Ensemble Learning

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Abstract

In this report we investigate the effect of mixture of classifiers on accuracy of classification three different datasets in comparison to using single classifier. We have reached diversity by diverse individual classifiers. Our results on classification of synthetic 2d gaussian, iris and satimage datasets show in some cases ensemble techniques will show promising results. This report is based on Machine Learning course.

Keywords: classification, ensemble learning, mixture of classifiers

1 Introduction

Classification is task of assigning a class to unknown samples, this is a vital part of every machine learning problem. In fact better classification results more accuracy in following parts of algorithm and finally higher performance. This is the reason why the improvement of this classifiers has remained an active research topic in past years. As we know every individual classifiers has its own capability in different part of feature space, by mixing several individual classifiers and an intelligent method for combining their results we can obtain an ensemble classifier with better classification accuracy.

Perhaps one of the earliest work on ensemble systems is Dasarathy and heela's 1979 paper [1], which discusses partitioning the feature space using two or more classifiers. As shown in figure 1 ensemble system must have two key components: an algorithm to generate individual classifiers $H_1, H_2, \dots H_M$ and a method for combining these classifiers.

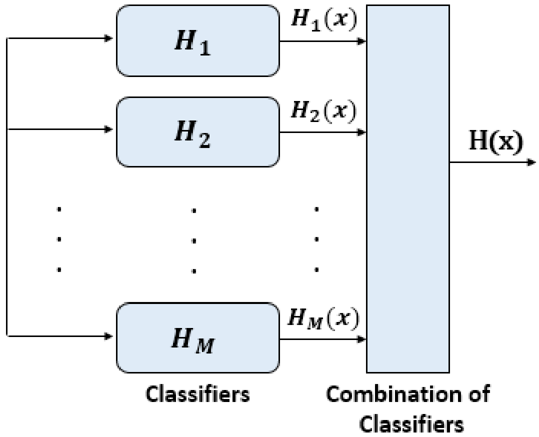

Figure 1: Ensemble Learning Block Diagram

In the following parts brief information about datasets is noted (2), and after developing technical details about implementation process and reporting results for different type of ensemble classifiers on different datasets (3,4), finally there will be conclusion about results.

2 Datasets

Three different datasets have been used to evaluate classification ability of RBF classifier. The first one is a two class named positive class and negative class by Gaussian distribution (Figure 1).

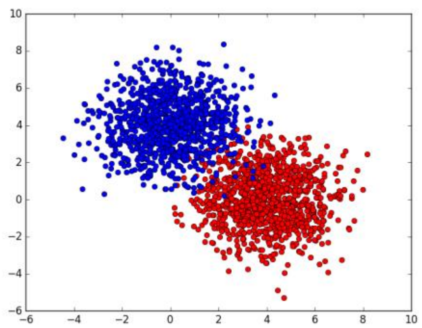

Figure 2: synthetic 2D Gaussian distribution

second one is iris datasets that consists of 3 different types of irises' (Setosa, Versicolour, and Virginica) petal and sepal length, stored in a 150x4 array, The rows being the samples and the columns being: Sepal Length, Sepal Width, Petal Length and Petal Width [1]. The third dataset is satimage, this dataset consists of the multi-spectral values of pixels in 3x3 neighborhoods in a satellite image, and the classification associated with the central pixel in each neighborhood. In this dataset there are 6 classes and 6435 samples (4435 training set and 2000 test set) with 36 attributes for every samples.

3 Implementation

Technically, it's not possible to reach better ensemble system using individual classifier with exactly same classification, therefore the key point to reach better performance for ensemble classifier is using diverse individual classifiers. According to [2] there are several ways to achieve diverse classifiers. (1) Using different training datasets to train individual classifiers, (2) Different training parameters for different classifiers, (3) Entirely different types of classifiers and (4) Generating different classifiers using random feature subsets.

In this task we have used entirely different types of classifiers to achieve diversity. Our collection of classifiers consist of *One*-Nearest Neighbor (1NN), k-Nearest Neighbor (kNN), Naive Bayesian (NB), Linear Support Vector Machine (LSVM), SVM with RBF kernel, SVM with Polynomial kernel, Decision Tree (DT) and Radial Basis Function (RBF) classifiers.

In implementation of our ensemble systems, we implemented two types of ensemble systems. The first one is a static combiners that use different classifiers as diverse individual classifiers and two non-trainable Majority Voting (MV) and Averaging combiners to combine singular classifiers, let us denote this system MVAV (figure 3). The second one is Stack Generalization (SG) system with Multi-Layer Perceptron (MLP) combiner.

