

CS294-248 Special Topics in Database Theory

Unit 4: AGM Bound, WCOJ

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Outline

- Today: the AGM bound. This is a mathematical formula that gives us $AGM(Q, \mathbf{D}) \stackrel{\text{def}}{=} \max_{\mathbf{D} \models \text{statistics}} |Q(\mathbf{D})|$.
- Thursday: Worst Case Optimal Join, by guest lecturer [Hung Ngo](#). An algorithm that computes $Q(\mathbf{D})$ in time $\tilde{O}(AGM(Q, \mathbf{D}))$.

Background on Cardinality Estimation

Cardinality Estimation 101 (1/3)

Given:

- Statistics on the input relations R_1, R_2, \dots
- A full conjunctive query Q

“Estimate”:

- The size $|Q(\mathbf{D})|$.

Numerous applications: query optimization, memory provisioning, data partitioning.

Cardinality Estimation 101 (2/3)

Bottom-up on the query plan:

- Selection $\sigma_p(R)$: assume **independence**:

$$|\sigma_p(R)| \approx \theta_p \cdot |R|$$

$$\theta_{p_1 \wedge p_2} \approx \theta_{p_1} \cdot \theta_{p_2}$$

Histograms, multidimensional histograms.

- Join $J(A, B, C) = R(A, B) \wedge S(B, C)$: assume **preservation of values**

$$\triangleright |J| \approx |R| \cdot \text{avg}(\text{deg}_S(C|B)) = \frac{|R| \cdot |S|}{|\text{Dom}(S.B)|}$$

$$\triangleright |J| \approx |S| \cdot \text{avg}(\text{deg}_R(A|B)) = \frac{|R| \cdot |S|}{|\text{Dom}(R.B)|}$$

- Heuristic: take the minimum:

$$|J| \approx \frac{|R| \cdot |S|}{\max(|\text{Dom}(R.B)|, |\text{Dom}(S.B)|)}$$

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Cardinality Estimation 101 (3/3)

- Notoriously hard to estimate cardinality of complex queries.
- No rigorous definition of the estimate: there is no probability space.
- How do we combine multiple sources of information?
 - ▶ We had two formulas for the join, why choose min?
 - ▶ Given $R(A, B, C)$ and histograms on A, B, C, AB, AC , how do we estimate $|\sigma_{A=2, B=4, C=6}(R)|$?

Upper Bound on the Output of a Query

The Output Bound Problem

Given statistics on the input \mathbf{D} , e.g. cardinalities, # distinct values,

Compute an upper bound B :

$$|Q(\mathbf{D})| \leq B$$

Challenge: make B tight.

Simple Examples

Assume $|R| \leq N$, $|S| \leq N$, $|T| \leq N$.

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

$$\max_D |Q(\mathbf{D})| = ?$$

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If $S.Y$ is a key:

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- $Q(X, Y, Z, U) = R(X, Y) \wedge S(Y, Z) \wedge T(Z, U)$. $\max_D |Q(D)| = ?$

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Notice the role of an **edge cover**

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Notice the role of an **edge cover**

- $Q(X, Y, Z) = R(X, Y) \wedge S(Y, Z) \wedge T(Z, X)$. $\max_D |Q(\mathbf{D})| = N^{\frac{3}{2}}$

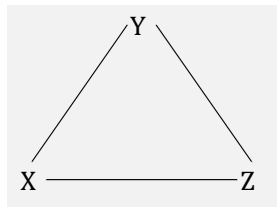
Here we use a **fractional edge cover**

AGM Bound: The Statement

Fractional Edge Covers

Query Q to hypegraph $G = (V, E)$.

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



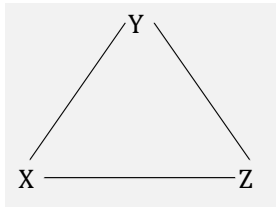
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Definition

A *fractional edge cover* is $\mathbf{w} = (w_e)_{e \in E}$, $w_e \geq 0$:
 $\forall x \in V, \sum_{e \in E: x \in e} w_e \geq 1$.



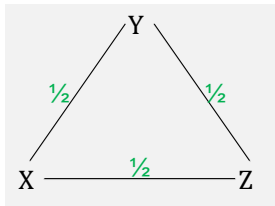
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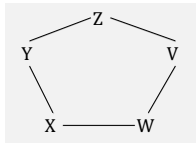
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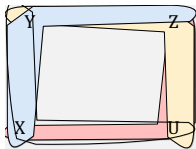


Examples

What are fractional edge covers?

