News Classifier Group Project

Wilson Fearn, Andrew Hale, Victor Lazaro, Spencer Seeger

1 Abstract

A machine learning approach was applied to the classification of articles found online. Several different machine learning algorithms (Naïve Bayes, Random Forest, and Support Vector Machine (SVM)) were applied to a set of 8 categories. After running these models, we found that the better machine learning algorithms were accurate about 95% of the time. This project can be applied to the real world for companies such as Facebook® or Google® when those companies try to suggest articles for a specific user to read.

2 Introduction

There are many different articles in the world today (either online or printed) with many more continuously being produced. With so many articles being created, it is hard to tell if a reader will appreciate what the article is about. While it is simple enough for a reader to read and discover on their own if they like the article, it would be much easier for the reader to have an already narrowed down selection of articles that they would like to read. This can be done by suggesting articles that are of the type of information they typically read about.

With how much data there is in the world, companies such as Facebook® or Google® already know what a users interests are and can suggest things that the user will likely find interesting. By using a classifier on new articles, companies would be able to give classification to these articles and recommend the articles to user based on the prevalent subjects of the paper. This would be useful for these companies as it would be able to get users to come back to their sites more often as the users want to get more articles that they know are already interesting for them. In this project, we attempt to classify new articles from online. This was done by using 3 different machine learning algorithms. Initially, the first results that were seen were very promising, with most of the accuracies being 88% or more. After this success was seen, we attempted to further improve the accuracy by changing parameters to fine tune the learning models. After finding good parameters, the best result that was seen was produced by the Support Vector Machine (SVM) with a final accuracy of about 95%.

3 Methods and Data

3.1 Data Sources

We obtained data by accessing online news platforms such as CNN, New York Times, and TechCrunch, and copying the links to articles. After getting these links, we assigned a link to a classification based on the topic the corresponding article discussed. The classifications used are weather, technology, religion, sports, politics, satire, nature, and travel. After all the links were assigned to topics, a script was run that downloaded the article from the link and paired the text to the classification. When the data was used for training and testing the models, the text was converted into an inverse document frequency value. These values represented how many times a word appeared and was scaled to the length of its document. The inverse document frequency values were used because these values are normalized to the length of the document. In other words, longer documents are not favored over shorter documents.

3.2 Data Instance Example

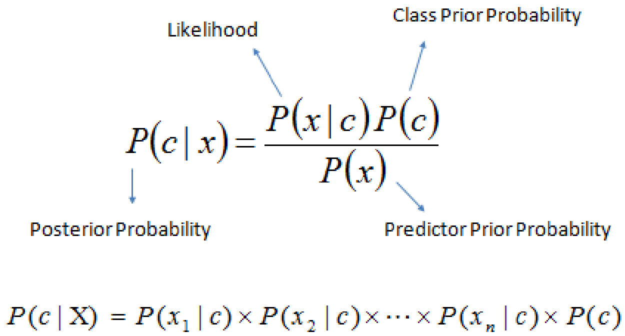
A data instance in the data set would look something like the following example, where word1, ..., wordn represent the inverse document frequency values for the words in the relevant article.

word1	...	wordn	Classification

3.3 Models

Naïve Bayes

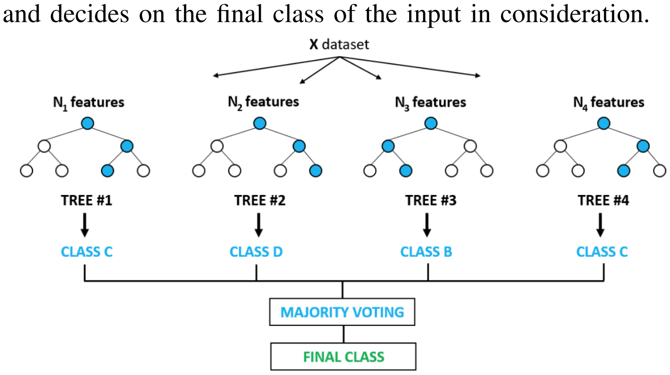
Naïve Bayes is a statistics based approach to classification. It learns the data by finding the probabilities of values occurring given some classification. After learning the input data, it then takes in unknown data and determines the probability of being an output class based upon the probability of those values showing up in the classes it was trained upon.



