

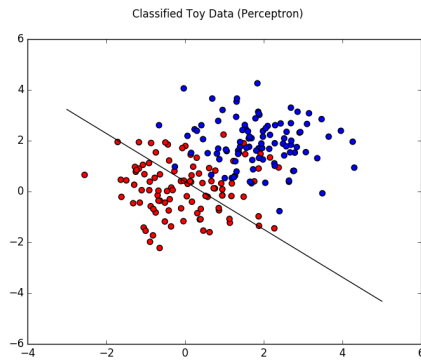
# 6.036 Project 1

Kevin

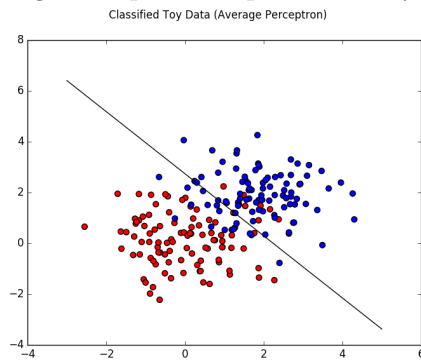
Due February 26th 2016

## I Implementing Classifiers

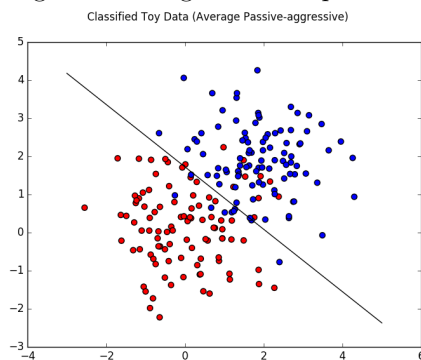
### 7) Perceptron Graph for Classifying Toy Data



### Average Perceptron Graph for Classifying Toy Data



### Average Passive Agressive Graph for Classifying Toy Data

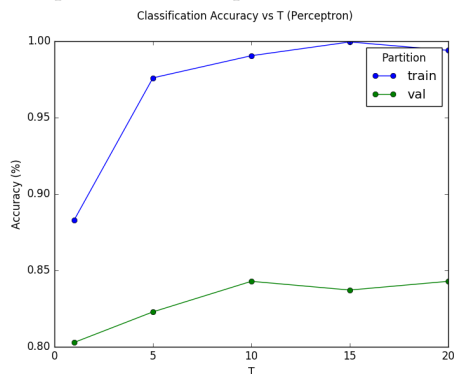


The three algorithms provide different decision boundaries because they all classify the data differently. For the Perceptron, we only update  $\theta$  when there is a mistake. For the Average Perceptron, we have something like the Perceptron algorithm, but  $\theta$  is now averaged at every point. This means that the theta at every point we train matters. What this means is that it doesn't matter if there was a mistake or not, there could be a change in the  $\theta$ . Lastly, the Passive Aggressive is like the average Perceptron in that all the  $\theta$  matter. However, how theta is updated is different.

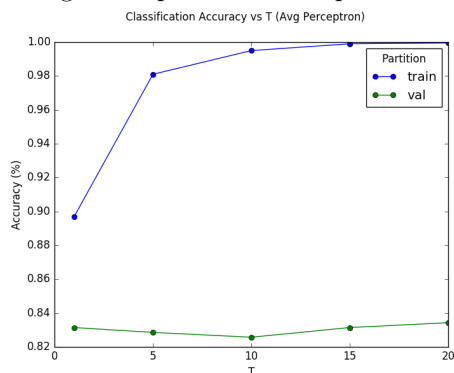
## II The Automatic Review Analyzer

9b) Training accuracy for perceptron: 0.9760 Validation accuracy for perceptron: 0.8229 Training accuracy for average perceptron: 0.9810 Validation accuracy for average perceptron: 0.8286 Training accuracy for average passive-aggressive: 0.9805 Validation accuracy for average passive-aggressive: 0.8429

