ML CS726 Fall'11 Project 1 Basic Classifiers

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1 Writeup

1.1 Warm up

WU1:Why is this computation equivalent to computing classification accuracy?

This computation is equivalent to computing classification accuracy because it first compares the ground truth classifications with the predictions, and where they are equal yields ones, otherwise zeros. The mean of this array is the number of correct divided by the total, which is equivalent to classification accuracy.

1.2 Decision Tree

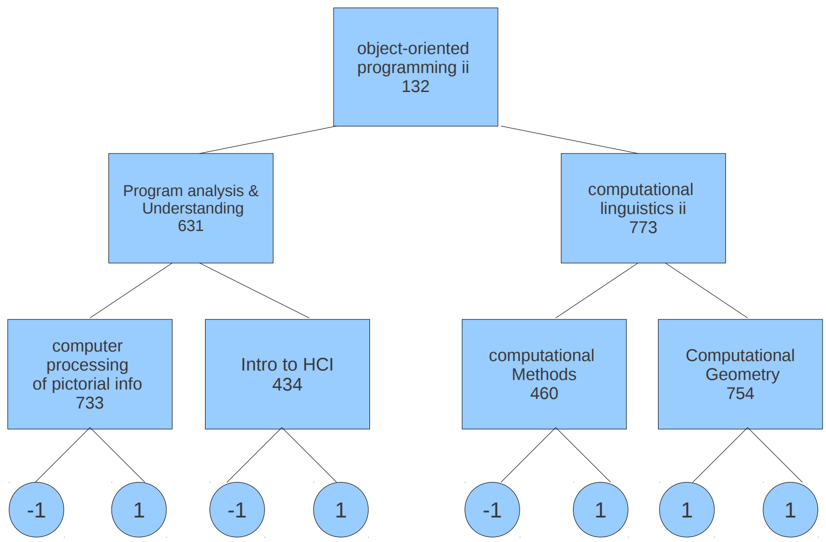
WU2: We should see training accuracy (roughly) going down and test accuracy (roughly) going up. Why does training accuracy tend to go down? Why is test accuracy not monotonically increasing?

Training accuracy tends to go down because we're training the algorithm on that data with answers. The design of the tree is s.t. we minimize the training error. However the test accuracy is not monotonically increasing because there maybe examples that the algorithm is not ready for. In another words the more the accuracy goes up on the training set the more algorithm will over-fit on that specific training set and thus not generalize well to the unseen test set.

WU3: You should see training accuracy monotonically increasing and test accuracy making a (wavy) hill. Which of these is guaranteed to happen a which is just something we might expect to happen? Why?

We can guarantee that the training accuracy will monotonically increase. This is because the deeper we go, the better our tree will fit the training data. By construction when the tree is complete as long as the training set is consistent we will have 0 error. We should expect the test set to make a wavy hill because we can't guarantee that our training set is representative of the test set, or the entire distribution datasets are taken from. So if we overfit it will go up, but we might focus on the right feature, or hope to do so, to increase the accuracy on the test set. But we can never guarantee that the accuracy of the test set will monotonically increase.

WU4: Train a decision tree on the CG data with a maximum depth of 3. If you look in `datasets.CFTookCG.courseIds` and `courseNames` you'll find the corresponding course for each feature. The first feature is a constant-one "bias" feature. Draw out the decision tree for this classifier, but put in the actual course names/ids as the features. Interpret this tree: do these courses seem like they are actually indicative of whether someone might take CG? The decision tree trained on the CG data with maximum depth 3 looks like:



Most of the features do seem like they would positively correlate with a student who has taken CG. According to the decision tree, students who have taken Computational Geometry, Pictorial Information and Computational Methods, and HCI are more likely to have taken CG. These courses are graduate courses which a student who is in graphics, geometry, or vision would take.

1.3 KNN

WU5: For the course recommender data, generate train/test curves for varying values of K and epsilon (you figure out what are good ranges, this time). Include those curves: do you see evidence of overfitting and underfitting? Next, using K=5, generate learning curves for this data.

For epsilon ball (figure 1), we can see clearly see overfitting. When epsilon is less than 3.5, the training accuracy is super high and the accuracy on test data is very low (lower than 0.5). Clearly it's been overfitted. When eps is greater than 6, it's underfitting because both the training and test accuracy are low. At this point epsilon is merely taking the average of all data points and thus underfitting.