[1]

Random Forest

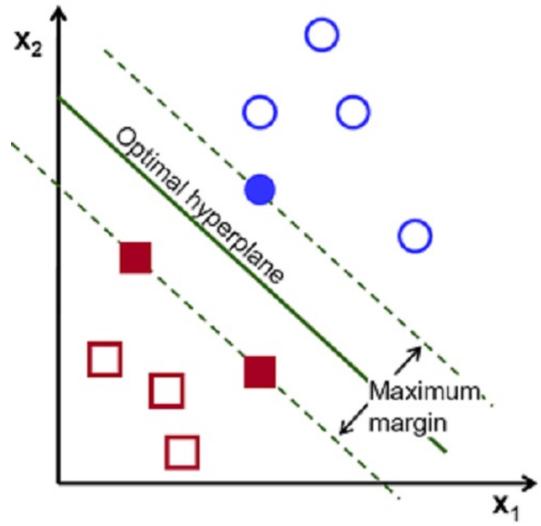
Random Forest is an example of an ensemble algorithm, combining several learning models which could contain the same kind or different kinds of machine learning algorithms. Each machine learning model votes on what the output should be, and the result is chosen by taking the most popular of those votes. The Random Forest Classifier creates several decision trees from randomly selected subsets of the training data. After each decision tree has voted, Random Forest aggregates those votes and decides on the final class of the input in consideration.



[2]

Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a classifier that fits a line to the given data similar to the way that a perceptron classifier does. The main difference between these two is that the SVM algorithm specifies characteristics about the line that cause it to fit the data better and allow for better generalized classifications that the perceptron might not be able to achieve without significantly more data. The algorithm specifies a line that separates the data in N-dimensional space, but line must divide the data in such a way that the distance between the line and the next adjoining datapoints, known as the margin, is maximized. The lines that run parallel to the dividing line and run through the next adjoining data points are called the support vectors, which is where the algorithm gets its name. For multi-class classification the algorithm trains several lines to separate the different classes, and then uses these lines to determine what class new data belongs to.



[3]

4 Initial Results

4.1 Naïve Bayes

The initial results of Nave Bayes were very promising. Nave Bayes was run with two different distributions. These distributions are a Multinomial distribution and a Bernoulli Distribution. Below is a table with the results.

Multinomial	Bernoulli
0.9119	0.7451

The Multinomial Distribution ended up having the best overall accuracy. This is because the Bernoulli distribution works better with discrete and boolean data rather than the inverse document frequency counts that were used for training.

4.2 Random Forest

In order to get a better idea of the quality of the Random Forest classifier on the news dataset, the algorithm was run with the default parameters. The most important parameters are: criterion (gini or entropy), number of estimators (number of different random trees that will vote), and min_sample_split (the minimum number of samples required to split an internal node). The defaults were gini, 10 estimators, and two samples required for splitting, resulting in an average accuracy of 0.8398 over five runs.

4.3 Support Vector Machine (SVM)

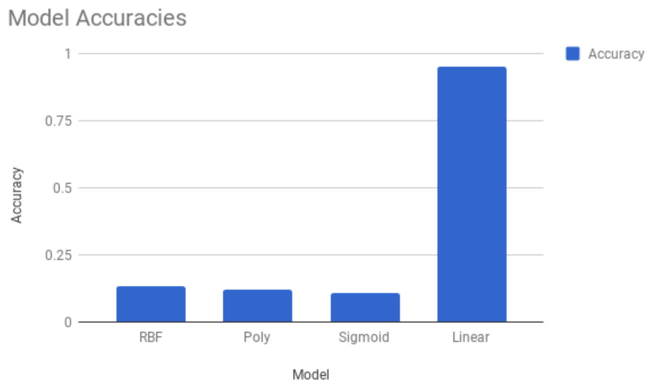
The SVM algorithm, similar to Perceptron, has different functions that can be used to model the dividing line in the data. Each is shown below along with the results of the classification with that function:

Model	Accuracy
RBF	0.1352
Poly	0.1212
Sigmoid	0.1077
Linear	0.9373

[1] http://www.saedsayad.com/naive_bayesian.htm

[2] http://www.globalsoftwaresupport.com/random-forest-classifier-bagging-machine-learning/

[3] https://aitrends.com/ai-insider/support-vector-machines-svm-ai-self-driving-cars/



The linear model vastly outperformed the others. This is most likely because different articles had word frequency values that strongly correlated with their subject, and so the word vectors plotted in vector were linearly separable. The other models had similar, poor, performance, which is likely because they tend to be used for non-linear data, and using them for linearly separable data most likely lead to significant overfitting.

