Bachelor/Master Thesis Thesis:
Geometric Gaussian Mixture Learning of Manifolds

Topic
Sometimes you need a probabilistic representation of a deterministic manifold and for many reasons having them in Gaussian Mixture form is useful.
Gaussian Mixtures are fitted to data using expectation maximization. The algorithm is not guaranteed to converge to the optimum, is data hungry and quite slow.

Problem
Is it possible to have a Gaussian Mixture representation for a manifold without sampling and coupling it with an expectation maximization step?

Prerequisite
* Firm grasp over Linear/Multilinear Algebra and Analysis
* PyTorch or an equivalent NumPy-like framework
* Some exposition to Functional Analysis and Differential Geometry is advantageous

References:

* Comprehensive Description of Uncertainty in Measurement for Representation and Propagation with Scalable Precision by Darijani
* Closed-Form Information-Theoretic Divergences for Statistical Mixtures by Nielsen
* Linear Functional Analysis (Undergraduate Level) by Youngson
* Linear Functional Analysis (Graduate Level) by Alt
* Differential Geometry of Curves and Surfaces (Undergraduate Level) by Tapp
* An Introduction to Manifolds (Graduate Level) by Tu
* Differential Geometry (Graduate Level) by Tu
* Discrete Differential Geometry (Undergraduate Level) by Crane

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