Title:

Geometric View of Optimal Transportation and Generative Adversarial Networks (GANs)

Abstract:

This work introduces an optimal transportation (OT) view of Generative Adversarial Networks (GANs). Natural data sets have intrinsic patterns, which can be summarized as the manifold distribution principle: the distribution of a class of data is close to a low dimensional manifold. GANs mainly accomplish two tasks: manifold learning and probability distribution transformation. The latter can be carried out using classical optimal transportation method.

From OT point of view, the generator computes the optimal transportation map, the discriminator computes the Wasserstein distance between the generated distribution and the real data distribution, both of them can be reduced to a convex geometric optimization process. Furthermore, OT theory discovers the intrinsic collaborative, instead of competitive, relation between the generator and the discriminator, and the fundamental reason for mode collapse.

Furthermore, we propose a novel generative model, which uses an autoencoder for manifold learning and OT map for distribution transformation. The AE-OT model improves the theoretic rigor and transparency, also computational stability and efficiency, especially it eliminates the mode collapse.

Experimental results validates our hypothesis, and demonstrates the advantages of our proposed model.