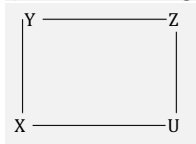


5-cycle



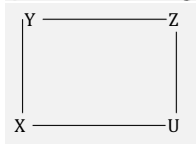
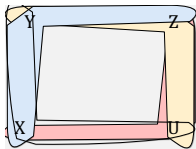
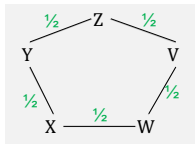
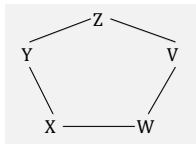
Loomis-Whitney:

$$R(X, Y, Z) \wedge S(Y, Z, U) \\ \wedge T(Z, U, X) \wedge K(U, X, Y)$$



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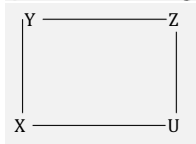
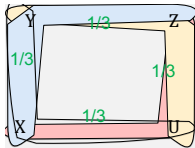
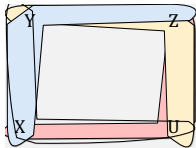
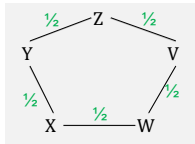
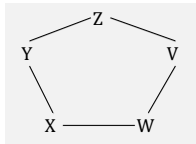
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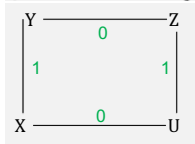
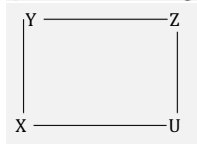
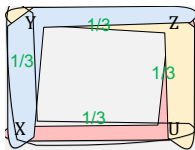
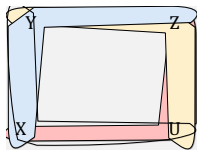
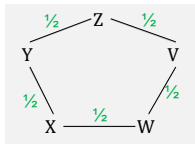
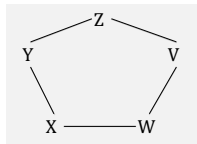
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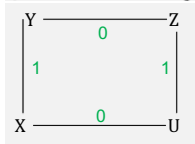
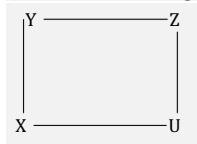
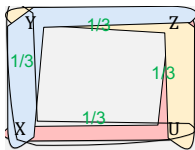
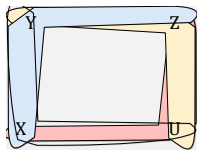
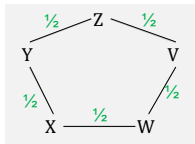
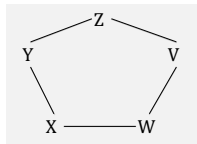
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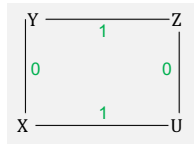
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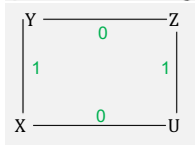
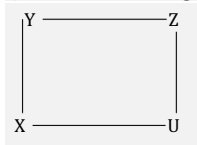
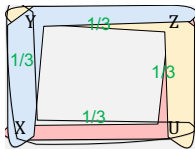
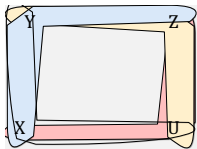
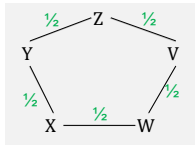
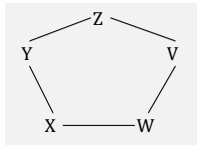
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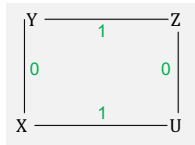
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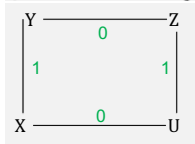
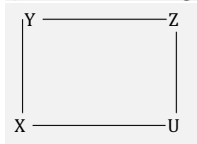
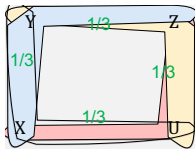
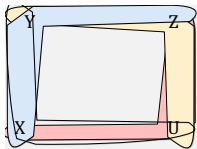
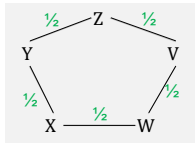
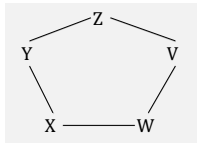
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Examples

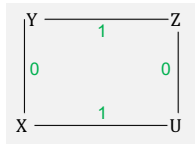
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Vertex of the edge covering polytope: no convex combination of others.

