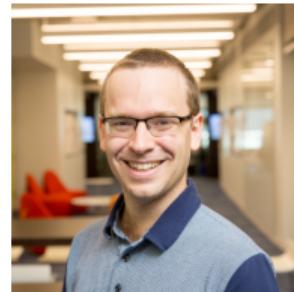


Clique Is Hard on Average for Unary Sherali-Adams

Kilian Risse



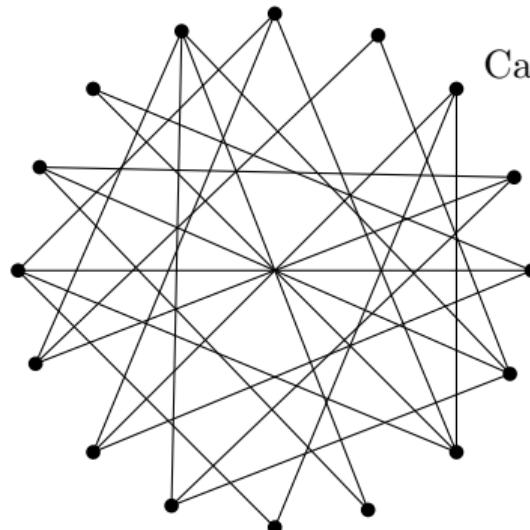
MIAO Seminar, January 2024



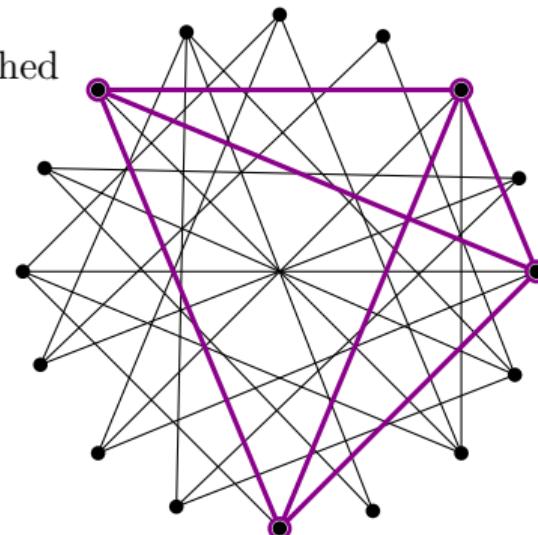
Joint work with Susanna de Rezende and Aaron Potechin

Planted Clique

- Erdős-Rényi random graph $G \sim \mathcal{G}(n, 1/2)$
 - max clique of size $\approx 2 \log n$
- Planted k -clique: $G \sim \mathcal{G}(n, 1/2, k)$
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Can these be distinguished
in poly-time?



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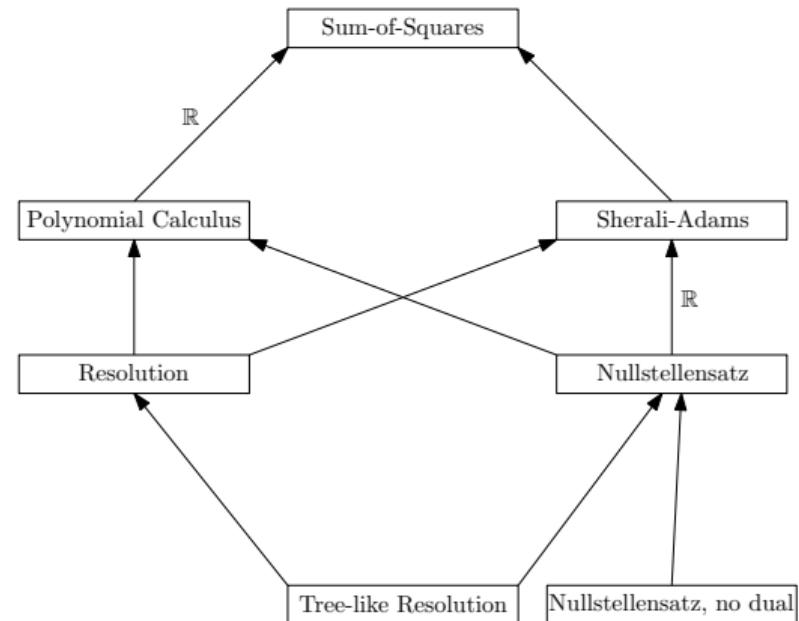
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Boils down to a size lower bound in **unary Sherali-Adams**

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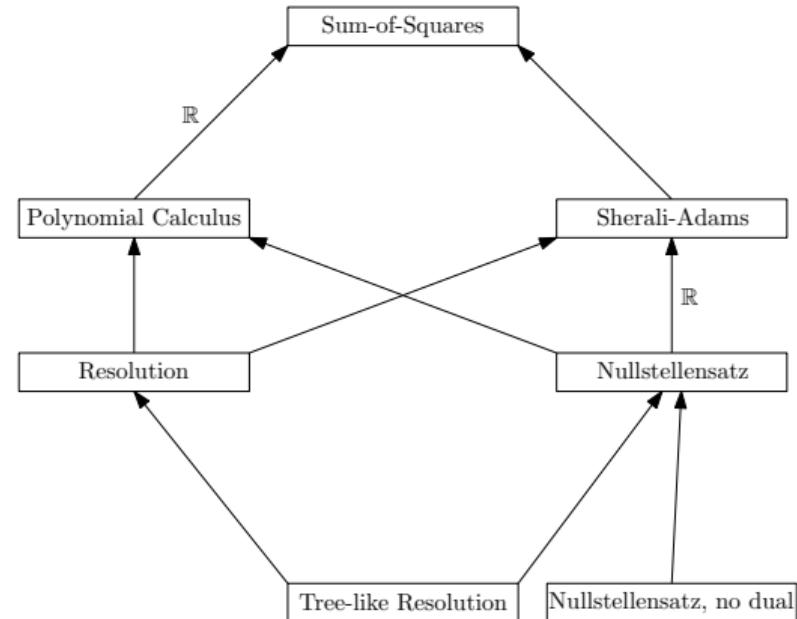


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- Optimal under Unique Games
Conjecture for many optimization problems
- Captures best algos for clique

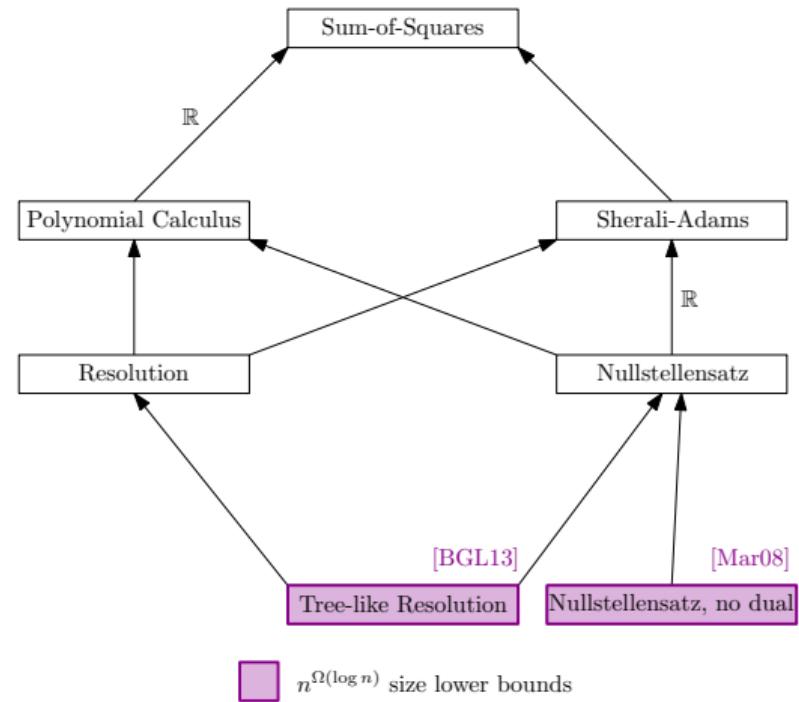


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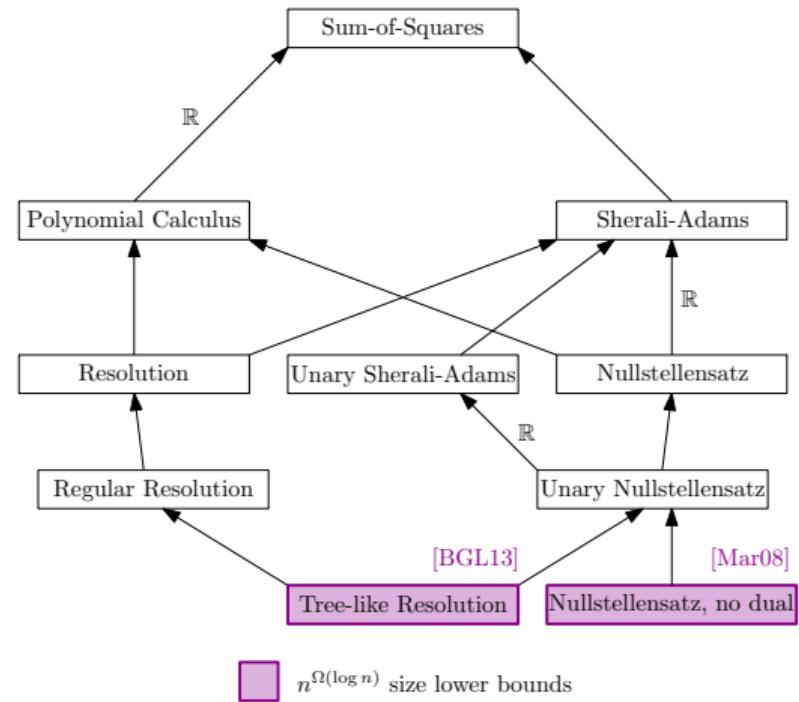


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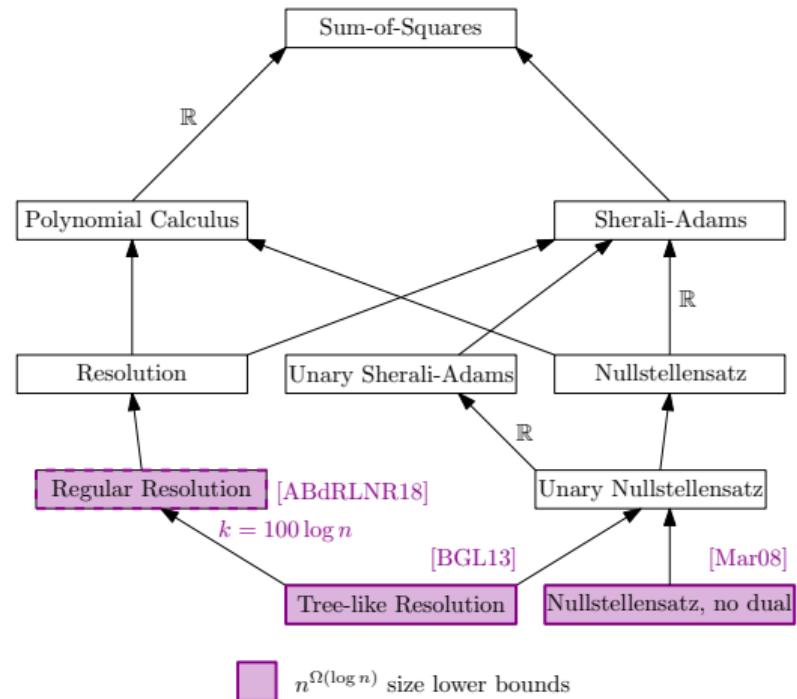


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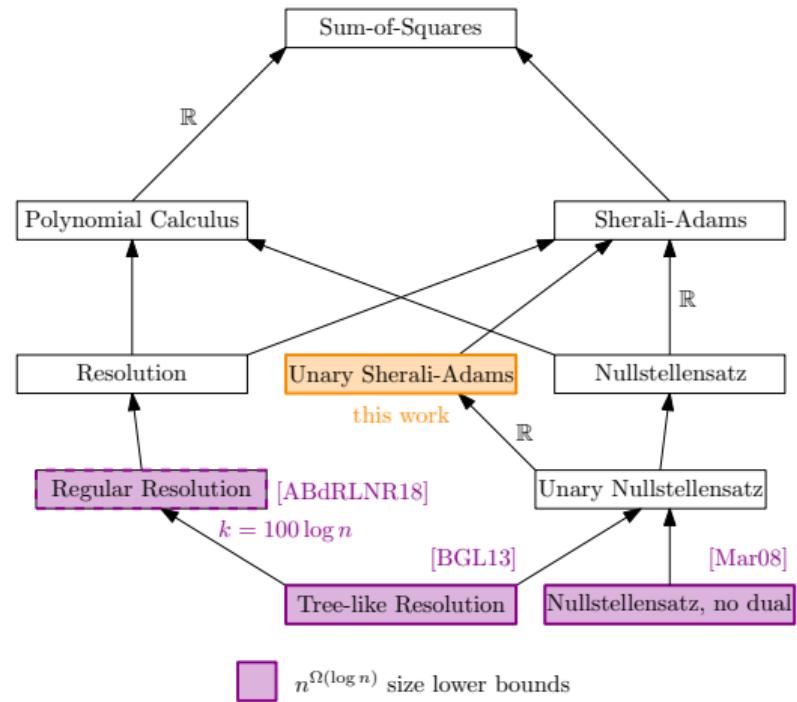


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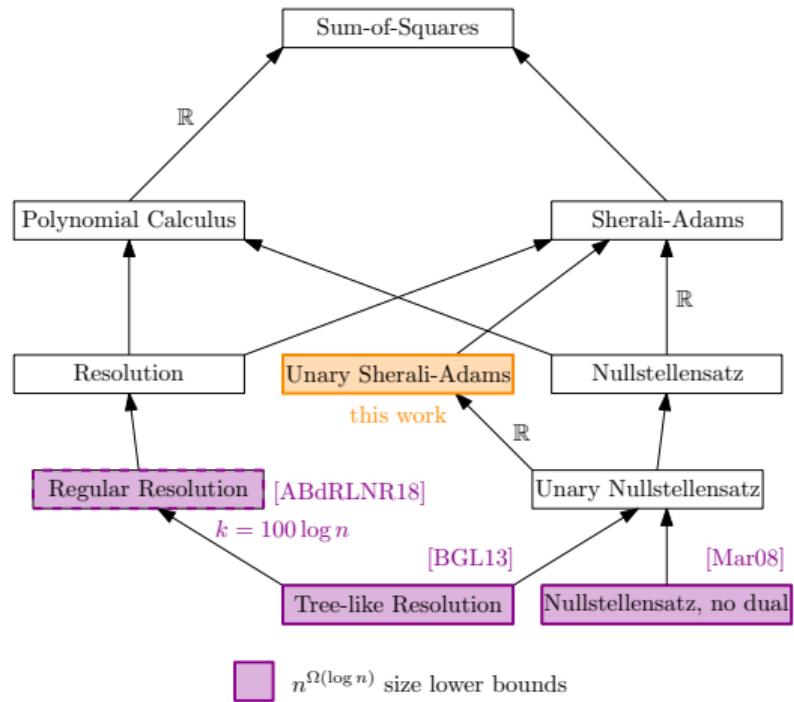


