# Asymptotic distribution of the diameter of a random elliptical cloud 

Yann Demichel

Joint work with A.-K. Fermin and P. Soulier


## Menu of the day

## Random cloud

- $\mathbb{X}$ is a random vector in $\mathbb{R}^{d}$ with $d \geq 1$ fixed
- $n \geq 1$ is the size of the cloud
- $\left\{\mathbb{X}_{i}\right\}_{1 \leq i \leq n}$ are independent vectors distributed as $\mathbb{X}$



## Menu of the day

Diameter of the cloud

- $\|\cdot\|$ is the Euclidean norm in $\mathbb{R}^{d}$

$$
D_{n}:=\max _{1 \leq i<j \leq n}\left\|\mathbb{X}_{i}-\mathbb{X}_{j}\right\|
$$



## Menu of the day

What is the asymptotic distribution of $D_{n}$ when $n \rightarrow \infty$ ?

## Answer?

- For special cases
- Depends on the distribution of $\mathbb{X}$


## Dichotomy

- Distributions supported by a bounded set
- Distributions 'approximatively' uniform
- Geometry of the support
- Distributions supported by an unbounded set
- Spherically symmetric distributions


## Menu of the day

## History : bounded support

- Uniform distribution supported by special planar sets (excluding balls or ellipsoids) : Appel, Najim and Russo (2002)
- Distributions with support included in the unit $d$-ball (including uniform in the $d$-ball, in the $d$-sphere, in spherical sectors) : Mayer and Molchanov (2007)
- Distributions supported by a polytope (included uniform or non-uniform in square, uniform in regular polygons, uniform in the unit $d$-cube) : Lao (2010)
- Distributions supported by a d-ellipsoid: Schrempp (2016)


## Menu of the day

## History : unbounded support

- Spherically symmetric normal distribution: Matthews and Rukhin (1993)
- Spherically symmetric Kotz distribution: Henze and Klein (1996)
- Power-tailed spherically decomposable distributions: Henze and Lao (2010)
- Spherically symmetric distributions : Jammalamadaka and Janson (2015)
$\rightarrow$ Open question : elliptically symmetric distributions?


## Apetizer

A naive question ...

Where are the points which can achieve the diameter?


## Apetizer

... a naive answer

$$
M_{n}:=\max _{1 \leq i \leq n}\left\|\mathbb{X}_{i}\right\|
$$

$D_{n}$ is achieved for a pair of diametrically opposed points each of them realizing $M_{n}$

If you believe in this, you need :

- To localize the vectors with large norms
- To control the asymptotic distribution of $M_{n}$

Precisely:

- Distribution of $\|\mathbb{X}\|$ ?
- Distribution of $\frac{1}{\|\mathbb{X}\|} \mathbb{X}$ conditional on $\|\mathbb{X}\|$ is large ?


## Today's ingredients

## Elliptical distribution : $\mathbb{X}=R \wedge \mathbb{U}$

where

- $\mathbb{U}=\left(U_{1}, \ldots, U_{d}\right)$ is uniform on the unit sphere $\mathcal{S}^{d-1}$
- $\Lambda$ is an invertible $d \times d$ matrix
- $R$ is a positive random variable independent of $\mathbb{U}$

In addition :
$R$ is in the max domain of attraction of the Gumbel distribution

## Today's ingredients

$R$ is in the max domain of attraction of the Gumbel distribution

There exists a differentiable function $\psi_{R}:(0, \infty) \rightarrow(0, \infty)$ such that

$$
\lim _{x \rightarrow \infty} \frac{\mathbb{P}\left(R>x+t \psi_{R}(x)\right)}{\mathbb{P}(R>x)}=\mathrm{e}^{-t}
$$

locally uniformly with respect to $t \in \mathbb{R}$

Such a function $\psi_{R}$ satisfies:

$$
\lim _{x \rightarrow \infty} \frac{\psi_{R}\left(x+t \psi_{R}(x)\right)}{\psi_{R}(x)}=1 ; \lim _{x \rightarrow \infty} \psi_{R}^{\prime}(x)=0 ; \lim _{x \rightarrow \infty} \frac{\psi_{R}(x)}{x}=0
$$