The AGM Bound [Atserias et al., 2013]

$$Q(\mathbf{X}) = R_1(\mathbf{Y}_1) \wedge \cdots \wedge R_m(\mathbf{Y}_m)$$

Theorem (Upper Bound)

For every fractional edge cover \mathbf{w} : $|Q| \leq |R_1|^{w_1} \cdots |R_m|^{w_m}$

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$AGM(Q) \stackrel{\text{def}}{=} \min_{\mathbf{w}} |R_1|^{w_1} \cdots |R_m|^{w_m}$ is “tight”.

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$$R(X, Y) \wedge S(Y, Z) \wedge T(Z, X) \qquad AGM(Q) = \min \begin{pmatrix} (|R| \cdot |S| \cdot |T|)^{1/2} \\ |R| \cdot |S| \\ |R| \cdot |T| \\ |S| \cdot |T| \end{pmatrix}$$

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Minimum over vertices of the edge-covering polytope. **WHY?**

Proof Outline

- Proof of the upper bound: [information inequalities](#) (a.k.a. entropic inequalities).
- Proof of the lower bound: construct a worst-case database instance by using [strong duality of linear optimization](#).

Proof of the Upper Bound

Entropic Vectors

Definition

Finite probability space $p : D \rightarrow [0, 1]$. $X = \text{r.v. with outcomes } D$.

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$h(XY) = \log 4$

X	p
a	3/4
b	1/4

$h(X) \leq \log 2$

Y	p
p	1/4
q	2/4
m	1/4

$h(Y) \leq \log 3$

\emptyset	p
	1

$h(\emptyset) = 0$

Shannon Inequalities

Basic Shannon Inequalities

$$h(\emptyset) = 0$$

$$h(\mathbf{U} \cup \mathbf{V}) \geq h(\mathbf{U})$$

Monotonicity

$$h(\mathbf{U}) + h(\mathbf{V}) \geq h(\mathbf{U} \cup \mathbf{V}) + h(\mathbf{U} \cap \mathbf{V})$$

Submodularity

A [Shannon inequality](#) is a consequence of these inequalities.

A Shannon Inequality

Example

$$h(XY) + h(YZ) + h(XZ) \geq 2h(XYZ)$$

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Note: X is covered 2 times in each expressions. Same for Y , same for Z .

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From Query to Information Inequality:

Example

$$Q(X, Y, Z) = R(X, Y) \wedge S(Y, Z) \wedge T(Z, X), \quad |Q| \leq (|R| \cdot |S| \cdot |T|)^{1/2}.$$

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For a general query $Q(\mathbf{X}) = R_1(\mathbf{Y}_1) \wedge \dots \wedge R_m(\mathbf{Y}_m)$:

$$\text{If } \sum_j w_j h(\mathbf{Y}_j) \geq h(\mathbf{X}) \text{ then } |R_1|^{w_1} \dots |R_m|^{w_m} \geq |Q|$$

Proof of the AGM Upper Bound: Part 2: $|Q| \leq |R_1|^{w_1} \dots |R_m|^{w_m}$

Theorem (Generalized Shearer's Inequality)

If \mathbf{w} is a frac. edge cover, then $w_1 h(\mathbf{Y}_1) + \dots + w_m h(\mathbf{Y}_m) \geq h(\mathbf{X})$.

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Proof following [Balister and Bollobás, 2012]. Convert to integers:

$$k_1 h(\mathbf{Y}_1) + \dots + k_m h(\mathbf{Y}_m) \geq k_0 h(\mathbf{X})$$

Each variable is “covered $\geq k_0$ times”.

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- Thus, $\mathbf{Y}_1 = \mathbf{X}$ and $k_1 \geq k_0$.

$$\dots \geq k_1 h(\mathbf{Y}_1) \geq k_0 h(\mathbf{X})$$

This completes the proof of the Upper AGM Bound.

