

Almost Optimal Sum of Squares Lower Bound for *Planted Clique*

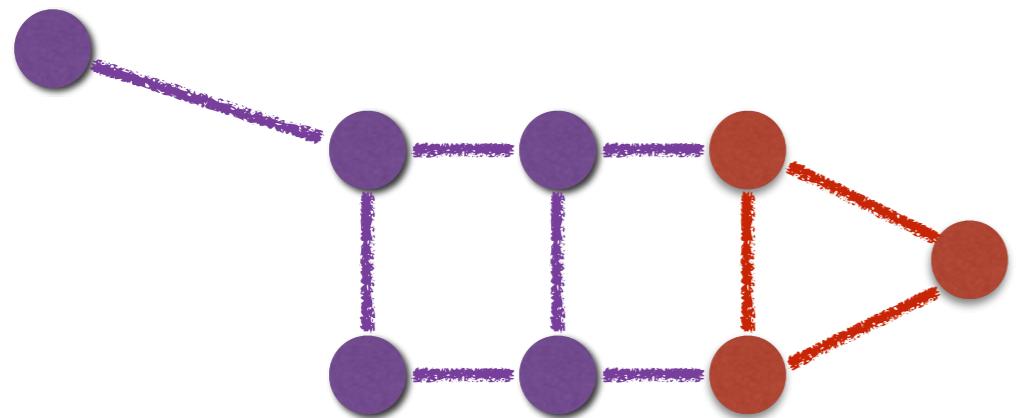
Pravesh K. Kothari
UT Austin

Based on joint works with Boaz Barak, Sam Hopkins, Jon Kelner,
Ankur Moitra and Aaron Potechin.

Clique in Random Graphs

find the largest set of vertices all connected to each other

in a random graph $G \sim G(n, \frac{1}{2})$

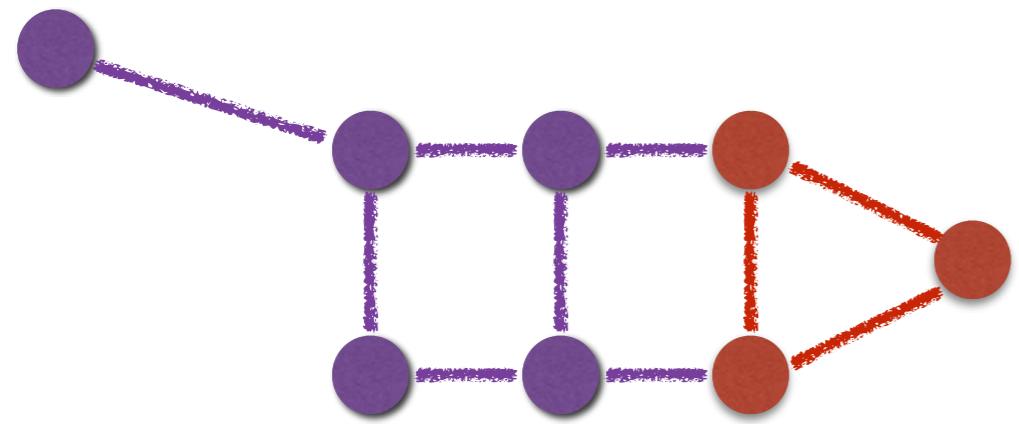


each edge in G with prob. 0.5

Clique in Random Graphs

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each edge in G with prob. 0.5

w.h.p. max clique $\sim 2 \log_2(n)$

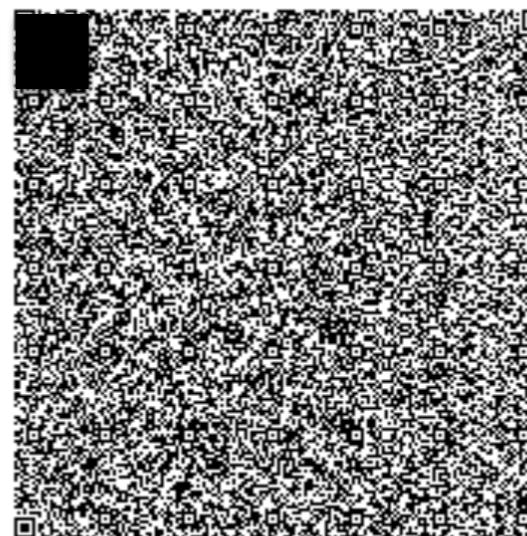
greedy finds cliques of size $\sim \log_2(n)$

Karp'76: hard to find cliques of size
 $\sim (1 + \epsilon) \log_2(n)$?

Planted Clique

[Jerrum'92, Kucera'95]

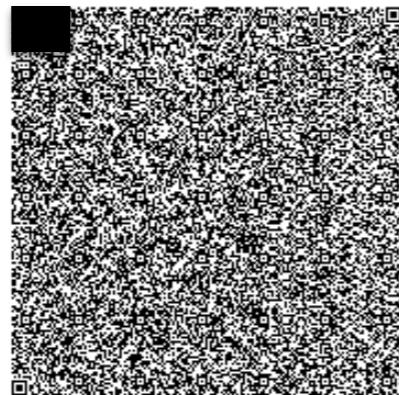
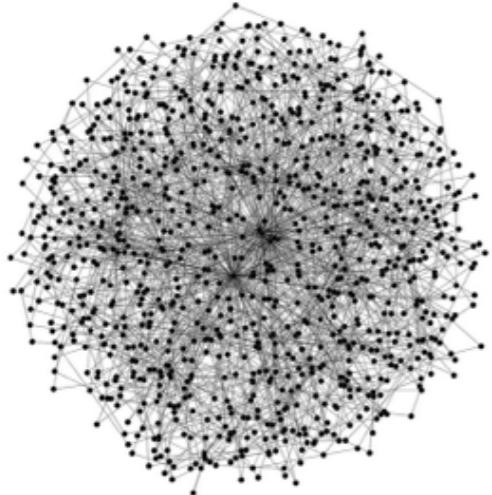
find an ω -clique added to a random graph $G \sim G(n, \frac{1}{2})$



