# Intrinsic persistent homology via density-based metric learning

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In this poster, I will explain a density-based method to address the problem of estimating topological features from data in high dimensional Euclidean spaces under the manifold assumption. The key of our approach is to consider a sample metric known as Fermat distance to robustly infer the homology the space of data points. I will show results that prove that such sample metric space GH-converges almost surely to the manifold itself endowed with an intrinsic (Riemannian) metric that accounts for both the geometry of the manifold and the density that produces the sample. This fact, joint with the stability properties of persistent homology, implies the convergence of the associated persistence diagrams, which overcome many weaknesses of the standard methods for homology inference. I will show that these intrinsic density-based diagrams are robust to the presence of (geometric) outliers in the input data and less sensitive to the particular embedding of the underlying manifold in the ambient space. Finally, I will exhibit a concrete application of these ideas to time series analysis, with examples in real data.

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