



Geometric Statistics

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Towards a classification of metrics on Symmetric Positive Definite matrices

Based on:

- *Is affine-invariance well defined on SPD matrices? A principled continuum of metrics*
- *Exploration of Balanced Metrics on Symmetric Positive Definite Matrices*

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Outline

1. A zoo of Riemannian metrics on $SPD(n)$

2. $GL(n)$ -invariant metrics

Paper 1: Is affine-invariance well defined on SPD matrices? A principled continuum of metrics

3. Balanced metrics

Paper 2: Exploration of Balanced Metrics on Symmetric Positive Definite Matrices

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A zoo of Riemannian metrics on $SPD(n)$

SPD matrices in applications

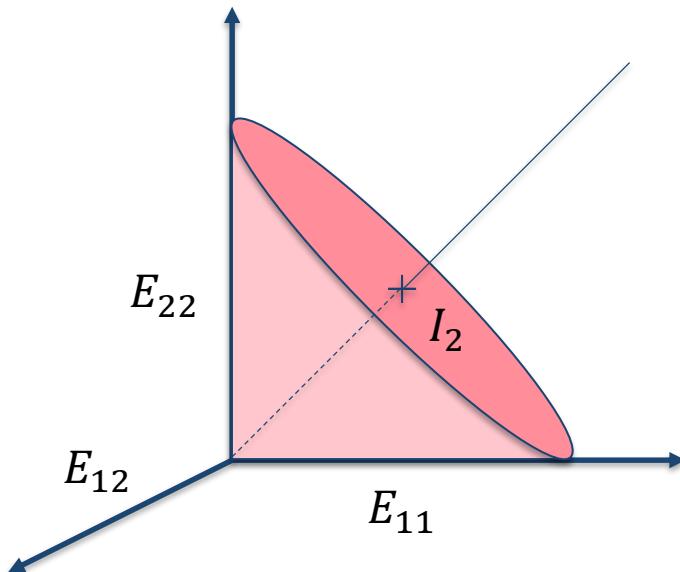
- Applications
 - Diffusion Tensor Imaging
 - Brain Computer Interfaces
 - Functional Magnetic Resonance Imaging
 - Computer Vision
 - RADAR
- SPD matrices
 - Diffusion tensors
 - Covariance matrices
 - Correlation matrices
 - Toeplitz matrices

Manifold of SPD matrices

Symmetric matrices $Sym(n) = \{M \in \mathbb{R}^{n \times n}, M = M^\top\}$

Spectral theorem $\Rightarrow eig(Sym(n)) \subset \mathbb{R}$

$SPD(n) := \{\Sigma \in Sym(n), eig(\Sigma) \subset \mathbb{R}_+^*\}$



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Matrix exponential $\exp M = \sum_{k=0}^{+\infty} \frac{M^k}{k!}$

Diffeomorphism $\exp: Sym(n) \rightarrow SPD(n)$ of inverse log

Power $\text{pow}_p = \exp \circ p \log: SPD(n) \rightarrow SPD(n)$

A zoo of Riemannian metrics on $SPD(n)$

Affine-invariant

Euclidean **Bogoliubov-Kubo-Mori**

Inverse-Euclidean

Cholesky

Fisher

Bures-Wasserstein

Polar-affine

Power-Euclidean

Square-root

Log-Euclidean

Ref: [1] Dryden et al. 2009, [2] Michor et al. 2000, [3] Dryden et al. 2010

A zoo of Riemannian metrics on $SPD(n)$

	$O(n)$ -invariant	Other
Positively curved	Bures-Wasserstein	
Flat	Euclidean Inverse-Euclidean Log-Euclidean Power-Euclidean Square-root	Cholesky
Negatively curved	Affine-invariant Polar-affine Fisher	
Other	Bogoliubov-Kubo-Mori	

Ref: [1] Dryden et al. 2009, [2] Michor et al. 2000, [3] Dryden et al. 2010

A zoo of Riemannian metrics on $SPD(n)$

Flat metrics

$$\Sigma \in SPD(n), X, Y \in T_\Sigma SPD(n)$$

Name	Power	Riemannian Metric
Power-Euclidean	p	$g_\Sigma^{E,p}(X, Y) = \frac{1}{p^2} \text{tr}(d\text{pow}_p(\Sigma)[X]d\text{pow}_p(\Sigma)[Y])$
Euclidean	$p = 1$	$g_\Sigma^E(X, Y) = \text{tr}(XY)$
Inverse-Euclidean	$p = -1$	$g_\Sigma^I(X, Y) = \text{tr}(\Sigma^{-2}X\Sigma^{-2}Y)$
Square-root	$p = 1/2$	$g_\Sigma^{E,1/2}(X, Y) = 4 \text{tr}(d\text{pow}_{1/2}(\Sigma)[X]d\text{pow}_{1/2}(\Sigma)[Y])$
Log-Euclidean	$p \rightarrow 0$	$g_\Sigma^L(X, Y) = \text{tr}(d\log(\Sigma)[X]d\log(\Sigma)[Y])$