Planted Clique

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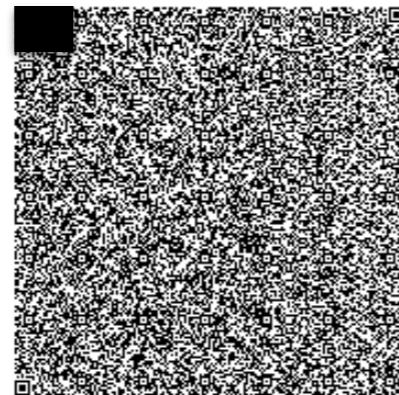
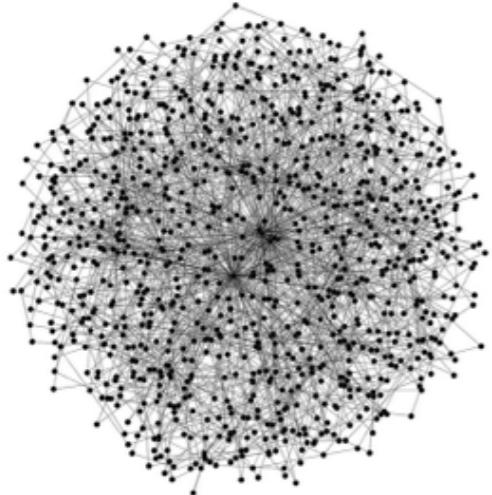


spectral algorithm: $\omega > cn^{1/2}$ [AKS'98]

Planted Clique

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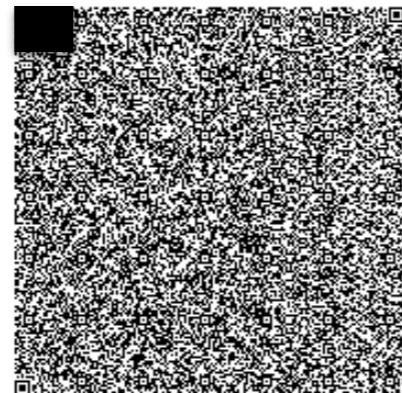
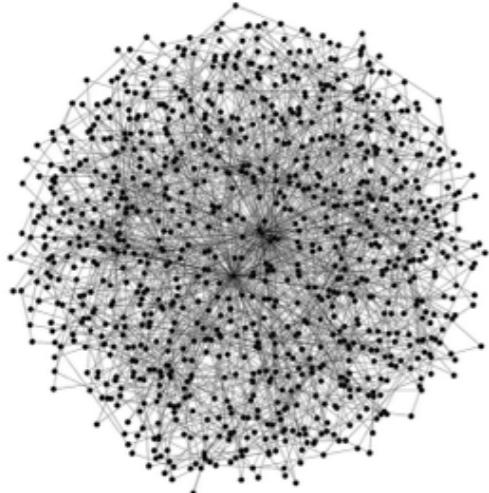
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no polynomial time algorithm when $\omega \ll \sqrt{n}$

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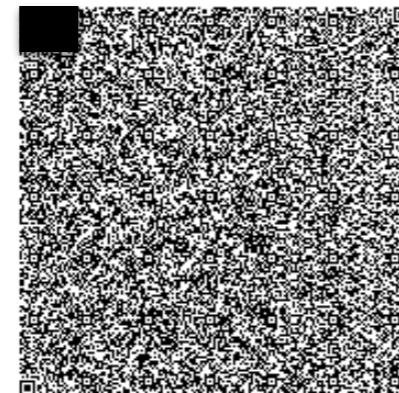
no polynomial time algorithm when $\omega \ll \sqrt{n}$

“Statistical Algorithms” MCMC Methods Lovász-Schrijver
[FGRVX’13] [Jer’92] [FK’00,03]

Planted Clique

[Jerrum'92, Kucera'95]

find an ω -clique added to a random graph $G \sim G(n, \frac{1}{2})$



central problem in average case complexity

Cryptography

[Jue'02, ABW'10]

Sparse PCA

[BR'13]

Motifs in Biological Networks

[Milo et. al. Science'02,
Lotem et. al. PNAS'14]

Nash Equilibrium

[HK'09]

Certifying Restricted Isometry Property

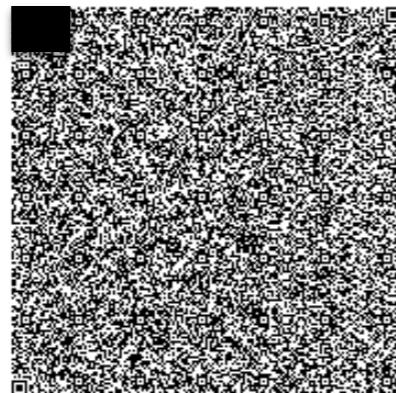
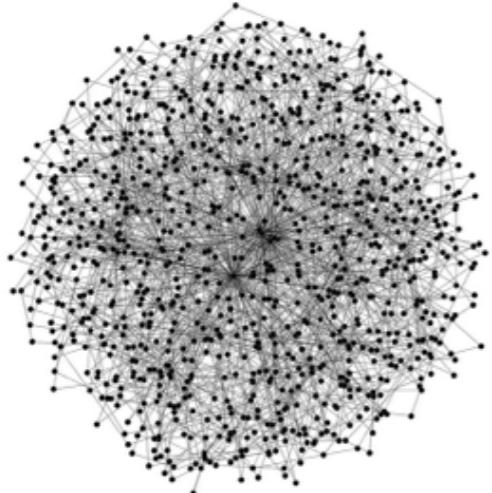
[KL'12]

Mathematical Finance [ABBG'09]

Planted Clique

[Jerrum'92, Kucera'95]

find an ω -clique added to a random graph $G \sim G(n, \frac{1}{2})$



a testbed for algorithmic techniques for
detecting “**signal**” (added clique) surrounded by
“**random noise**” (random graph)

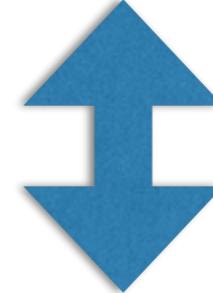
Sum of Squares SDP

[Grigoriev-Vorobjov99, Shor87, Nesterov99, Parrilo00, Lasserre01]

hierarchical strengthening of the
basic SDP/spectral algo.



d: “degree” in the hierarchy.



$n^{O(d)}$: running time

Sum of Squares SDP

[Grigoriev-Vorobjov99, Shor87, Nesterov99, Parrilo00, Lasserre01]

highly successful convex
relaxation for comb. optimization.



SPARSEST CUT [ARVO4]

UNIQUE GAMES [ABS10, BRS12, GS12]

....breaks known integrality gap instances for
weaker hierarchies in **polynomial** time for

**UNIQUE GAMES, BALANCED SEPARATOR,
MAX CUT**

[BBHKSZ12, OZ13, DMN13]

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... optimal amongst all poly size SDPs for a large class. **[LRS15]**

Sum of Squares SDP

[Grigoriev-Vorobjov99, Shor87, Nesterov99, Parrilo00, Lasserre01]

highly successful convex
relaxation for comb. optimization.



...successful for other *average case* problems.

