A novel notion of barycenter for probability distributions based on optimal weak mass transport.

Elsa Caselles (IRIT CNRS, Toulouse)

Abstract: Optimal transport has had a significant impact in the machine learning community recently, as it provides meaningful and implementable distances between probability distributions. In particular, the computation of the Wasserstein-2 distance amounts to finding a transport plan that minimises the quadratic average cost of transporting mass from a source probability measure onto a target one. In this context, a natural method for averaging a finite family of probability measures is to compute their Fréchet mean, with respect to the Wasserstein-2 distance, which corresponds to the Wasserstein barycenter. The goal of the presentation is to present theoretical features and potential applications to ML of barycenters of probability measures analogously defined in terms of optimal weak transport, or more precisely quadratic barycentric

transport costs. We also discuss their interpretation in the light of convex ordering between probability measures and we show that, rather than averaging the input distributions in a geometric way (as the Wasserstein barycenter based on classic optimal transport does) weak barycenters extract common geometric information shared by all the input distributions, encoded as a latent random variable that underlies all of them.