

Chapter 19

Classification with Axis-Aligned Rectangular Boundaries

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ABSTRACT

This chapter presents a new method for binary classification that classifies input data into two regions separated by axis-aligned rectangular boundaries. Given the number of rectangular regions to use, this algorithm automatically finds the best boundaries that are determined concurrently. The formulation of the optimization problem involves minimizing the sum of minimum functions. To solve this problem, the author introduces underestimation of the minimum function with piecewise linear and convex envelope, which results in mixed integer and linear programming. The author shows several results of the algorithm and compares the effects of each term in the objective function. Finally, the chapter demonstrates that the method can be used in image capturing application to determine the optimal scheme that minimizes the total readout time of pixel data.

INTRODUCTION

The main goal of a classification problem is to figure out an efficient algorithm to come up with good decision classifiers to categorize random input data into several groups. The classified results give better representation of underlying structure of input data and make it easier to handle them in more complex processing stage afterwards. Each classification algorithm is designed to handle data in a systematic way, based on the assumptions it makes on its input data and how it will be used.

Many applications involving image data usually make an assumption that image data is given as a rectangular shape rather than an arbitrary form. Thus, if you want to apply classification methods to image data and feed the results to other image processing or computer vision algorithms, the classified regions must be reformulated into rectangular shape. Also, treating the object of interest as a bounding box is a common technique to make it easier to handle multiple complicated objects at the same time. Both cases require a separate method to transform a specific region or data points to a rectangular box and using a simple straightforward method may not give the best results.

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In this chapter, we would like to propose a classification method that does the two tasks at the same time, data classification and determining rectangular boundaries. The classification method will automatically choose multiple rectangular regions to separate data. Each rectangular region is axis-aligned, which means that its sides are aligned to the axes of orthogonal coordinate system and it is not allowed to rotate to arbitrary angles.

In the following sections, we will present several properties that good classification methods should have. Then, we will explain details about our algorithm and demonstrate it satisfies the properties stated. Also, we will show the application for image capturing that utilizes our classification method. Finally, further research topics and conclusion are given.

BACKGROUND

Classification has been intensively studied in machine learning and pattern recognition (Jain, Duin & Mao, 2000). Researchers have developed tons of methods to tackle their problems and various approaches have evolved to handle specific applications. Here, we would like to mainly focus on the characteristics of the resulting decision boundaries that each classification technique provides. In some real world applications, users might have very specific constraints on the geometry of decision boundaries they will get in the end. Even more, users sometimes want to construct their boundaries to have certain shapes, such as circles, ellipses or polygons. However, most of classifiers do not explicitly focus on the geometry of results they provide. One main approach in classification is based on similarity matching. Popular methods such as template matching, the minimum distance classifier and k-nearest neighbor algorithm fall into this category. Although these methods usually results in piece-wise linear decision boundaries, the classifiers are implicitly determined and no control on the boundaries is provided to users.

Another main approach is the probabilistic approach. The Bayes decision rule (Fukunaga, 1990) and a logistic classifier (Anderson, 1982) try to maximize a likelihood function to construct decision rules. Depending on which assumption they make on the distribution of data, they result in linear or quadratic decision boundaries, which we don't have any control on as the previous cases. The third category of classifiers is to explicitly determine decision boundaries by optimizing classification error costs. These methods allow direct handling of the geometry of the decision rules. However, many approaches such as Fisher's linear discriminant and the perceptron are limited to a linear case. Another popular approach in machine learning is to use support vector machines (Cortez & Vapnik, 1995). This class of methods is based on optimizing classification errors while maximizing the geometric margin to provide a maximum-margin hyperplane that separates the data. Even though this approach is effective for various applications, extension to nonlinear classification is not trivial. The kernel trick is applied to achieve nonlinear decision boundaries, but they are no longer explicitly handled in the original input space.

The goal of this work is to find a good classifier that is suitable for the specific application: finding multiple axis-aligned rectangular decision boundaries for binary input data. Before going into the details of our approach, we propose four desirable characteristics that our classification algorithm should have so that it can be easily applied to real world applications.

Automatic Classification

Once the algorithm gets all labeled input data, it is desired to work by itself. Users can not always guide or train classification process if the size of input data is large or clustering should be done many times iteratively.

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