# The hidden clique problem and graphical models 

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## Outline

(1) Finding a clique in a haystack
(2) A spectral algorithm
(3) Improving over the spectral algorithm

Finding a clique in a haystack

## General Problem

$$
G=(V, E) \text { a graph. }
$$

$$
S \subseteq V \text { supports a clique (i.e. }(i, j) \in E \text { for all } i, j \in S \text { ) }
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Problem : Find $S$.

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## Example 1: Zachary's karate club



Fig. 2. Application of the eigenvector-based method to the karate club

## A catchier name

Finding a terrorist cell in a social network

## Toy example: 150 nodes, 15 highly connected



Here binary data: Can generalize...

## Of course not the first $15 .$. .



Where are the highly connected nodes? $10^{21}$ possilities.

## An efficient algorithm



## The model [Alon,Krivelevich,Sudakov 1998]

- Choose $S \subseteq V$ with $|S|=k$ uniformly at random.
- Add an edge $(i, j)$ for each pair s.t. $i, j \in S$.
- Add an edge for each other pair $(i, j)$ independently with prob $p$.

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G \sim \mathbb{G}(n, p, k)
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Will assume $p=1 / 2$

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## Question

How big $k$ has to be for us to find the clique?

## If you could wait forever

> Exhaustive SEARCH
> Input: Graph $G=(V, E)$, Clique size $k$
> Output : Clique of size $k$
> 1: For all $S \subset V,|S|=k ;$
> 3: Check if $G S$ is a clique;
> 4: Output all cliques found;

## If you could wait forever

> Exhaustive search
> Input : Graph $G=(V, E)$, Clique size $k$
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> 1: For all $S \subset V,|S|=k$;
> 3: $\quad$ Check if $G_{S}$ is a clique;
> 4: Output all cliques found;

Works if $k>k_{*}$, typical size of largest clique in $G \sim \mathbb{G}(n, 1 / 2, k)$ that is not supported on $S$.

## Largest random clique

Largest clique that does not share any vertex with $S$
Equivalently $G \sim \mathbb{G}(n-k, 1 / 2,0) \approx \mathbb{G}(n, 1 / 2,0)$.

Idea: compute expected number of cliques of size $k$

## Largest random clique

Expected nb of cliques of size $k$

$$
\mathbb{E} N(k)=\binom{n}{k} \mathbb{P}\{(1, \ldots, k) \text { form a clique }\}
$$

$$
k_{*}(n) \approx 2 \log _{2} n
$$

## Largest random clique

Expected nb of cliques of size $k$

$$
\begin{aligned}
\mathbb{E} N(k) & =\binom{n}{k} \mathbb{P}\{(1, \ldots, k) \text { form a clique }\} \\
& =\binom{n}{k} 2^{-k(k-1) / 2} \\
& \leq\left(\frac{n e}{k}\right)^{k} 2^{-k(k-1) / 2} \\
& \leq\left(\frac{n e}{k} 2^{-(k-1) / 2}\right)^{k}
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## Largest random clique



## Can we do it in reasonable time?

Naive Algorithm
Input : Graph $G=(V, E)$, Clique size $k$ Output : Clique of size $k$
1: Sort vertices by degree;
2: Check if the $k$ vertices with largest degree form a clique;
3: If yes, output them;

## When does naive work?

For $i \notin S$

$$
\begin{gather*}
d_{i} \sim \operatorname{Binom}(n-1,1 / 2) \approx \operatorname{Normal}(n / 2, n / 4) \\
\mathbb{P}\left\{d_{i} \geq \frac{n}{2}+\frac{n^{1 / 2}}{2} t\right\} \leq e^{-t^{2} / 2} \leq \frac{1}{n^{2}}
\end{gather*}
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Proposition

## With high probability



Works for $k \geq 2 \sqrt{n \log n}$

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With high probability

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\begin{aligned}
& \max _{i \notin S} d_{i} \leq \frac{n}{2}+\sqrt{n \log n} . \\
& \min _{i \in S} d_{i} \geq \frac{n}{2}+k-1-\sqrt{n \log n} .
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Works for $k \geq 2 \sqrt{n \log n}$

