Manifold Learning with Random Errors and Inverse Problems

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We consider applications of the geometric Whitney problem on how a Riemannian manifold (M,g) can be constructed when one is given a discrete metric space (X,d_X), e.g. a point cloud with approximate distances, that approximates the manifold. This problem is closely related to manifold learning, where a smooth n-dimensional surface $S\subset {\mathbb R}^m$, $m>n$ needs to be constructed to approximate a point cloud in ${\mathbb R}^m$. These questions are encountered in differential geometry, machine learning, and in inverse **problems** in various applications. The determination of a Riemannian manifold includes the construction of its topology, differentiable structure, and metric.

We consider the recent developments on the problem from geometric and statistical point of views, in particular the recent results when the data is given with random errors.

References:
[1] C. Fefferman, S. Ivanov, Y. Kurylev, M. Lassas, H. Narayanan: Reconstruction and interpolation of manifolds I: The geometric Whitney problem. arXiv:1508.00674

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