

# Locally Adaptive Techniques for Pattern Classification

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## INTRODUCTION

Pattern classification is a very general concept with numerous applications ranging from science, engineering, target marketing, medical diagnosis and electronic commerce to weather forecast based on satellite imagery. A typical application of pattern classification is mass mailing for marketing. For example, credit card companies often mail solicitations to consumers. Naturally, they would like to target those consumers who are most likely to respond. Often, demographic information is available for those who have responded previously to such solicitations, and this information may be used in order to target the most likely respondents. Another application is electronic commerce of the new economy. E-commerce provides a rich environment to advance the state-of-the-art in classification because it demands effective means for text classification in order to make rapid product and market recommendations.

Recent developments in data mining have posed new challenges to pattern classification. Data mining is a knowledge discovery process whose aim is to discover unknown relationships and/or patterns from a large set of data, from which it is possible to predict future outcomes. As such, pattern classification becomes one of the key steps in an attempt to uncover the *hidden knowledge* within the data. The primary goal is usually predictive accuracy, with secondary goals being speed, ease of use, and interpretability of the resulting predictive model.

While pattern classification has shown promise in many areas of practical significance, it faces difficult challenges posed by real world problems, of which the most pronounced is Bellman's *curse of dimensionality*: it states the fact that the sample size required to perform accurate prediction on problems with high dimensionality is beyond feasibility. This is because in high dimensional spaces data become extremely

sparse and are apart from each other. As a result, severe bias that affects any estimation process can be introduced in a high dimensional feature space with finite samples.

Learning tasks with data represented as a collection of a very large number of features abound. For example, microarrays contain an overwhelming number of genes relative to the number of samples. The Internet is a vast repository of disparate information growing at an exponential rate. Efficient and effective document retrieval and classification systems are required to turn the ocean of bits around us into useful information, and eventually into knowledge. This is a challenging task, since a word level representation of documents easily leads 30000 or more dimensions.

This chapter discusses classification techniques to mitigate the curse of dimensionality and reduce bias, by estimating feature relevance and selecting features accordingly. This issue has both theoretical and practical relevance, since many applications can benefit from improvement in prediction performance.

## BACKGROUND

In a classification problem an observation is characterized by  $q$  feature measurements  $\mathbf{x} = (x_1, \dots, x_q) \in \mathcal{R}^q$  and is presumed to be a member of one of  $J$  classes,  $L_j$ ,  $j = 1, \dots, J$ . The particular group is unknown, and the goal is to assign the given object to the correct group using its measured features  $\mathbf{x}$ .

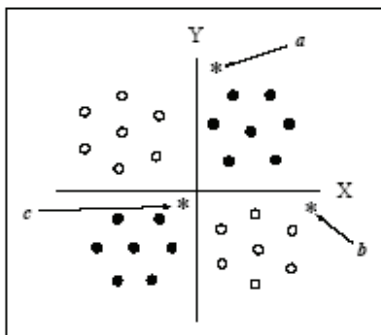
Feature relevance has a *local* nature. Therefore, any chosen fixed metric violates the assumption of locally constant class posterior probabilities, and fails to make correct predictions in different regions of the input space. In order to achieve accurate predictions, it becomes crucial to be able to estimate the different degrees of relevance that input features may have in various locations of the feature space.

Consider, for example, the rule that classifies a new data point with the label of its closest training point in the measurement space (*1-Nearest Neighbor rule*). Suppose each instance is described by 20 features, but only three of them are relevant to classifying a given instance. In this case, two points that have identical values for the three relevant features may nevertheless be distant from one another in the 20-dimensional input space. As a result, the similarity metric that uses all 20 features will be misleading, since the distance between neighbors will be dominated by the large number of irrelevant features. This shows the effect of the curse of dimensionality phenomenon, that is, in high dimensional spaces distances between points within the same class or between different classes may be similar. This fact leads to highly biased estimates. Nearest neighbor approaches (Ho, 1998; Lowe, 1995) are especially sensitive to this problem.

In many practical applications things are often further complicated. In the previous example, the three relevant features for the classification task at hand may be dependent on the location of the query point, i.e. the point to be classified, in the feature space. Some features may be relevant within a specific region, while other features may be more relevant in a different region. Figure 1 illustrates a case in point, where class boundaries are parallel to the coordinate axes. For query *a*, dimension *X* is more relevant, because a slight move along the *X* axis may change the class label, while for query *b*, dimension *Y* is more relevant. For query *c*, however, both dimensions are equally relevant.

These observations have two important implications. Distance computation does not vary with equal strength or in the same proportion in all directions

Figure 1. Feature relevance varies with query locations



in the feature space emanating from the input query. Moreover, the value of such strength for a specific feature may vary from location to location in the feature space. Capturing such information, therefore, is of great importance to any classification procedure in high dimensional settings.

### MAIN THRUST

Severe bias can be introduced in pattern classification in a high dimensional input feature space with finite samples. In the following we introduce adaptive metric techniques for distance computation, capable of reducing the bias of the estimation.

Friedman (Friedman, 1994) describes an adaptive approach (the Machete and Scythe algorithms) for classification that combines some of the best features of kNN learning and recursive partitioning. The resulting hybrid method inherits the flexibility of recursive partitioning to adapt the shape of the neighborhood  $N(\mathbf{x}_0)$  of query  $(\mathbf{x}_0)$ , as well as the ability of nearest neighbor techniques to keep the points within  $N(\mathbf{x}_0)$  close to the point being predicted. The method is capable of producing nearly continuous probability estimates with the region  $N(\mathbf{x}_0)$  centered at  $(\mathbf{x}_0)$ , and the shape of the region separately customized for each individual prediction point.

The major limitation concerning the Machete/Scythe method is that, like recursive partitioning methods, it applies a “greedy” strategy. Since each split is conditioned on its “ancestor” split, minor changes in an early split, due to any variability in parameter estimates, can have a significant impact on later splits, thereby producing different terminal regions. This makes the predictions highly sensitive to the sampling fluctuations associated with the random nature of the process that produces the training data, and therefore may lead to high variance predictions.

In (Hastie & Tibshirani, 1996), the authors propose a discriminant adaptive nearest neighbor classification method (DANN) based on linear discriminant analysis. Earlier related proposals appear in (Myles & Hand, 1990; Short & Fukunaga, 1981). The method in (Hastie & Tibshirani, 1996) computes a local distance metric as a product of weighted within and between sum of squares matrices. The authors also describe a method to perform global dimensionality reduction, by pooling the local dimension information over all points in



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