

# Parametric information geometry with the package Geomstats

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<https://github.com/geomstats/geomstats>

# What is a statistical manifold ?

## Random vector, negative log-likelihood

$$\mathbf{x} \sim f(\cdot; \theta), \quad \theta \in \mathcal{M}$$

$$\mathcal{L}(\theta; \mathbf{x}) = -\log f(\mathbf{x}; \theta)$$

## Fisher information metric

$$\langle \xi, \eta \rangle_{\theta}^{\text{FIM}} = \text{vec}(\xi)^T \underbrace{\mathbb{E}_{\mathbf{x} \sim f(\cdot; \theta)} [\text{Hess } \mathcal{L}(\theta; \mathbf{x})]}_{\text{Fisher information matrix}} \text{vec}(\eta)$$

(Set of constraints, Fisher information metric) = a Riemannian manifold

## Example: covariance matrices

$$\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \Sigma), \quad \theta = \Sigma \in \mathcal{S}_p^{++}$$

$$\langle \xi, \eta \rangle_{\Sigma}^{\mathcal{S}_p^{++}} = \text{Tr}(\Sigma^{-1} \xi \Sigma^{-1} \eta)$$

# Code example: geodesic interpolation of binomial distributions

For well-known statistical manifolds:

- Fisher information metric, exponential/logarithmic maps, geodesics, and distances,
- closed-form expressions or numerical solvers from the **numerics module** of Geomstats.

```
from geomstats import backend as gs
from geomstats.information_geometry.binomial import BinomialDistributions

manifold = BinomialDistributions(5)

point_a = .4
point_b = .7

times = gs.linspace(0, 1, 100)
geodesic = manifold.metric.geodesic(initial_point=point_a, end_point=point_b)(times)

middle = geodesic(.5)
print(middle)

>>> 0.5550055679356352
```

## Code example: custom manifold

Custom statistical manifolds from its probability distribution function:

- Fisher information metric from automatic differentiation,
- geodesics computed with the **numerics module** of Geomstats.

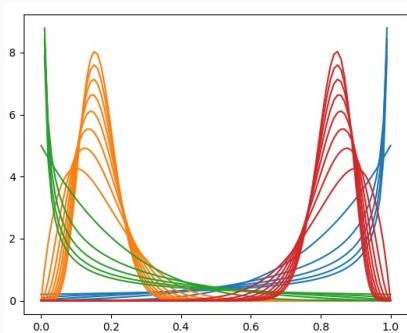
```
class MyInformationManifold(InformationManifoldMixin):
    def __init__(self):
        self.dim = 2
    def point_to_pdf(self, point):
        means = point[..., 0]
        stds = point[..., 1]
        def pdf(x):
            constant = (1. / gs.sqrt(2 * gs.pi * stds**2))
            return constant * gs.exp(-((x - means) ** 2) / (2 * stds**2))
        return pdf

metric = FisherRaoMetric(
    information_manifold=MyInformationManifold(), support=(-10, 10))
```

# Machine learning

Compatible with

- NumPy, Autograd, PyTorch, and TensorFlow,
- **learning module** of Geomstats: K-means, K-medoids, Nearest centroid classifier, PCA, ...



**Figure 1:** Probability density functions of beta distributions and a K-means clustering (colours) using the statistical manifold of beta distributions.