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11:00 AM
258 Hurley Hall

Title: Information Geometry: Geometrization of Statistical Inference and Information

Abstract:

Information Geometry is the differential geometric study of the manifold of probability models, and promises to be a unifying geometric framework for investigating statistical inference, information theory, machine learning, etc. Instead of using metric for measuring distances on such manifolds, these applications often use "divergence functions" for measuring proximity of two points (that do not impose symmetry and triangular inequality), for instance Kullback-Leibler divergence, Bregman divergence, f-divergence, etc. Divergence functions are tied to generalized entropy (for instance, Tsallis entropy, Renyi entropy, phi-entropy) and cross-entropy functions widely used in machine learning and information sciences. It turns out that divergence functions enjoy pleasant geometric properties – they induce what is called "statistical structure" on a manifold M: a Riemannian metric g together with a pair of torsion-free affine connections D, D*, such that D and D* are both Codazzi coupled to g while being conjugate to each other. Divergence functions also induce a natural symplectic structure on the product manifold MxM for which M with statistical structure is a Lagrange submanifold. We recently characterize holomorphicity of D, D* in the (para-)Hermitian setting, and show that statistical structures (with torsion-free D, D*) can be enhanced to Kahler or para-Kahler manifolds. The surprisingly rich geometric properties of statistical manifolds may supply a rich set of geometric tools for statistical inference, information science, and machine learning.