[BKS'14,15]

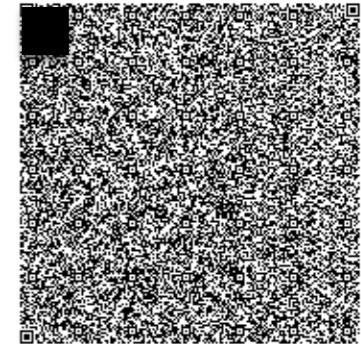
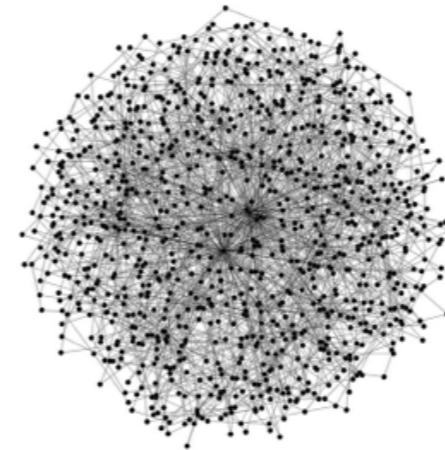
PLANTED SPARSE VECTOR, DICTIONARY LEARNING

SOS vs Planted Clique?

[Meka-Wigderson'13]



?
vs



SOS

Planted Clique

SoS vs Planted Clique? [Meka-Wigderson'13]

Conjecture [Meka-Wigderson'13]

Polytime SoS cannot find $\tilde{o}(\sqrt{n})$ -size planted cliques.

SOS

Planted Clique

\tilde{o} ignores $n^{o(1)}$ factors.

SoS vs Planted Clique? [Meka-Wigderson'13]

Conjecture [Meka-Wigderson'13]

Const. d -SoS cannot find $\tilde{o}(\sqrt{n})$ -size
planted cliques.

SOS

Planted Clique

\tilde{o} ignores $n^{o(1)}$ factors.

SOS vs Planted Clique?

[Meka-Potechin-Wigderson'15]	d	$\tilde{O}(n^{\frac{1}{d}})$
[Deshpande-Montanari'15]	4	$\tilde{O}(n^{\frac{1}{3}})$
[Hopkins-K-Potechin'15] [Raghavendra-Schramm'15]	4	$\tilde{O}(\sqrt{n})$

\tilde{O} ignores $n^{o(1)}$ factors.

SOS vs Planted Clique?

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[Barak-Hopkins-Kelner-K-Moitra-Potechin'16]	d	$\tilde{O}(\sqrt{n})$

Proving MW Conj. for all d!

SoS vs Planted Clique?

[Meka-Potechin-Wigderson'15]

d $\tilde{O}(n^{\frac{1}{d}})$

[Deshpande-Montanari'15]

$\tilde{O}(n^{\frac{1}{d}})$

[Hopkins-K-Potechin'15]

[Raghavendra-Schramm'15]

“Bayesian” view of
SoS Algorithm.

[Barak-Hopkins-Kelner-K-
Moitra-Potechin'16]

d $\tilde{O}(\sqrt{n})$

Proving MW Conj. for all d!

Talk Plan

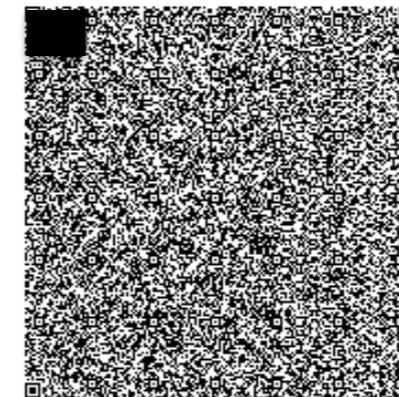
- 1. Sum of Squares Proofs and Pseudodistributions**
- 2. Meka-Wigderson Pseudodistribution**
- 3. MW Pseudodistribution is not PSD**
- 4. The Bayesian Pseudodistribution**

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Planted Clique

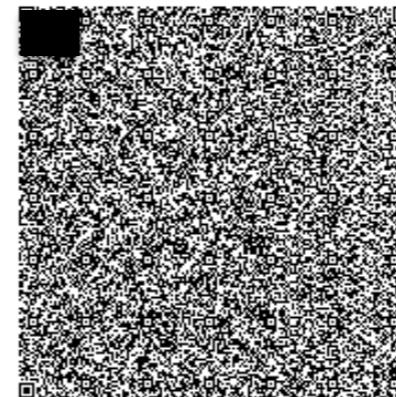
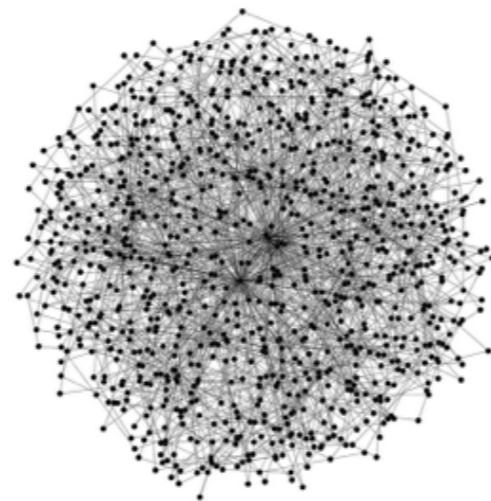
[Jerrum'92, Kucera'95]



Is there an ω clique in G ?

Planted Clique

[Jerrum'92, Kucera'95]



x indicates a clique

x indicates a set of size ω

x is a vector of 0-1 indicators.

Is this set of poly-equations feasible?

$$x_i x_j = 0 \quad \forall i \neq j \text{ in } G$$

Is there an ω clique in G ?



$$\sum x_i = \omega$$

$$x_i^2 = x_i \quad \forall i$$

Sum of Squares Algorithm

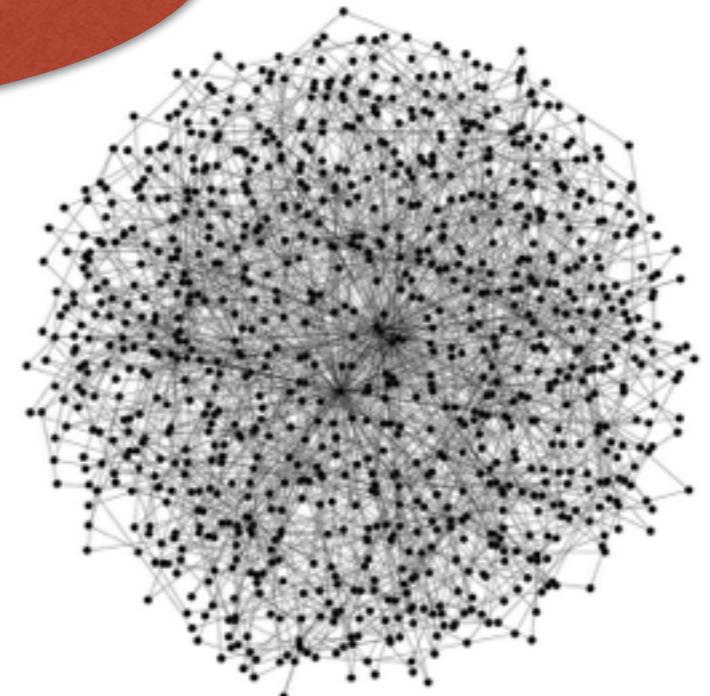
Is this set of poly-equations feasible?

