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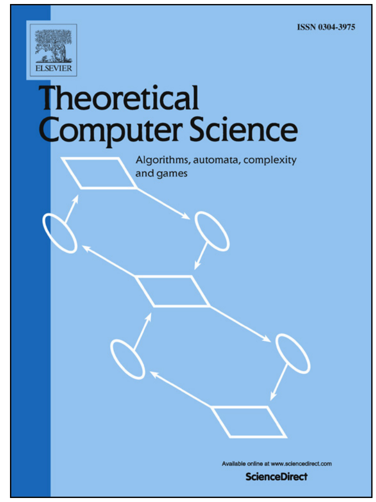

Large width nearest prototype classification on general distance spaces

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Large width nearest prototype classification on general distance spaces

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Abstract

In this paper we consider the problem of learning nearest-prototype classifiers in any finite distance space; that is, in any finite set equipped with a distance function. An important advantage of a distance space over a metric space is that the triangle inequality need not be satisfied, which makes our results potentially very useful in practice. We consider a family of binary classifiers for learning nearest-prototype classification on distance spaces, building on the concept of large-width learning which we introduced and studied in earlier works. Nearest-prototype is a more general version of the ubiquitous nearest-neighbor classifier: a prototype may or may not be a sample point. One advantage in the approach taken in this paper is that the error bounds depend on a 'width' parameter, which can be sample-dependent and thereby yield a tighter bound.

1. Introduction

Learning Vector Quantization (LVQ) and its various extensions introduced by Kohonen [22] are used successfully in many machine learning tools and applications. Learning pattern classification by LVQ is based on adapting a fixed set of labeled prototypes in Euclidean space and using the resulting set of prototypes in a nearest-prototype rule (winner-take-all) to classify any point in the input space. As [21] mentions, LVQ fails if Euclidean representation is not well-suited for the data; and there have been extensions of LVQ to try to allow different metrics [21, 26] and take advantage of samples for which a more confident (or a large margin) classification can be obtained. Generalization error bounds with