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Results of similar flavor:

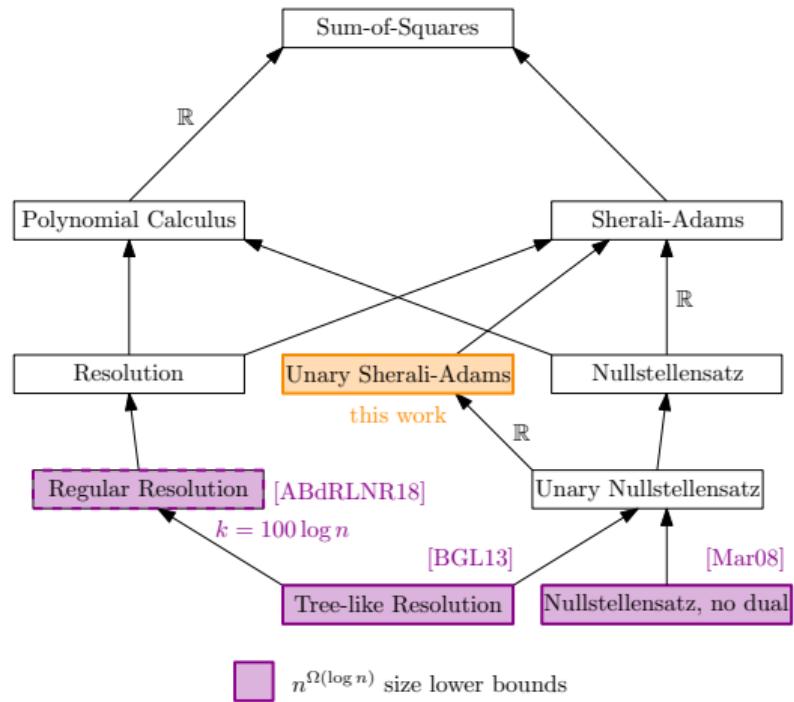
- Monotone & bounded depth **circuits**
[Rossman08, Rossman10]
- Resolution:
 - non-tight lower bounds [BIS07, Pang21]
 - weak encoding [LPRT17, DGGM20]
- Degree lower bounds for SoS
[MPW15, ..., BHKKMP19, Pang21]



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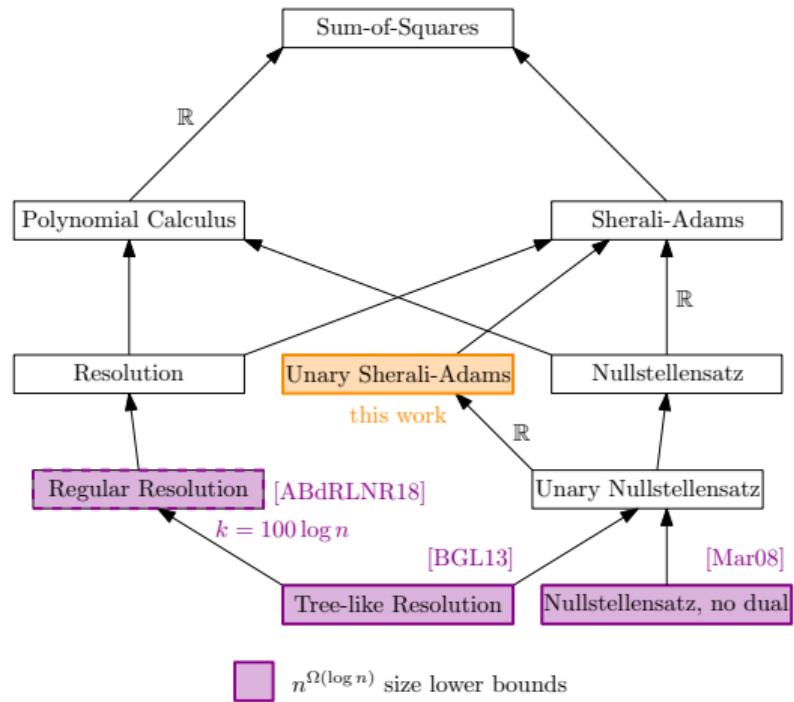


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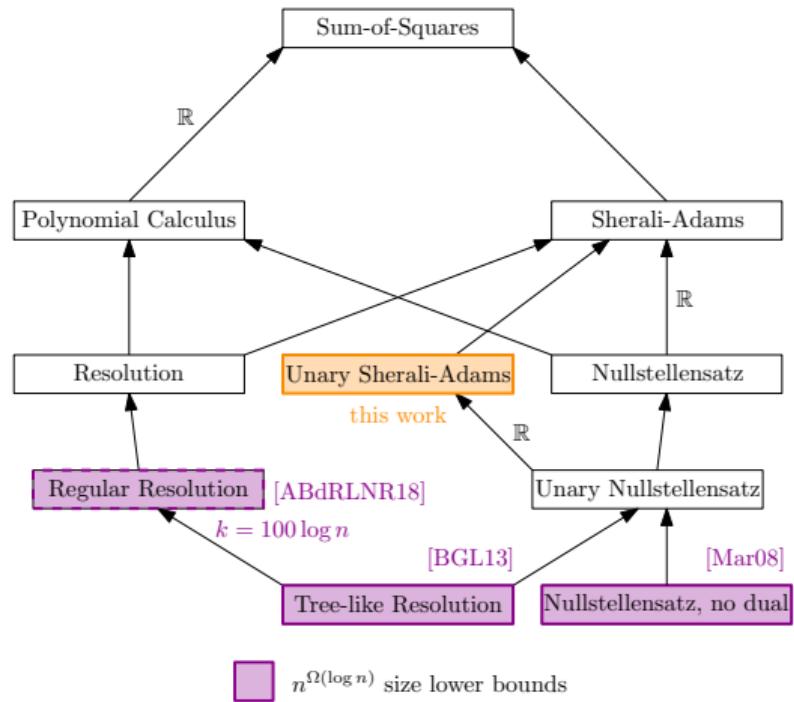


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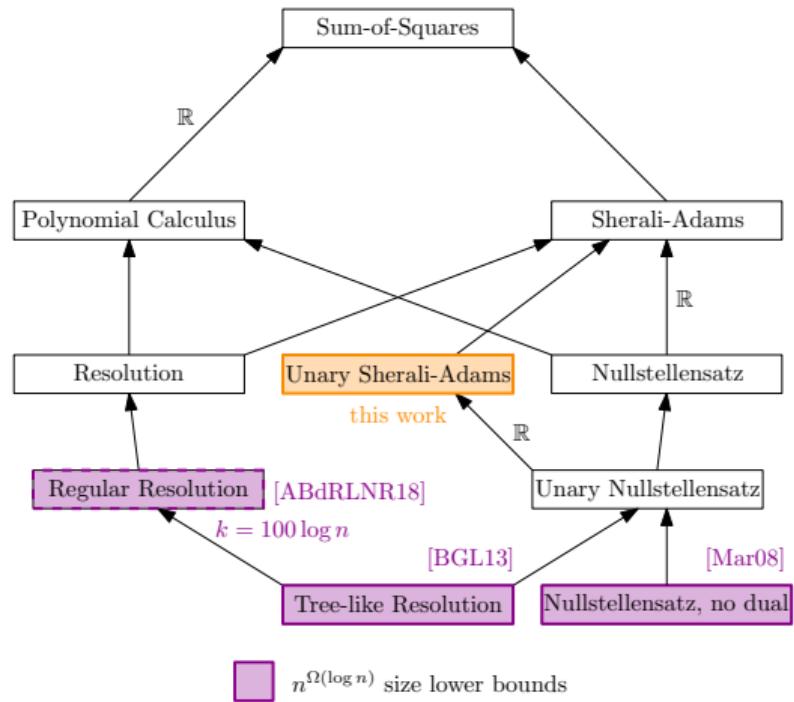


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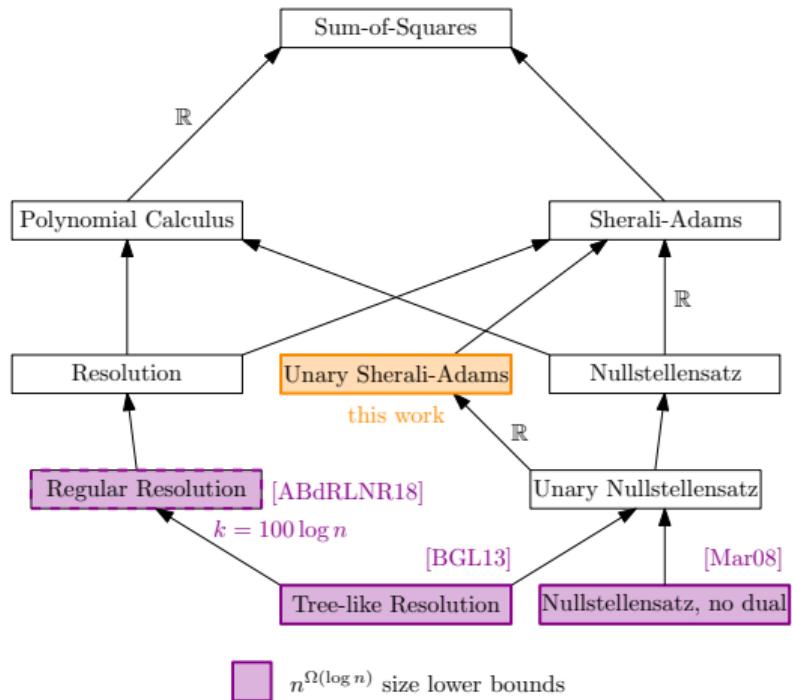
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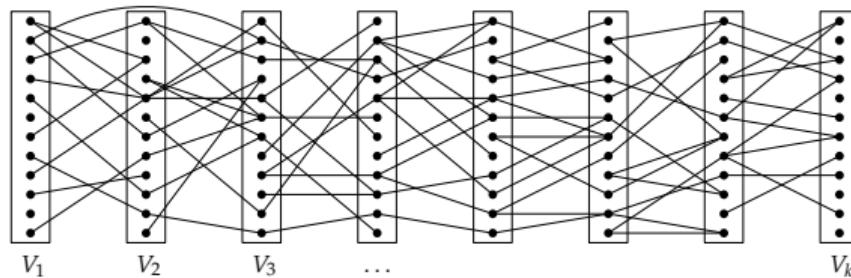
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- Seems to require new techniques...



Clique Formula & unary Sherali-Adams

Clique Formula: Block Encoding

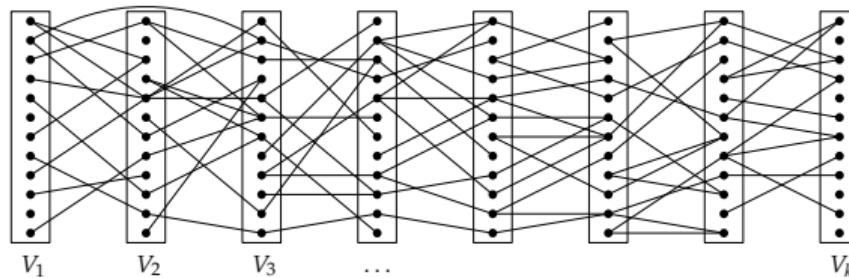
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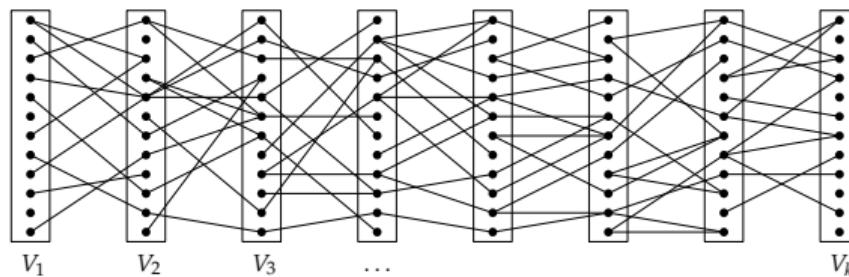
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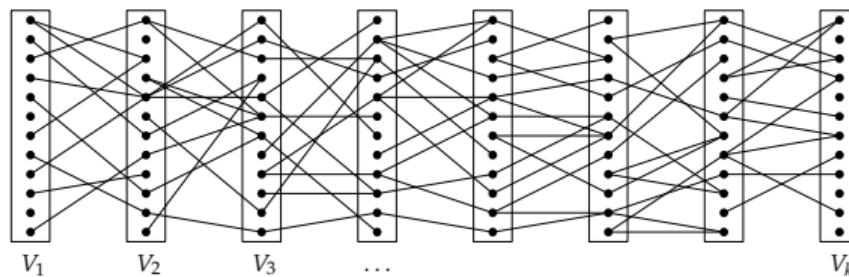
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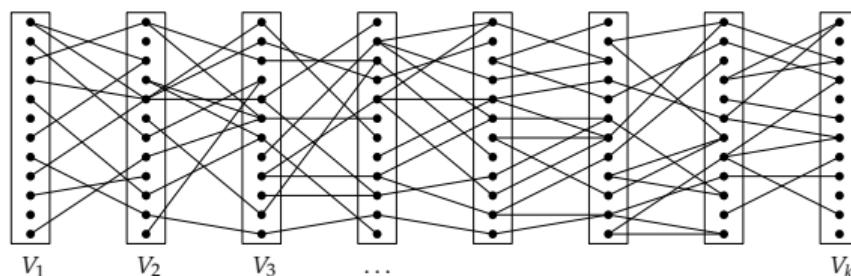
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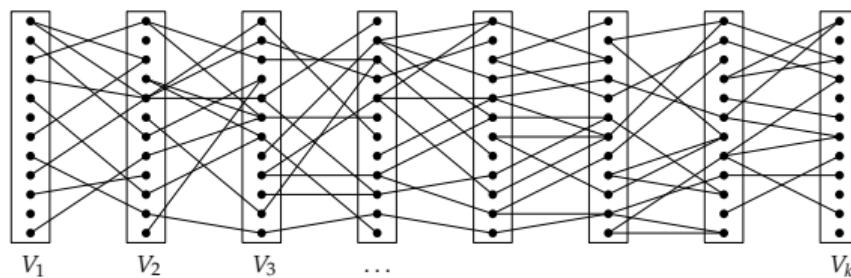
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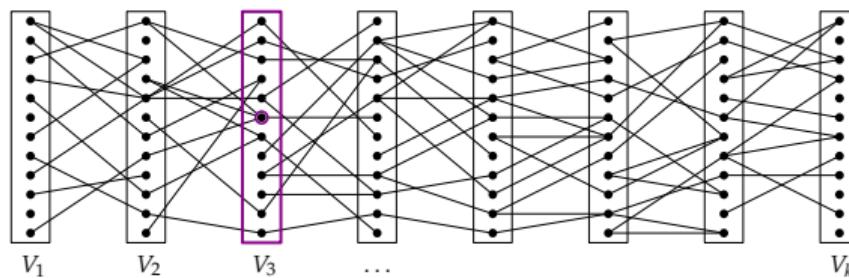
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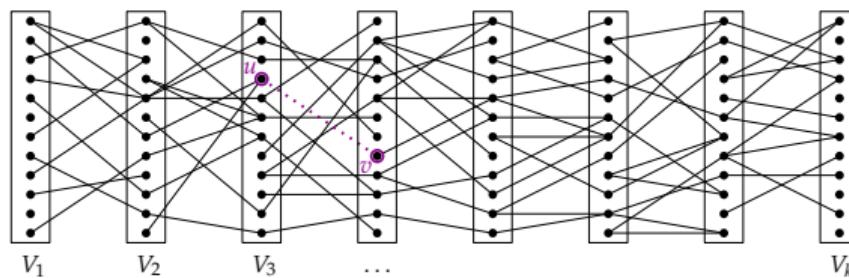
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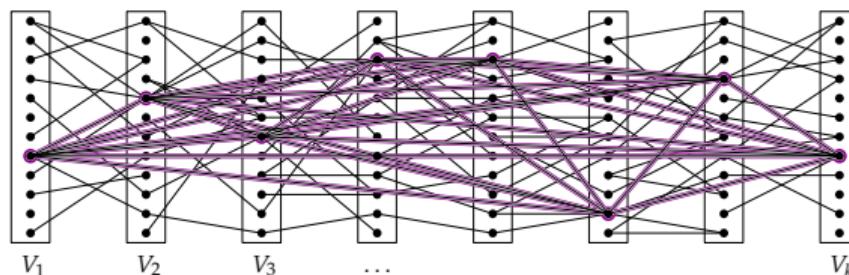
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$\text{clique}(G, k)$ sat if and only if there is a k -clique with a single vertex per block