4.4 Overall

From this initial analysis, SVM with the linear model seemed to yield the best results of any of them. This is because SVMs tend to work well in high-dimensional space. Typically this is because we can use a kernel trick in the SVM algorithm to transform the data to look for higher order features that may be linearly separable. However, in this case, that was unnecessary. Evidently, there were word frequency values that correlated strongly enough with each document classification that new data was largely linearly separable when plotted in N-dimensional space. This makes intuitive sense, since seeing the word Trump, for example, would be strongly correlated with the politics or satire classifications, and plotting these documents in vector space would reflect that. Since Nave Bayes uses probabilities to find its results, and Random Forest splits on individual words, they may have produced similar results by simply increasing the amount of data that we used.

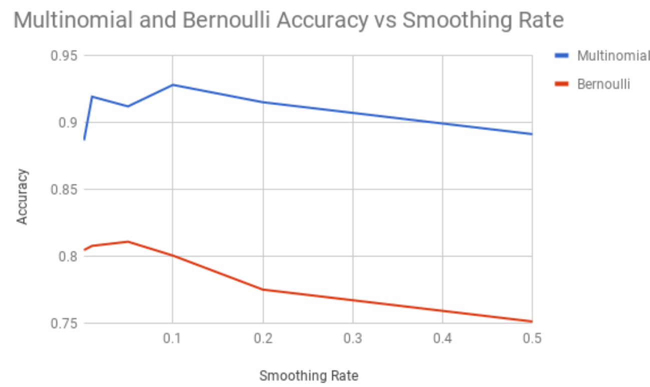
5 Model Improvement

After seeing such high accuracies with the initial results, the parameters were adjusted to see if the accuracy of the models could be improved.

5.1 Naïve Bayes

For Naïve Bayes, changing parameters were tested on both the Multinomial distribution and the Bernoulli distribution. For both of the distributions, the parameter changed was an alpha level. This alpha level corresponded to the smoothing rate that the distribution would apply to the data. By changing this smoothing rate, it tries to connect missing data points (places in the data where a number has not yet appeared) by making the fit more or less tight.

Smoothing Rate	Multinomial	Bernoulli
0.5	0.8911917098	0.7512953368
0.2	0.9150259067	0.7751295337
0.1	0.9279792746	0.8005181347
0.05	0.9119170984	0.810880829
0.01	0.8911917098	0.8077720207
0.001	0.8865284974	0.8046632124



In the graph, we can see that when the smoothing rate is too high or too low, the accuracy decreased. When the smoothing rate is too low, the probability distribution tries to overfit the training data that it has seen. When the smoothing rate is too high, the probability distribution loses some information about the probabilities and tries to treat values too similar to other numbers. As the graph also shows, the multinomial and bernoulli distributions were affected the same by the smoothing rate. This was expected since only the data was trying to be smoothed out and the distribution itself was still modeling the values given to it. In other words, both distributions reacted the same because missing data was trying to be filled in.

5.2 Random Forest

Using Scikit-Learns Random Search algorithm, we were able to train the model using several combinations of values for the parameters mentioned above in order to improve the accuracy. The table below shows the resulting accuracy of running the Random Forest tree on different parameters. Note that the Sample Split column in the following table is the Minimum size a sample needs to be to split.

Sample Split	Criterion	Estimators	Mean Acc.
2	gini	10	0.8399
2	gini	275	0.9259
2	entropy	275	0.9067
10	entropy	50	0.8948
10	entropy	275	0.9114
10	gini	275	0.9233