## A spectral algorithm

Idea

$$
W_{i j}= \begin{cases}+1 & \text { if }(i, j) \in E \\ -1 & \text { otherwise }\end{cases}
$$

## Want to find $u_{S}$ from $W$.

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\begin{aligned}
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W=u_{S} u_{S}^{\top}+Z-Z_{S, S}
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W=u_{S} u_{s}^{\top}+Z-Z_{s, S}
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$\left(Z_{i j}\right)_{i<j}$ i.i.d.

$$
Z_{i j}= \begin{cases}+1 & \text { with probability } 1 / 2 \\ -1 & \text { with probability } 1 / 2\end{cases}
$$

$\left(Z_{S, S}\right)_{i j}=Z_{i j}$ if $i, j \in S$ and $=0$ otherwise

Idea

$$
W=u_{S} u_{S}^{\top}+Z-Z_{S, S}
$$

## With overwhelming probability



## Idea

$$
W=u_{S} u_{S}^{\top}+Z-Z_{S, S}
$$

With overwhelming probability

$$
\begin{aligned}
\left\|u_{S} u_{S}\right\|_{2} & =k \\
\|Z\|_{2} & \approx 2 \sqrt{n} \\
\left\|Z_{S, S}\right\|_{2} & \approx 2 \sqrt{k} \ll\|Z\|_{2} .
\end{aligned}
$$

## Use matrix perturbation theory

Unperturbed matrix

$$
\begin{aligned}
W_{0}= & u_{S} u_{S}^{\top}, \\
& \lambda_{1}\left(W_{0}\right)=k, \lambda_{2}\left(W_{0}\right)=\cdots=\lambda_{n}\left(W_{0}\right)=0
\end{aligned}
$$

## The sin theta theorem

$\widehat{u}_{S}=u_{S} / \sqrt{k}$ principal eigenvector of $W_{0}$ $v$ principal eigenvector of $W$

$$
\begin{aligned}
\left\|v-\widehat{u}_{S}\right\|_{2} & \leq \sqrt{2} \sin \theta\left(v, \widehat{u}_{S}\right) \leq \frac{\sqrt{2}\left\|Z+Z_{S, S}\right\|_{2}}{\lambda_{1}\left(W_{0}\right)-\lambda_{2}(W)} \\
& \leq \frac{3 \sqrt{n}}{k-3 \sqrt{n}}
\end{aligned}
$$

## Summarizing

## Proposition

For $k \geq 100 \sqrt{n}$, whp

$$
\left\|v-\widehat{u}_{S}\right\|_{2} \leq \frac{1}{10}
$$

## Let's check how does it work. . .

Histogram of eA\$val


$$
n=2000, k=100
$$

## Let's check how does it work. . .



$$
n=2000, k=100
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## Spectral algorithm: First attempt

Naive Spectral Algorithm
Input : Graph $G=(V, E)$, Clique size $k$
Output : Clique of size $k$
1: Compute first eigenvector $v$ of matrix $W=W(G)$;
2: Sort vertices by value of $\left|v_{i}\right|$;
3: Check if the $k$ vertices with largest value form a clique;
4: If yes, output them;

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## Where is the problem?

## Spectral algorithm

## Spectral Algorithm

Input : Graph $G=(V, E)$, Clique size $k$
Output : Clique of size $k$
1: Compute first eigenvector $v$ of matrix $W=W(G)$;
2: Sort vertices by value of $\left|v_{i}\right|$;
3: Let $R \subseteq V$ be the set of $k$ vertices with largest value;
4: For $i \in V$
5: $\quad$ If $\operatorname{deg}_{R}(i)>3 k / 4$, let $S \leftarrow S \cup\{i\}$;
6: Output $S$;

## Why is this a good trick?

- By the perturbation bound $R$ is roughly good: $R \cap S>0.9 \cdot k$.
- All the vertices in $S$ pass the test.
- For $i \notin S, \mathbb{E d e g}_{R}(i)=k / 2$ and $\operatorname{deg}_{R}(i)<3 k / 4$ whp.