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- Boolean variables $x_1, \dots, x_m, \bar{x}_1, \dots, \bar{x}_m$
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Today: only $p = 1/2$ and hence $D \approx 2 \log n$

Proof Ideas

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 - small on axioms: for all monomials m , axioms $p \in \mathcal{P}$
$$|\mu(m \cdot p)| \leq \delta$$
- Implies a $\mu(1)/\delta$ unary Sherali-Adams size lower bound to refute \mathcal{P} :

$$\sum_{p_i \in \mathcal{P}} \sum_{m \in q_i} \underbrace{c_m \mu(m \cdot p_i)}_{\geq -|c_m|\delta} + \sum_{\substack{A, B \subseteq [n] \\ c_{A,B} \geq 0}} \underbrace{c_{A,B} \mu\left(\prod_{i \in A} x_i \prod_{j \in B} \bar{x}_j\right)}_{\geq -|c_{A,B}|\delta} = -\mu(M)$$

How to Lower Bound Magnitude of Coefficients

- Write LP to search for min size unary Sherali-Adams refutation of \mathcal{P}
- Lower bound size by duality: craft a δ -pseudo-measure μ for \mathcal{P} which is linear,
 - almost non-negative: for monomials $m = \prod_{i \in A} x_i \prod_{j \in B} \bar{x}_j$
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Goal

Construct a $n^{-\Omega(\log n)}$ -pseudo-measure for $\text{clique}(G, k)$, where $G \sim \mathcal{G}(n, k, 1/2)$ and $k \leq n^{0.1}$

linear operator μ such that $\mu(m) \geq -n^{-\Omega(\log n)}$ and $|\mu(m \cdot p)| \leq n^{-\Omega(\log n)}$, while $\mu(1) \approx 1$

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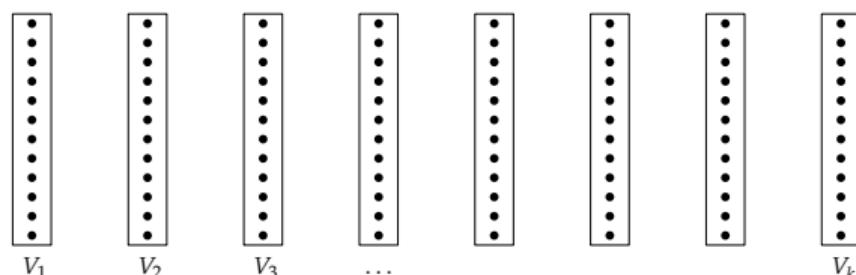
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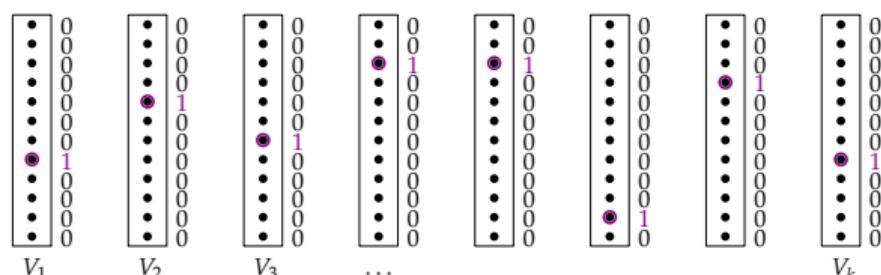
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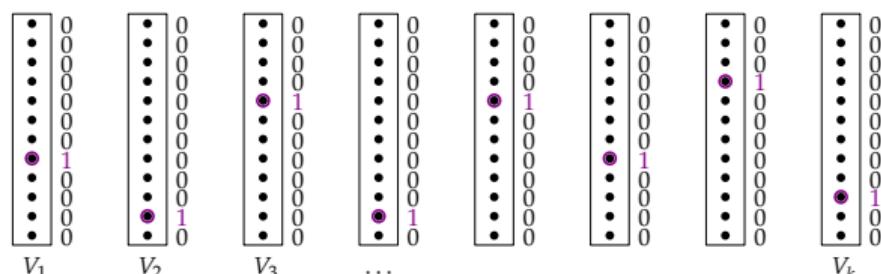
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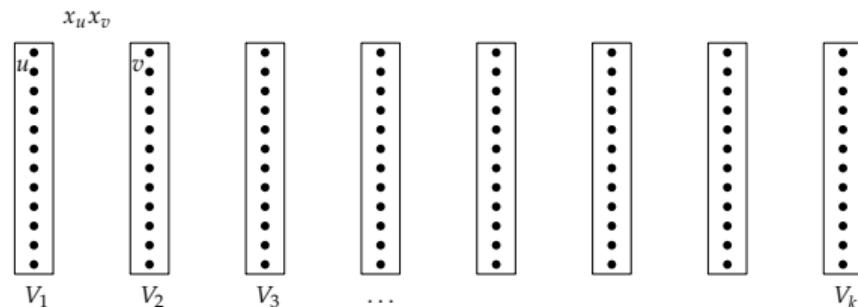
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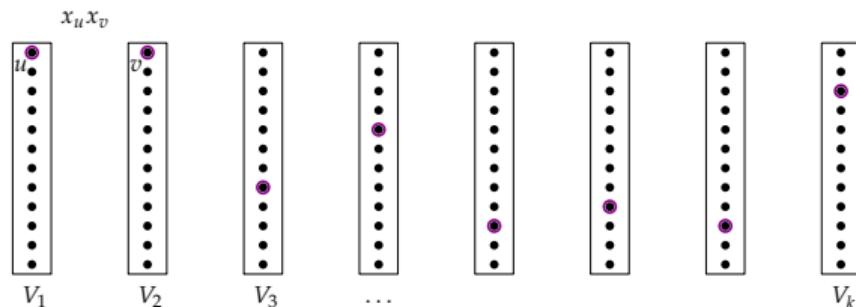
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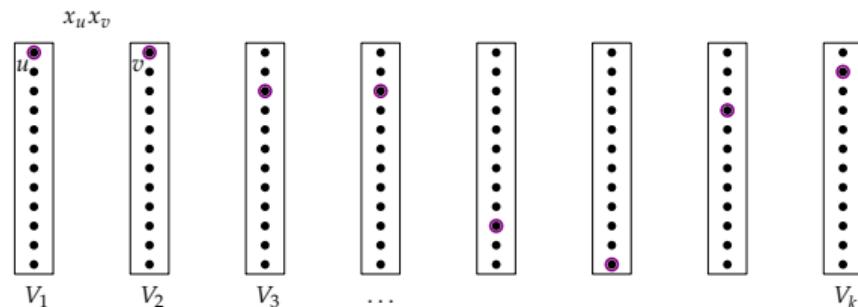
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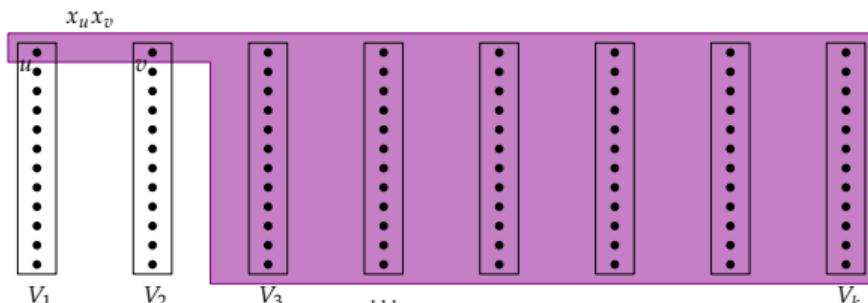
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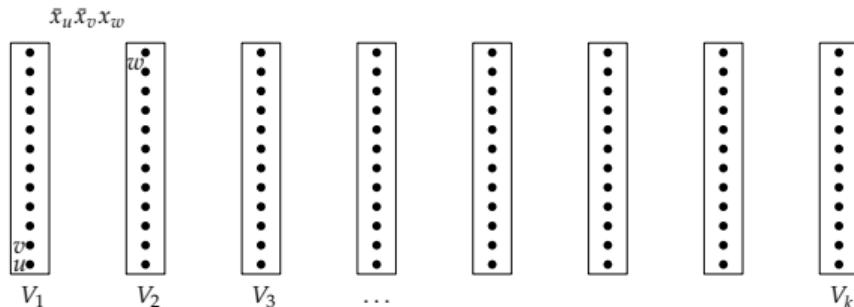
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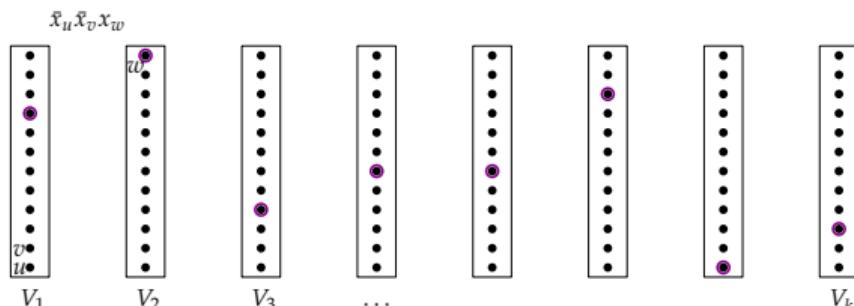
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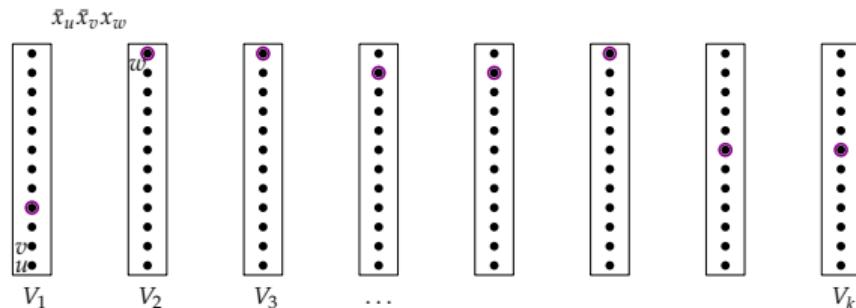
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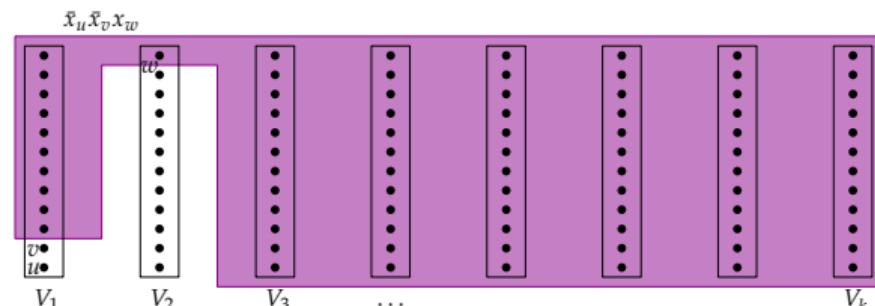
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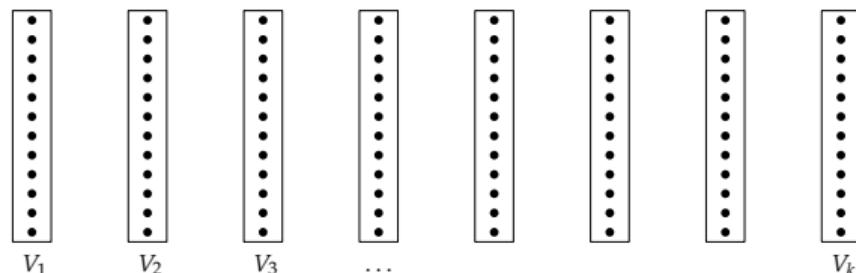
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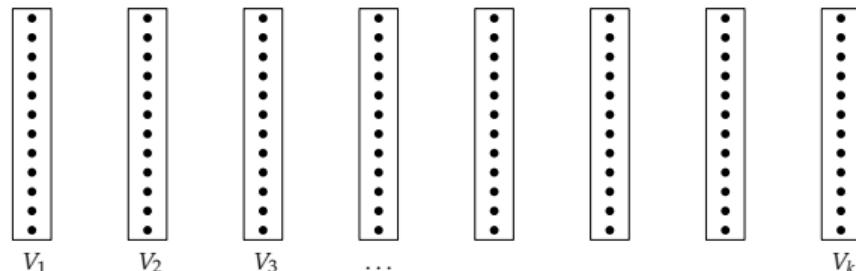
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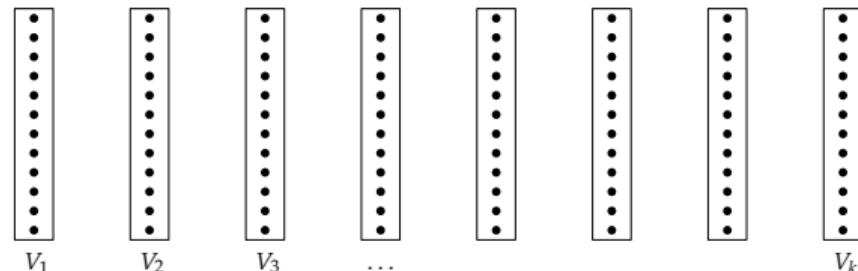
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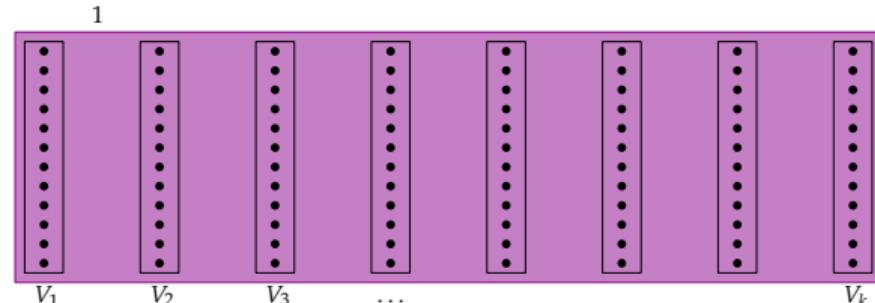
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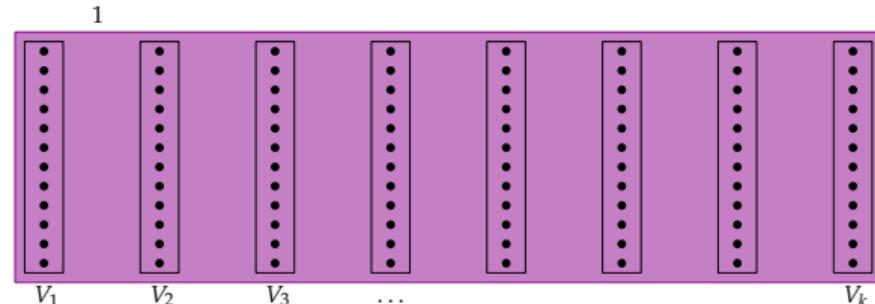
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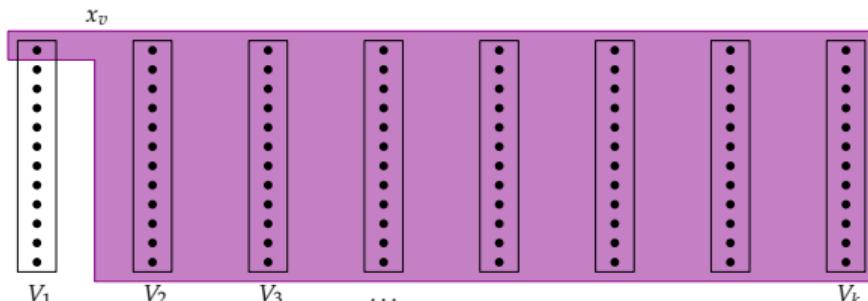
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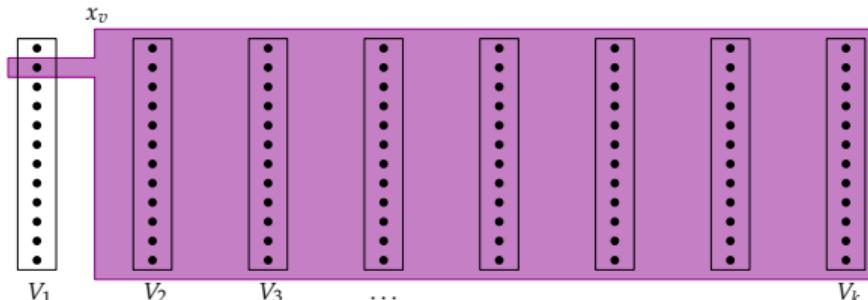
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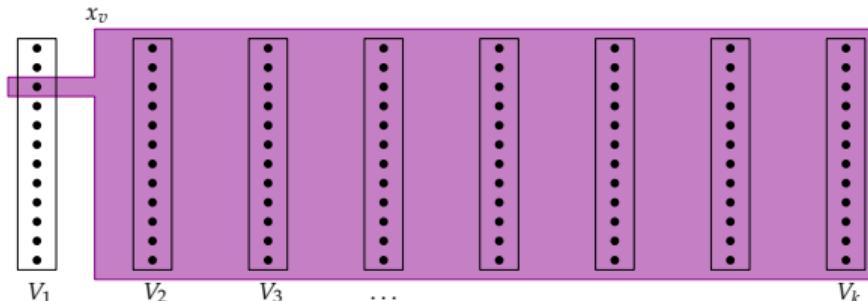
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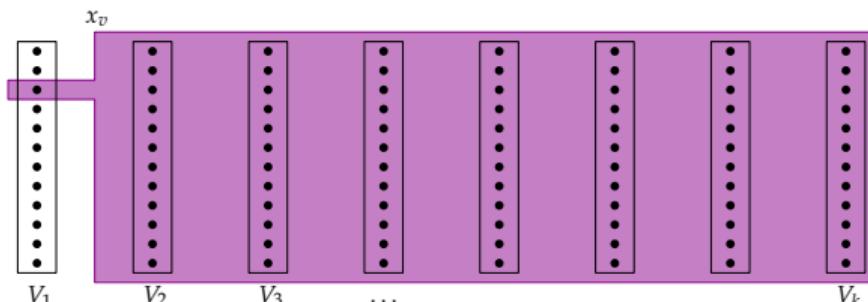
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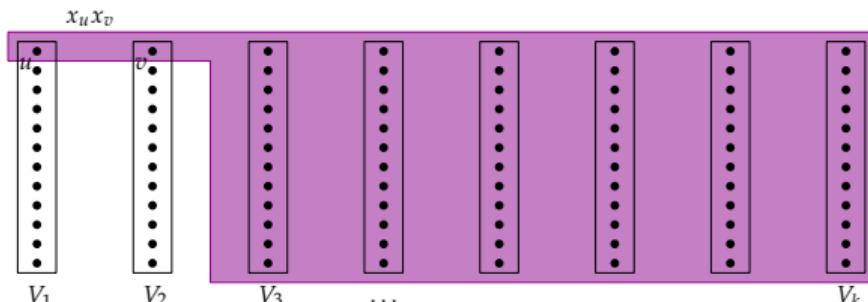
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Construct a $n^{-\Omega(\log n)}$ -pseudo-measure for $\text{clique}(G, k)$, where $G \sim \mathcal{G}(n, k, 1/2)$ and $k \leq n^{0.1}$

