

# Hilbert geometry of the symmetric positive-definite bicone

## Application to the geometry of the extended Gaussian family

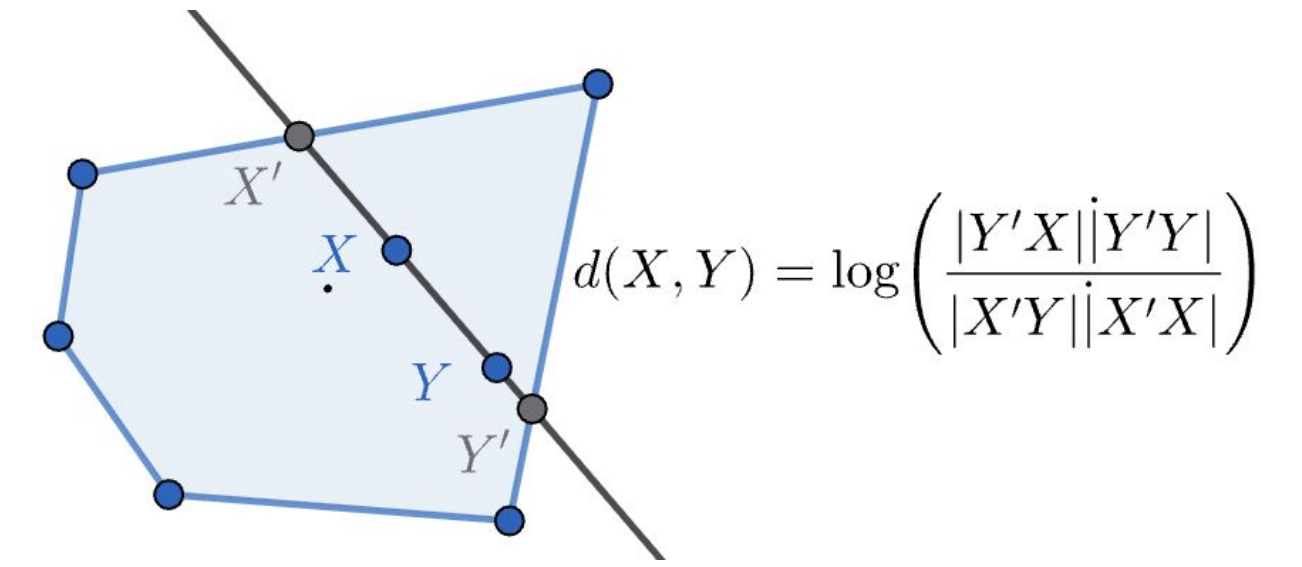
Jacek Karwowski  
Department of Computer Science  
University of Oxford, UK