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$$x_i^2 = x_i \quad \forall i$$

$$\sum_i x_i = \omega$$

μ : “a prob. dist. on ω cliques.”



μ : “knowledge” of large cliques in G .

Sum of Squares Algorithm



μ : a prob. dist. on ω -cliques.

$E = E_\mu$, q : any polynomial.

μ satisfies constraints.

$$\mathbb{E}[q(x) \left(\sum x_i - \omega \right)] = 0$$

$$\mathbb{E}[q(x)x_i x_j] = 0 \quad i \not\sim j \text{ in } G$$

$$\mathbb{E}[q(x) \left(\sum x_i^2 - x_i \right)] = 0 \quad \forall i$$

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μ is positive semidefinite. $\mathbb{E}[q^2] \geq 0$

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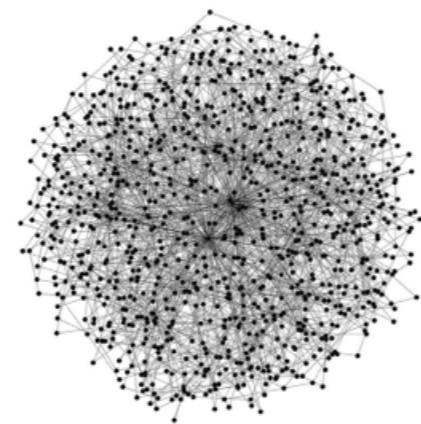
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μ is normalized. $\mathbb{E}[1] = 1$

Sum of Squares Algorithm



μ : a prob. dist. on ω -cliques.

$\mathbb{E} = \mathbb{E}_\mu$, q : any polynomial.

\mathbb{E} is linear.

Moments $\mathbb{E}[\prod_{i \in S} x_i]$

$$\mathbb{E}[q(x) \left(\sum x_i - \omega \right)] = 0$$

μ satisfies constraints.

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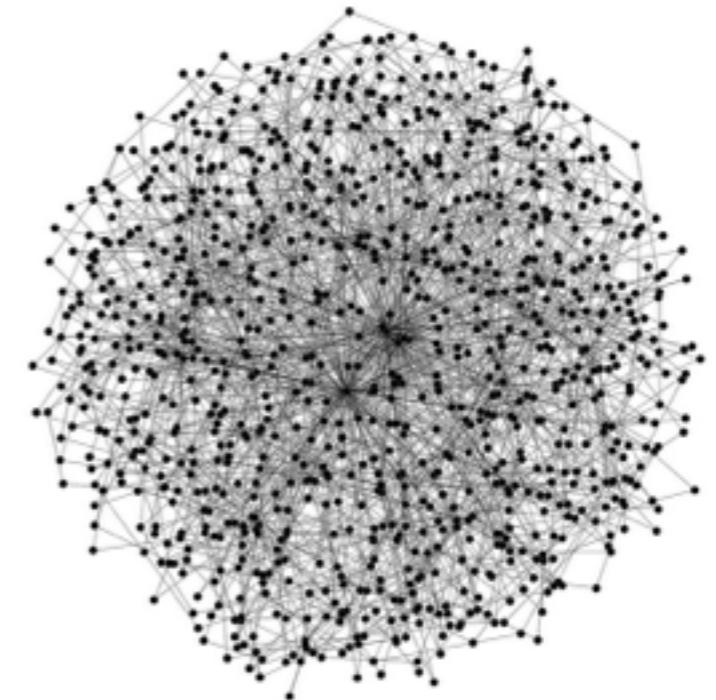
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Sum of Squares Algorithm

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$\tilde{\mu}$: “a *pseudo* dist. on ω cliques.”



$\tilde{\mu}$: “knowledge” of large cliques in G .

Sum of Squares Algorithm

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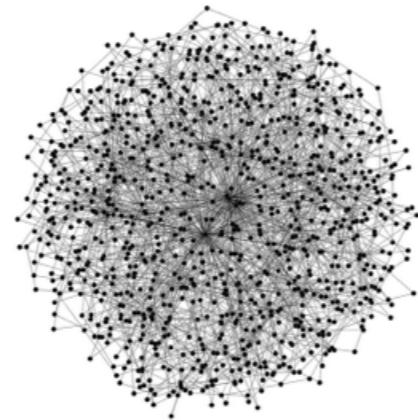
$\tilde{\mu}$: “a *pseudo* dist. on ω cliques.”



of a “**computationally bounded**” agent

$\tilde{\mu}$: “knowledge” of large cliques in G .

Sum of Squares Algorithm



$\tilde{\mu}$: a prob. dist. on ω -cliques.

$$\tilde{\mathbb{E}} = \tilde{\mathbb{E}}_{\tilde{\mu}}$$

$\tilde{\mathbb{E}}$ is linear.

PseudoMoments $\tilde{\mathbb{E}}[\prod_{i \in S} x_i]$

$$\tilde{\mathbb{E}}[q(x) \left(\sum x_i - \omega \right)] = 0$$

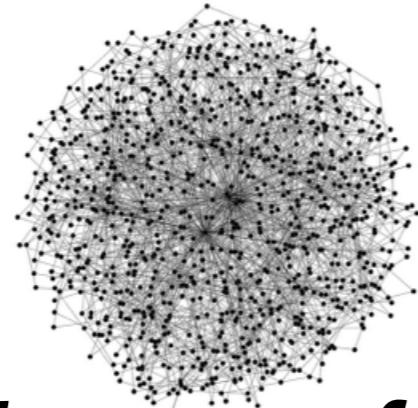
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$\tilde{\mu}$ is positive semidefinite. $\tilde{\mathbb{E}}[q(x)^2] \geq 0$

$\tilde{\mu}$ is normalized. $\tilde{\mathbb{E}}[1] = 1$

Sum of Squares Algorithm



$\tilde{\mu}$: a prob. dist. on ω -cliques.

$$\tilde{\mathbb{E}} = \tilde{\mathbb{E}}_{\tilde{\mu}}$$

Total degree of argument of $\tilde{\mathbb{E}}$ is at most d !

$\tilde{\mathbb{E}}$ is linear.