linear operator μ such that $\mu(m) \geq -n^{-\Omega(\log n)}$ and $|\mu(m \cdot p)| \leq n^{-\Omega(\log n)}$, while $\mu(1) \approx 1$

- **Idea 1:** Let $\mu(m)$ be the fraction of relevant assignments m rules out
 - For tuple t relevant assignment ρ_t is $\rho_t(x_v) = 1$ if $v \in t$ and 0 otherwise
 - Associate m with rectangle $Q(m)$ consisting of tuples t such that $\rho_t(m) = 1$
- **Attempt 1:** $\mu(m) = \frac{|Q(m)|}{n^k}$

- $\mu(1) = 1$ & $\mu(m) \geq 0$
- $\mu(\sum_{v \in V_1} x_v - 1) = 0$
- $\mu(x_u x_v) = n^{-2}$



Pseudo-Measure: Construction, Failed Attempt II

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Problem: no k -cliques in the graph!

Pseudo-Measure: Construction, Successful Attempt

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[BHKKMP13]

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Interlude: Fourier Characters

Fourier Characters

- Character χ_e for each potential edge $e = \{u, v\}$, i.e., if u, v in distinct blocks,

$$\chi_e(G) = \begin{cases} 1 & \text{if } e \in E(G), \text{ and} \\ -1 & \text{if } e \notin E(G). \end{cases}$$

- For set E of potential edges we let $\chi_E(G) = \prod_{e \in E} \chi_e(G)$. In particular $\chi_\emptyset(G) = 1$.

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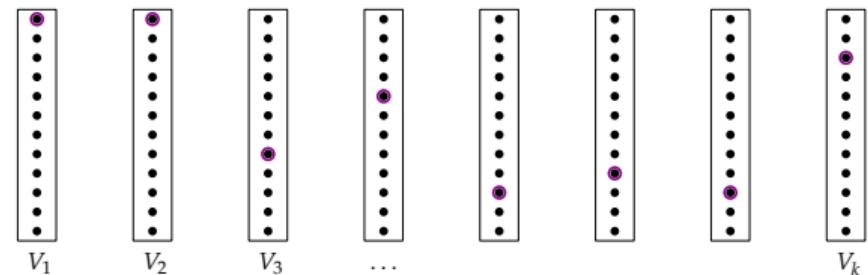
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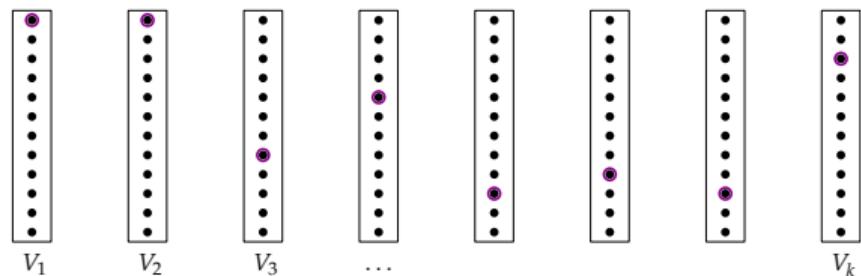
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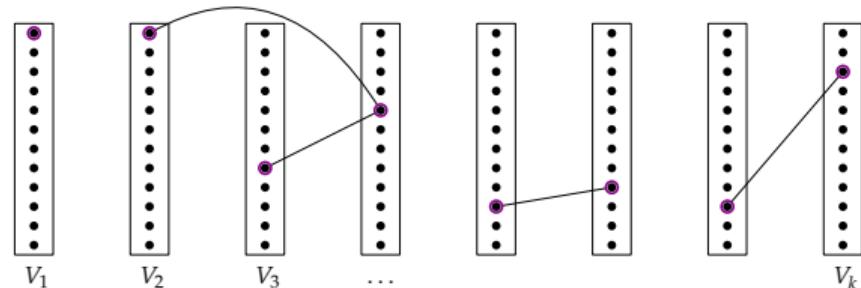
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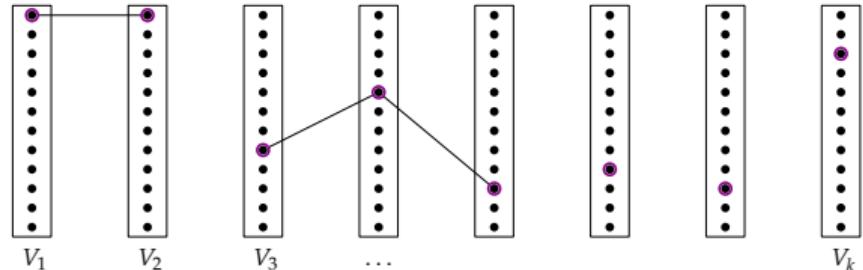
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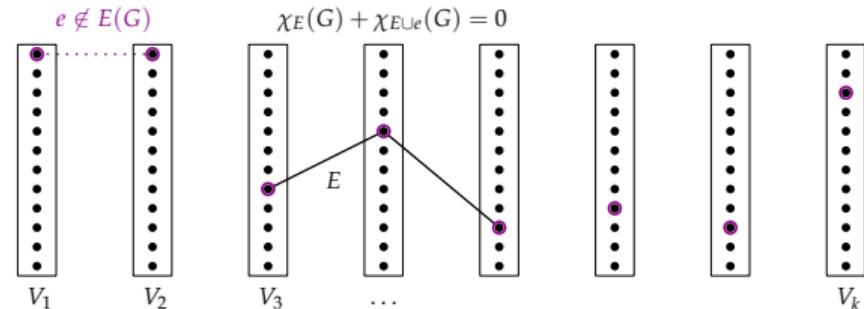
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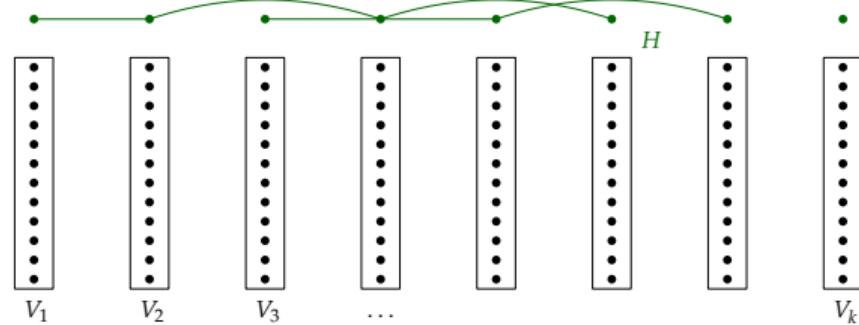
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Fourier Characters: Pattern Graphs

Convenient to identify edge sets that “look the same”