Ref: [1] Dryden et al. 2009, [3] Dryden et al. 2010

A zoo of Riemannian metrics on $SPD(n)$

Negatively curved metrics with symmetric structure

- **Affine-invariant metrics**

- Affine transformation of a random vector $X \mapsto AX + B$
- Transformation of its covariance matrix $\Sigma \mapsto A\Sigma A^\top$
- Group action $\begin{cases} GL(n) \times SPD(n) \rightarrow SPD(n) \\ (A, \Sigma) \mapsto A\Sigma A^\top \end{cases}$
- One-parameter family of affine-invariant metrics, with $\alpha > 0$ and $\beta > -\alpha/n$
$$g_\Sigma^A(X, Y) = \alpha \operatorname{tr}(\Sigma^{-1}X\Sigma^{-1}Y) + \beta \operatorname{tr}(\Sigma^{-1}X) \operatorname{tr}(\Sigma^{-1}Y)$$

- **Fisher metric**

- Multivariate centered Gaussian model $p_\Sigma(x) = \frac{1}{\sqrt{2\pi}^n} \frac{1}{\sqrt{\det \Sigma}} \exp\left(-\frac{1}{2} x^\top \Sigma^{-1} x\right)$
- Fisher metric $g_\Sigma^F(X, Y) = \frac{1}{2} \operatorname{tr}(\Sigma^{-1}X\Sigma^{-1}Y)$

Ref: [4] Pennec et al. 2006, [5] Amari, Nagaoka 2000, [6] Skovgaard 1984

A zoo of Riemannian metrics on $SPD(n)$

Negatively curved metrics with symmetric structure

- **Polar-affine metric**

- Polar decomposition $\begin{cases} GL(n) \rightarrow SPD(n) \times O(n) \\ A \mapsto (\sqrt{AA^\top}, \sqrt{AA^\top}^{-1}A) \end{cases}$
- Quotient manifold and submersion $\begin{cases} GL(n) \rightarrow GL(n)/O(n) \\ A \mapsto A.O(n) \end{cases}$
- ‘Polar’ diffeomorphism $\begin{cases} GL(n)/O(n) \rightarrow SPD(n) \\ A.O(n) \mapsto \sqrt{AA^\top} \end{cases}$
- Frobenius inner product on $GL(n)$ is $O(n)$ -invariant so it induces a metric on the quotient $GL(n)/O(n)$ and on $SPD(n)$, called the polar-affine metric

- **Questions**

- Do ‘Affine-invariant’ and ‘Polar-affine’ metrics belong to a wider family?
- Does there exist a one-parameter family of polar-affine metrics?

Ref: [7] Zhang, Su, Klassen, Le, Srivastava 2018

In the following sections

- **Section 2: $GL(n)$ -invariant metrics**
 - Unification of Affine-invariant and Polar-affine metrics
 - Definition of Power-affine and Deformed-affine metrics
 - Relation with the Log-Euclidean metric
 - Relation with the Fisher metric
- **Section 3: Balanced metrics**
 - Relation between Affine-invariant, Euclidean and Inverse-Euclidean metrics
 - Relation between BKM, Euclidean and Log-Euclidean metrics
 - Principle of balanced metric
 - Definition of Mixed-power-Euclidean metrics

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$GL(n)$ -invariant metrics

**Is affine-invariance well defined on SPD matrices?
A principled continuum of metrics**

Affine-invariant VS Polar-affine

'Quotient space' formalism

- Quotient manifold and submersion $\begin{cases} GL(n) \rightarrow GL(n)/O(n) \\ A \mapsto A \cdot O(n) \end{cases}$
- $O(n)$ -invariant inner product on $GL(n)$, with $\alpha > |\alpha'|$ and $\beta > -(\alpha + \alpha')/n$

$$\langle X | Y \rangle = \alpha \operatorname{tr}(XY^\top) + \alpha' \operatorname{tr}(XY) + \beta \operatorname{tr} X \operatorname{tr} Y$$

- Affine-invariant metric $\begin{cases} GL(n)/O(n) \rightarrow SPD(n) \\ A \cdot O(n) \mapsto AA^\top \end{cases}$
- Polar-affine metric $\begin{cases} GL(n)/O(n) \rightarrow SPD(n) \\ A \cdot O(n) \mapsto \sqrt{AA^\top} \end{cases}$

pow₂

Affine-invariant VS Polar-affine

'Group action' formalism

- Affine-invariant action $\eta^1: \begin{cases} GL(n) \times SPD(n) \rightarrow SPD(n) \\ (A, \Sigma) \mapsto A\Sigma A^\top \end{cases}$

$$(\eta^2(A, \Sigma))^2 = \eta^1(A, \Sigma^2)$$

- Polar-affine action $\eta^2: \begin{cases} GL(n) \times SPD(n) \rightarrow SPD(n) \\ (A, \Sigma) \mapsto \sqrt{A\Sigma^2 A^\top} \end{cases}$

