## Maximum likelihood threshold of a graph

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## Gaussian graphical models


$X=\left(X_{1}, X_{2}, X_{3}, X_{4}\right) \sim \mathcal{N}(0, \Sigma)$

The non-edges of $G$ record the conditional independence structure of $X$ :

$$
\begin{gathered}
X_{1} \Perp X_{4} \mid\left(X_{2}, X_{3}\right) \\
X_{1} \Perp X_{3} \mid\left(X_{2}, X_{4}\right) \\
\Rightarrow\left(\Sigma^{-1}\right)_{14}=0,\left(\Sigma^{-1}\right)_{13}=0 .
\end{gathered}
$$

$\mathbb{S}^{m}=m \times m$ symmetric real matrices $\mathbb{S}_{>0}^{m}=$ pos. def. matrices in $\mathbb{S}^{m}$
$\mathbb{S}_{\geq 0}^{m}=$ psd matrices in $\mathbb{S}^{m}$

$$
\text { Let } G=(V, E) \text { with }|V|=m
$$

$$
\begin{aligned}
\mathcal{M}_{G}= & \left\{\Sigma \in \mathbb{S}_{>0}^{m}:\left(\Sigma^{-1}\right)_{i j}=0\right. \text { for all } \\
& i, j \text { s.t. } i \neq j, i j \notin E\}
\end{aligned}
$$

## Definition

The centered Gaussian graphical model associated to the graph $G$ is the set of all multivariate normal distributions $\mathcal{N}(0, \Sigma)$ such that $\Sigma \in \mathcal{M}_{\mathcal{G}}$.

## Maximum likelihood estimation

Goal: Find $\Sigma$ that best explains data
Observations: $Y_{1}, \ldots, Y_{n}$
Sample covariance matrix: $S=\frac{1}{n} \sum_{i=1}^{n} Y_{i} Y_{i}^{\top}$
If the MLE exists, it is the unique positive definite matrix $\Sigma$ that satisfies:

$$
\begin{gathered}
\Sigma_{i j}=S_{i j} \text { for } i j \in E \text { and } i=j \\
(\Sigma)_{i j}^{-1}=0 \text { for } i j \notin E \text { and } i \neq j
\end{gathered}
$$

When $n \geq m$, the MLE exists with probability one. What about the case when $m \gg n$ ?

## Question (Lauritzen)

For a given graph $G$ what is the smallest $n$ such that the MLE exists with probability one?

## Maximum likelihood threshold

## Definition

We call the smallest $n$ such that the MLE exists with probably one (i.e. for generic data) the maximum likelihood threshold, or, mlt.

## Proposition (Buhl 1993)

$$
\text { clique number of } G \leq m / t(G) \leq \text { tree width of } G+1
$$

- Clique number: $\omega(G)=$ size of a largest clique of $G$
- Chordal graph: A graph with no induced cycle of length $\geq 4$.
- Chordal cover of $G=(V, E)$ : A graph $H=$ ( $V, E^{\prime}$ ) such that $H$ is chordal and $E \subseteq E^{\prime}$.
- Tree width: $\tau(G)=$ $\min \{\omega(H)-1: H$ is a chordal cover of $G\}$.

$$
\omega(G)=3, \tau(G)=3
$$

Chordal cover of $G$ :


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Notice that these bounds can be far away from each other. Consider for example, $G=G r_{k_{1}, k_{2}}$, the $k_{1} \times k_{2}$ grid graph:

$\omega(G)=$ size of largest clique $=2$
$\tau(G)=$ tree width $=\min \left(k_{1}, k_{2}\right)$

## Geometry of Gaussian graphical models

$\circ|V|=m \quad \circ \mathbb{S}^{m}:=m \times m$ symmetric real matrices

- $\mathbb{S}_{>0}^{m}:=$ pos. def. matrices in $\mathbb{S}^{m} \quad \circ \mathbb{S}_{\geq 0}^{m}:=$ psd matrices in $\mathbb{S}^{m}$
- Let $\pi_{G}$ be the projection map that extracts the entries of $\Sigma$ corresponding to the vertices and edges of $G$ :

$$
\begin{aligned}
\pi_{G}: \mathbb{S}^{m} & \rightarrow \mathbb{R}^{V+E} \\
\phi_{G}(\Sigma) & =\left(\sigma_{i i}\right)_{i \in V} \oplus\left(\sigma_{i j}\right)_{i j \in E}
\end{aligned}
$$



$$
\begin{gathered}
\phi_{G}\left(\left[\begin{array}{lll}
1 & 2 & 3 \\
2 & 1 & 2 \\
3 & 2 & 1
\end{array}\right]\right) \\
=(1,1,1,2,2)^{T}
\end{gathered}
$$