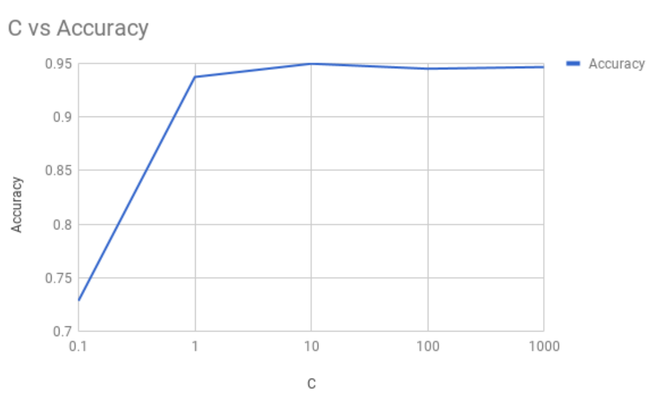
As shown above, keeping the default parameters the same, but increasing the number of voters to 275 caused an improvement of almost 9%. Note that 275 was used because it produced the best results after running random search over several parameters. This behavior was expected since the more models that are being trained, the higher the chances of the majority correctly classifying the novel instance. With a higher number of estimators, tuning the other parameters produced minimal changes. Using Gini Impurity as a measure of the quality of splitting a node resulted in a better average accuracy than regular entropy. The best results were found by using a minimum of 2 samples for splitting, Gini Impurity, and 275 estimators, which resulted in 92.5% of the test dataset being correctly classified.

5.3 SVM

The main parameter used in SVM is a parameter called C. This parameter determines how much the algorithm penalizes points being on the wrong side of the classification line. Thus, high C would tend to lead to overfitting, while a low C would increase generalization and ignore potential noise. The table below shows the results testing across different C parameters:

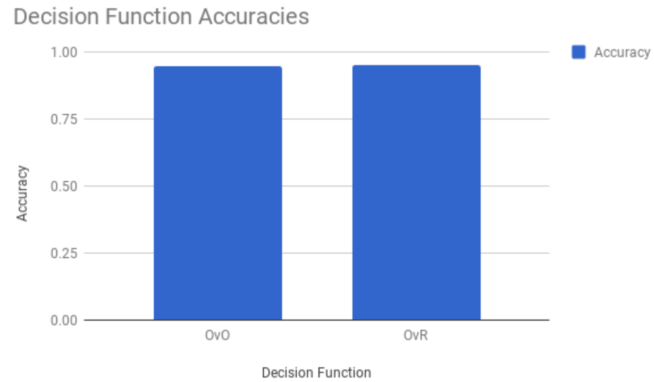
C	Accuracy
0.1	0.7284
1	0.9373
10	0.9497
100	0.945
1000	0.9466

We had the best results at a C of 10, and it is interesting to note that increasing C by orders of magnitude did little to change the results. Like we hypothesized earlier, this data was most likely linearly separable and therefore did not have many points which were on the wrong side of the classification line. This would mean that we would most likely only see a significant drop in accuracy at very high levels of C. On the other hand, we see a significant drop between a C of 1 and a C of .1. This is likely due to the program trying to generalize too much and allowing for too many exceptions.



A second parameter that we tested was the shape of the decision functions, which determines how many lines the SVM algorithm uses to separate the data. The two values for this parameter are One vs One (OvO) and One vs Rest (OvR). One vs One trains a separate classifier for each class individually against other individual classes, creating a total of $\frac{N(N-1)}{2}$ classifiers, one for each class pair. One vs Rest, on the other hand, trains a classifier for each class against all of the other classes collectively. The results for this parameter are below:

	OvO	OvR
Accuracy	0.9450	0.9497



There is little difference between the results for these two parameters, but One vs Rest did do better by a small margin. This could be due to simple chance since the accuracies are so close, but it could also have to do with ambiguity between individual classes that is not as apparent when considering all of the classes together. An example of this is with the politics and satire classes. These may be difficult to tell apart, in some cases even for humans, so a classifier meant to identify just the difference between these two would have a hard time doing so. On the other hand, a classifier that had to distinguish between politics and all the other classes collectively might have a greater chance of success. Unsurprisingly, this classifier would still have trouble telling apart categories such as politics or satire, which is why the differences between OvO and OvR are very slight.

6 Final Results

Once again, SVM outperformed both of the other algorithms, but by less than before the parameters were adjusted: Random Forest is the only algorithm that made a significant improvement, reaching 0.9259 in its best case (as compared to its initial value of 0.8398). However, SVM did make some progress (from an initial 0.9373 to 0.9497 at its best), and Naïve Bayes also had a small improvement (from an initial 0.9119 to reaching 0.9259). These results still show, though, that SVM was the best algorithm (as previously mentioned).

7 Future Work

Future work could include running a grid search to optimize the parameters used for each of these things. By using grid search, we would be able to find the optimal parameters for each algorithm and then be able to decide which algorithm was the best overall for our data classification. We would also like to expand our dataset to include satirical articles of each original classification to see if the algorithms could successfully determine between ”fake” news and actual articles.