## Today's ingredients

## Distribution of $\wedge \mathbb{U}$

Supported by the ellipsoid $\left\{\Sigma u: u \in \mathcal{S}^{d-1}\right\}$ where

$$
\Sigma:=\Lambda^{\prime} \Lambda
$$

is (up to a constant) the covariance matrix of $\mathbb{X}$

The ellipsoid is centered at the origin and has $d$ axes directed by the eigenvectors of $\Sigma$ with semi-length the square roots of the corresponding eigenvalues

$$
\lambda_{1}=\cdots=\lambda_{\mathbf{m}}>\lambda_{\mathbf{m}+1} \geq \cdots \geq \lambda_{d}>0
$$

ordered and repeated, where $1 \leq \mathbf{m} \leq d$ is the multiplicity of the largest one. If $\mathbf{m}=d$ we have a spherical distribution.

## Today's ingredients

## Distribution of $\wedge \mathbb{U}$

Up to an orthogonal transformation we may assume that

$$
\Lambda=\operatorname{diag}\left(\sqrt{\lambda_{1}}, \sqrt{\lambda_{2}}, \ldots, \sqrt{\lambda_{d}}\right)
$$

## Starter

## Localization principle for $R$

If $\mathbb{V}$ is a bounded random variable then the vector $R \mathbb{V}$ has a large norm iif $R$ is large and $\mathbb{V}$ is close to its maximum.

Therefore, when $\mathbb{X}=R \wedge \mathbb{U}$ is large then $\|\mathbb{X}\|$ is of order $\sqrt{\lambda_{1}} R$ and $\mathbb{X}$ is located near the dominant eigenspace associated with $\lambda_{1}$ :

$$
\|\mathbb{X}\|=\sqrt{\lambda_{1}} R\left(1-\sum_{k=\mathbf{m}+1}^{d} \frac{\lambda_{1}-\lambda_{k}}{\lambda_{1}} U_{k}^{2}\right)^{1 / 2}
$$

## Starter

Theorem [FDS, 2015]
Define the functions $\psi$ and $\phi$ on $(0, \infty)$ by

$$
\psi(x)=\sqrt{\lambda_{1}} \psi_{R}\left(\frac{x}{\sqrt{\lambda_{1}}}\right) \text { and } \phi(x)=\left(\frac{\psi(x)}{x}\right)^{1 / 2}
$$

Then, as $x \rightarrow \infty$,

$$
\mathbb{P}(\|\mathbb{X}\|>x) \sim C_{\mathbf{m}}(\phi(x))^{d-\mathbf{m}} \mathbb{P}\left(R>\frac{x}{\sqrt{\lambda_{1}}}\right)
$$

where

$$
C_{\mathbf{m}}:=\frac{\Gamma\left(\frac{d}{2}\right)}{\Gamma\left(\frac{\mathbf{m}}{2}\right)} 2^{(d-\mathbf{m}) / 2}\left(\prod_{k=\mathbf{m}+1}^{d} \frac{\lambda_{1}}{\lambda_{1}-\lambda_{k}}\right)^{1 / 2}
$$

In particular, $\|\mathbb{X}\|$ is also in the max domain of attraction of the Gumbel distribution

## Starter

Theorem [FDS, 2015]
Define $\Theta=\frac{1}{\|\mathbb{X}\|} \mathbb{X}=\left(\Theta_{1}, \ldots, \Theta_{d}\right)$.
Then, as $x \rightarrow \infty$, conditionally on $\|\mathbb{X}\|>x$,

$$
\left(\frac{\|\mathbb{X}\|-x}{\psi(x)}, \Theta_{1}, \ldots, \Theta_{\mathbf{m}}, \frac{\Theta_{\mathbf{m}+1}}{\phi(x)}, \ldots, \frac{\Theta_{d}}{\phi(x)}\right)
$$

converges in distribution to

$$
\left(E, \Theta^{(\boldsymbol{m})}, \sqrt{\frac{\lambda_{\boldsymbol{m}+1}}{\lambda_{1}-\lambda_{\boldsymbol{m}+1}}} G_{\boldsymbol{m}+1}, \ldots, \sqrt{\frac{\lambda_{d}}{\lambda_{1}-\lambda_{d}}} G_{d}\right)
$$

where $E$ is an exponential random variable with mean $1, \Theta^{(\mathbf{m})}$ is uniformly distributed on $\mathcal{S}^{\boldsymbol{m}-1}, G_{\boldsymbol{m}+1}, \ldots, G_{d}$ are independent standard Gaussian random variables, and all components are independent.