For KNN (figure 2), when k=1, it's overfitting, the test accuracy is perfect while the testing accuracy is only 0.5. There is no clear sign of underfitting there, but when k gets bigger (k=8,9,10), from figure 2 we can see the training accuracy is going lower and lower and the testing accuracy is getting lower as well. That is an indication of underfitting.
The learning curve for KNN with K=5 is figure 3.

Figure 1: epsilon on varying values of eps

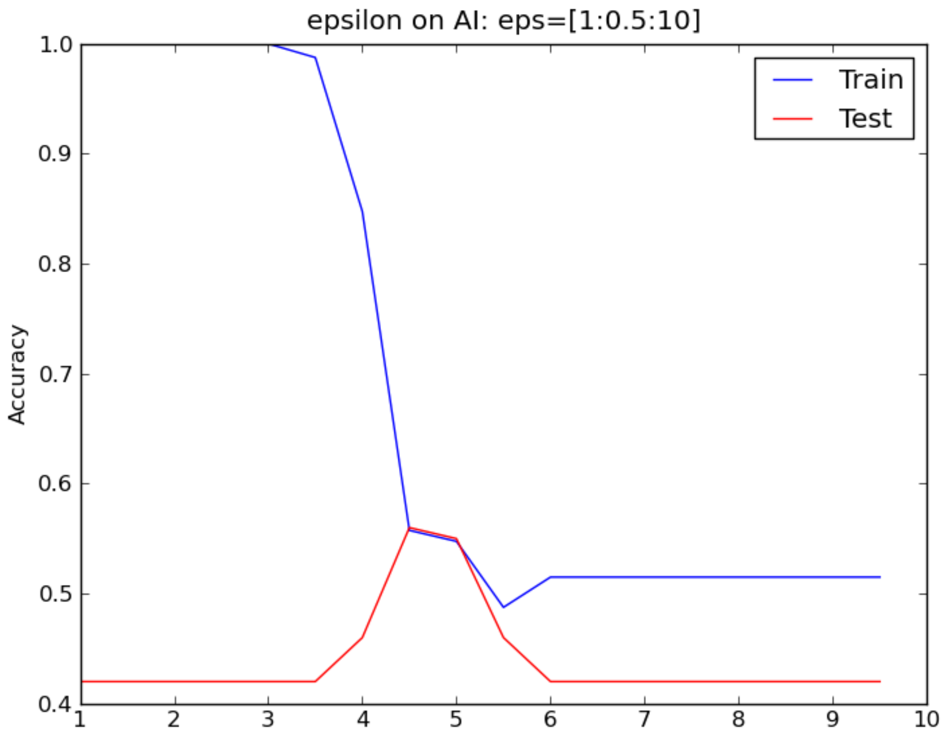
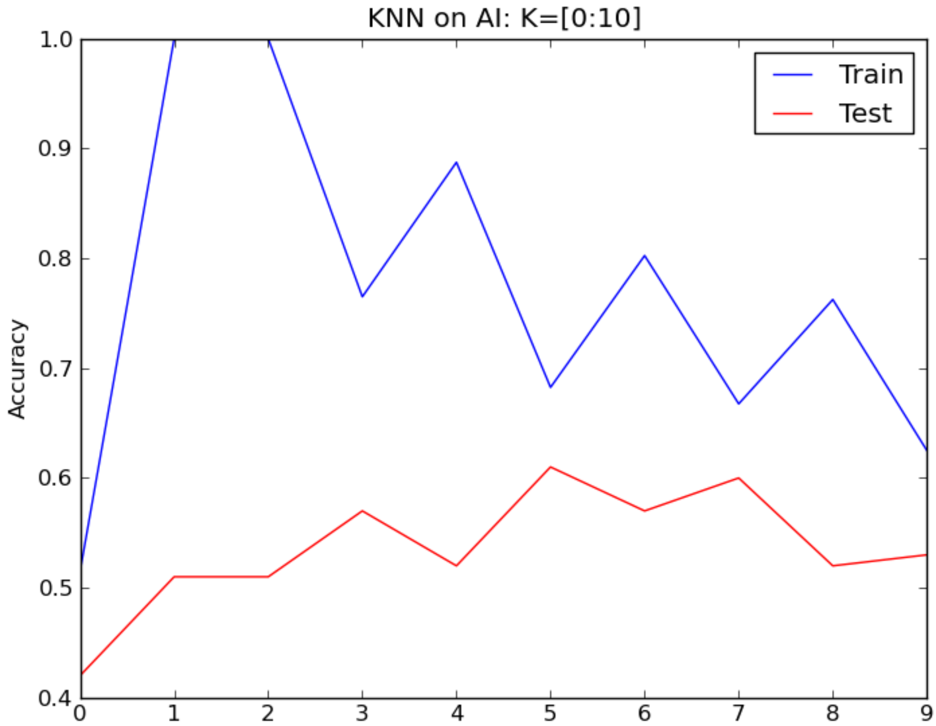