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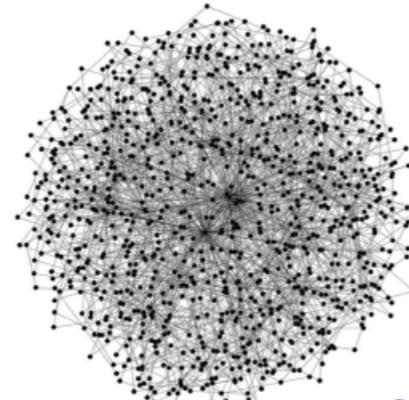
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Total degree of argument of $\tilde{\mathbb{E}}$ is at most d !

$\tilde{\mathbb{E}}$ is linear.

PseudoMoments $\tilde{\mathbb{E}}[\prod_{i \in S} x_i]$

Computed using SDP on $n^{O(d)}$ variables = 0
and constraints!
 $\tilde{\mu}$ satisfies all constraints in G

$$\tilde{\mathbb{E}}[q(x)(x_i^2 - x_i)] = 0 \quad \forall i$$

$\tilde{\mu}$ is positive semidefinite. $\tilde{\mathbb{E}}[q(x)^2] \geq 0$

$\tilde{\mu}$ is normalized. $\tilde{\mathbb{E}}[1] = 1$

Sum of Squares Proofs

Is this set of poly-equations feasible?

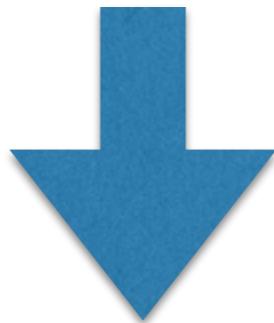
$$x_i x_j = 0 \quad \forall i \neq j \text{ in } G$$

$$x_i^2 = x_i \quad \forall i$$

$$\sum_i x_i = \omega$$

Duality

No \tilde{x} satisfying constraints



Proof of unsatisfiability in a specific form.

Sum of Squares Proofs

Is this set of poly-equations feasible?

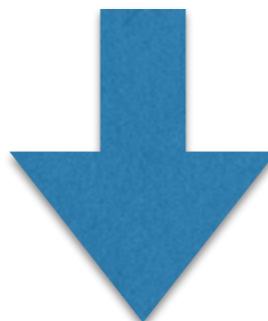
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Duality

No \tilde{x} satisfying constraints



SoS Refutation

There exist $\deg d$ polynomials f and g

1. $f = 0$ on solutions.
2. g is sum of squares of $\deg d/2$ polynomials, and

$$-1 = f + g$$

Proving Lower Bounds

Is this set of poly-equations feasible?

$$x_i x_j = 0 \quad \forall i \neq j \text{ in } G$$

$$x_i^2 = x_i \quad \forall i$$

$$\sum_i x_i = \omega$$

Goal

For $d = \Theta(1)$ and $\omega = n^{0.5-o(1)}$, show that there is a pseudo-expectation satisfying all the constraints, w.h.p. when $G \sim G(n, \frac{1}{2})$.

SoS “thinks” there’s a large clique in a random graph!

Talk Plan

1. Sum of Squares Proofs and Pseudodistributions
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The MW Moments

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$\tilde{\mathbb{E}}[x_S]$ (pseudo) prob. of $S \subseteq C$

The MW Moments

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$$x_i x_j = 0 \quad \forall i \neq j \text{ in } G$$

$$x_i^2 = x_i \quad \forall i$$

“fake” planted clique

$\tilde{\mathbb{E}}[x_S]$ (pseudo) prob. of $S \subseteq C$

The MW Moments

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$\tilde{\mathbb{E}}[x_S]$ (pseudo) prob. of $S \subseteq C$



Every vertex is equally likely to be in C .

$$\tilde{\mathbb{E}}[x_i] \approx \left(\frac{\omega}{n}\right)$$



sloppy calculations only.

The MW Moments

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$$x_i x_j = 0 \quad \forall i \neq j \text{ in } G$$
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$$\sum_i x_i = \omega$$

$\tilde{\mathbb{E}}[x_S]$ (pseudo) prob. of $S \subseteq C$



Every vertex is equally likely to be in C .

$$\tilde{\mathbb{E}}[x_i] \approx \left(\frac{\omega}{n}\right)$$

Every edge is equally likely to be in C .

$$\tilde{\mathbb{E}}[x_i x_j] \approx \begin{cases} \left(\frac{\omega}{n}\right)^2 & \text{if } i \sim j \\ 0 & \text{otherwise.} \end{cases}$$

The MW Moments

Is this set of poly-equations feasible?

$$\begin{aligned}x_i x_j &= 0 \quad \forall i \neq j \text{ in } G \\x_i^2 &= x_i \quad \forall i\end{aligned}$$
$$\sum_i x_i = \omega$$

$\tilde{\mathbb{E}}[x_S]$ (pseudo) prob. of $S \subseteq C$



$$\tilde{\mathbb{E}}[x_S] \approx \begin{cases} \left(\frac{\omega}{n}\right)^{|S|} & \text{if } S \text{ is a clique} \\ 0 & \text{otherwise.} \end{cases}$$

$$\tilde{\mathbb{E}}[x_S] = \begin{cases} \Theta(1) \left(\frac{\omega}{n}\right)^{|S|} (1 + O(n^{-|S|})) & \text{if } S \text{ is a clique} \\ 0 & \text{otherwise.} \end{cases}$$

The MW Moments

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- 4. The Bayesian Pseudodistribution**

MW Moments are not PSD...

Theorem

[Kelner]

There is a degree 2 polynomial $p = p_G$ such that
for $\omega \gg n^{\frac{1}{3}}$, w.h.p. over G $\tilde{E}_{MW}[p(x)^2] < 0$

generalizes to higher d .

MW Moments are not PSD...

Theorem

[Kelner]

There is a degree 2 polynomial $p = p_G$ such that
for $\omega \gg n^{\frac{1}{3}}$, w.h.p. over G $\tilde{\mathbb{E}}_{MW}[p(x)^2] < 0$

1. MW moments are “fishy” w.r.t
Bayesian reasoning

Intuition

MW Moments are not PSD...

Theorem

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1. MW moments are “

Bayesian reasoning

2. $\exists q$ s.t., $\deg(q) = 4$,

$q(x) \geq \omega^5$ if x indicates an ω -clique,

$\tilde{\mathbb{E}}_{MW}[q(x)] \approx n\omega^2$ w.h.p. over $G \sim G(n, \frac{1}{2})$.

Intuition

MW Moments are not PSD...

Theorem

[Kelner]

There is a degree 2 polynomial $p = p_G$ such that
for $\omega \gg n^{\frac{1}{3}}$, w.h.p. over G $\tilde{\mathbb{E}}_{MW}[p(x)^2] < 0$

1. MW moments are “

Bayesian reasoning

2. $\exists q$ s.t., $\deg(q) = 4$,

$q(x) \geq \omega^5$ if x indicates an ω -clique,

$\tilde{\mathbb{E}}_{MW}[q(x)] \approx n\omega^2$ w.h.p. over $G \sim G(n, \frac{1}{2})$.