## Starter

$\|\mathbb{X}\|$ is in the max domain of attraction of the Gumbel distribution

Thus:

- Consider $a_{n}>0$ such that $\mathbb{P}\left(\|\mathbb{X}\|>a_{n}\right) \sim \frac{1}{n}$
- Set $b_{n}=\psi\left(a_{n}\right)$

Then :

- $\lim _{n \rightarrow \infty} a_{n}=\infty$ and $\lim _{n \rightarrow \infty} \frac{b_{n}}{a_{n}}=0$
- For all $t \in \mathbb{R}$,

$$
\lim _{n \rightarrow \infty} \mathbb{P}\left(\frac{M_{n}-a_{n}}{b_{n}} \leq t\right)=\mathrm{e}^{-\mathrm{e}^{-t}}
$$

## Starter

## Corollary [FDS, 2015]

Let $c_{n}=\phi\left(a_{n}\right)$ and define the points

$$
P_{n, i}=\left(\frac{\left\|\mathbb{X}_{i}\right\|-a_{n}}{b_{n}}, \Theta_{i, 1}, \ldots, \Theta_{i, \mathbf{m}}, \frac{\Theta_{i, \mathbf{m}+1}}{c_{n}}, \ldots, \frac{\Theta_{i, d}}{c_{n}}\right)
$$

Then, the point processes $\sum_{i=1}^{n} \delta_{P_{n, i}}$ converge weakly to a PPP $\sum_{i=1}^{\infty} \delta_{P_{i}}$ on $\mathbb{R} \times \mathcal{S}^{\mathbf{m}-1} \times \mathbb{R}^{d-\mathbf{m}}$ with

$$
P_{i}=\left(\Gamma_{i}, \Theta_{i}^{(\mathbf{m})}, \sqrt{\frac{\lambda_{\mathbf{m}+1}}{\lambda_{1}-\lambda_{\mathbf{m}+1}}} G_{i, \mathbf{m}+1}, \ldots, \sqrt{\frac{\lambda_{d}}{\lambda_{1}-\lambda_{d}}} G_{i, d}\right)
$$

where $\left\{\Gamma_{i}\right\}$ are the points of a PPP on $(-\infty, \infty]$ with mean measure $\mathrm{e}^{-t} \mathrm{~d} t,\left\{\Theta_{i}^{(\boldsymbol{m})}\right\}$ are i.i.d. vectors uniformly distributed on $\mathcal{S}^{\boldsymbol{m}-1}$ and $\left\{G_{i, k}\right\}$ are i.i.d. standard Gaussian variables, all sequences being mutually independent.

## Main course

## Conclusion

Vectors $\mathbb{X}_{i}=\left\|\mathbb{X}_{i}\right\| \Theta_{i}$ with the largest norm concentrate around the dominant eigenspace in such a way that

- $\left\|\mathbb{X}_{i}\right\| \sim a_{n}+b_{n} \Gamma_{i}$ with $a_{n} \rightarrow \infty$ and $b_{n}=o\left(a_{n}\right)$
- The $\mathbf{m}$ first coordinates of $\Theta_{i}$ are uniform on $\mathcal{S}^{\mathbf{m}-1}$
- The $d-\mathbf{m}$ other coordinates of $\Theta_{i}$ tend to 0 with rate $c_{n} \rightarrow 0$ with Gaussian fluctuations


## Main course

## Last question

Are these large vectors always diametrically opposed?

- If $\mathbf{m}=1: \mathcal{S}^{\mathbf{m}-1}$ has only one direction

Thus two vectors with a large norm will be on opposite sides and their distance is automatically large, typically twice as large as the norm of each one.
We expect that $D_{n}$ behaves roughly like $2 a_{n}$

- If $\mathbf{m}>1: \mathcal{S}^{\mathbf{m}-1}$ has an infinite number of directions

Thus two vectors with a large norm can be close to each other and their distance will be typically much smaller than twice their norm.
We expect then a corrective term when comparing $D_{n}$ to $2 a_{n}$

