## Logarithmic Voronoi cells for Gaussian models

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## Gaussian models: general

Let $X$ be an $m$-dimensional random vector, which has the density function

$$
p_{\mu, \Sigma}(x)=\frac{1}{(2 \pi)^{m / 2}(\operatorname{det} \Sigma)^{1 / 2}} \exp \left\{-\frac{1}{2}(x-\mu)^{T} \Sigma^{-1}(x-\mu)\right\}, \quad x \in \mathbb{R}^{m}
$$

with respect to the parameters $\mu \in \mathbb{R}^{m}$ and $\Sigma \in \mathrm{PD}_{m}$.
Such $X$ is distributed according to the multivariate normal distribution, also called the Gaussian distribution $\mathcal{N}(\mu, \Sigma)$.

For $\Theta \subseteq \mathbb{R}^{m} \times \mathrm{PD}_{m}$, the statistical model

$$
\mathcal{P}_{\Theta}=\{\mathcal{N}(\mu, \Sigma): \theta=(\mu, \Sigma) \in \Theta\}
$$

is called a Gaussian model. We identify the Gaussian model $\mathcal{P}_{\Theta}$ with its parameter space $\Theta$.

## Gaussian models: general

For a sampled data consisting of $n$ vectors $X^{(1)}, \cdots, X^{(n)} \in \mathbb{R}^{m}$, we define the sample mean and sample covariance as

$$
\bar{X}=\frac{1}{n} \sum_{i=1}^{n} X^{(i)} \quad \text { and } \quad S=\frac{1}{n} \sum_{i=1}^{n}\left(X^{(i)}-\bar{X}\right)\left(X^{(i)}-\bar{X}\right)^{T}
$$

respectively. The log-likelihood function is defined as

$$
\ell_{n}(\mu, \Sigma)=-\frac{n}{2} \log \operatorname{det} \Sigma-\frac{1}{2} \operatorname{tr}\left(S \Sigma^{-1}\right)-\frac{n}{2}(\bar{X}-\mu)^{T} \Sigma^{-1}(\bar{X}-\mu)
$$

## Proposition (A., Hoșten)

Consider the Gaussian model with parameter space $\Theta=\Theta_{1} \times\left\{I d_{m}\right\}$ for some $\Theta_{1} \subseteq \mathbb{R}^{m}$. For any point in this model, its logarithmic Voronoi cell is equal to its Euclidean Voronoi cell.

## Algebraic models

In practice, we will only consider models given by parameter spaces of the form $\Theta=\mathbb{R}^{m} \times \Theta_{2}$ where $\Theta_{2} \subseteq P_{m}$. Thus, a Gaussian model is a subset of $\mathrm{PD}_{m}$. The log-likelihood function is then

$$
\ell_{n}(\Sigma, S)=-\frac{n}{2} \log \operatorname{det} \Sigma-\frac{n}{2} \operatorname{tr}\left(S \Sigma^{-1}\right)
$$

All Gaussian models discussed in this talk are algebraic. In other words,

$$
\Theta=\mathcal{V} \cap \mathrm{PD}_{m},
$$

where $\mathcal{V} \subseteq \mathbb{C}^{m}$ is a variety given by polynomials in the entries of $\Sigma=\left(\sigma_{i j}\right)$.

## Natural questions

Fix a Gaussian model $\Theta \subseteq \mathrm{PD}_{m}$.
(1) The maximum likelihood estimation problem (MLE):

Given a sample covariance matrix $S \in \mathrm{PD}_{m}$, which matrix $\Sigma \in \Theta$ did it most likely come from? In other words, we wish to maximize $\ell_{n}(\Sigma, S)$ over all points $\Sigma \in \Theta$.

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(2) Computing logarithmic Voronoi cells:

Given a matrix $\Sigma \in \Theta$, what is the set of all $S \in \mathrm{PD}_{m}$ that have $\Sigma$ as a global maximum when optimizing the function $\ell_{n}(\Sigma, S)$ over $\Theta$ ?

The set of all such matrices $S \in \mathrm{PD}_{m}$ is the logarithmic Voronoi cell at $\Sigma$.