Discussion

- Shearer's inequality: apply submodularity repeatedly, in **any** order!
- Shearer inequalities correspond 1-1 to fractional edge covers.
- Any inequality is an upper bound on $|Q|$: $AGM(Q)$ is the smallest.
- How tight is $AGM(Q)$ upper bound? **Next**

Proof of the Lower Bound

Proof of the AGM Lower Bound

By example:

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Primal program:

Minimize

$$w_R \log |R| + w_S \log |S| + w_T \log |T|$$

where \mathbf{w} is frac. edge cover:

$$X : \quad w_R + \quad \quad w_T \geq 1$$

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$$v_X + v_Y + v_Z$$

where \mathbf{v} is “frac. vertex packing”:

$$R : \quad v_X + \quad v_Y \leq \log |R|$$

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Take optimum \mathbf{v} , define: $\text{Dom}(X) \stackrel{\text{def}}{=} \llbracket 2^{v_X} \rrbracket$, $\text{Dom}(Y) \stackrel{\text{def}}{=} \llbracket 2^{v_Y} \rrbracket$, $\text{Dom}(Z) \stackrel{\text{def}}{=} \llbracket 2^{v_Z} \rrbracket$.

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Worst-case instance (cartesian products): $R^* \stackrel{\text{def}}{=} \text{Dom}(X) \times \text{Dom}(Y)$, S^* , $T^* \stackrel{\text{def}}{=} \dots$

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$$|Q^*| = \lfloor 2^{v_X} \rfloor \cdot \lfloor 2^{v_Y} \rfloor \cdot \lfloor 2^{v_Z} \rfloor \geq \frac{1}{8} 2^{v_X + v_Y + v_Z}$$

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Worst-case instance (cartesian products): $R^* \stackrel{\text{def}}{=} \text{Dom}(X) \times \text{Dom}(Y)$, $S^*, T^* \stackrel{\text{def}}{=} \dots$

$$|Q^*| = \lfloor 2^{v_X} \rfloor \cdot \lfloor 2^{v_Y} \rfloor \cdot \lfloor 2^{v_Z} \rfloor \geq \frac{1}{8} 2^{v_X + v_Y + v_Z} = \frac{1}{8} 2^{w_1^* \log |R| + w_2^* \log |S| + w_3^* \log |T|} = \frac{1}{8} 2^{AGM(Q)}$$

Special Case: $|R| = |S| = \dots = N$

Definition

Fix a hypergraph (V, E) ; $(v_X)_{X \in V} \in \mathbb{R}_+^{|V|}$ is a **fractional vertex packing** if:

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Then: $R = [N^{v_X}] \times [N^{v_Y}]$, $S = [N^{v_Y}] \times [N^{v_Z}]$, $T = [N^{v_X}] \times [N^{v_Z}]$.

$$Q = [N^{v_X}] \times [N^{v_Y}] \times [N^{v_Z}]$$

Examples

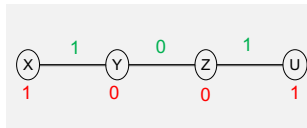
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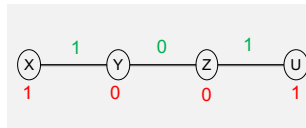


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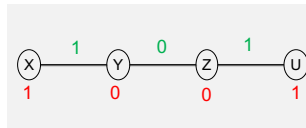


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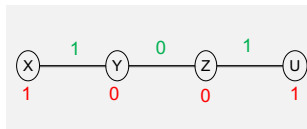
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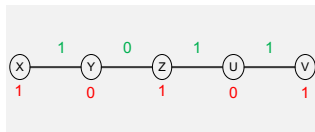
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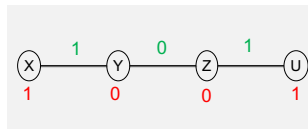


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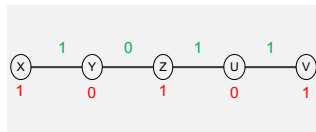
$$R(\textcolor{red}{X}, Y) \wedge S(Y, Z) \wedge T(Z, \textcolor{red}{U})$$

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$$R = T = [\textcolor{red}{N}] \times [1], S = K = [1] \times [\textcolor{red}{N}]$$



Summary of the AGM Bound

- Upper / lower bound: fractional **edge cover** / **vertex packing**.
- Their equality follows from strong duality.
- The worst-case instance of the AGM bound is a **Product Database**.
- Full CQs only. Otherwise, ignore non-head variables.