$n\omega^2 \ll \omega^5$ when $\omega \gg n^{\frac{1}{3}}$

Intuition

Going Bayesian

$G \sim G(n, \frac{1}{2})$ and $H: (H, C) \sim G(n, \frac{1}{2}, \omega)$

Intuition

“indistinguishable” for efficient algos.

$(H, C) \sim G(n, \frac{1}{2}, \omega)$:random graph + planted ω -clique.

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Let $\omega = \varepsilon\sqrt{n}$, $\deg(1) = \frac{n}{2} + \sqrt{n}$

Event D

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MW: The Simple Moments

Is this set of poly-equations feasible?

$$x_i x_j = 0 \quad \forall i \neq j \text{ in } G$$
$$x_i^2 = x_i \quad \forall i$$
$$\sum_i x_i = \omega$$

$\tilde{\mathbb{E}}[x_S]$ (pseudo) prob. of $S \subseteq C$



$$\tilde{\mathbb{E}}[x_S] \approx \begin{cases} \left(\frac{\omega}{n}\right)^{|S|} & \text{if } S \text{ is a clique} \\ 0 & \text{otherwise.} \end{cases}$$

$$\tilde{\mathbb{E}}[x_S] = \begin{cases} \Theta(1) \left(\frac{\omega}{n}\right)^{|S|} (1 + O(n^{-|S|})) & \text{if } S \text{ is a clique} \\ 0 & \text{otherwise.} \end{cases}$$

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large when ω ,
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Proof
Idea

$(H, C) \sim G(n, \frac{1}{2}, \omega)$:random graph + planted ω -clique.

“prior” $\Pr[1 \in C] = \frac{\omega}{n}$ $\deg(1) = \frac{n}{2} + \Delta$

“posterior” $\Pr[1 \in C \mid D]$?

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Let $\omega = \varepsilon\sqrt{n}$, $\deg(1) = \frac{n}{2} + \sqrt{n}$

Event D

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1. $\mathbb{E}_{(H,C)}[x_1 | D] \approx \frac{\omega}{n}(1 + 2\epsilon)$
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“posterior”

$\Pr[1 \in C | D]$?

If $1 \notin C$,

$\deg(1) \sim \mathcal{N}(\frac{n}{2}, \frac{n}{4})$

If $1 \in C$,

$\deg(1) \sim \mathcal{N}(\frac{n}{2} + \omega, \frac{n}{4})$

“higher deg vertex more likely to be in the clique”

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$$\Pr[1 \in C \mid D] = \frac{\omega}{n} \frac{\exp\left(\frac{2(\Delta-\omega)^2}{n}\right)}{\exp\left(\frac{2\Delta^2}{n}\right)} \approx \frac{\omega}{n} \exp\left(\frac{2\Delta\omega}{n}\right) \approx \frac{\omega}{n} \left(1 + \frac{2\Delta\omega}{n}\right)$$

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Going Bayesian

MW moments are “fishy” w.r.t Bayesian reasoning.

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Can



notice?

Bayesian Reasoning

$\exists q$ s.t., $\deg(q) = 4$, $q(x) \geq \omega^5$ if x indicates an ω -clique,
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$$r_i(j) = \begin{cases} +1 & \text{if } i \sim j \\ 0 & \text{if } j = i \\ -1 & \text{if } i \not\sim j \end{cases}$$

$$q(x) = \sum_{i \leq n} \left(\sum_{j \leq n} r_i(j) x_j \right)^4$$

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Proof
Idea

x indicates an ω -clique

$$\text{for any } i: x_i = 1 \quad \left(\sum_{j \leq n} r_i(j)x_j \right)^4 \gtrapprox \omega^4$$

There are ω such i .

Bayesian Reasoning

$\exists q$ s.t., $\deg(q) = 4$, $q(x) \geq \omega^5$ if x indicates an ω -clique,

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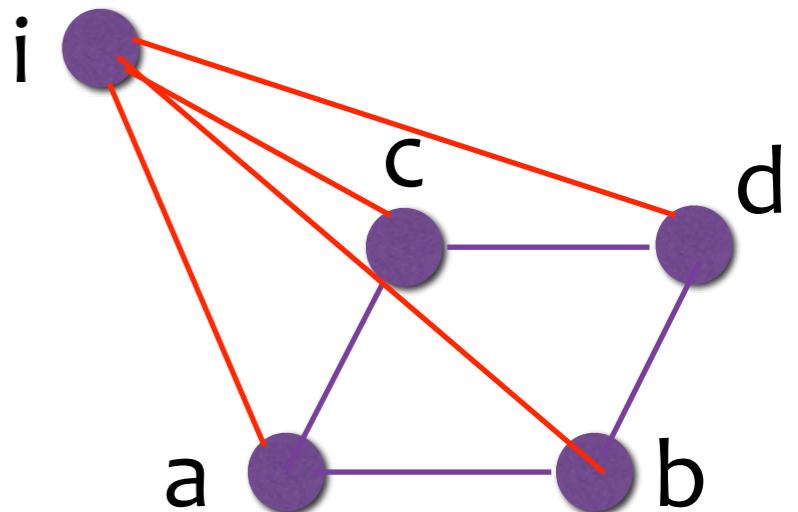
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Proof
Idea

$$\mathbb{E}_G \tilde{\mathbb{E}} \left[\left(\sum_{j \leq n} r_i(j)x_j \right)^4 \right] = \sum_{a,b,c,d} \mathbb{E}_G \left[r_i(a)r_i(b)r_i(c)r_i(d) \tilde{\mathbb{E}}[x_a x_b x_c x_d] \right]$$

notice

$$i \notin \{a, b, c, d\}$$



Bayesian Reasoning

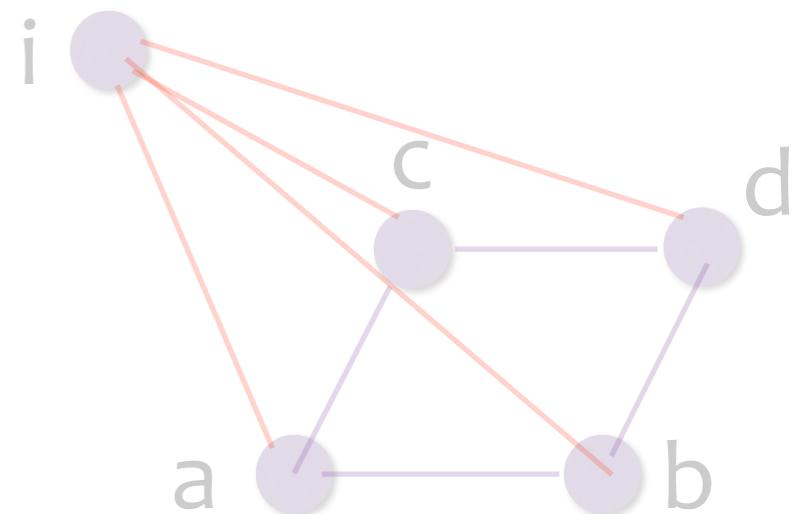
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Proof
Idea

suppose
 $i \notin \{a, b, c, d\}$

$$\mathbb{E}_G \tilde{\mathbb{E}} \left[\left(\sum_{j \leq n} r_i(j)x_j \right)^4 \right] = \sum_{a,b,c,d} \mathbb{E}_G \left[r_i(a)r_i(b)r_i(c)r_i(d) \tilde{\mathbb{E}}[x_a x_b x_c x_d] \right]$$



