Perceptron Algorithm

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1 Aim

The aim of this report is to show the evaluation results of the Perceptron algorithm on Unigram, Bigram and Trigram models.

2 Standard binary Perceptron

In Standard binary Perceptron, we are testing the accuracy of all three models without updating the weights(zero weights) of their bag of words.

3 Randomized order of training instances(shuffled/single pass)

In this, we are randomizing the order of the training set and updating the weights once.

4 Multiple passes over the training instances(shuffled/multiple pass)

In this, we are training our model by updating the weights on shuffled data set in each pass and calculating its accuracy.

5 Averaging weight vectors(shuffled/single pass/averaging)

In this, we take the average of all the updated weight vectors of each iteration and calculate the accuracy on that averaged weight vector.

Model	Unigram	Bigram	Trigram
Standard Binary Perceptron	50%	50%	50%
Single Pass/Shuffled Train Set	78.75%	74.50%	75%
Multiple Pass/Shuffled Train Set	84.25%	81.50%	78.75%
Multiple Pass/Shuffled/Averaged	84.75%	80.25%	77.50%

6 Extra Features

I am implementing bigram and trigram models as extra features and comparing the results between all three models. I chose bigram and trigram features because it can give the tokens some context of the sentiment but it does increase the size of the dataset of training set. As we can see from the table that the accuracy is best with unigrams rather than bigrams or trigrams. The unigram model works faster than the other two as well.

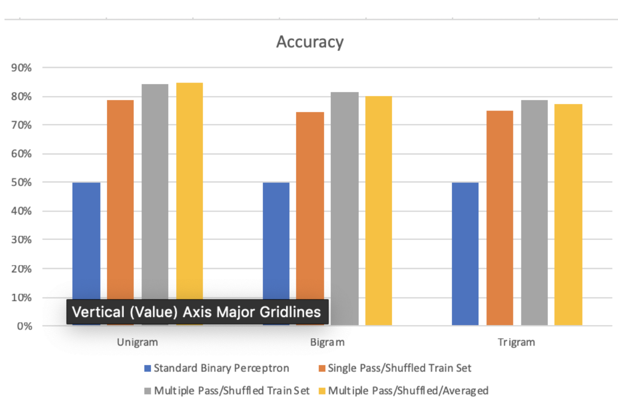

Figure 1: Comparison of Accuracy

7 Learning Progress

The learning progress of the perceptron algorithm can be seen by analyzing its error percentage on the training set calculated on each iteration which is shown below.

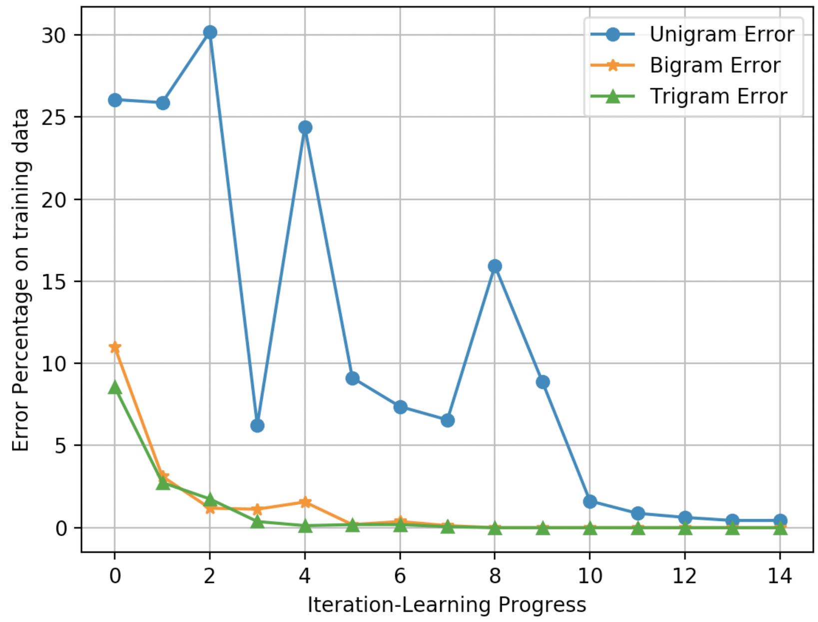

Figure 2: Learning Progress

8 Most positively weighted features of each class

Model	Pos Class	Neg Class
Unigram	see, fun, great, well, quite, good, American, seen, back, job	bad, worst, only, plot, supposed, boring, script, looks, could, nothing
Bigram	the best, is life, and it, to keep, there are, i have, is very, as much, he is, the most	have been, the only, supposed to, should have, the worst, into a, to be, it even, a bad, the plot
Trigram	of the best, but it is, best friend is, i have seen, that he is, the iron giant, friend s wedding, he does not, due to the, nothing short of	of the worst, could have been, should have been, would have been have been a, a bunch of, for a film, it is just, there is not, did not have

The features makes sense as Pos Class and Neg Class contains tokens which represent positive and negative sentiments respectively.

9 Performance on different Domain

If we apply these features on different domains such as Laptop reviews or restaurant reviews, the unigram model might generalize fine but its not ideal.
Since bigram and trigram models contains more context of the current dataset, I don't think they can be used with other domains for proper classification.

10 Better Features for new domain

Domain	Positive	Negative
Laptop Reviews	amazing, awesome, best, better, recommended, fast, decent, enough, support, nice	bad, lag, hard, defective, complaint, damage, issues, disappointed, costly, lacks
Restaurant Reviews	tasty, delicious, good, fresh, friendly, attentive, spicy, good, nice, ambience	bad, spoiled, dirty, cold, overpriced, rude, dry, slow, bland, dull