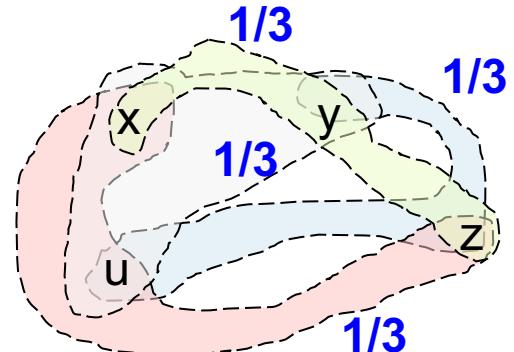


Fractional Edge Cover

- 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:

$$Q(X_1, \dots, X_k) = R_1(\text{Vars}_1) \wedge \dots \wedge R_m(\text{Vars}_m)$$

- 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

Examples

Examples

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 $
$R(x,y) \wedge S(y,z) \wedge T(z,x)$	$\frac{1}{2}, \frac{1}{2}, \frac{1}{2}$	$(R \times S \times T)^{\frac{1}{2}}$	$\leq \min((R \times S \times T)^{\frac{1}{2}}, R \times S , R \times T , S \times T)$
	1,1,0	$ R \times S $	
	1,0,1	$ R \times T $	
	0,1,1	$ S \times T $	
$A(x,y,z) \wedge B(x,y,u) \wedge C(x,z,u) \wedge D(y,z,u)$			

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 $	
$A(x,y,z) \wedge B(x,y,u) \wedge C(x,z,u) \wedge D(y,z,u)$	1/3, 1/3, 1/3, 1/3	$(A \times B \times C \times D)^{1/3}$	

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 $	
$A(x,y,z) \wedge B(x,y,u) \wedge C(x,z,u) \wedge D(y,z,u)$	$\frac{1}{3}, \frac{1}{3}, \frac{1}{3}, \frac{1}{3}$	$(A \times B \times C \times D)^{\frac{1}{3}}$	$\min(\dots)$
	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 $	
	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 $	
	
$R(x,y) \wedge S(y,z) \wedge T(z,u) \wedge K(u,v)$			

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 $	
$A(x,y,z) \wedge B(x,y,u) \wedge C(x,z,u) \wedge D(y,z,u)$	$\frac{1}{3}, \frac{1}{3}, \frac{1}{3}, \frac{1}{3}$	$(A \times B \times C \times D)^{\frac{1}{3}}$	$\min(\dots)$
	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 $	

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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	1,1,0	$ R \times S $	
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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 $	
	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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	1,1,0	$ R \times S $	
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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

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

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 \mathbf{Q} in time $\tilde{O}(\text{AGM}(\mathbf{Q}))$
- “Worst case optimal”

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?

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- 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_{i1}, R_{i2}, \dots be all relations containing x

Compute $D = \Pi_x(R_{i1}) \cap \Pi_x(R_{i2}) \cap \dots$

for every value $v \in D$ do:

 Compute Q ,

 where R_{i1}, R_{i2}, \dots are restricted to $x = v$

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

Generic Join Example

$Q(x,y,z) = R(x,y) \wedge S(y,z) \wedge T(z,x)$,
Assume $|R|=|S|=|T|=N$, then:

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

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

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

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

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/* 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

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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)

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for c in C **do**

output (a,b,c)

Runtime:
 $\tilde{O}(N^{3/2})$

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

 for t2 in R2 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 $\text{AGM}(Q)$
- Proof is simple and instructive; we will show for special case $|R_1| = \dots = |R_m| = N$
- In this case $\text{AGM}(Q) = N^{\min(w_1 + \dots + w_m)}$

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 $\text{AGM}(Q) = N^{\rho^*}$

Why?