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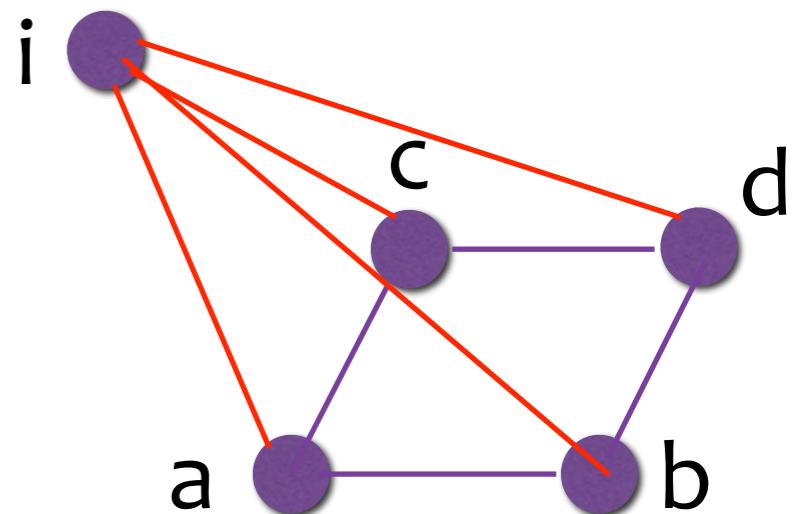
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$$\begin{aligned} \mathbb{E}_G \tilde{\mathbb{E}} \left[\left(\sum_{j \leq n} r_i(j)x_j \right)^4 \right] &= \sum_{a,b,c,d} \mathbb{E}_G \left[r_i(a)r_i(b)r_i(c)r_i(d) \tilde{\mathbb{E}}[x_a x_b x_c x_d] \right] \\ &\approx \sum_{a,b,c,d} \mathbb{E}_G[r_i(a)r_i(b)r_i(c)r_i(d)] \cdot \tilde{\mathbb{E}}[x_a x_b x_c x_d] \end{aligned}$$

Notice
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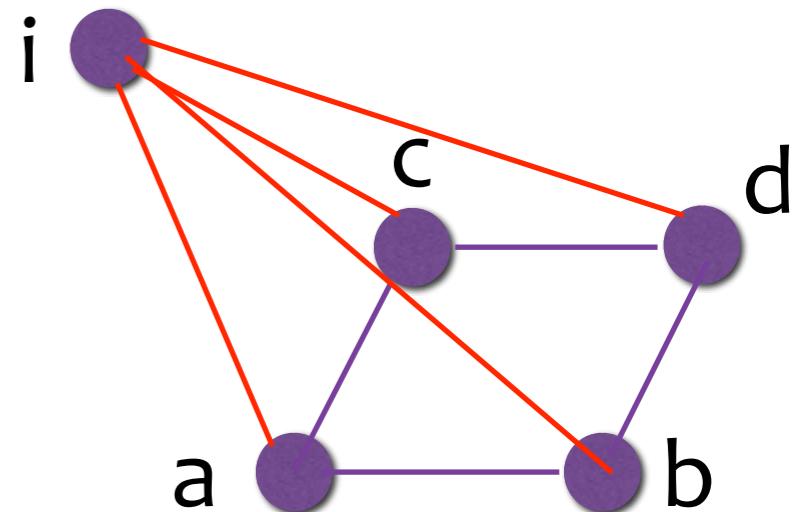
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Use Markov.



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$$n\omega^2 \ll \omega^5 \quad \text{when} \quad \omega \gg n^{\frac{1}{3}}$$

Fixing MW at degree 4

Is this set of poly-equations feasible?

$$\begin{aligned}x_i x_j &= 0 \quad \forall i \neq j \text{ in } G \\x_i^2 &= x_i \quad \forall i\end{aligned}\quad \sum_i x_i = \omega$$

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where $r_S = \sum_i \Pi_{j \in S} r_i(j)$

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[HKP'15]
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approximate eigen-split of MW Mom. matrix
norm of random matrices with limited dependence

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doesn’t even generalize to $d = 6$.

Talk Plan

- 1. Sum of Squares Proofs and Pseudodistributions**
- 2. Meka-Wigderson Pseudodistribution**
- 3. MW Pseudodistribution is not PSD**
- 4. The Bayesian Pseudodistribution**

Bayesian Reasoning

SoS seems to “reason” about $\text{deg}(i)$.

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1. $\text{top}(G)$:highest degree vertex in G

$$\mathbb{E}_{G \sim G(n, \frac{1}{2})} \quad \tilde{\mathbb{E}}[x_{\text{top}(G)}] \approx \mathbb{E}_{(H, C)}[1(C)_{\text{top}(H)}]$$

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$$\mathbb{E}_{G \sim G(n, \frac{1}{2})} \tilde{\mathbb{E}}[x_{top(G)} x_{bot(G)}] \approx \mathbb{E}_{(H,C)}[1(C)_{top(H)} 1(C)_{bot(H)}]$$

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• • •

THE BAYESIAN COMMANDMENT

PSEUDOEXPECTATION SHALL SATISFY ALL
SIMPLE BAYESIAN TESTS

THE BAYESIAN COMMANDMENT

For every “*simple*” map $\{0, 1\}^{\binom{[n]}{2}} \rightarrow p_G(x)$

$$\mathbb{E}_{G \sim G(n, \frac{1}{2})} \tilde{\mathbb{E}}[p_G(x)] \approx \mathbb{E}_{(H, C) \sim G(n, \frac{1}{2}, \omega)} [p_H(1(C))]$$

$$G = \{g_{\{i,j\}}\}_{i,j \in [n]} \quad g_{\{i,j\}} = \begin{cases} +1 & \text{if } \{i,j\} \text{ is an edge in } G. \\ -1 & \text{otherwise.} \end{cases}$$

p_G is a polynomial in \mathbf{x} and $\{g_{\{i,j\}}\}_{i,j \in [n]}$

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degree of p_G in \mathbf{x} .