Frank Nielsen  
Sony Computer Science Laboratories Inc.  
Tokyo, Japan

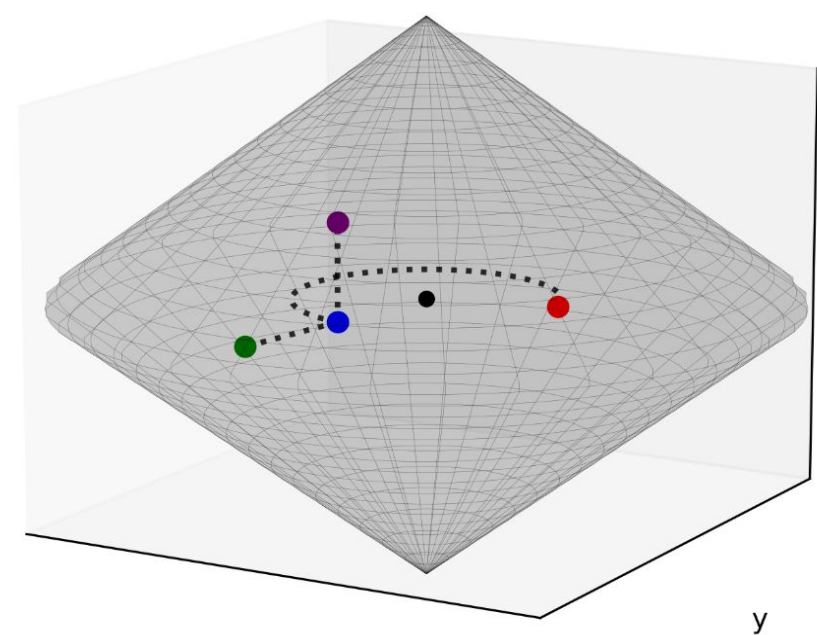
### Our work in one (long) sentence

Our work finds a closed-form Hilbert metric for the open bicone of real symmetric positive-definite matrices, fully characterizes its invariance properties, and outlines potential applications