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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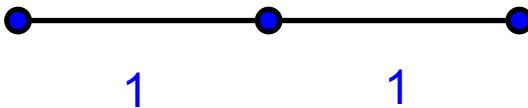
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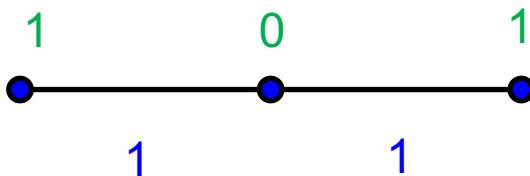
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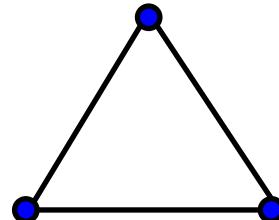
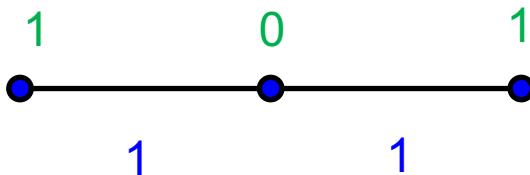
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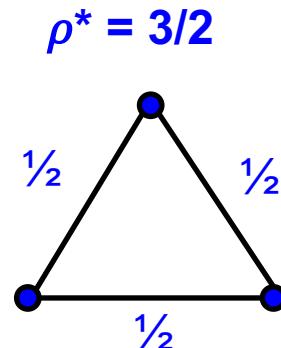
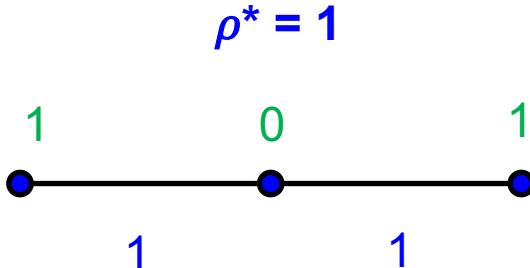


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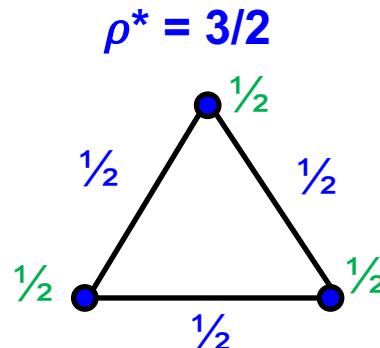
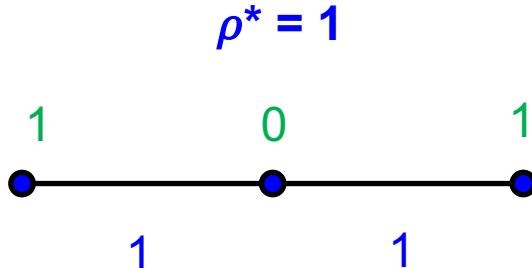


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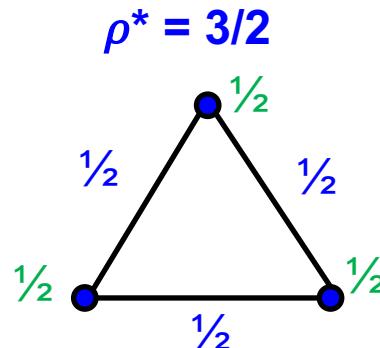
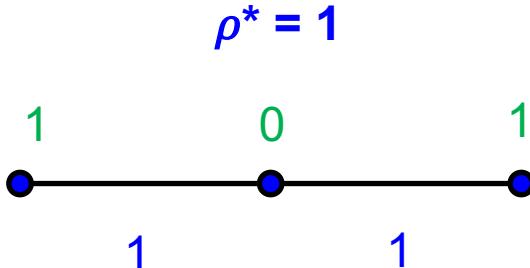


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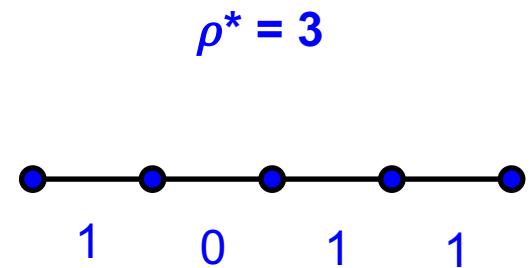
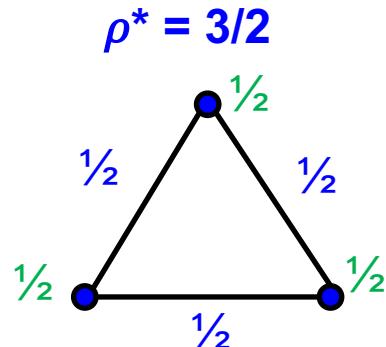
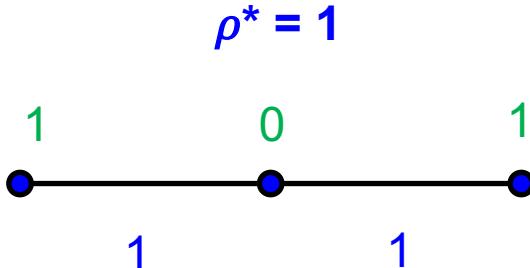