## Logarithmic Voronoi cells

## Proposition (A., Heaton \& A., Hoșten)

Logarithmic Voronoi cells are covex sets.
The maximum likelihood degree (ML degree) of $\Theta$ is the number of complex critical points in $\operatorname{Sym}_{m}(\mathbb{C})$ when optimizing $\ell_{n}(\Sigma, S)$ over $\Theta$ for a generic matrix $S$.

For $\Sigma \in \Theta$, the log-normal matrix space at $\Sigma$ is the set of $S \in \operatorname{Sym}_{m}(\mathbb{R})$ such that $\Sigma$ appears as a critical point of $\ell_{n}(\Sigma, S)$. The intersection of this space with $\mathrm{PD}_{m}$ is the log-normal spectrahedron $\mathcal{K}_{\Theta} \Sigma$ at $\Sigma$.

The logarithmic Voronoi cell at $\Sigma$ is always contained in the log-normal spectrahedron at $\Sigma$.

## Example: Cl model $X 1 \Perp X 3$ and $X 1 \Perp X 3 \mid X 2$

Consider the model $\Theta$ given parametrically as

$$
\Theta=\left\{\Sigma=\left(\sigma_{i j}\right) \in \mathrm{PD}_{3}: \sigma_{13}=0 \text { and } \sigma_{12} \sigma_{23}-\sigma_{22} \sigma_{13}=0\right\} .
$$

This model is the union of two linear four-dimensional planes. It has ML degree 2. The log-normal spectrahedron of each point $\Sigma \in \Theta$ is an ellipse. Each log-Voronoi cell is given as:



## Spectrahedral cells

When are logarithmic Voronoi cells equal to the log-normal spectrahedra?
Theorem (A., Hoșten)
If $\Theta$ is a linear concentration model or a model of ML degree one, the logarithmic Voronoi cell at any $\Sigma \in \Theta$ equals the log-normal spectrahedron at $\Sigma$. In particular, this includes both undirected and directed graphical models.

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Let $G=(V, E)$ be a simple undirected graph with $|V(G)|=m$. A concentration model of $G$ is the model

$$
\Theta=\left\{\Sigma \in \operatorname{PD}_{m}:(\Sigma)_{i j}^{-1}=0 \text { if } i j \notin E(G) \text { and } i \neq j\right\}
$$

The logarithmic Voronoi cell at $\Sigma$ is:

$$
\log \operatorname{Vor}_{\Theta}(\Sigma)=\left\{S \in \mathrm{PD}_{m}: \Sigma_{i j}=S_{i j} \text { for all } i j \in E(G) \text { and } i=j\right\}
$$

## Example

The concentration model of $\begin{array}{llll}1 & 2 & 3 & 4 \\ \bullet & \bullet\end{array}$ is defined by

$$
\Theta=\left\{\Sigma=\left(\sigma_{i j}\right) \in \mathrm{PD}_{4}:\left(\Sigma^{-1}\right)_{13}=\left(\Sigma^{-1}\right)_{14}=\left(\Sigma^{-1}\right)_{24}=0\right\} .
$$

Let $\Sigma=\left(\begin{array}{rrrr}6 & 1 & \frac{1}{7} & \frac{1}{28} \\ 1 & 7 & 1 & \frac{1}{4} \\ \frac{1}{7} & 1 & 8 & 2 \\ \frac{1}{28} & \frac{1}{4} & 2 & 9\end{array}\right)$.
Then $\log \operatorname{Vor}_{\Theta}(\Sigma)=\left\{(x, y, z):\left(\begin{array}{cccc}6 & 1 & x & y \\ 1 & 7 & 1 & z \\ x & 1 & 8 & 2 \\ y & z & 2 & 9\end{array}\right) \succ 0\right\}$.

## Covariance models and the bivariate correlation model

Let $A \in \mathrm{PD}_{m}$ and let $\mathcal{L}$ be a linear subspace of $\operatorname{Sym}_{m}(\mathbb{R})$. Then $A+\mathcal{L}$ is an affine subspace of $\operatorname{Sym}\left(\mathbb{R}^{m}\right)$. Models defined by $\Theta=(A+\mathcal{L}) \cap \mathrm{PD}_{m}$ are called covariance models.