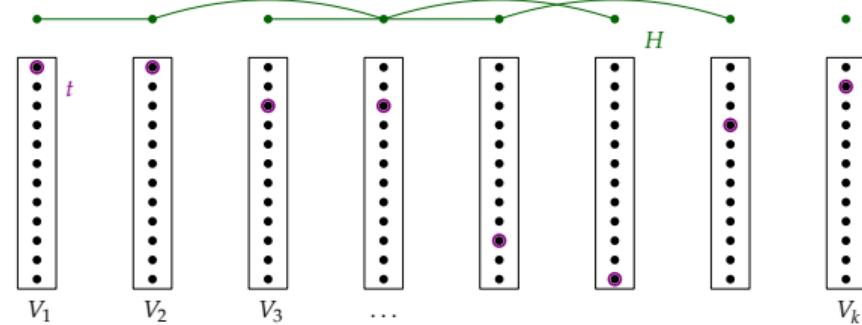
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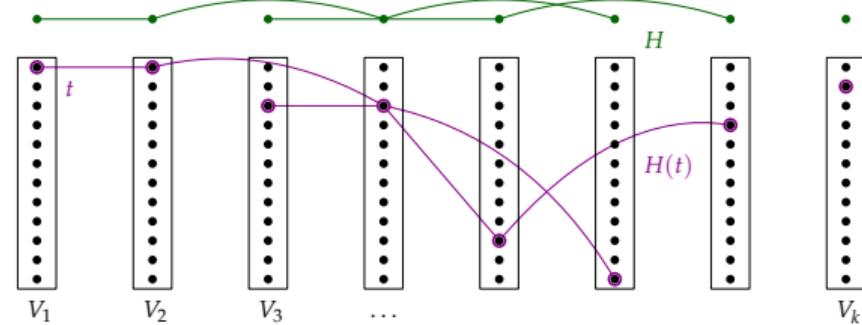
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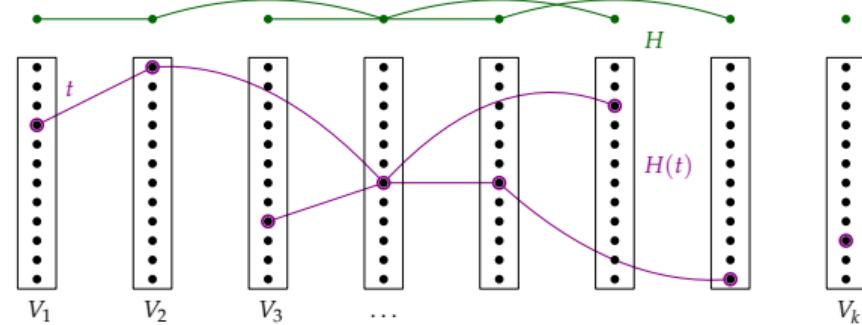
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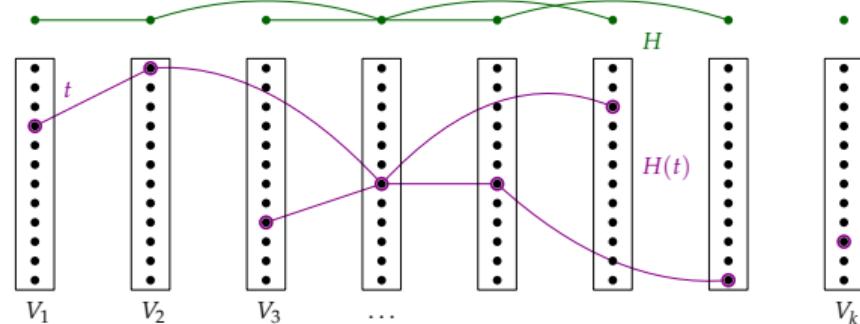
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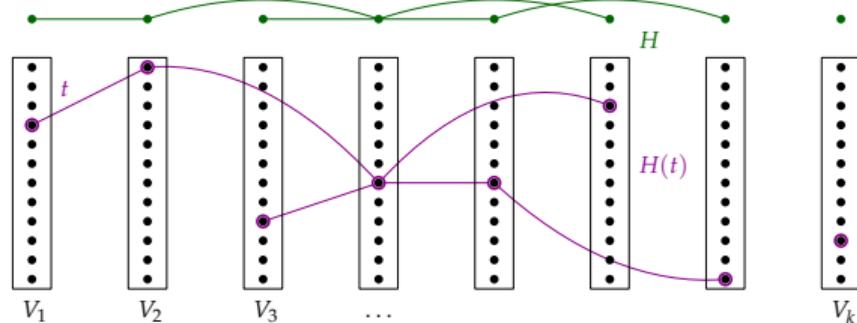
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Back to Pseudo-Calibration

Pseudo-Measure by Pseudo-Calibration

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Pseudo-Calibration: 2nd Moment Calculation

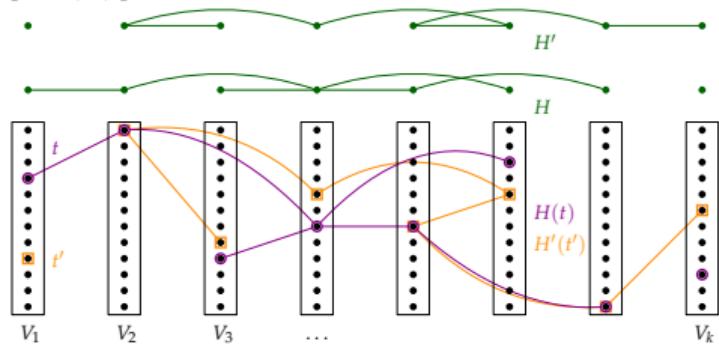
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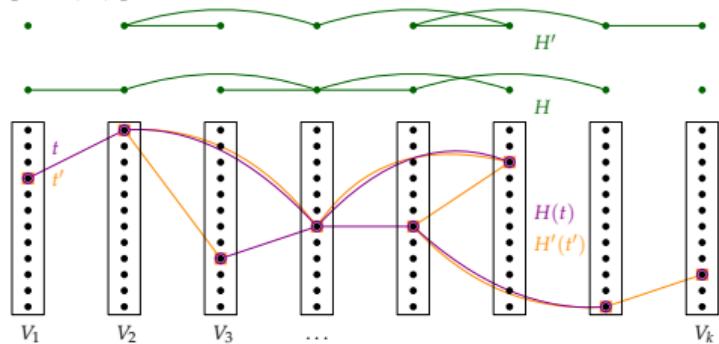
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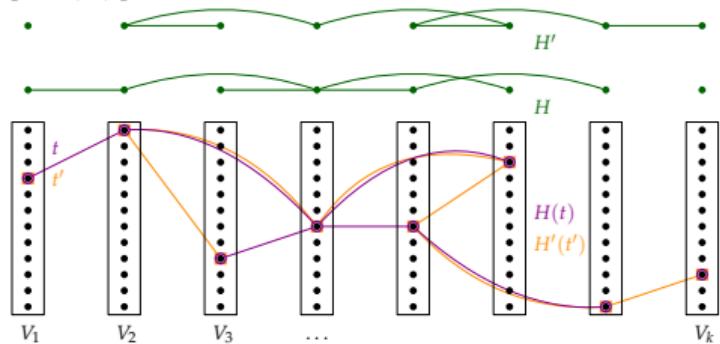
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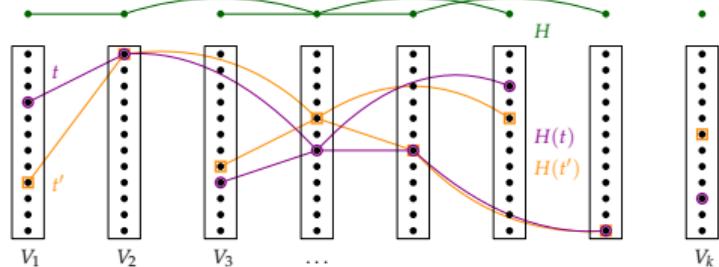
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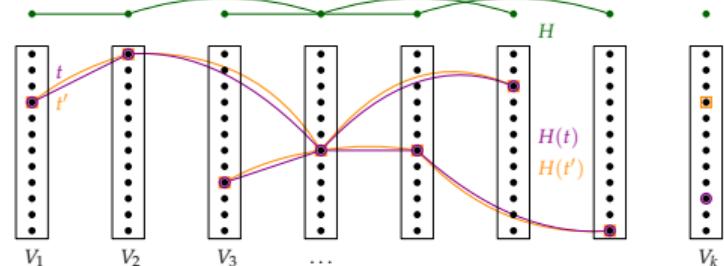
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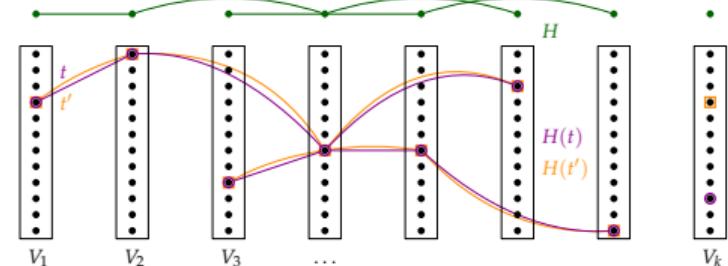
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$$\begin{aligned}\mathbb{E}[\mu_0^2(1)] &= n^{-2k} \sum_{H \subseteq \binom{k}{2}} \sum_{t, t'} \mathbb{E}[\chi_{H(t)}(G) \chi_{H(t')}(G)] \\ &= n^{-2k} \sum_{H \subseteq \binom{k}{2}} |\{(t, t') : t_{V(E(H))} = t'_{V(E(H))}\}| \\ &= n^{-2k} \sum_{H \subseteq \binom{k}{2}} n^{|V(E(H))| + 2(k - |V(E(H))|)} \\ &= \sum_{H \subseteq \binom{k}{2}} n^{-|V(E(H))|}\end{aligned}$$



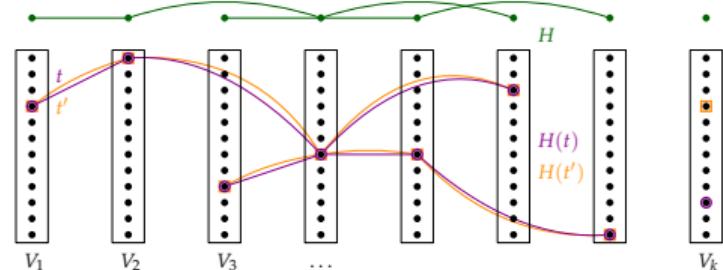
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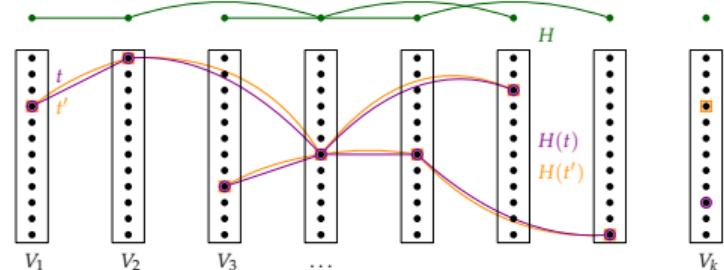
$$\mathbb{E}[\mu_0^2(1)] = \sum_{H \subseteq \binom{[k]}{2}} n^{-|V(E(H))|}$$



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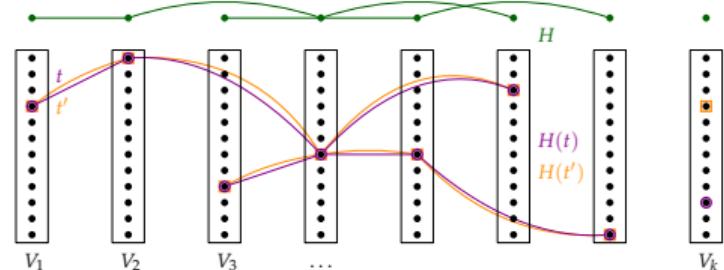
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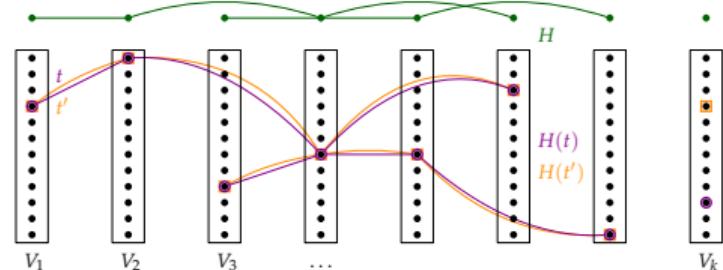
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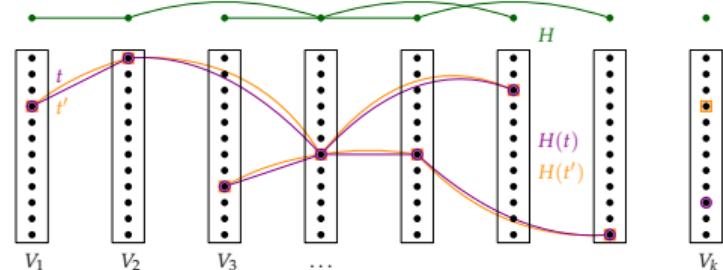
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$= 1 + n^{-\Omega(1)}$, if only sum H with $|V(E(H))| \leq \eta \log n$.