Figure 2: KNN on varying values of K



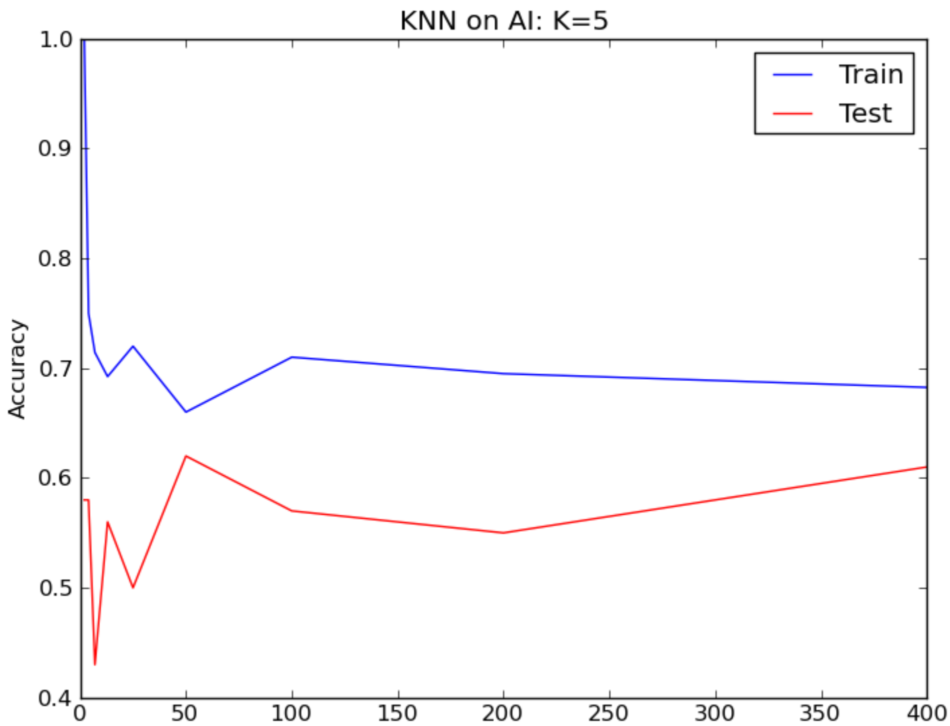
1.4 Perceptron

WU6: Take the best perceptron you've been able to find so far on the AI data. Look at the top five positive weights (those with highest value) and top five negative weights (those with lowest value). Which features do these correspond to? Can you explain why these might get these features as the "most indicative"? Why is it hard to interpret "large weight" as "most indicative"? How do these large weighted features compare to the features selected by the decision tree?

The features corresponding to the top 5 positive weight were:

1. (weight: 9) 'computer processing of pictorial information'
2. (weight: 8) 'advanced computer graphics'
3. (weight: 7) 'database management systems'
4. (weight: 5) 'data structures'

Figure 3: Learning curve of KNN with K=5



5. (weight: 5) 'introduction to information technology' (also weight 5 are 'computer networks (417)','computational methods')

The features corresponding to the top 5 negative weights were:

1. (weight: -8) 'honors seminar'
2. (weight: -6) 'introduction to c programming'
3. (weight: -5) 'program analysis and understanding'
4. (weight: -5) 'object-oriented programming i'
5. (weight: -4) 'computer networks (711)', 'bias', 'introduction to human-computer interaction'

The 5 most negative weights include a non-CS major class, a 200-level 1 credit Pass/Fail course, and an introductory course 131. This is likely because in the first case non-CS majors will not take 421 and in the case of the other two courses some of the students just starting in CS may not continue in the program long enough to take 421. The 5 most positive courses are mostly graduate level courses, which makes it more likely that they have taken AI.

It is difficult to interpret large weights as "most indicative" because there may exist a groups of more indicative features which have distributed weights among themselves.

The top 4 levels of the decision tree contain the 4 most positive weights from the perceptron, where if the students took those courses the decision tree's prediction agrees with the perceptron. However, there are numerous courses used in the decision tree that do not appear in the most positive and negative weights.