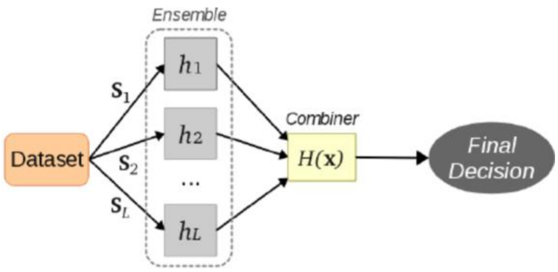

Figure 3: Ensemble static combiner MVAV

4 Results

4.1 Synthetic 2D gaussian

We have utilized these two ensemble systems MVAV and SG to classify synthetic 2D gaussian, the corresponding results are showing in figure 4 and 5.

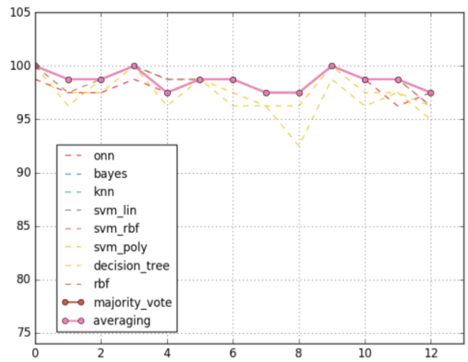

Figure 4: Classification results on synthetic 2D gaussian by ensemble system MVAV.

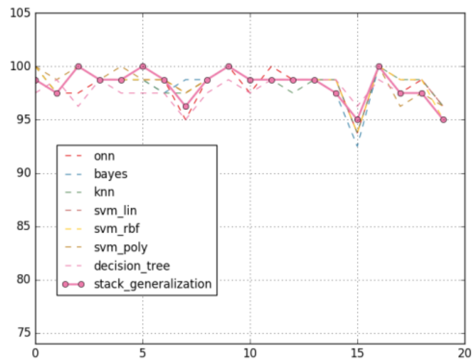

Figure 5: Classification results on synthetic 2D gaussian by ensemble system SG.

4.2 Iris Dataset

We have done similar tests on classification of iris dataset with MVAV and SG ensemble systems and figures 6 and 7 are showing respectively performance of these systems to classify this dataset.

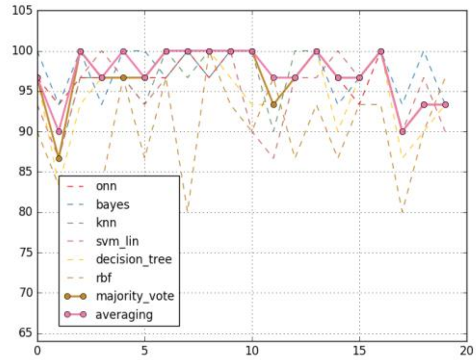

Figure 6: Classification results on iris dataset by ensemble system MVAV.

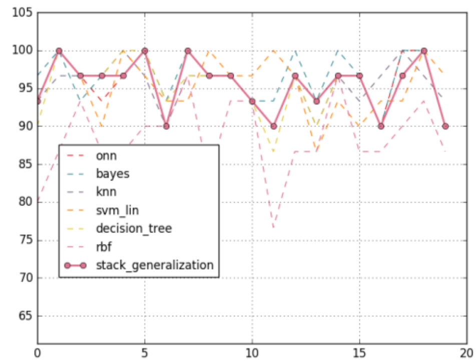

Figure 7: Classification results on iris dataset by ensemble system SG.

4.3 Satimage Dataset

We continued our experiments to test ensemble systems' ability to classify satimage dataset. Figures 8 and 9 are results on satimage dataset by MVAV and SG ensemble systems.

5 Conclusion

As shown in results on three different datasets, mixture of individual classifiers with diverse classification ability will perform better than singular classifiers. Employing more diverse individual classifiers will improve performance ensemble classifiers, in other words by combining predictions, more robust and accurate models nearly always improve without the need for the high-degree of fine tuning required for single-model solutions.

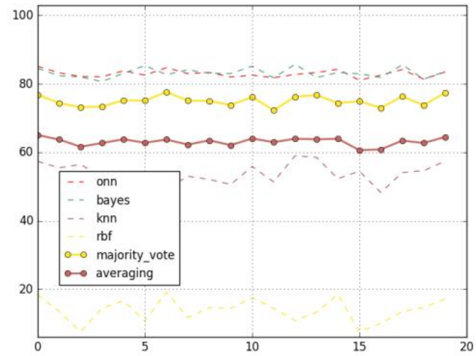

Figure 8: Classification results on satimage dataset by ensemble system MVAV.

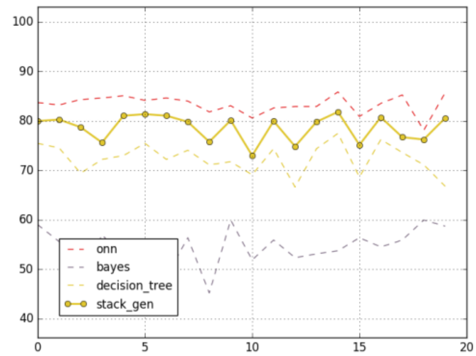

Figure 9: Classification results on satimage dataset by ensemble system SG.

References

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