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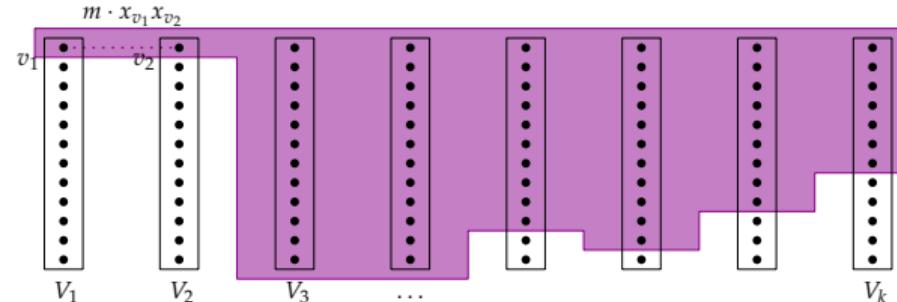
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Edge Axioms

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- m monomial; $e = \{v_1, v_2\} \notin E(G)$ for $v_1 \in V_1$ and $v_2 \in V_2$; edge axiom $x_{v_1}x_{v_2}$
- Write $Q = Q(m \cdot x_{v_1}x_{v_2})$
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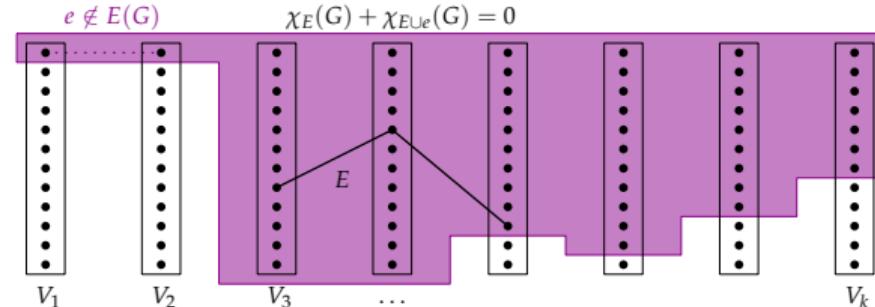
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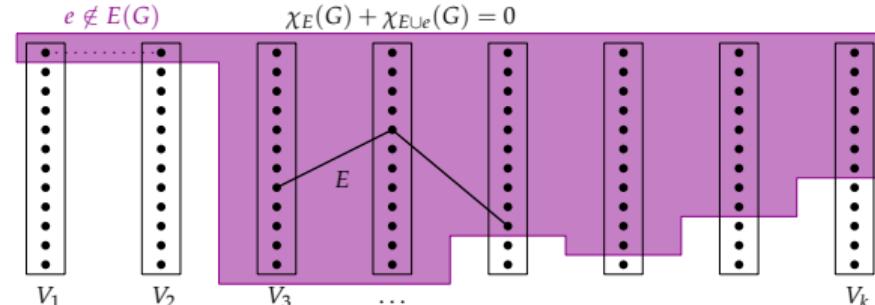


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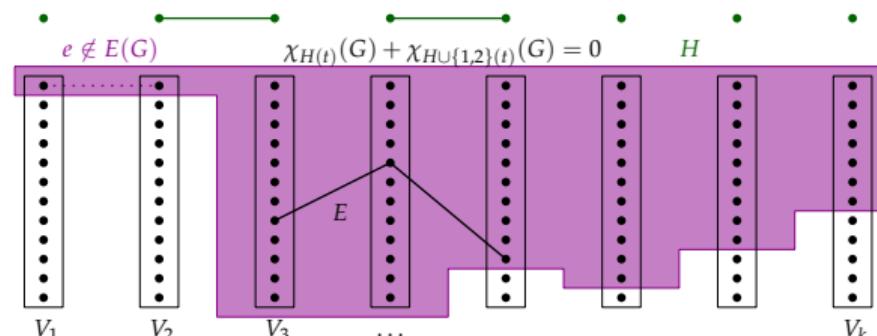
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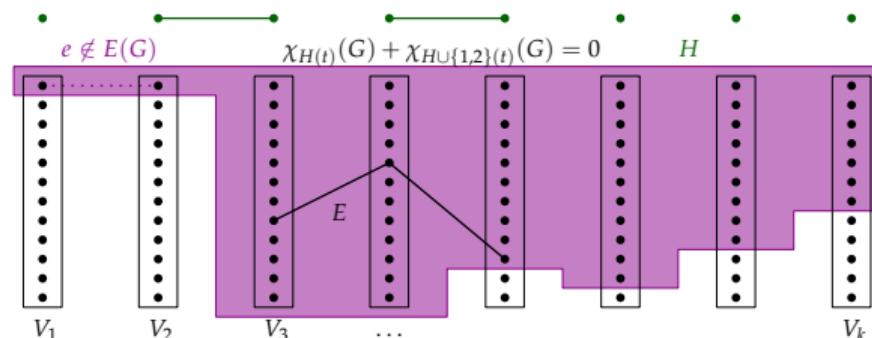
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Lemma

With high probability over $G \sim \mathcal{G}(n, k, 1/2)$ it holds for any H and Q that

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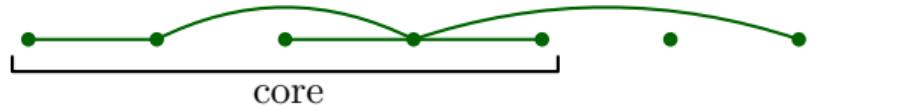
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Back to Edge Axioms

Edge Axioms, Successful Attempt

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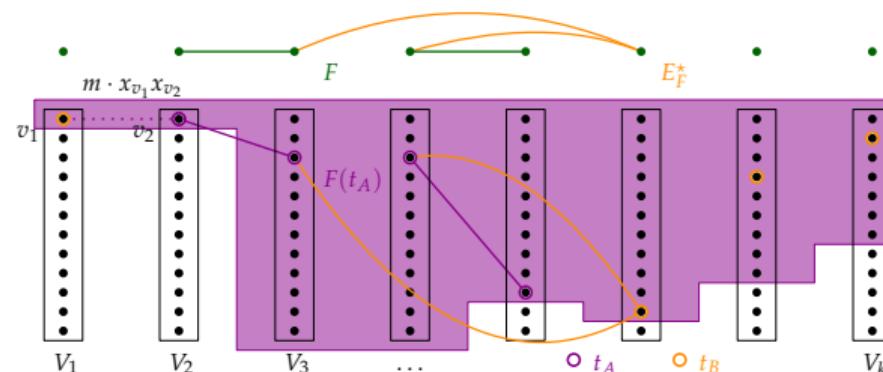
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Edge Axioms, Successful Attempt

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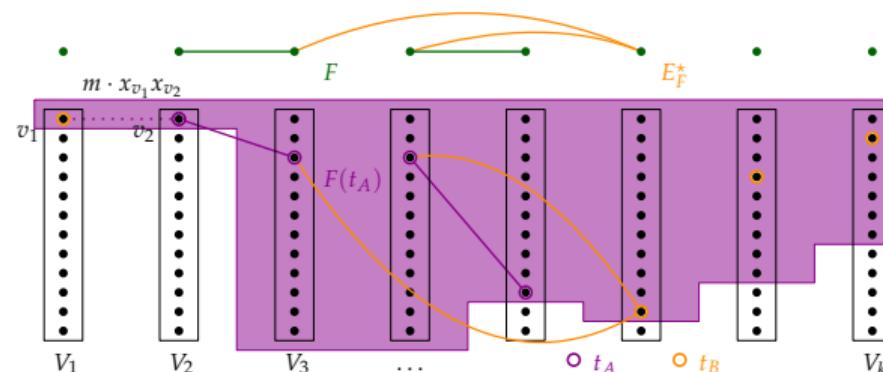
$$\sum_{t_B \in Q_{[k]} \setminus V(E(\textcolor{green}{F}))} \sum_{\textcolor{red}{E \subseteq E_F^*}} \chi_{\textcolor{red}{E}(t_A \cup t_B)}(G)$$



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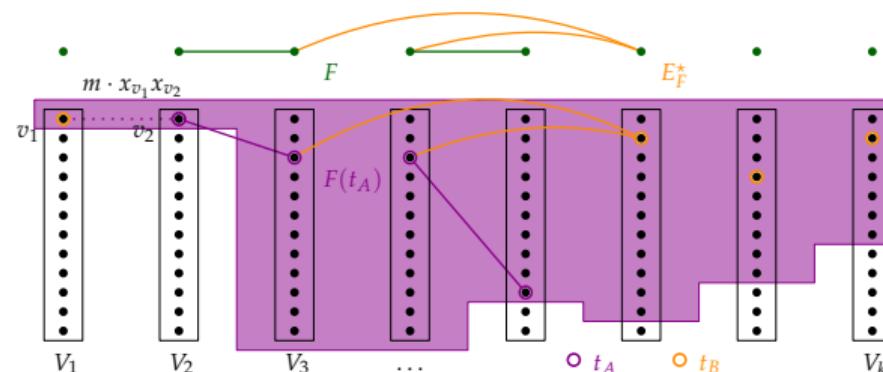
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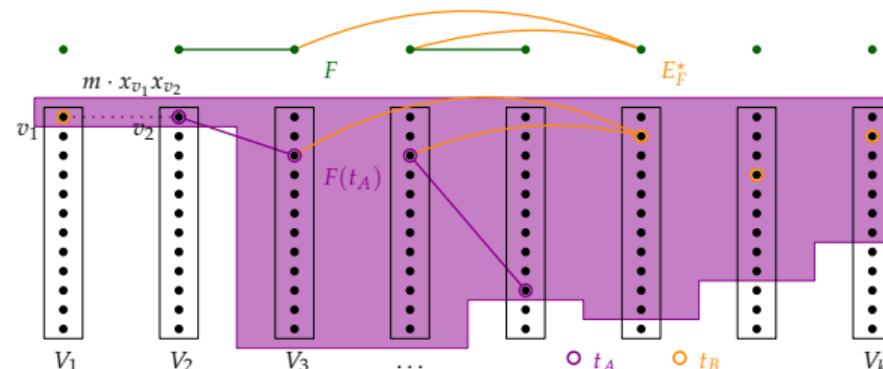
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- Fact:** common neighborhoods behave as expected in random graphs: for small tuple $\textcolor{blue}{t}$, that is, $|\textcolor{blue}{t}| \leq d$, we have

$$|N^\cap(\textcolor{blue}{t}) \cap V_i| = |\bigcap_{u \in \textcolor{blue}{t}} N(u) \cap V_i| = (1 \pm n^{-1/5}) \left(\frac{1}{2}\right)^{|\textcolor{blue}{t}|} n$$

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Summary & Recap

Proof Summary

- Duality gives the notion of a δ -pseudo-measure
- We construct a $n^{-\Omega(\log n)}$ -pseudo-measure for clique by Pseudo-Calibration:

$$\mu(m) = n^{-k} \sum_{\substack{H \subseteq \binom{[n]}{2} \\ \text{vc}(H) \leq d}} \sum_{t \in Q(m)} \chi_{H(t)}(G)$$

- We argued that
 - μ is large on 1: $\mu(1) \approx 1$
 - μ is small on edge-axioms: $|\mu(m \cdot x_u x_v)| \leq n^{-\Omega(\log n)}$
- It remains to argue that
 - μ is basically non-negative: $\mu(m) \geq -n^{-\Omega(\log n)}$

Recap & Some Open Problems

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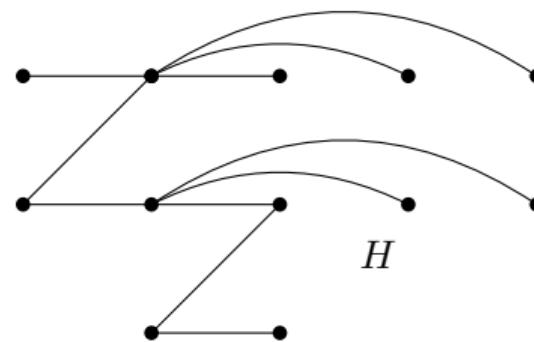
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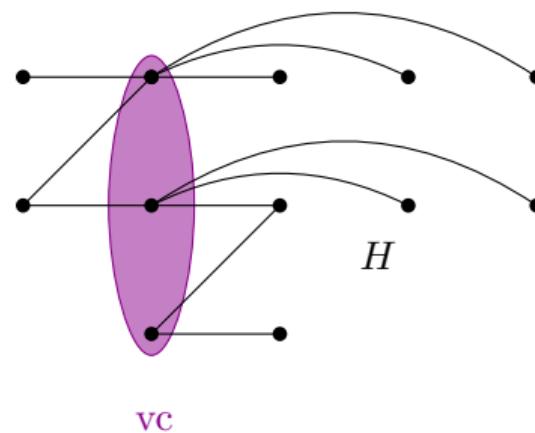
Further Material

Cores

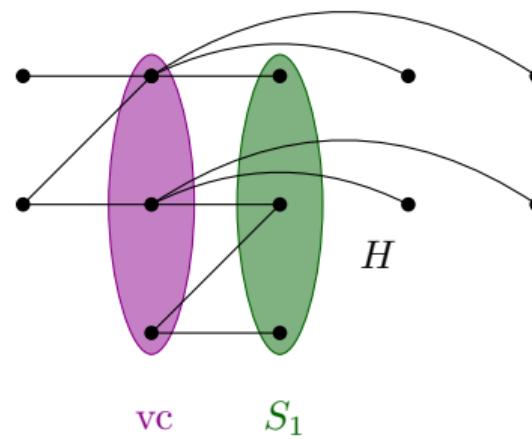
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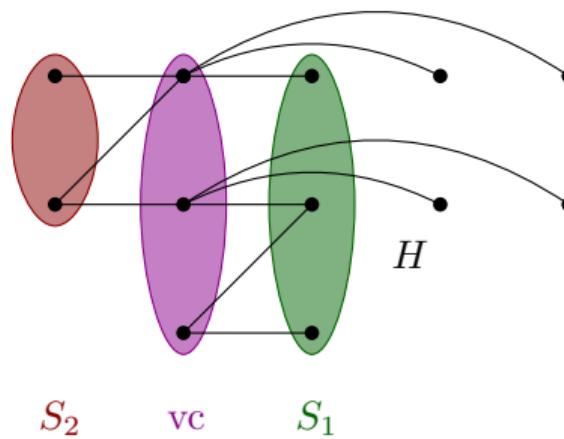


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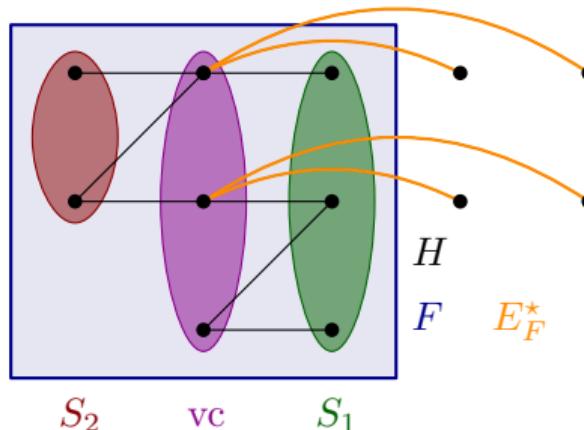
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On the (Almost) Non-Negativity of μ

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\Rightarrow on some rectangles Q the measure does not concentrate around $|Q|/n^k$