for extended Gaussian distributions: i.e., distributions formed by completing the Gaussian family with degenerate covariance (supported on a subspace) or degenerate precision ("kind of uniform distribution on an affine subspace") cases.

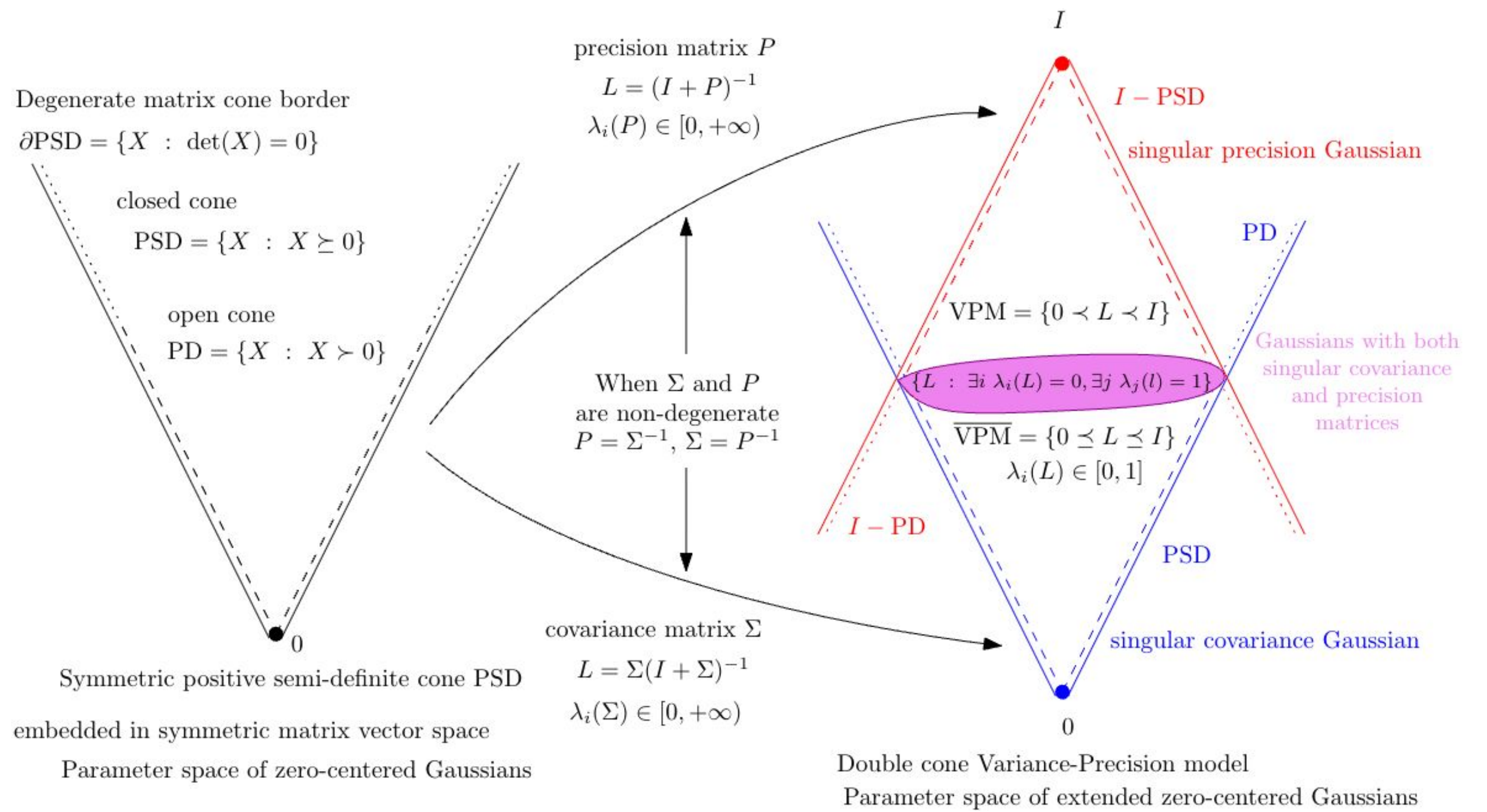
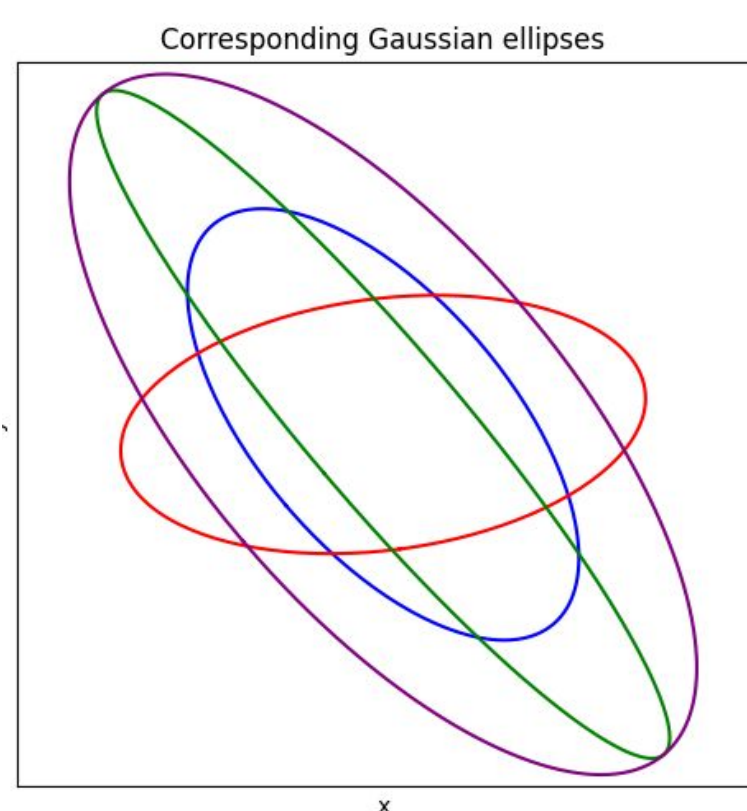
### Hilbert geometry



