

Geometric Gaussian Mixture Learning of Manifolds

Probability, Geometry

Topic

A deterministic manifold may/can be represented probabilistically by a Gaussian Mixture (GM), providing access to probabilistic tools for uncertainty representation and propagation.

Conventionally, GMs are learned from sampled data using Expectation Maximization (EM) which is slow and is not guaranteed to converge to the global optimum. This project investigates whether the geometry of a manifold can instead be used to construct its corresponding GM directly.

Problem

The central question of this project is:

Can a Gaussian Mixture representation of a manifold be constructed directly from its geometry, without sampling and Expectation Maximization?

The project will investigate geometry-induced Gaussian mixtures for manifold representations, focusing on local geometric approximations and their probabilistic interpretation.

Prerequisites

- Firm grasp of Linear/Multilinear Algebra and Analysis
- PYTORCH or an equivalent NUMPY-like framework
- Some exposure to Functional Analysis and Differential Geometry is advantageous

References

- A Geometric Gaussian Mixture Representation of Plane Curves by Ali Darijani, Benedikt Stratmann, Jürgen Beyerer
- Closed-Form Gaussian Mixture Representations of d-Dimensional Triangulated Domains by Ali Darijani, Benedikt Stratmann, Uwe D. Hanebeck, Ratan Bahadur Thapa, Jürgen Beyerer, Nehal Afifi

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