

Praxis der Forschung:

Divergence Based Learning of Gaussian Mixtures

Problem Statement:

Within the realm of probabilistic AI; parametric families reduce an inherently infinite dimensional problem to a finite dimensional one. Due to their universal approximation and simple generative property, Gaussian mixture methods are a promising direction to overcome multimodal inference and fast sample generation. However, learning the Gaussian mixture that corresponds to a dataset is a challenging task. We aim to improve the state of the art in Gaussian mixture learning by means of alternative divergence measures.

Learning Outcomes?

- Getting to know alternative divergence measures beside the familiar Kullback-Leibler divergence and why they are useful.
- The nice properties of the said divergence measures when they are applied to Gaussian mixture.
- Improving the traditional Expectation-Maximization algorithm for Gaussian mixture learning.
- Investigating guarantees of convergence if alternative divergence measures are used.
- Implementing the proposed methods in Python and evaluating them on synthetic and real world datasets.
- Writing a research level publication.

Prerequisite?

- Solid Background in Analysis and Linear Algebra.
- First Exposure to Python Programming.
- First Exposure to Software Development Using GitLab.

Number of Students?

- Ideally 2 but flexible

A Couple of References

- Encyclopedia of Distances by Deza and Deza
- Closed-Form Information-Theoretic Divergences for Statistical Mixtures by Nielsen
- Divergence measures and message passing by Minka
- Black Box Variational Inference by Blei

Contact:
Ali Darijani

ali.darijani@iosb.fraunhofer.de
ali.darijani@kit.edu
KIT/Fraunhofer Building 70.16, R124