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“*simple*” map



low ins. and sol. degree.

THE BAYESIAN COMMANDMENT

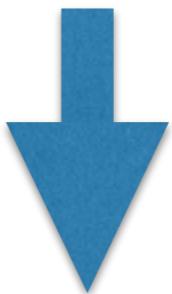
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$$\mathbb{E}_{G \sim G(n, \frac{1}{2})} \tilde{\mathbb{E}}[p_G(x)] = \mathbb{E}_{(H, C) \sim G(n, \frac{1}{2}, \omega)} [p_H(1(C))]$$

$$\tilde{\mathbb{E}}[x_S] : \{0, 1\}^{\binom{[n]}{2}} \rightarrow \mathbb{R} \quad \tilde{\mathbb{E}}[x_S] = \sum_{T \subseteq \binom{[n]}{2}} \widehat{\tilde{\mathbb{E}}[x_S]}(T) \cdot \chi_T$$

Bayesian Commandment

Observation



Low Degree Fourier coefficients
of $\tilde{\mathbb{E}}[x_S]$ determined!

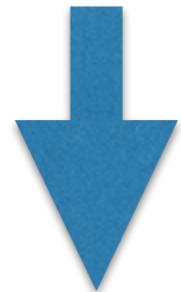
THE BAYESIAN COMMANDMENT

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Bayesian Commandment



Observation

No choice in
the operator!

Low Degree Fourier coefficients
of $\tilde{\mathbb{E}}[x_S]$ determined!

The Bayesian Pseudomoments

$$\tilde{\mathbb{E}}[x_S] = \sum_{T \subseteq \binom{[n]}{2} : |V(T)| \leq \tau} \widehat{\tilde{\mathbb{E}}[x_S]}(T) \chi_T$$

use a **truncated** Fourier polynomial as the pseudomoment.

Easy

$\tilde{\mathbb{E}}$ satisfies all constraints!

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Main Technical
Lemma

For every q , $\deg(q)$ at most $d/2$

$\tilde{\mathbb{E}}[q(x)^2] \geq 0$ w.h.p. over $G \sim G(n, \frac{1}{2})$

The Bayesian Pseudomoments

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$$M(I, J) = \tilde{\mathbb{E}}[x_{I \cup J}]$$

Moment Matrix

$$M \approx M_{struct} + M_{random}$$

M_{struct} eigenvectors are low-degree functions of graph

M_{random} eigenvectors are high-degree functions of graph

The Bayesian Pseudomoments

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Moment Matrix

$$M \approx M_{\text{struct}} + M_{\text{random}}$$

M_{struct} eigenvectors are low-degree functions of graph
fine by construction of the operator!

M_{random} eigenvectors are high-degree functions of graph
“random-like” -Wigner-like in appropriate subspaces

Main Theorem

For every d , Bayesian \tilde{E} satisfies all the constraints whenever $\omega \ll n^{0.5-\varepsilon}$.

$$d = \Theta(1) , \epsilon = o_d(1)$$

Conclusions

General procedure to construct SoS LB witness.

unify SoS LBs, prove LBs for planted problems, 2->4 norm...

Bayesian view of SoS

Applications to upper bounds?

Thank you for your attention.

Acknowledgment

Some illustrations based on Boaz's inputs.

Bayesian Reasoning

Is the set of poly-equations feasible?

$$x_i x_j = 0 \quad \forall i \neq j \text{ in } G \quad \sum_i x_i = \omega$$
$$x_i^2 = x_i \quad \forall i$$

$$\tilde{\mathbb{E}}[x_i] \approx \left(\frac{\omega}{n}\right) \quad \text{Vertex } i : \quad \deg(i) = \frac{n}{2} + \Delta, \Delta \pm \Theta(\sqrt{n})$$

$$\text{If } i \notin C, \quad \deg(i) \sim \mathcal{N}\left(\frac{n}{2}, \frac{n}{4}\right) \quad \text{If } i \in C, \quad \deg(i) \sim \mathcal{N}\left(\frac{n}{2} + \omega, \frac{n}{4}\right)$$

Given $\deg(i)$, posterior “probability” of i is in C ?

$$\Pr[i \in C] \cdot \frac{\Pr[\deg(i) = q \mid i \in C]}{\Pr[i \in C] \Pr[\deg(i) = q \mid i \in C] + \Pr[i \notin C] \Pr[\deg(i) = q \mid i \notin C]}$$



sloppy calculations only.

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MW violates Bayesian reasoning.

$$r_i(j) = \begin{cases} +1 & \text{if } i \sim j \\ 0 & \text{if } j = i \\ -1 & \text{if } i \not\sim j \end{cases}$$

$$\mathbb{E}_{G \sim G(n, \frac{1}{2})} \tilde{\mathbb{E}}[\langle r_i, x \rangle^4] \approx \|x\|^4$$
$$\approx \omega^2$$

r_i is treated as a random vector.



sloppy calculations only.

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sloppy calculations only.

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prob i is in C

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If $\omega \gg n^{\frac{1}{3}}$ pseudo expectation is too small.



sloppy calculations only.

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SoS captures “low-instance degree” Bayesian reasoning?

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“instance degree” of $\sum_S p_S x_S = \deg \text{ of } p_S \text{ edge indicators}$

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“instance degree” of $\sum_S p_S x_S = \deg$ of p_S edge indicators

SoS captures “low-instance degree” Bayesian reasoning.

degree of vertices, number of triangles, etc.

Bayesian Reasoning

Is this set of poly-equations feasible?

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[**Kelner**]

for $\omega \gg n^{1/3}$ and some constant c,

w.h.p. $\tilde{\mathbb{E}}[(\langle r_i, x \rangle^2 - cx_i)^2] < 0$

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MW Pseudomoments work for $\omega \ll n^{\frac{1}{\frac{d}{2}+1}}$.

[MPW'15]
[DM'15]
[HKP'15]

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For every “*simple*” map $G \rightarrow p_G(x)$

$$\mathbb{E}_{G \sim G(n, \frac{1}{2})} [\tilde{\mathbb{E}}[p_G(x)]] = \mathbb{E}_{(H, C) \sim G(n, \frac{1}{2}, \omega)} [p_G(1(C))]$$

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$$= \mathbb{E}_{(H, C) \sim G(n, \frac{1}{2}, \omega)} [1(S \subseteq C) \chi_T(H)]$$

match “moments” (Fourier coeffs) with planted dist.

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completely determined by the “planted” distribution!

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build an operator that satisfies **all** Bayesian constraints of **low-instance degree**.

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build an operator that satisfies
of **low-instance degree**

No choice in the operator if want to satisfy all Bayesian constraints!

For every “**simple**” map $G \rightarrow p_G(x)$

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