### Variance-Precision Model



James' parametrization of the space of 2x2 symmetric positive-definite matrices.



### Hilbert distance in VPM

**Theorem** (Hilbert distance on  $\text{VPM}(n)$ ). Given two matrices  $A, B \in \text{VPM}(n)$ ,

$$d_H(A, B) = \log \frac{\max(\lambda_{\max}, \mu_{\max})}{\min(\lambda_{\min}, \mu_{\min})}$$

where

$$\lambda_{\min} = \lambda_{\min}(B^{-1}A), \quad \lambda_{\max} = \lambda_{\max}(B^{-1}A),$$

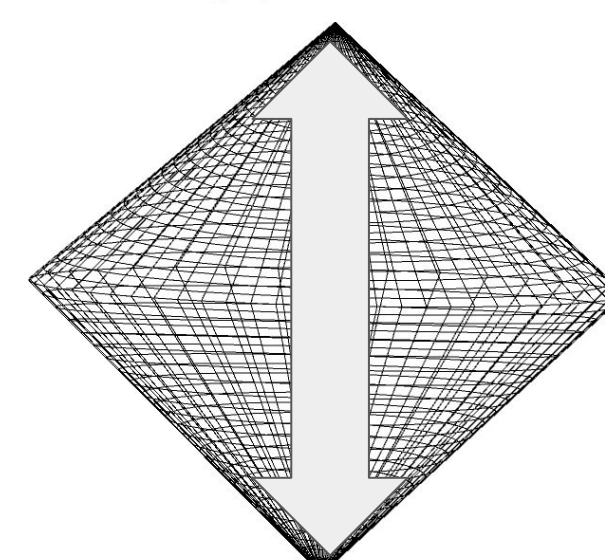
are the minimal and maximal eigenvalues of the  $B^{-1}A$  matrix, and

$$\mu_{\min} = \lambda_{\min}((I - B)^{-1}(I - A)), \quad \mu_{\max} = \lambda_{\max}((I - B)^{-1}(I - A)),$$

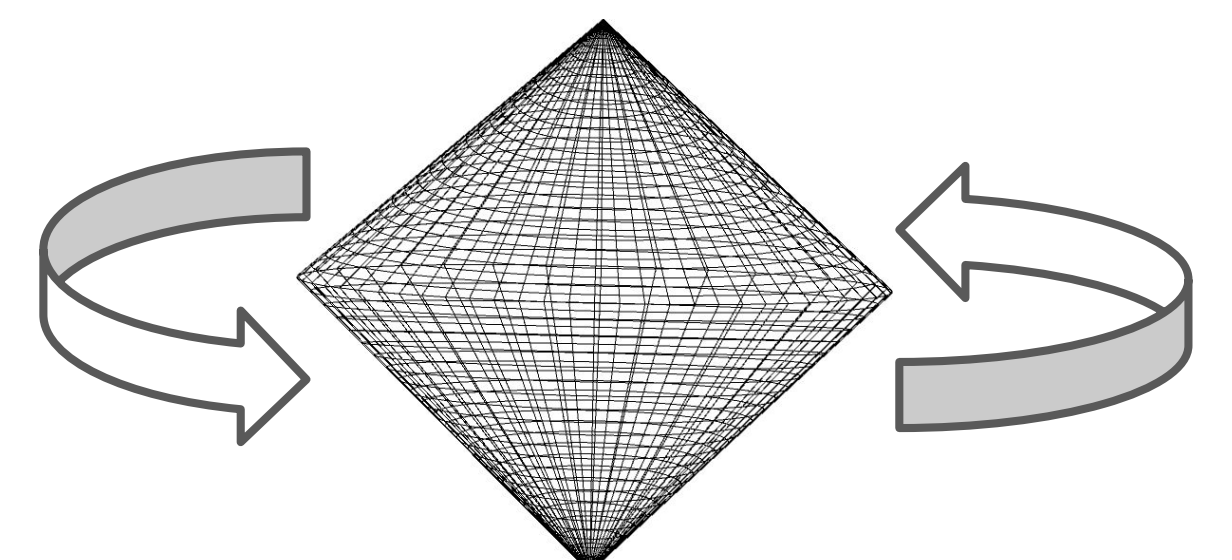
are the minimal and maximal eigenvalues of the  $(I - B)^{-1}(I - A)$  matrix.

### Classification of isometries of VPM

**Theorem** (Classification of VPM isometries). The group of isometries of  $\text{VPM}(n)$  for  $n > 1$  is generated by conjugation by orthonormal matrices  $X \mapsto U^T X U$  for  $U \in O(n)$  and inversion  $X \mapsto I - X$ .