Affine-invariant VS Polar-affine

Unification and generalization

- Polar-affine metric $g^{A,2}$ $\text{pow}_2: (SPD(n), 4g^{A,2}) \rightarrow (SPD(n), g^A)$
- Power-affine metric $g^{A,p}$ $\text{pow}_p: (SPD(n), p^2 g^{A,p}) \rightarrow (SPD(n), g^A)$
- Deformed-affine metric $g^{A,f}$ $f: (SPD(n), g^{A,f}) \rightarrow (SPD(n), g^A)$
- These metrics are $GL(n)$ -invariant under $\begin{cases} GL(n) \times SPD(n) \rightarrow SPD(n) \\ (A, \Sigma) \mapsto f^{-1}(Af(\Sigma)A^\top) \end{cases}$
- Relation with the log-Euclidean metric

$$\lim_{p \rightarrow 0} g^{A,p}(X, Y) = g^L(X, Y)$$

$GL(n)$ -invariant metrics

Relation with the Fisher metric

- Centered Gaussian model

$$p_{\Sigma}(x) = \frac{1}{\sqrt{2\pi}^n} \frac{1}{\sqrt{\det \Sigma}} \exp \left(-\frac{1}{2} x^\top \Sigma^{-1} x \right)$$

- Deformed centered Gaussian model

$$p_{\Sigma}^f(x) = \frac{1}{\sqrt{2\pi}^n} \frac{1}{\sqrt{\det f(\Sigma)}} \exp \left(-\frac{1}{2} x^\top f(\Sigma)^{-1} x \right)$$

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Balanced metrics

**Exploration of Balanced Metrics on Symmetric
Positive Definite Matrices**

α -connections of the centered Gaussian model

- The Fisher metric is the affine-invariant metric
- The m -connection ($\alpha = -1$) is the Euclidean Levi-Civita connection
- The e -connection ($\alpha = +1$) is the inverse-Euclidean Levi-Civita connection
- Note that:
 - $g_{\Sigma}^A(X, Y) = \text{tr}((\Sigma^{-1}X\Sigma^{-1})Y) = \text{tr}(X(\Sigma^{-1}Y\Sigma^{-1}))$
 - $g_{\Sigma}^E(X, Y) = \text{tr}(XY)$
 - $g_{\Sigma}^I(X, Y) = \text{tr}((\Sigma^{-1}X\Sigma^{-1})(\Sigma^{-1}Y\Sigma^{-1}))$
- And:
 - $g_{\Sigma}^{BKM}(X, Y) = \text{tr}(d\log(\Sigma)[X]Y) = \text{tr}(Xd\log(\Sigma)[Y])$
 - $g_{\Sigma}^F(X, Y) = \text{tr}(XY)$
 - $g_{\Sigma}^L(X, Y) = \text{tr}(d\log(\Sigma)[X]d\log(\Sigma)[Y])$

Ref: [5] Amari, Nagaoka 2000

Principle of balanced metrics

- **Definition:**
 - Two flat metrics g et g^*
 - Their respective Levi-Civita connections ∇ and ∇^*
 - Their respective parallel transports Π and Π^*
 - The balanced bilinear form g^0 is defined by $g_\Sigma^0(X, Y) = \text{tr}((\Pi_{\Sigma \rightarrow I_n} X)(\Pi_{\Sigma \rightarrow I_n}^* Y))$
- **Theorem:** If g^0 is a metric, then $(SPD(n), g^0, \nabla, \nabla^*)$ is a dually-flat manifold.

Mixed-power-Euclidean metrics

- **Definition:** Given two powers $p, q \neq 0$, we can define the balanced form

$$g_{\Sigma}^{E,p,q}(X, Y) = \text{tr}(d\text{pow}_p(\Sigma)[X]d\text{pow}_q(\Sigma)[Y])$$