## Main course

## Theorem [FDS, 2015]

Assume that $\mathbf{m}=1$, i.e. $\lambda_{1}>\lambda_{2}$.
Then

$$
\frac{D_{n}-2 a_{n}}{b_{n}} \xrightarrow{(\mathrm{~d})} \max _{i, j \geq 1}\left\{\Gamma_{i}^{+}+\Gamma_{j}^{-}-\frac{1}{4} \sum_{k=2}^{d} \frac{\lambda_{k}}{\lambda_{1}-\lambda_{k}}\left(G_{i, k}^{+}+G_{j, k}^{-}\right)^{2}\right\}
$$

where $\left\{\Gamma_{i}^{ \pm}\right\}$are the points of a PPP with mean measure $\frac{1}{2} \mathrm{e}^{-t} \mathrm{~d} t$ on $\mathbb{R}$, and $\left\{G_{i, k}^{ \pm}\right\}$are i.i.d. standard Gaussian variables, independent of the points $\left\{\Gamma_{i}^{ \pm}\right\}$.

## Main course

Theorem [FDS, 2015]
Assume that $\mathbf{m}>1$.
Then, for all $t \in \mathbb{R}$,

$$
\lim _{n \rightarrow \infty} \mathbb{P}\left(\frac{D_{n}-2 a_{n}}{b_{n}}+d_{n} \leq t\right)=\mathrm{e}^{-\mathrm{e}^{-t}}
$$

where

$$
d_{n}=\frac{\mathbf{m}-1}{2} \log \frac{a_{n}}{b_{n}}-\log \log \frac{a_{n}}{b_{n}}-\log C_{\mathbf{m}}^{\prime}
$$

with

$$
C_{\mathbf{m}}^{\prime}=(2 d-\mathbf{m}-1) 2^{\mathbf{m}-4} \pi^{-1 / 2} \Gamma\left(\frac{\mathbf{m}}{2}\right)\left(\prod_{k=\mathbf{m}+1}^{d} \frac{\lambda_{1}}{\lambda_{1}-\lambda_{k}}\right)^{-1 / 2}
$$

## Main course

Example : bivariate Gaussian variable with correlation $\rho \in(0,1)$

$$
\mathbb{X}=R \wedge \mathbb{U} \quad \text { with } \quad R=\sqrt{\chi_{2}^{2}} \quad \text { and } \quad \Lambda^{\prime} \Lambda=\Sigma=\left(\begin{array}{ll}
1 & \rho \\
\rho & 1
\end{array}\right)
$$

- Eigenvalues: $\lambda_{1}=1+\rho$ and $\lambda_{2}=1-\rho$
- Eigenspaces : $\operatorname{span}\{(1,1)\}$ and $\operatorname{span}\{(-1,1)\}$
- Multiplicity : $\mathbf{m}= \begin{cases}1 & \text { if } \rho \neq 0 \\ 2 & \text { if } \rho=0\end{cases}$


## Main course

Set $a_{n}=\sqrt{(1+\rho) \log n}$ and $b_{n}=\sqrt{\frac{1+\rho}{2 \log n}}$

- If $\rho \neq 0$ then

$$
\frac{D_{n}-2 a_{n}}{b_{n}} \xrightarrow{(\mathrm{~d})} \max _{i, j \geq 1}\left\{\Gamma_{i}^{+}+\Gamma_{j}^{-}-\frac{1-\rho}{8 \rho}\left(G_{i}^{+}+G_{j}^{-}\right)^{2}\right\}
$$

where $\left\{\Gamma_{i}^{ \pm}\right\}$are the points of a PPP with mean measure $\frac{1}{2} \mathrm{e}^{-t} \mathrm{~d} t$ on $\mathbb{R}$, and $\left\{G_{i}^{ \pm}\right\}$are i.i.d. standard Gaussian variables, independent of the points $\left\{\Gamma_{i}^{ \pm}\right\}$.

- If $\rho=0$ then for all $t \in \mathbb{R}$,

$$
\lim _{n \rightarrow \infty} \mathbb{P}\left(\frac{D_{n}-2 a_{n}}{b_{n}}+d_{n} \leq t\right)=\mathrm{e}^{-\mathrm{e}^{-t}}
$$

where

$$
d_{n}=\frac{1}{2} \log \log n-\log \log \log n+\log (4 \sqrt{2 \pi})
$$

## Main course



The two points $\boldsymbol{\Delta}$ realizing the diameter

- They concentrate around the diagonal at rate $\mathrm{O}(\log n)$
- Fluctuations are Gaussian variables with variance $\frac{1-\rho}{2 \rho}$


## Dessert

Possible generalizations thanks the localization principle

## Distribution of $\mathbb{X}$

$$
\mathbb{X}=R \lambda(\mathbb{U}) \text { with } \lambda \text { a bounded function }
$$