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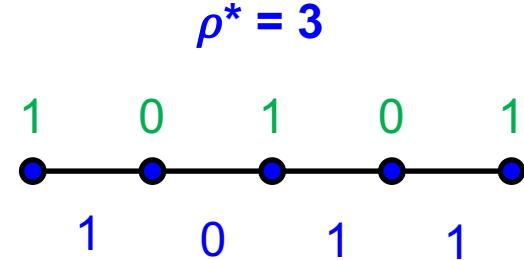
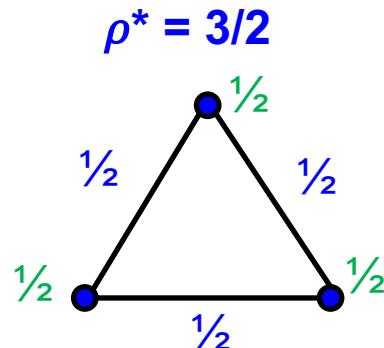
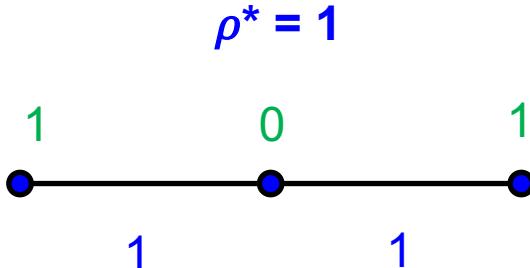


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The Bound is Tight

Fact Fix a fractional vertex packing $v = (v_x)_{x \in \text{Nodes}}$. Then there exists a database such that $|R_1| \leq N, \dots, |R_m| \leq N$ and $|Q| = N^{\sum_x v_x}$

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Proof. For every relation R_j with variables x_{i_1}, x_{i_2}, \dots define the instance $|R_j| = [N^{v_{i_1}}] \times [N^{v_{i_2}}] \times \dots$ where $[k] = \{1, 2, \dots, k\}$.

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(a) $|R_j| = N^{v_{i_1} + v_{i_2} + \dots} \leq N$ (why?)

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$$(a) |R_j| = N^{v_{i_1} + v_{i_2} + \dots} \leq N \quad (\text{why?})$$

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

Example

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

- Assume $|R|=|S|=|T|=N$.

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- Assume $|R|=|S|=|T|=N$.
- Optimal vertex packing: $v_x = v_y = v_z = 1/2$
- Define:
 $D_x = [N^{1/2}] = \{1, 2, \dots, N^{1/2}\}$
 $D_y = [N^{1/2}]$
 $D_z = [N^{1/2}]$

Example

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

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- Define: $D_x = [N^{1/2}] = \{1, 2, \dots, N^{1/2}\}$
 $D_y = [N^{1/2}]$
 $D_z = [N^{1/2}]$
- Define $R = D_x \times D_y$, $S = D_y \times D_z$, $T = D_z \times D_x$.

Example

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- Define: $D_x = [N^{1/2}] = \{1, 2, \dots, N^{1/2}\}$
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 $D_z = [N^{1/2}]$
- 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^{expanded})

Examples

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

Examples

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

- $Q^{\text{exp}}(X, Y, Z) = R(X, Y, Z) \wedge S(Y, Z),$

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

- $Q^{\text{exp}}(X, Y, Z) = R(X, Y, Z) \wedge S(Y, Z),$
- Edge cover: 1,0
- $\text{AGM}(Q^{\text{exp}}) = |R|$

Examples

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

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- $\text{AGM}(Q^{\text{exp}}) = |R|$

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Examples

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- 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