## Improving over the spectral algorithm

## We proved this

Theorem
If $k \geq 100 \sqrt{n}$ then spectral algorithm finds the clique.

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If $k \geq 100 \sqrt{n}$ then spectral algorithm finds the clique.

Can we make 100 as small as we want?

Not without a new idea...

Histogram of eA\$val


$$
n=2000, k=30
$$

## Not without a new idea...



$$
n=2000, k=30
$$

## Tight analysis

$$
W=u_{S} u_{S}^{\top}+Z-Z_{S, S} \approx u_{S} u_{S}^{\top}+Z
$$

Low-rank deformation of a random matrix (e.g. Knowles, Yin 2011)

## Proposition

If $k>(1+\epsilon) \sqrt{n}$, then $\left\langle u_{S}, v\right\rangle \geq \min (\epsilon, \sqrt{\epsilon}) / 2$.
Viceversa, if $k<(1-\epsilon) \sqrt{n}$, then $\left|\left\langle u_{S}, v\right\rangle\right| \leq n^{-1 / 2+\delta}$.

## The test set idea

Enhanced Spectral Algorithm
Input : Graph $G=(V, E)$, Clique size $k$
Output : Clique of size $k$
1: For $T \subseteq V,|T|=2, T$ is a clique;
2: $\quad$ Let $V_{T}=\left\{i \in V \backslash T: \operatorname{deg}_{T}(i)=2\right\}$
and let $G_{T}$ be the induced graph;
3: $\quad$ Run Spectral Algorithm $\left(G_{T}, k-2\right)$;
4: If a clique $S$ of size $k-2$ is found, return $S \cup T$;

## Why is this a good trick?

$$
V_{T}^{\prime} \approx \frac{n}{4}
$$

Looking for clique of size $k-2$.

```
If Spectral succeeds for }k\geqc\sqrt{}{n}\mathrm{ , then Enhanced Spectral works
for }k-2\geqc\sqrt{}{n/4}\mathrm{ .
Equivalently for k}\geq\mp@subsup{c}{}{\prime}\sqrt{}{n}\mathrm{ with
```

$$
c^{\prime}=c / 2+0.000001
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## Iterating the same idea

## Enhanced Spectral Algorithm

Input : Graph $G=(V, E)$, Clique size $k$
Output : Clique of size $k$
1: For $T \subseteq V,|T|=s, T$ is a clique;
2: $\quad$ Let $V_{T}=\left\{i \in V \backslash T: \operatorname{deg}_{T}(i)=2\right\}$ and let $G_{T}$ be the induced graph;
3: Run Spectral Algorithm $\left(G_{T}, k-s\right)$;
4: If a clique $S$ of size $k-s$ is found, return $S \cup T$;

## The state of the art for polynomial algorithms

Theorem
Enhanced Spectral(s) finds cliques of size $c 2^{-s / 2} \sqrt{n}$ in time $O\left(n^{s+c_{0}}\right)$.

## What about really efficient algorithms?

```
Theorem (Dekel, Gurel-Gurevitch, Peres, 2011)
If k}>1261\sqrt{}{n}\mathrm{ then there exists an algorithm with complexity O( }\mp@subsup{n}{}{2})\mathrm{ that
finds the clique with high probability.
```

Theorem (Deshpande, Montanari, 2013)
 $O\left(n^{2} \log n\right)$ that finds the clique with high probability.

## What about really efficient algorithms?

## Theorem (Dekel, Gurel-Gurevitch, Peres, 2011)

If $k \geq 1.261 \sqrt{n}$, then there exists an algorithm with complexity $O\left(n^{2}\right)$ that finds the clique with high probability.


## What about really efficient algorithms?

## Theorem (Dekel, Gurel-Gurevitch, Peres, 2011)

If $k \geq 1.261 \sqrt{n}$, then there exists an algorithm with complexity $O\left(n^{2}\right)$ that finds the clique with high probability.

Theorem (Deshpande, Montanari, 2013)
If $k \geq(1+\epsilon) \sqrt{n / e}$, then there exists an algorithm with complexity $O\left(n^{2} \log n\right)$ that finds the clique with high probability.