The bivariate correlation model is the covariance model

$$
\Theta=\left\{\Sigma_{x}=\left(\begin{array}{ll}
1 & x \\
x & 1
\end{array}\right): x \in(-1,1)\right\} .
$$

This model has ML degree 3. For a general matrix $S=\left(S_{i j}\right) \in \mathrm{PD}_{2}$, the critical points are given by the roots of the polynomial

$$
f(x)=x^{3}-b x^{2}-x(1-2 a)-b,
$$

where $b=S_{12}$ and $a=\left(S_{11}+S_{22}\right) / 2$ [Améndola and Zwiernik].

The bivariate correlation model
Fix $c \in(-1,1)$ so $\Sigma_{c} \in \Theta$. The log-normal spectrahedron of $\Sigma_{c}$ is

$$
\begin{aligned}
\mathcal{K}_{\Theta}\left(\Sigma_{c}\right) & =\left\{S \in \mathrm{PD}_{2}: f(c)=0\right\} \\
& =\left\{S \in \mathrm{PD}_{2}: a=\left(b c^{2}-c^{3}+b+c\right) / 2 c\right\} \\
& =\left\{S_{b, k}=\left(\begin{array}{cc}
k & b \\
b & 2 a-k
\end{array}\right) \succ 0: \begin{array}{c}
0 \leq k \leq 2 a, \\
a=\left(b c^{2}-c^{3}+b+c\right) / 2 c
\end{array}\right\} .
\end{aligned}
$$

Theorem (A., Hoșten)
Let $\Theta$ be the bivariate correlation model and let $\Sigma_{c} \in \Theta$. If $c>0$, then

$$
\log \operatorname{Vor}_{\Theta}\left(\Sigma_{c}\right)=\left\{S_{b, k} \in \mathcal{K}_{\Theta}\left(\Sigma_{c}\right): b \geq 0\right\}
$$

If $c<0$, then

$$
\log \operatorname{Vor}_{\Theta}\left(\Sigma_{c}\right)=\left\{S_{b, k} \in \mathcal{K}_{\Theta}\left(\Sigma_{c}\right): b \leq 0\right\}
$$

If $c=0$, then $\log \operatorname{Vor}_{\Theta}\left(\Sigma_{0}\right)=\{\operatorname{diag}(k, 2 a-k): a \geq 1 / 2,0 \leq k \leq 2 a\}$.

## The bivariate correlation model

Important things to note:

- The log-Voronoi cell of $\Sigma_{c}$ is strictly contained in the log-normal spectrahedron of $\Sigma_{c}$.
- Logarithmic Voronoi cells of $\Theta$ are semi-algebraic sets! This is extremely surprising!
The logarithmic Voronoi cell and the log-normal spectrahedron at $c=1 / 2$ :



## The boundary: transcendental? algebraic?

Given a Gaussian model $\Theta$ and $\Sigma \in \Theta$, the matrix $S \in \mathrm{PD}_{m}$ is on the boundary of $\log \operatorname{Vor}_{\Theta}(\Sigma)$ if $S \in \log \operatorname{Vor}_{\Theta}(\Sigma)$ and there is some $\Sigma^{\prime} \in \Theta$ such that $\ell(\Sigma, S)=\ell\left(\Sigma^{\prime}, S\right)$.

The bivariate correlation models fit into a larger class of models known as unrestricted correlation models. Such a model is given by the parameter space

$$
\Theta=\left\{\Sigma \in \operatorname{Sym}\left(\mathbb{R}^{m}\right): \Sigma_{i i}=1, i \in[m]\right\} \cap \mathrm{PD}_{m}
$$

When $m=3$, the model is a compact spectrahedron known as the elliptope. Its ML degree is 15 .

## Conjecture

The logarithmic Voronoi cells for general points on the elliptope are not semi-algebraic; in other words, their boundary is defined by transcendental functions.

## Thanks!



