CS221: Project Progress Report

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1 Introduction

We are tackling the problem of identifying articles that could be potentially dangerous to a brand. Our approach has two steps. First, we take in a set of articles and classify them into categories. In the final application, this could be done by pulling articles from the internet daily. Once these categories are identified, in the second step, we create an impact score for the brand in question. The articles with top impact scores can be provided to the client as having high potential for impact to the brand.

This problem has a rich application of various algorithms for natural language processing. Since proposing this project, we have explored a few algorithms to create a better sense of what an impact score can be. We looked into utilizing unsupervised learning algorithms like GloVe and supervised algorithm implementations like Naive Bayes. These have given us better impact scores. Further more, it feels like we could perform some more fine tuning to come up with better models to bring a richer understanding of the *impact score*

2 Model

2.1 Classification

In making progress for the project, we decided to give more weight to the impact score analysis section, since that's the more novel component of the solution approach. Our classification currently still uses a simple Stochastic Gradient Descent classifier. We found it's accuracy to be nearly 82 percent and thought we can improve upon that in the later parts of the project.

We still did look at using the Naive Bayes algorithm to perform classification, since that's what literature reported is it's primary use. It performed slightly better at classification than SGD but not by much.

2.2 Impact Score

Talk a bit about how GloVe and NB are good fits to calculate the impact score We explored and implemented a Naive Bayes classifier as an alternative classifier to build the model.

The Naive Bayes algorithm provides a very simple framework that builds on the probabilistic model based on training data. The algorithm is based on a statistical classification method called Bayes Theorem.

In order to understand how naive Bayes classifiers work, we can represent Bayes rule as the following probabilistic model as follows:

$$Posteriorprobability = \frac{conditionalprobability * priorprobability}{evidence}$$

Bayes' theorem forms the core of the whole concept of naive Bayes classification. The posterior probability, in the context of a classification problem, can be interpreted as: "What is the probability that a particular

object belongs to class i given its observed feature values?" The answer to this question gives us a score of how much a document is relevant to a given topic.

Impact score needs to be a number that represents how relevant or impactful will a particular article be to the brand. Hence, we extended our previous approach of having a dictionary of words that are relevant to the brand and applying some NLP algorithms to come up with a score of how closely does the article's content relate to the dictionary relevant to the brand.

3 Algorithm

3.0.1 GloVe

3.0.2 Naive Bayes

The Naive Bayes algorithm: Naive Bayes consists of multiple algorithms, like Multinomial Naive Bayes and Multi-variate Bernoulli Naive Bayes.

We found that the Multinomial Naive Bayes algorithm is well suited for our project. This is because this algorithm gives us the "term" frequency of a dictionary of words of a specific brand. The term frequency is defined as the "number of times a given term appears in a given document". In practice the term frequency is often normalized by dividing the raw term frequency by the length of the document.

The term frequency can then be used to compute the max likelihood estimate based on the training data.

The algorithm to use for training using Naive Bayes:
function Train NaiveBayes(D, C)
for each category:
Calculate the prior probability num-docs = number of docs in D
num-category = number of docs in category

$$priorprobability[category] \leftarrow log\frac{N_c}{N_{doc}}$$

V = vocabulary of D
docs[category] <- append d for d subset of D in specified category
for each word in V:
Count(w,c) <- num of occurences of w in docs[category]

$$priorprobability[category] \leftarrow log\frac{count(w,c)+1)}{\sum_w count(w,c)+|V|)}$$

return priorprobability
We can then use the priorprobability to test our data to get the maximum likleihood.

4 Implementation

5 Preliminary Results