Non-Negativity: Decomposition of Rectangles

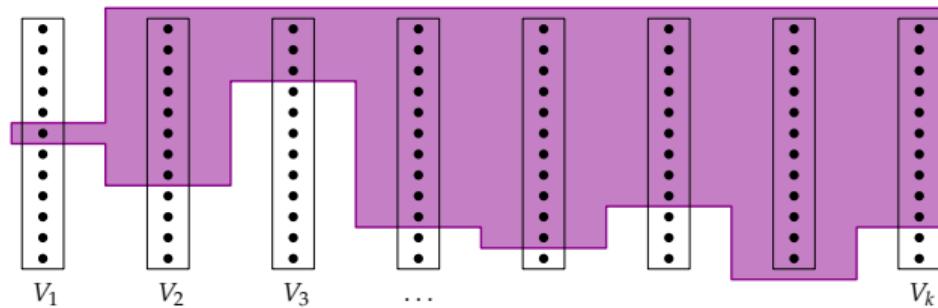
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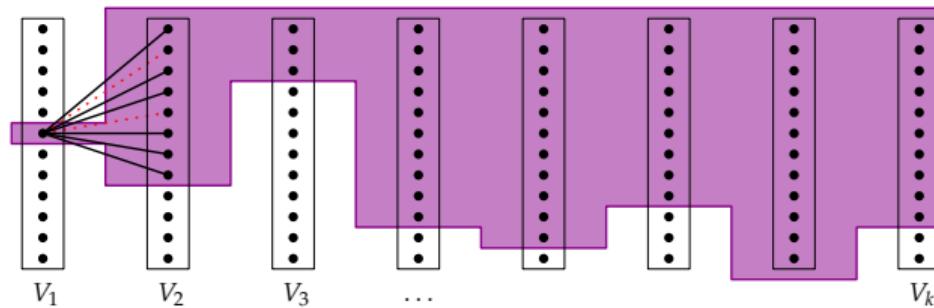
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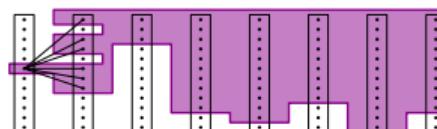
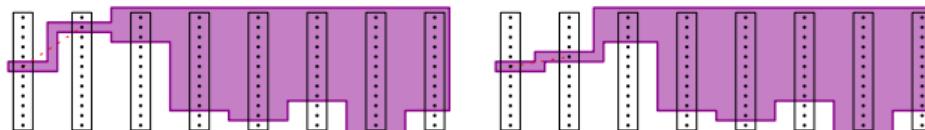
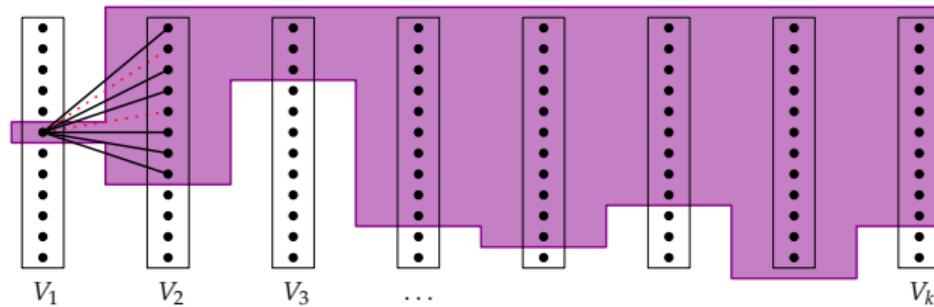
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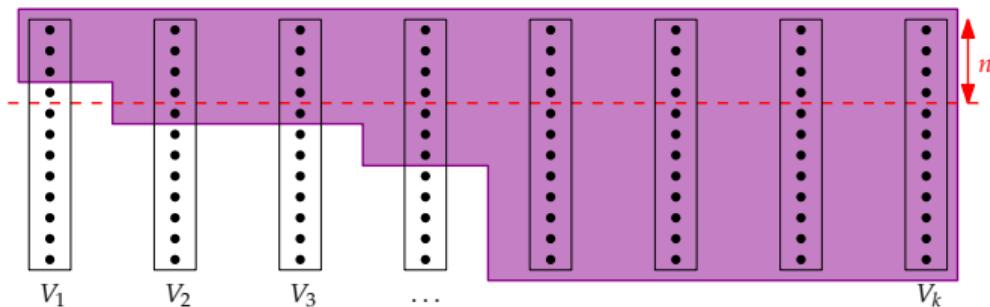
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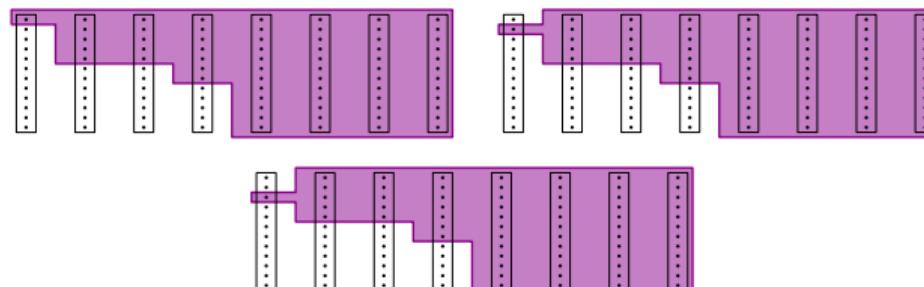
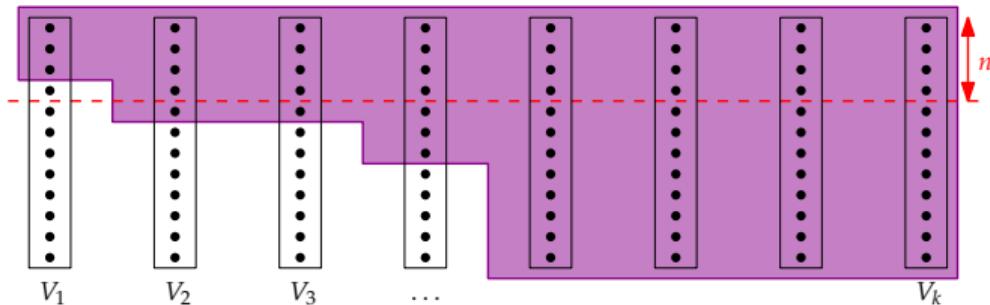
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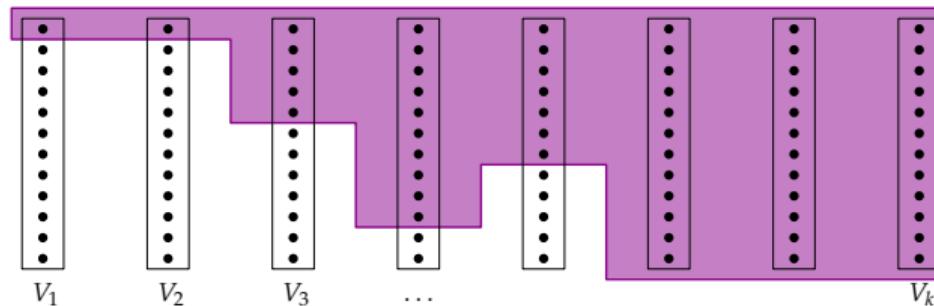
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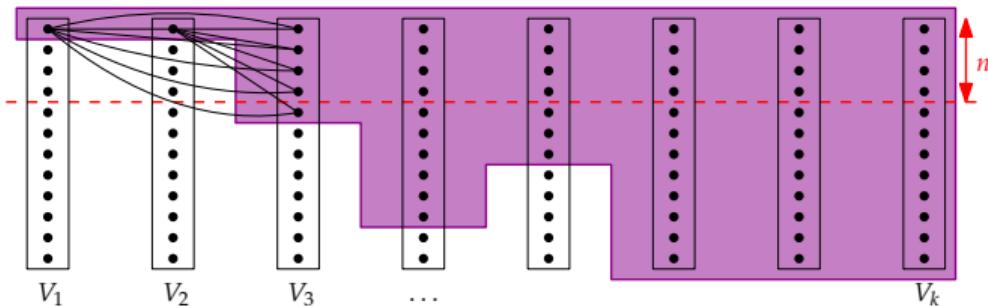
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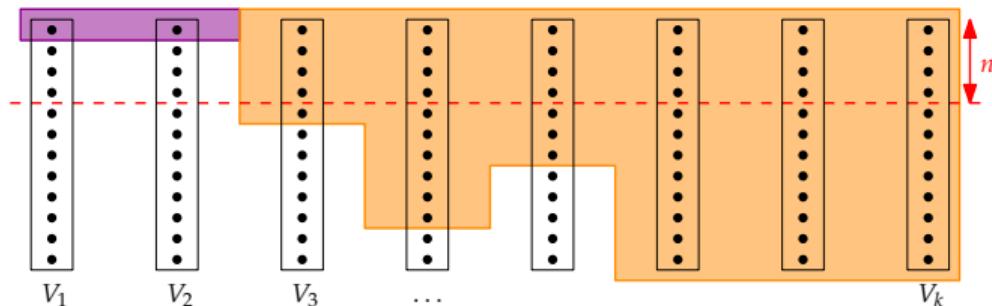
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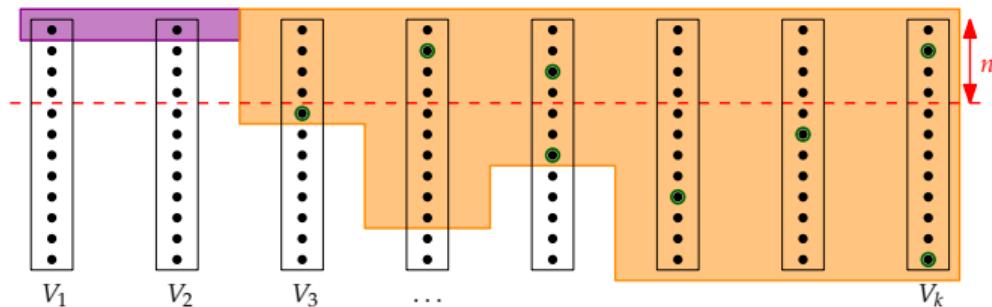
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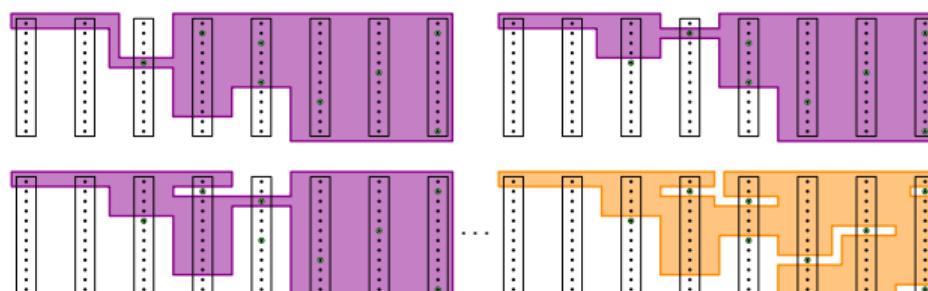
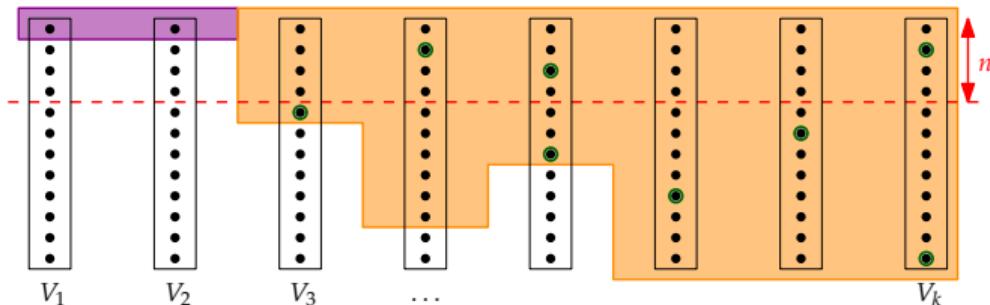
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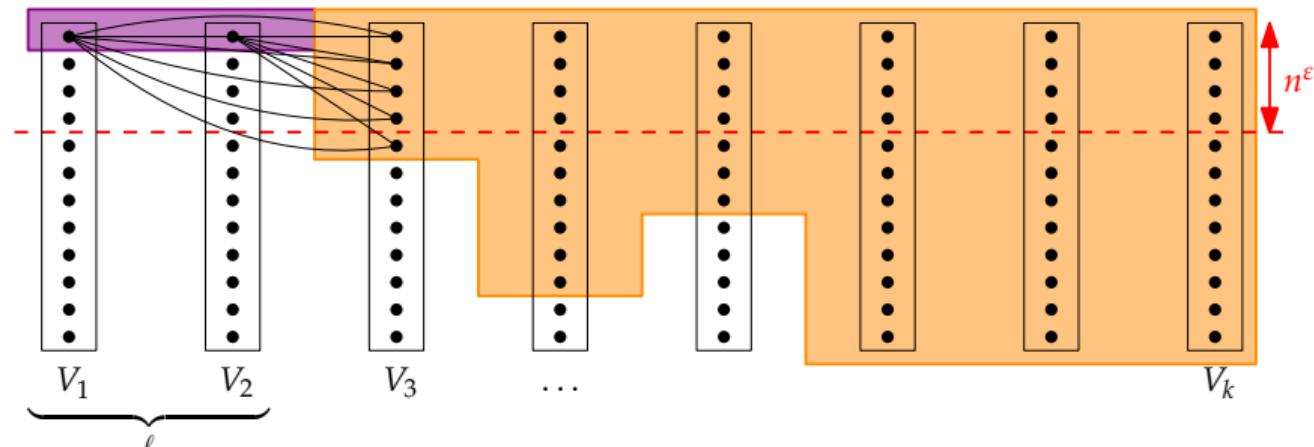
Non-Negativity: Decomposition of Rectangles II

- Decomposition partitions rectangle Q_0 into collection \mathcal{Q} , of size $n^{\varepsilon \log n}$, such that each rectangle $Q \in \mathcal{Q}$ satisfies
 - Q is an edge-axiom hence $\mu(Q) \geq -n^{-10\varepsilon \log n}$, or
 - Q is small; $|Q| \approx n^{k-d}$ thus $\mu(Q) \geq -n^{-10\varepsilon \log n}$, or
 - Q has large, well-behaved blocks & singletons adjacent to Q
 - We show that μ concentrates on such Q around strictly positive value
- May conclude for any monomial m that $\mu(m) \geq -n^{-\Omega(\log n)}$

