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Geometrical learning, descriptive geometry, and biomimetic pattern recognition

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Abstract

Studies on learning problems from geometry perspective have attracted an ever increasing attention in machine learning, leaded by achievements on information geometry. This paper proposes a different geometrical learning from the perspective of high-dimensional descriptive geometry. Geometrical properties of high-dimensional structures underlying a set of samples are learned via successive projections from the higher dimension to the lower dimension until two-dimensional Euclidean plane, under guidance of the established properties and theorems in high-dimensional descriptive geometry. Specifically, we introduce a hyper sausage like geometry shape for learning samples and provides a geometrical learning algorithm for specifying the hyper sausage shapes, which is then applied to biomimetic pattern recognition. Experimental results are presented to show that the proposed approach outperforms three types of support vector machines with either a three degree polynomial kernel or a radial basis function kernel, especially in the cases of high-dimensional samples of a finite size.
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Keywords: Information geometry; High-dimensional descriptive geometry; Biomimetic pattern recognition; Geometry learning; RBF network; Support vector machine

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1. Introduction

Traditional statistical learning and modeling are based on one parametric models that are featured by pre-designed distribution functions with unknown parameters. Tasks of learning are made from a set of samples to determine unknown parameters and to select an appropriate one among candidate parametric models that have a same configuration but different complexity. After learning, the obtained parametric model can be used for a variety of tasks such as pattern recognition and decision making.

Considering that a family of distribution functions with unknown parameters represents a manifold in a high-dimensional parametric space and that a set of samples also represents a manifold in the parametric space, a learning task can be regarded as projection between the manifolds in the parametric space under guidance of the relationship between information and geometrical properties of these manifold. Studies along this direction started three decades ago by exploring a quasi Pythagorean relation of the classic Kullback–Leibler information measure on the manifolds [4]. Pioneered by Amari [1], instrumental advances have been made since early 80s via considering Riemann geometry and building up the celebrated relation between Rao's Fisher information matrix [10] and Riemann metrics.

Studies on information geometry are featured by investigating parametric models or equations from a geometrical perspective, i.e., we need firstly to have parametric models or equations and then study their geometrical properties. Other efforts on learning from geometry perspective, e.g., generalized projection geometry for harmony learning [17], are also basically of this category. In this paper, we investigate learning tasks from a different geometrical perspective in help of high-dimensional descriptive geometry. Geometrical properties of high-dimensional structures are learned via successive projections from n-dimension to $n-1$-dimension under guidance of those established properties and theorems in high-dimensional descriptive geometry [14]. In Section 2, we describe the main ideas of high-dimensional description geometry and demonstrate geometrical learning via successive projections from a higher dimension to a lower dimension. In Section 3, we introduce a hyper sausage like geometrical configuration for representing pattern class and show how high-dimensional descriptive geometry could be used for specifying the hyper sausages, which is then applied to biomimetic pattern recognition. Moreover, experimental results are presented in Section 4 to show the promising results of the proposed approach in comparison with three types of support vector machine (SVMs) with either a three degree polynomial kernel or a radial basis function kernel. Finally, we conclude in Section 5.

2. High dimensional description geometry and successive projections

To model a set of points in a high-dimensional space by statistical learning usually involves finding a compact representation for these sample points in terms of parametric functions and equations. Finding a compact representation in a

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