



Non-linear dimensionality reduction: Riemannian metric estimation and the problem of geometric discovery

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(Submitted on 30 May 2013)

In recent years, manifold learning has become increasingly popular as a tool for performing non-linear dimensionality reduction. This has led to the development of numerous algorithms of varying degrees of complexity that aim to recover manifold geometry using either local or global features of the data.

Building on the Laplacian Eigenmap and Diffusionmaps framework, we propose a new paradigm that offers a guarantee, under reasonable assumptions, that any manifold learning algorithm will preserve the geometry of a data set. Our approach is based on augmenting the output of embedding algorithms with geometric information embodied in the Riemannian metric of the manifold. We provide an algorithm for estimating the Riemannian metric from data and demonstrate possible applications of our approach in a variety of examples.

Comments: 32 pages

Subjects: **Machine Learning (stat.ML)**

Cite as: **arXiv:1305.7255 [stat.ML]**

(or **arXiv:1305.7255v1 [stat.ML]** for this version)

Submission history

From: Marina Meila [[view email](#)]

[v1] Thu, 30 May 2013 21:16:04 GMT (1181kb,D)

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