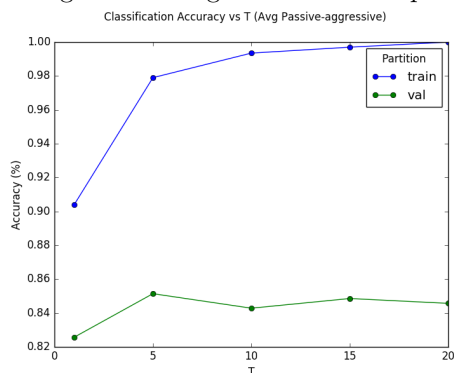
10) Perceptron vs T Graph



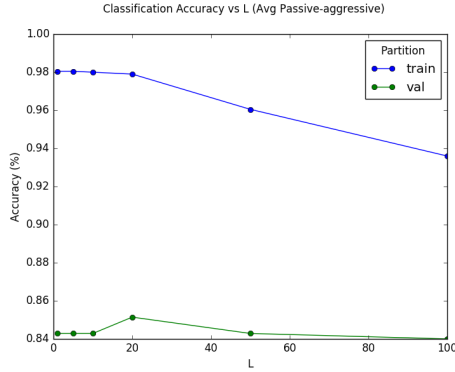
Average Perceptron vs T Graph



Average Passive Aggressive vs T Graph



### Average Passive Agressive vs L Graph



- 10a) No, they do not behave the same. This is when our  $T$  value goes up, we are beginning to overfit our data. This would sometimes have a negative effect of our accuracy for the classifier. However, when we increase our  $\lambda$  value, we tend to underfit our classifier with the training cases.

However, for our validation accuracies, when increasing both our  $T$  and  $\lambda$ , we tend to get and increase in accuracy and maybe a drop in accuracy after a certain value. The reason we do not get the same behaviour is because for the training values, we use those to train the classifier, but if we use them too much we tend to overclassify. However, for the validation, we only use them once and have them to validate our classifier.

- 10b) The best algorithm was the average passive aggressive with an accuracy in the validation of about 85 – 86 percent.
- 10c) After tinkering around with the values of  $T$  and  $\lambda$ , I found that the optimal values of  $T$  and  $\lambda$  were 5 and 20, respectively.
- 11a) The accuracy value from the Average Passive-Aggressive Algorithm with  $T = 5$  and  $\lambda = 20$  for the Training set was 0.979. **The accuracy value from the Algorithm for the Test set was 0.8457142857142858.**
- 11b) The top ten most explanatory word features were:  
 "[ 'best', 'great', 'delicious', 'perfect', 'wonderful', 'excellent', 'love', 'highly', 'use', '!' ]"

## III New Features and Challenge

- 12) The changes I made in my code were changing the unigram feature set. What I did was that I removed the common or stop words and I put a threshold to the number of times a word should appear in the dataset.

The changes I made would be useful because stop words aren't really used for determining things and classifying. They are present everywhere and don't contribute, but rather most likely will hurt the accuracy of our classifier.

As for the changes with the threshold, which I set as  $> 6$ , I made the changes in order that we delete less prevalent words because they would most likely be outliers in our training. This would hurt our  $\theta$  classification if they were all outliers. Thus, it would be better to take them all out.

The baseline we are working with is:

Training accuracy for average passive-aggressive: 0.9790

Validation accuracy for average passive-aggressive: 0.8514

This baseline was measured with the average passive-aggressive algorithm with a  $T$  value of 5 and  $\lambda$  value of 20. In order to compare equally, we retain the same algorithm and the same  $\lambda$  and  $T$  values.

It turns out with the changes we made, the performance was actually the same as before. However, the training was less overfitted than before. Thus, we could actually deem the classifier to be a better one than before. The results were:

Training accuracy for average passive-aggressive: 0.9615  
Validation accuracy for average passive-aggressive: 0.8514