Inversion



Conjugation

### Comparison with AIRM

Affine-Invariant  
Riemannian distance:

$$\rho(Q_1, Q_2) = \sqrt{\sum_{i=1}^n \log^2 \lambda_i(Q_1 Q_2^{-1})}.$$

Comparison of the AIRM vs Hilbert VPM distances. By  $\text{Mob}(Q_1, Q_2)$  we denote the Möbius transformation  $\text{Mob}(Q_1, Q_2) = (I - Q_1)^{-1}(I - Q_2)$ .

|                              | AIRM distance                                   | Hilbert VPM distance                                                                                                     |
|------------------------------|-------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------|
| Eigenvalues:                 | $\{\lambda_i(Q_1 Q_2^{-1})\}_{1 \leq i \leq n}$ | $\lambda_1(Q_1 Q_2^{-1}), \lambda_n(Q_1 Q_2^{-1})$<br>$\lambda_1(\text{Mob}(Q_1, Q_2)), \lambda_n(\text{Mob}(Q_1, Q_2))$ |
| Invariance under a map:      | $X \mapsto X^{-1}$                              | $X \mapsto I - X$                                                                                                        |
| Invariance under congruence: | $\text{GL}(n)$                                  | $O(n)$                                                                                                                   |

### Extension to the boundary

**Proposition** (Lower bounding Hilbert VPM distance)

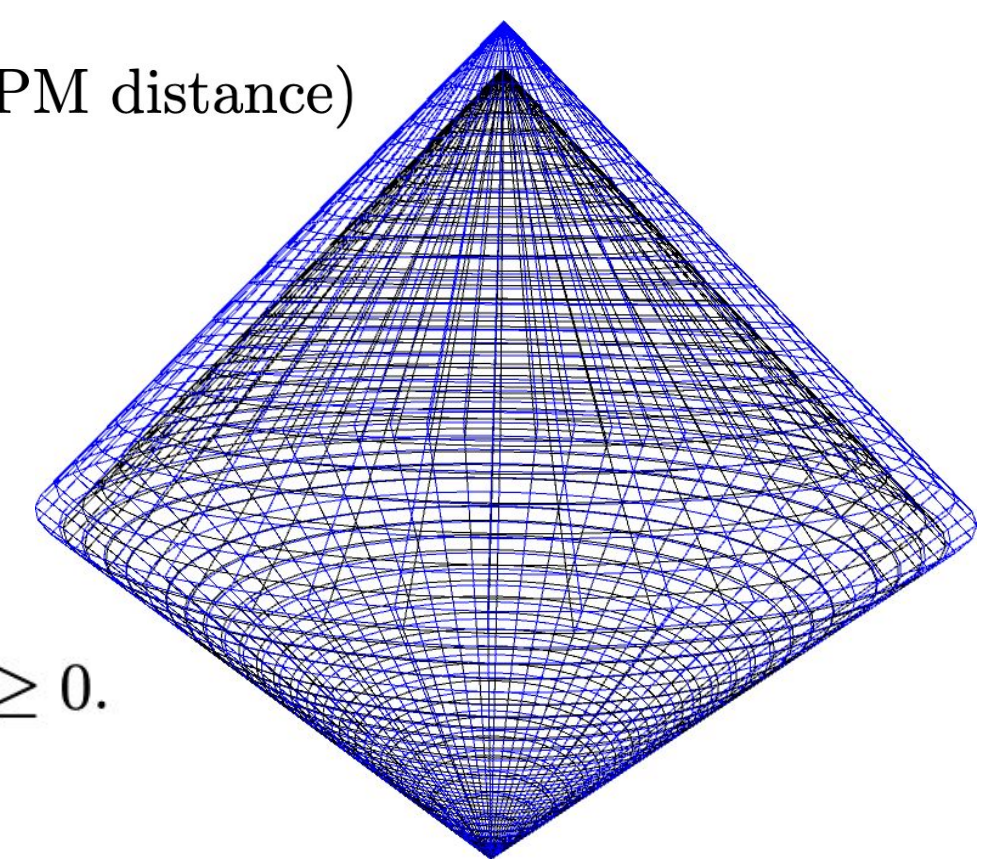
$$\forall \epsilon > 0, \forall S_1, S_2 \in \text{VPM}(n)$$

$$d_H(S_1, S_2) \geq d_{H, \epsilon}(S_1, S_2).$$

where:

$$\overline{\text{VPM}}_{\epsilon} = \{-\epsilon I \preceq X \preceq (1 + \epsilon) I\}, \quad \epsilon \geq 0.$$