- Cone of sufficient statistics: $\mathcal{C}_{G}:=\phi_{G}\left(\mathbb{S}_{>0}^{m}\right)$.
- For a given $S \in \mathbb{S}_{\geq 0}^{m}$, the MLE exists if and only if $\phi_{G}(S) \in \operatorname{int}\left(\mathcal{C}_{G}\right)$.
- $\mathcal{C}_{G}$ is the convex dual to the cone of concentration matrices $\mathcal{K}_{G}$


## Geometry of maximum likelihood estimation

Concentration matrices: $K$


Covariance matrices: $\Sigma$


Uhler, Geometry of maximum likelihood estimation in Gaussian graphical models (2012)
Light orange: $\mathcal{K}_{G}$, cone of concentration matrices, Purple: $\mathcal{K}_{G}^{-1}$, cone of covariance matrices, Gray: Set of positive definite completions of $S$, Dark orange: $\mathcal{C}_{G}$, Cone of sufficient statistics

## Geometry of maximum likelihood estimation

Concentration matrices: $K$
Covariance matrices: $\Sigma$


Blue: $S(m, n) \cap \mathbb{S}_{\geq 0}$, Set of $m \times m$ positive semi-definite symmetric matrices of rank $\leq n$

## Geometry of maximum likelihood estimation

Covariance matrices: $\Sigma$


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## Rank of a graph

## Definition

Let $S(m, n):=\left\{\Sigma \in \mathbb{S}^{m}: \operatorname{rank}(\Sigma) \leq n\right\}$.
The rank of a graph $G$ is the minimal $n$ such that $\operatorname{dim} \phi_{G}(S(m, n))=\operatorname{dim} \mathcal{C}_{G}=|V|+|E|$

Proposition (Uhler 2012)

$$
m / t(G) \leq \operatorname{rank}(G)
$$

Goal: Connect the rank of a graph to combinatorial rigidity theory.

Method: Use algebraic matroids, in particular compare the rigidity matroid and the symmetric minor matroid.

## Combinatorial Rigidity Theory

The study of rigidity deals with with bar and joint frameworks. A framework is a graph $G$ embedded in $\mathbb{R}^{n}$.


Rigid in $\mathbb{R}^{2}$

A graph $G$ is called rigid if, for generic points $\mathbf{p}_{1}, \ldots, \mathbf{p}_{m} \in \mathbb{R}^{n}$, the only continuous deformations that preserve the distances $\left\|\mathbf{p}_{i}-\mathbf{p}_{j}\right\|_{2}$ for $i j \in E$ are rotations and translations.


Not rigid in $\mathbb{R}^{2}$

## The rigidity matroid

A matroid $M$ is a pair $(E, I)$ where $E$ is a finite set of elements, called the ground set and $I$ is a collection of subsets of $E$, called the independent sets.

Consider the map $\psi_{n}: \mathbb{R}^{n \times m} \rightarrow \mathbb{R}^{m(m-1) / 2}$

$$
\left(\mathbf{p}_{1}, \ldots, \mathbf{p}_{m}\right) \mapsto\left(\left\|\mathbf{p}_{i}-\mathbf{p}_{j}\right\|_{2}^{2}: 1 \leq i<j \leq m\right) .
$$

This is polynomial map with an associated matroid:

- $E=$ columns of the Jacobian at a generic point
- $I=$ all collections of independent columns

This matroid is called the $\mathbf{n}$-dimensional generic rigidity matroid, denoted $\mathcal{A}(n)$.

- Spanning sets in the matroid are called (generically infinitesimally) rigid graphs.
- Bases in the matroid are called (generically) isostatic graphs.


## Laman's Theorem

- To be a spanning set in $\mathcal{A}(n)$ must have $n m-\binom{n+1}{2} \leq|E|$.
- Conversely, to be independent must have $n m-\binom{n+1}{2} \geq|E|$.


## Theorem (Laman 1970)

A graph $G=(V, E)$ is a basis (isostatic) in the rigidity matroid $\mathcal{A}(2)$ if and only if

- $|E|=2 m-3$, and
- For every induced subgraph

$$
G_{W}=\left(W, E_{W}\right),\left|E_{W}\right| \leq 2|W|-3
$$



## Back to the rank of a graph

Concentration matrices: $K$
$\mathbb{S}_{\succ 0}^{m}$


Covariance matrices: $\Sigma$


Blue: $S(m, n) \cap \mathbb{S}_{\geq 0}$, Set of $m \times m$ positive semi-definite symmetric matrices of rank $\leq n$

## Symmetric minor matroid

## Definition

Let $I \subset \mathbb{K}\left[x_{1}, \ldots, x_{r}\right]$ be a prime ideal. This defines an algebraic matroid with ground set $\left\{x_{1}, \ldots, x_{r}\right\}$, and $K \subseteq\left\{x_{1}, \ldots, x_{r}\right\}$ an independent set if and only if $I \cap \mathbb{K}[K]=\langle 0\rangle$.
$S(m, n)$ is an algebraic set whose defining ideal $I_{n}$ is generated by the $(n+1) \times(n+1)$-minors of a $m \times m$ symmetric matrix $\Sigma=\left(\sigma_{i j}\right)$.

