# Sample Complexity of Testing the Manifold Hypothesis

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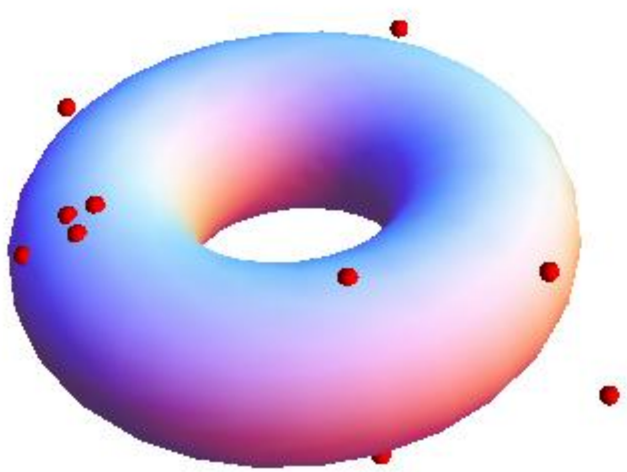

Manifold learning is based on the hypothesis that data in high dimensional Euclidean spaces usually lie in the *vicinity of a low dimensional submanifold*.

Can this hypothesis be tested using limited data?

# Low dimensional manifolds with bounded volume and curvature

Let $\mathcal{G}_e = \mathcal{G}_e(k, V, \tau)$ be the family of Riemannian $k-$submanifolds of the unit ball in $\mathbb{R}^n$, with volume $\leq V$ and curvature $\leq \kappa$.

Low curvature

high curvature

# A positive result

Let $\mathcal{P}$ be a probability distribution supported in the unit ball from which data $x_1, \ldots, x_s$ is drawn i.i.d. If s is greater than

$$C\left(\min\left(\left(\frac{1}{\epsilon^2}\right)\log^4\left(\frac{N_p}{\epsilon}\right), N_p\right)\frac{N_p}{\epsilon^2} + \frac{1}{\epsilon^2}\log\frac{1}{\delta}\right)$$

where $N_p$ is $V\left(C\left(k \max(\frac{1}{\epsilon}, \kappa)\right)\right)^k$

Then, independent of ambient dimension n,

$$\mathbf{P}\left[\sup_{\mathcal{G}}\left|\frac{\Sigma_{i=1}^{s}\mathbf{d}(\mathcal{M}, x_i)^2}{s} - \int \mathbf{d}(\mathcal{M}, x)^2 d\mathcal{P}(x)\right| < \epsilon\right] > 1-\delta$$

# K-means

In particular, this improves the best known upper bound on the sample complexity of k-means from $O(\frac{k^2+\log\frac{1}{\delta}}{\epsilon^2})$ to

$$O\left(\frac{k\min\left(k,\frac{\log^4(k/\epsilon)}{\epsilon^2}\right)+\log\frac{1}{\delta}}{\epsilon^2}\right)$$

Aspects of the proof:

1. Estimates for the volumes of balls in Riemannian manifolds
2. Bounding the Fat-Shattering dimension using Random Projections onto a low-dimensional subspace.