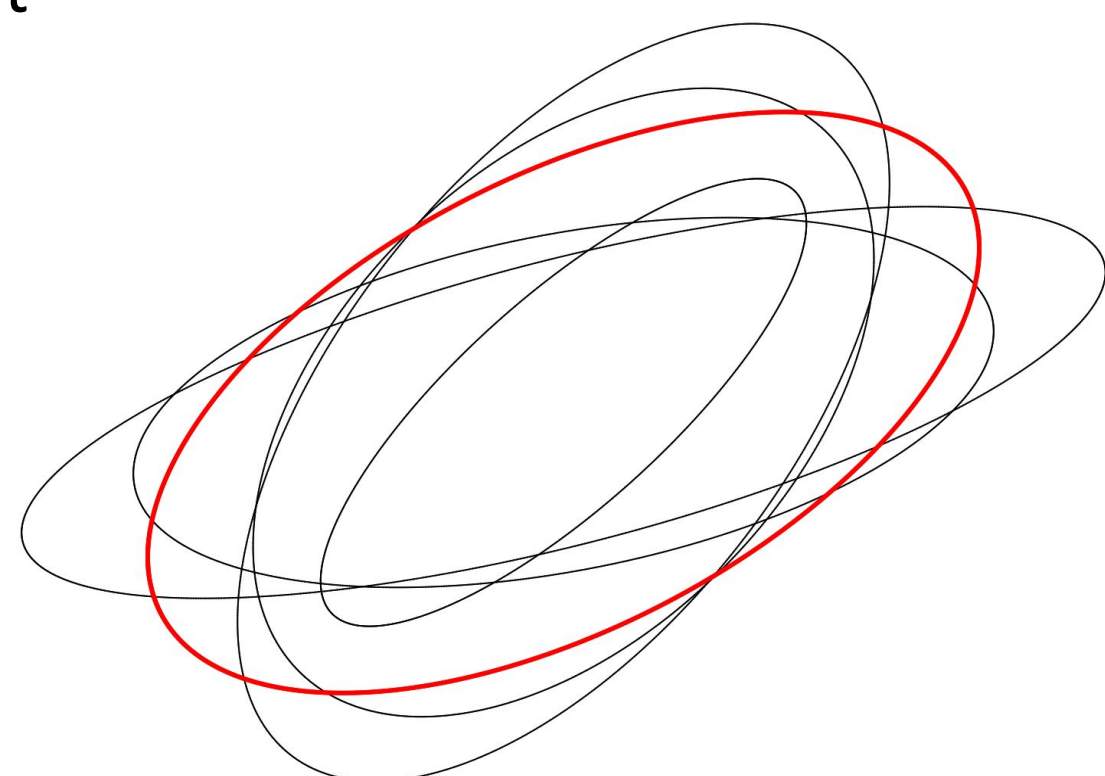
For  $S_1, S_2 \in \partial \overline{\text{VPM}}(n)$ ,  $d_H(S_1, S_2) = +\infty$  but  $d_{H, \epsilon}(S_1, S_2) < +\infty$ .



### Smallest Enclosing Ball

Straight-line geodesics in Hilbert geometry allow for easy implementation of various geometric primitives.

Here, an example implementation of Badoiu and Clarkson iterative geodesic-cut algorithm for approximating Smallest Enclosing Ball.



### Extension to non-centered Gaussians

Using Calvo-Oller embedding, we can map non-centered Gaussians into positive-definite matrices, and thus, into VPM.

$$(\mu, \Sigma) \mapsto \Sigma_{\mu}^{+} = \begin{bmatrix} \Sigma + \mu \mu^{\top} & \mu \\ \mu^{\top} & 1 \end{bmatrix} \in \text{PD}(n + 1).$$

If you'd like to read more, see the full paper (arXiv:2508.14369) QR code →