Limitation of AGM: only **cardinalities**. Next: extensions to **other stats**.

Extensions of the AGM Bound

Simple Functional Dependencies

Given functional dependencies, query output is \ll AGM bound.

Example: $R(X, Y) \wedge S(Y, Z)$: N^2 becomes N when $Y \rightarrow Z$.

An FD $U \rightarrow V$ is **simple** if U is a single variable.

Method [Khamis et al., 2016]:

- **Expand** Q to Q^+ by replacing each atom $R(Y)$ with $R'(Y^+)$.
- Compute the AGM bound of Q^+ .
- This bound is tight. **Proof: very useful exercise.**

Example

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

Fractional edge covers: $(1, 1, 0), (1, 0, 1), (0, 1, 1), (1/2, 1/2, 1/2)$

$$|Q| \leq \min(|R| \cdot |S|, |R| \cdot |T|, |S| \cdot |T|, \sqrt{|R| \cdot |S| \cdot |T|})$$

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Fractional edge covers: $(\textcolor{red}{1}, 0, 0), (0, 1, 1)$

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

Discussion

The expansion procedure is very easy, but limited only to simple FDs:

$AGM(Q^+)$ is always an upper bound on Q 's output, but may not be tight.

Example

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

$$A: XZ \rightarrow U;$$

$$B: YU \rightarrow X$$

Expansion is useless ($Q^+ = Q$).

More Statistics

Statistics for a relation $R(U, V, W, \dots)$:

- Its cardinality $|R|$.
- Number distinct values of an attribute / set of attributes, e.g. $|R.X|$.
- Max degree of an attribute / set of attributes, e.g. $\max(\deg_R(VW|U))$.
- The max degree of a projection, e.g. $\max(\deg_R(V|U))$.
- The ℓ_p -norm of some degree sequence, e.g. $\|\deg_R(V|U)\|_2$.

Will use entropic inequalities, beyond Shearer

Example

$R =$

U	V	W
a	1	m
a	1	n
a	2	m
a	3	m
b	1	m
b	5	m

$$|R| = 6$$

$$|R.U| = 2$$

$$|R.V| = 4$$

$$|R.UV| = 5$$

$$\max(\deg_R(VW|U)) = 4$$

$$\max(\deg_R(V|U)) = 3$$

Conditional Entropy

The *Conditional Entropy*

$$h(\mathbf{V}|\mathbf{U}) \stackrel{\text{def}}{=} h(\mathbf{UV}) - h(\mathbf{U})$$

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What it means: $h(\mathbf{V}|\mathbf{U}) = \mathbb{E}_{\mathbf{u}}[h(\mathbf{V}|\mathbf{U} = \mathbf{u})]$

The submodularity inequality can be written equivalently as:

$$h(\mathbf{V}|\mathbf{U}) \geq h(\mathbf{V}|\mathbf{UW})$$

From Entropy to Statistics

Fix a joint probability distribution of the variables \mathbf{X} , with support $R(\mathbf{X})$:

$$h(\mathbf{X}) \leq \log |R|$$

$$h(\mathbf{V}|\mathbf{U}) \leq \log (\max \deg_R(\mathbf{V}|\mathbf{U}))$$

$$h(\mathbf{UV}) + (p-1)h(\mathbf{V}|\mathbf{V}) \leq \log ||\deg_R(\mathbf{V}|\mathbf{U})||_p^p$$

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Assume $|R| = |S| = |T| = N$:

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If the FDs $XZ \rightarrow U$ and $YU \rightarrow X$ hold:

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

$$\begin{aligned} & \log |R| + \log |S| + \log |T| + \log \max \deg_A(U|XZ) + \log \max \deg_B(X|YU) \geq \\ & \geq h(XY) + h(YZ) + h(ZU) + h(U|XZ) + h(X|YU) \end{aligned}$$

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$$|Q| \leq \sqrt{|R| \cdot |S| \cdot |T| \cdot \max(\deg(U|XZ)) \cdot \max(\deg(X|YU))}$$

Discussion

- AGM/Shearer limited to cardinality statistics.
- More general statistics require general entropic inequalities.
- Everything gets harder: fractional edge cover no longer sufficient, order of the submodularity matters.
- Can we compute the upper bound? Is it tight? Yes and no, it's complicated [Suciu, 2023].
- Do they work in practice? Yes, but you need to do the engineering work [Deeds et al., 2023].



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