As you discovered last week, computational learning theory makes it possible for us to analyze learning algorithms. It provides tools that allow us to answer questions such as “what is learnable”, “how many examples do we need in order to learn a classifier with certain accuracy”, etc. In addition, theoretical work sometimes leads to the development of very practical algorithms, such as AdaBoost. This week you will continue your study of AdaBoost, as well as other ensemble methods.

1 Boosting and Bagging

1.1 Reading

Please read the following:

- Alpaydin, Sections 17.1-17.4 and 17.6-17.7.

- Since the reading in Alpaydin refers to the bias-variance tradeoff, you might also find it useful to read Sections 4.3 and 4.7.

2 The Effect of Noise

We have often discussed the potential impact of noise on classifier learning. This week you will have the opportunity to explore the effects of class noise on ensembles of decision trees and other learners.

2.1 Reading

Please read “An Experimental Comparison of Three Methods for Constructing Ensembles of Decision Trees: Bagging, Boosting, and Randomization” by Dietterich, which appeared in the Machine Learning Journal in 2000. In this paper, Dietterich compares the effectiveness of randomization, bagging, and boosting for improving the classification accuracy of C4.5 on 33 data sets from the UC Irvine Machine Learning Repository. He finds that AdaBoost performs better, on average, than Bagging. However, when class noise is added to the data sets, he finds that, on average, Bagging outperforms AdaBoost. This has been observed by others as well. (Why might we expect AdaBoost to be affected more significantly by noise in the data?)

2.2 An Experimental Comparison of Two Methods for Constructing Ensembles: Bagging and Boosting

The results presented in Dietterich’s paper are quite extensive and convincing. However, one of the issues we’ve discussed frequently this semester is reproducibility. This week you will empirically assess boosted and bagged decision trees, both with and without class noise.

In addition, it is interesting to consider whether we would observe the same general behavior with a different base classifier. So you will also explore the behavior of Boosting and Bagging with other learners as your base classifiers: decision stumps, Naive Bayes, and 3-NN.

The product of your investigation will be a summary of your findings.

2.2.1 Empirical Evaluation: Comparing Algorithms on Data Sets with No Noise

Before assessing the impact of class noise on learning, it is important to determine the baseline performance of each algorithm:

- J48

- AdaBoostM1 with J48 as base classifier
• Bagging with J48 as base classifier

as well as the same for Decision Stumps, Naive Bayes, and 3-NN. You already know how to find J48, Naive Bayes, and 3-NN in Weka. In addition, you can find Decision Stumps in the “trees” folder, and you’ll find AdaBoostM1 and Bagging in the “meta” folder. You will need to set some parameters for AdaBoostM1 and Bagging. For AdaBoostM1, set the number of iterations to 50. You can also modify the seed for the random number generator, if you’d like. Don’t modify “useResampling”, and don’t worry about the weight threshold. For Bagging, set the number of iterations to 100 and the bagSizePercent to 100. Again, you can modify the seed for the random number generator. Be sure to set the base classifier appropriately in all cases. That includes setting the parameters for J48. For instance, set the confidence factor to 0.10 in order to do pruning at the 0.1 level, as Dietterich did.

The data sets to be evaluated are as follows:
• vehicle
• sick
• kr-vs-kp
• audiology
• hypothyroid

You can find the data sets in

/home/faculty/andrea/shared/cs374/EnsembleData

You’ll note that all of these are were tested by Dietterich and that he evaluated pruned versions of the C4.5 trees on these data sets.

For all of the above, perform 10 x 10-fold cross validation. (This is the default setting in the Weka Experimenter.) Your report should give the error percentage of each algorithm on each of the data sets. You can refer to Table 1 in Dietterich’s paper for ideas on how to present the results.

2.2.2 Empirical Evaluation: Comparing Algorithms on Data Sets with Noise

Now you’re ready to assess the impact of noise on each of the algorithms. I’ve already prepared the necessary files for you. You’ll find noisy versions of each of the above data sets in the same EnsembleData directory. There are three noise levels per data set: 5%, 10%, and 20%.

Now run each of the algorithms again (doing 10 x 10-fold cross-validation), this time on the noisy data sets. (First compare the 5% noise sets. Then the 10%. And finally the 20%.) Give tables with the resulting error percentages. You can, again, follow the format suggested in Table 1 of the paper. How do your results compare to Dietterich’s? Are you observing the same general trends?

In addition to providing the tables and giving a high level summary of the highlights, list and briefly discuss four interesting observations or other points that are relevant to the experiments you just completed.

2.3 The Tutorial Meeting

For the tutorial meeting, be prepared to:

• Explain the differences between bagging and boosting.
• Discuss the Dietterich paper.
• Present your empirical results and observations.