Non-Negativity: Concentration of Measure

Lemma

For any well-behaved rectangle Q with ℓ singletons,

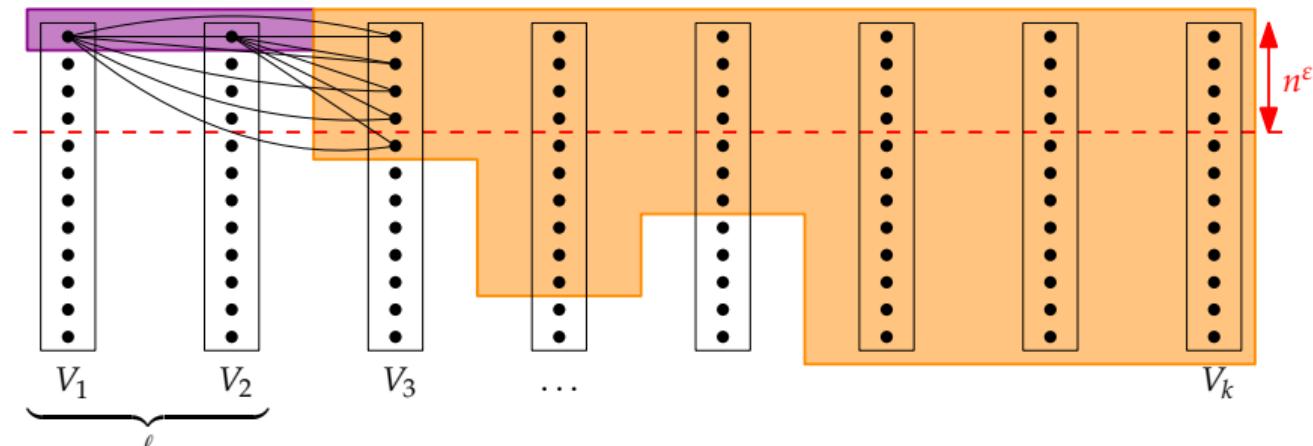


Non-Negativity: Concentration of Measure

Lemma

For any well-behaved rectangle Q with ℓ singletons, with high probability, it holds that

$$\mu(Q) = 2^{\ell(k-(\ell+1)/2)} \cdot |Q|n^{-k} \cdot (1 \pm n^{-\varepsilon})$$

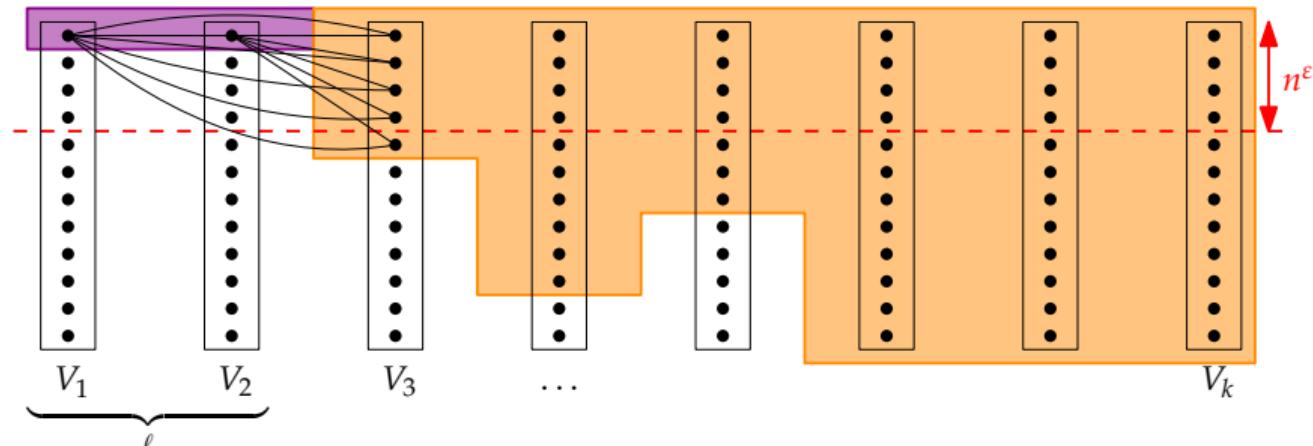


Non-Negativity: Concentration of Measure

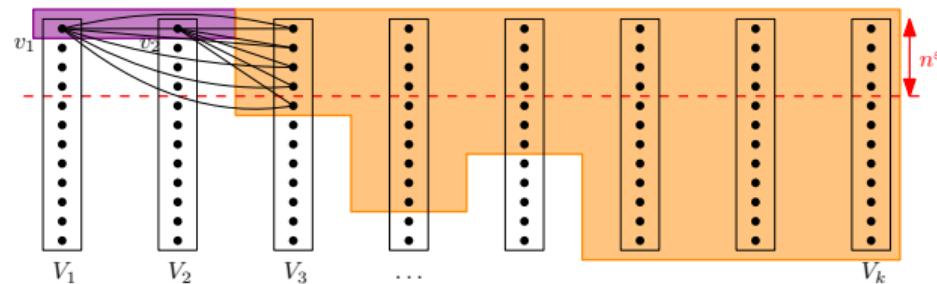
Lemma

For any well-behaved rectangle Q with ℓ singletons, with high probability, it holds that

$$\mu(Q) = \underbrace{2^{\ell(k-(\ell+1)/2)}}_{\# \text{conditioned edges}} \cdot \underbrace{|Q|n^{-k}}_{\text{expectation}} \cdot (1 \pm n^{-\varepsilon})$$

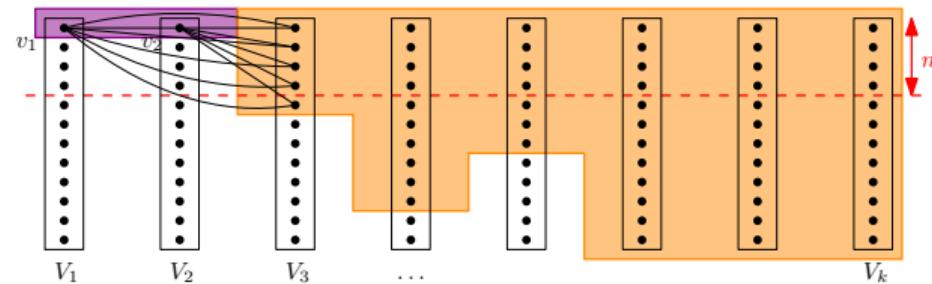


Non-Negativity: Concentration of Measure, Proof Idea



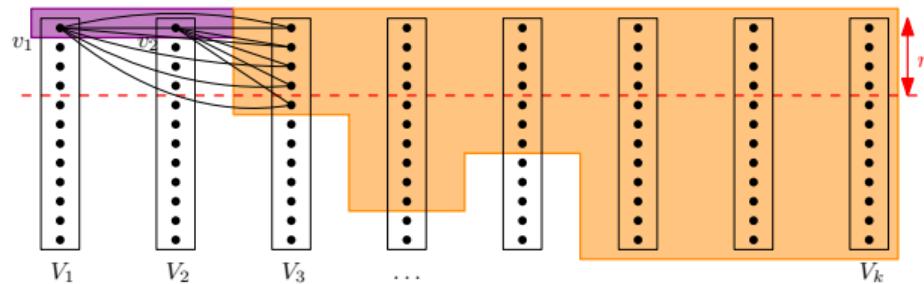
$$\mu(Q) = n^{-k} \sum_{\substack{H: \\ \text{vc}(H) \leq d}} \sum_{t \in Q} \chi_{H(t)}(G)$$

Non-Negativity: Concentration of Measure, Proof Idea



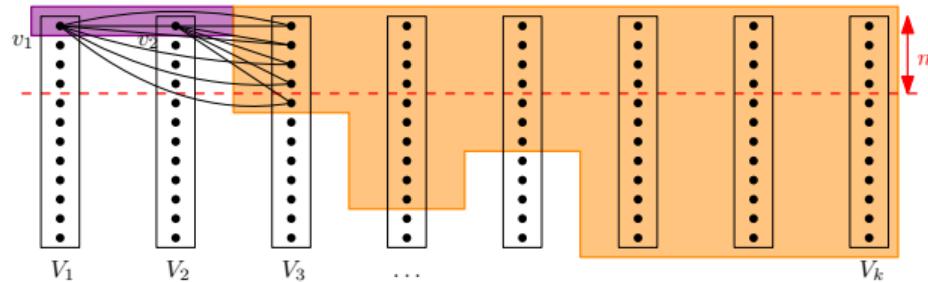
$$\mu(Q) = n^{-k} \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \notin H}} \sum_{t \in Q} \chi_{H(t)}(G) + \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \in H}} \sum_{t \in Q} \chi_{H(t)}(G)$$

Non-Negativity: Concentration of Measure, Proof Idea



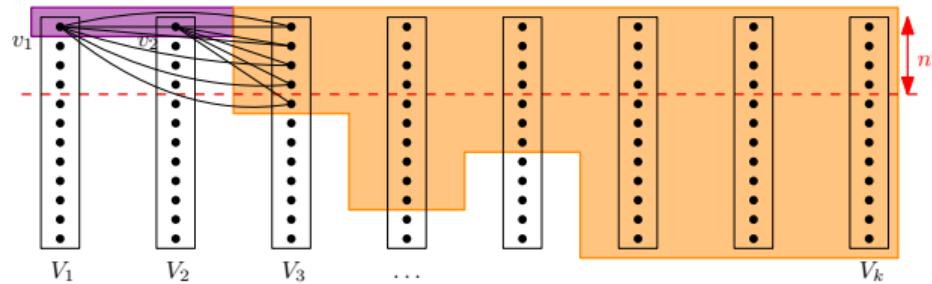
$$\begin{aligned}\mu(Q) &= n^{-k} \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \notin H}} \sum_{t \in Q} \chi_{H(t)}(G) + \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \in H}} \sum_{t \in Q} \chi_{H(t)}(G) \\ &= 2 \cdot n^{-k} \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \in H}} \sum_{t \in Q} \chi_{H(t)}(G)\end{aligned}$$

Non-Negativity: Concentration of Measure, Proof Idea



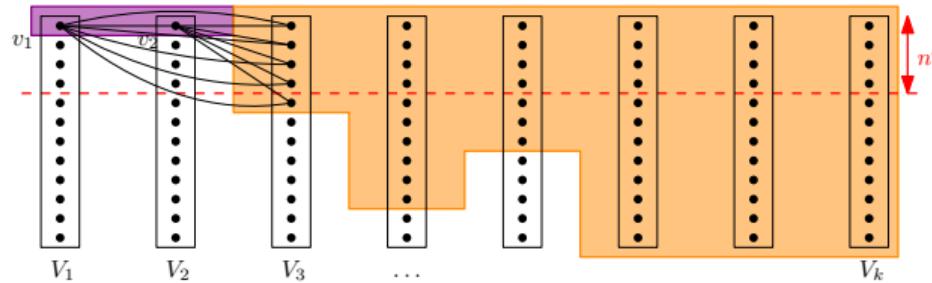
$$\begin{aligned}
 \mu(Q) &= n^{-k} \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \notin H}} \sum_{t \in Q} \chi_{H(t)}(G) + \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \in H}} \sum_{t \in Q} \chi_{H(t)}(G) \\
 &= 2 \cdot n^{-k} \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \in H}} \sum_{t \in Q} \chi_{H(t)}(G) + n^{-k} \underbrace{\sum_{\substack{H: \\ \text{vc}(H) = d \\ \text{vc}(H \cup \{1,2\}) = d+1}} \sum_{t \in Q} \chi_{H(t)}(G)}_{\text{like edge axiom } \approx n^{-\Omega(\log n)}}
 \end{aligned}$$

Non-Negativity: Concentration of Measure, Proof Idea



$$\mu(Q) \approx 2 \cdot n^{-k} \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \in H}} \sum_{t \in Q} \chi_{H(t)}(G)$$

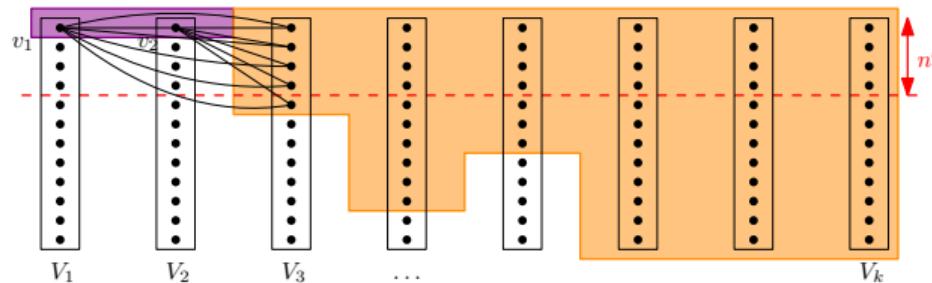
Non-Negativity: Concentration of Measure, Proof Idea



$$\mu(Q) \approx 2 \cdot n^{-k} \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \in H}} \sum_{t \in Q} \chi_{H(t)}(G)$$

- Finally left with sum over H with all conditioned edges present

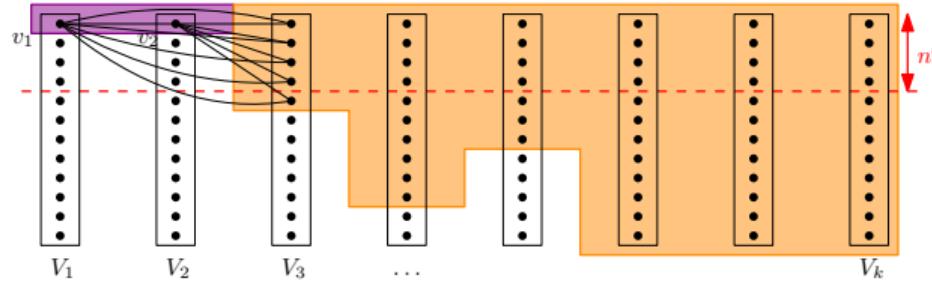
Non-Negativity: Concentration of Measure, Proof Idea



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- As $\ell < d$, there is at least one unconditioned edge left

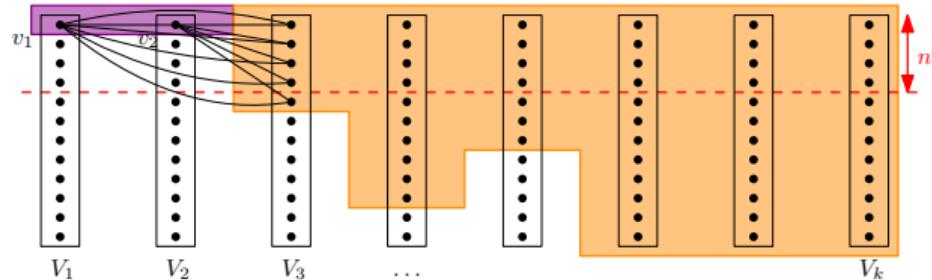
Non-Negativity: Concentration of Measure, Proof Idea



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- Rely on [cores](#) as in edge-axioms

Non-Negativity: Concentration of Measure, Proof Idea



$$\mu(Q) \approx 2 \cdot n^{-k} \sum_{\substack{H: \\ \text{vc}(H) \leq d \\ \{1,2\} \in H}} \sum_{t \in Q} \chi_{H(t)}(G)$$

- Finally left with sum over H with all conditioned edges present
- As $\ell < d$, there is at least one unconditioned edge left
- Rely on **cores** as in edge-axioms
- Cores with **single edge** have concentration $(1 \pm n^{-\varepsilon})$