The set $S(m, n)$ has an associated algebraic matroid:

- ground set $=\left\{\sigma_{i j}: i<j\right\}$,
- independent sets $=$ graphs $G$ such that $\pi_{G}(S(m, n))=\mathbb{R}^{V+E}$

This matroid is called the rank $n$ symmetric minor matroid

## Remark

If $G$ is an independent set in the rank $n$ symmetric minor matroid then $\operatorname{rank}(G) \leq n$, and consequently, $m / t(G) \leq n$. (Uhler 2012)

## Rigidity Matroid $\cong$ Symmetric Minor Matroid

## Theorem (Gross-Sullivant)

- A graph $G$ has $\operatorname{rank}(G)=n$ if and only if $G$ is an independent set in the $(n-1)$-dimensional rigidity matroid $\mathcal{A}(n-1)$ and not an independent set in $\mathcal{A}(n-2)$.
- The $(n-1)$-dimensional rigidity matroid $\mathcal{A}(n-1)$ is isomorphic to the rank $n$ symmetric minor matroid.


## Proof.

Compare the Jacobian of the map

$$
\left(\mathbf{p}_{1}, \ldots, \mathbf{p}_{m}\right) \mapsto\left(\left\|\mathbf{p}_{i}-\mathbf{p}_{j}\right\|_{2}^{2}: 1 \leq i<j \leq m\right)
$$

to the Jacobian of the map

$$
\left(\mathbf{p}_{1}, \ldots, \mathbf{p}_{m}\right) \mapsto\left(\mathbf{p}_{i} \cdot \mathbf{p}_{j}: 1 \leq i<j \leq m\right)
$$

This means that we can bound the mlt of a graph by checking whether $G$ is an independent set in $\mathcal{A}(n-1)$.

## Laman's Theorem

## Corollary (Laman's Theorem)

Let $G=(V, E)$ be a graph, if for all subgraphs $G^{\prime}=\left(V^{\prime}, E^{\prime}\right)$ of $G$

$$
\# E^{\prime} \leq 2\left(\# V^{\prime}\right)-3
$$

then $m / t(G) \leq 3$.


## Definition

Let $G$ be a graph and $r \in \mathbb{N}$. The $r$-core of $G$ is the graph obtained by successively removing vertices of $G$ of degree $<r$.

## Theorem (Gross-Sullivant, Ben-David)

Let $G$ have an empty n-core, then $\operatorname{rank}(G) \leq n$.
$\Rightarrow \boldsymbol{m l t}\left(G r_{k_{1}, k_{2}}\right)=3$


Elizabeth Gross, UH Mānoa

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## Planar graphs



## Theorem (Gross-Sullivant)

If $G$ is a planar graph then $m / t(G) \leq 4$.

## Proof.

- Cauchy's theorem implies that every edge graph of simplicial 3-polytope is rigid.
- Edge count $\rightarrow \mathrm{G}$ isostatic $\rightarrow \operatorname{rank}(G) \leq 4$
- Every planar graph is a subgraph of a graph of a simplicial 3-polytope.


## Cycle-Free Coloring

## Theorem (Gross-Sullivant 2018)

Let $G$ be a graph and $V_{1}, \ldots, V_{k}$ a partition of the vertices of $G$ such that
(1) for all $i, V_{i}$ is an independent set of $G$ and
(2) for all $i \neq j, G\left(V_{i}, V_{j}\right)$ has no cycles.

Then $\operatorname{rank}(G) \leq k$.


## Score matching estimator

The score matching estimator is a computationally efficient and consistent estimator for Gaussian graphical models (Hyvärinen 2005, Forbes-Lauritzen 2014) .

## Definition

We call the smallest $n$ such that the scoring matching exists with probably one (i.e. for generic data) the scoring matching threshold, or, smt.

## Theorem (Gross-Sullivant)

Let $G$ be a graph. Then

$$
\operatorname{smt}(G)=\operatorname{rank}(G)
$$

## Some questions

- How are the boundary components of $\mathcal{C}_{G}$ related to the circuits in the rigidity matroid?
- Maximum likelihood threshold has a natural rigidity theory analogue: are they equivalent?
- Determine the score matching threshold for Gaussian graphical models with symmetries. Can the same methods be used here?
- How different can the maximum likelihood threshold be from the weak maximum likelihood threshold?


## Thank you

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