The behavior of $\mathbb{X}$ given that its norm is large and then the behavior of $D_{n}$ will be determined by the maxima of $\|\lambda\|$ :

- If they are isolated points, we obtain results similar to the case $\mathbf{m}=1$
- Otherwise, if $\|\lambda\|$ is constant on non empty open subsets of $\mathcal{S}^{d-1}$, we obtain results similar to the case $\mathbf{m}>1$


## Dessert

Possible generalizations thanks the localization principle

## Non Euclidean diameter

Another open question in Jammalamadaka and Janson :
Asymptotic of the $\ell^{q}$-diameter of a random spherical cloud?
Consider :

- Spherical distribution : $\Lambda=\mathrm{I}_{\mathrm{d}}$ i.e. $\mathbb{X}:=R \mathbb{U}$
- The $\ell^{q}$-diameter of the cloud :

$$
D_{n}^{(q)}:=\max _{1 \leq i<j \leq n}\left\|\mathbb{X}_{i}-\mathbb{X}_{j}\right\|_{q}
$$

where, for $q \geq 1,\|x\|_{q}$ is the $\ell^{q}$-norm of a vector $x \in \mathbb{R}^{d}$

## Dessert

## Non Euclidean diameter

For $d \geq 2$ and $q \geq 1, q \neq 2$, the maximum of the $\ell^{q}$-norm is achieved on the Euclidean sphere $\mathcal{S}^{d-1}$ at isolated points:

- If $q \in[1,2)$ then $\max _{u \in \mathcal{S}^{d-1}}\|u\|_{q}=d^{1 / q-1 / 2}$ achieved at the $2^{d}$ diagonal points $\left( \pm d^{-1 / 2}, \ldots, \pm d^{-1 / 2}\right)$
- If $q \in(2, \infty)$, then $\max _{u \in \mathcal{S}^{d-1}}\|u\|_{q}=1$ achieved at the $2 d$ intersections of the axes with $\mathcal{S}^{d-1}$

Therefore the localization phenomenon will occur : a spherical vector $\mathbb{X}$ such that $\|\mathbb{X}\|_{q}$ is large must be close to the direction of one of these maximum, and $D_{n}^{(q)}$ will be achieved by points which are nearly diametrically opposed along one of these directions.

## Dessert

Theorem [FDS, 2015]
If $q \in[1,2)$, then

$$
\frac{D_{n}^{(q)}-2 a_{n}^{(q)}}{b_{n}^{(q)}} \xrightarrow{(d)} \max _{1 \leq i \leq 2^{d-1}} \max _{i, i^{\prime} \geq 1}\left\{\Gamma_{i_{i, j}^{+}}^{+}+\Gamma_{i^{\prime}, j}^{-}-\frac{q-1}{4} \sum_{k=1}^{d}\left(G_{i, j, k}^{+}+G_{i^{\prime}, j, k}^{-}\right)^{2}\right\}
$$

where $\Gamma_{i, j}^{ \pm}$are the points of independent PPP on $(-\infty, \infty]$ with mean measure $2^{-d} \mathrm{e}^{-t} \mathrm{~d} t$ and $\left(G_{i, j, 1}^{ \pm}, \ldots, G_{i, j, d}^{ \pm}\right)$are i.i.d. Gaussian vectors with covariance matrix

$$
\frac{1}{d(2-q)}\left(\begin{array}{cccc}
d-1 & -1 & \ldots & -1 \\
-1 & d-1 & \ldots & -1 \\
\vdots & \vdots & \ddots & \vdots \\
-1 & \ldots & -1 & d-1
\end{array}\right)
$$

## Dessert

Theorem [FDS, 2015]
If $q \in(2, \infty)$, then

$$
\frac{D_{n}^{(q)}-2 a_{n}^{(q)}}{b_{n}^{(q)}} \xrightarrow{(\mathrm{d})} \max _{1 \leq i \leq d}\left\{\Gamma_{i}^{+}+\Gamma_{i}^{-}\right\}
$$

where $\left\{\Gamma_{i}^{ \pm}\right\}$are independent Gumbel random variables with location parameter $\log 2 d$.

## Thank you for your attention

Complete recipes in :
The diameter of an elliptical cloud
A.-K. Fermin, Y. Demichel and P. Soulier

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