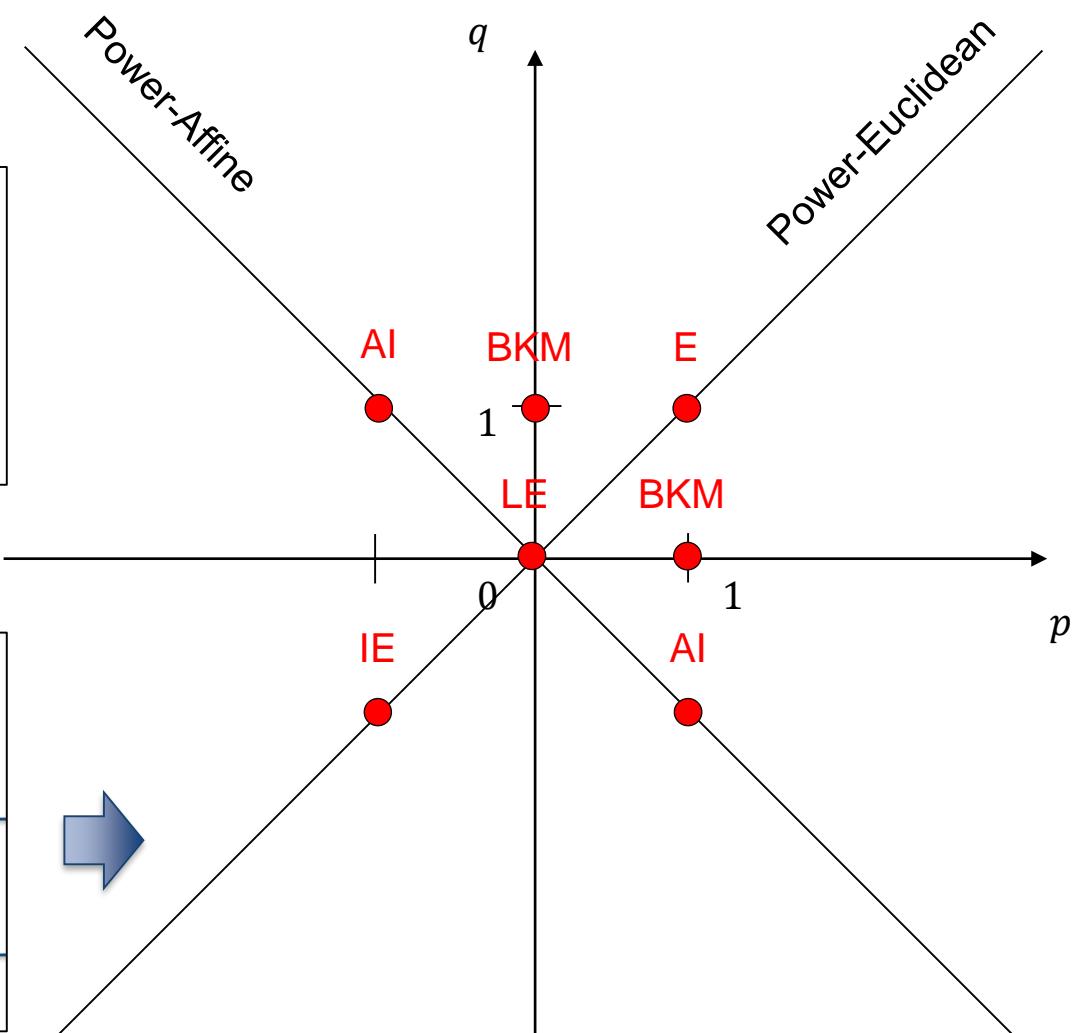
- **Theorem:** It is symmetric and positive-definite, hence it is a metric.
- **Corollary:** The space $(SPD(n), g^{E,p,q}, \nabla^{E,p}, \nabla^{E,q})$ is dually-flat (where $\nabla^{E,p}$ and $\nabla^{E,q}$ are the Levi-Civita connections of the metrics $g^{E,p}$ and $g^{E,q}$)

Summary

Affine-invariant	Euclidean	Bogoliubov-Kubo-Mori
Inverse-Euclidean	Fisher	Cholesky
Bures-Wasserstein	Polar-affine	Power-Euclidean
Square-root	Log-Euclidean	



Flat	Euclidean	Inverse-Euclidean
	Log-Euclidean	
	Power-Euclidean	Square-root
Negatively curved	Affine-invariant	Polar-affine
	Fisher	
Other	Bogoliubov-Kubo-Mori	



Mixed-Power-Euclidean metrics $g^{E,p,q}$

Conclusion

- **Power-affine metrics**
 - Unified framework for affine-invariant, polar-affine and Fisher metrics
- **Mixed-power-Euclidean metrics**
 - Unified framework for power-Euclidean, power-affine and BKM metrics
- The **log-Euclidean metric** appears as a limit case in both frameworks, but also in the alpha-Procrustes framework [8, Ha Quang]
- **Future works**
 - Unified framework for power-Euclidean, power-affine and alpha-Procrustes metrics
 - Generalization to Positive Semi-Definite (PSD) matrices: boundary, strata...

References

- [1] Dryden, Koloydenko, Zhou, Non-Euclidean Statistics for Covariance Matrices with Applications to Diffusion Tensor Imaging. *Annals of Applied Statistics*, 2009
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- [6] Skovgaard, A Riemannian geometry of the multivariate normal model. *Scand. Journal of Statistics*, 1984
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Thank you for your attention



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