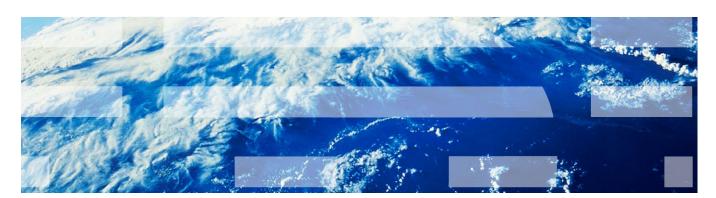


## **E6895 Advanced Big Data Analytics Final Project:**

## Recommending News Based on Twitter Profiles

Justin Tse Cindy Xu





## **Project Tasks**

The overall goal of the project is to be able to recommend news articles based off of a user's tweets. This can be separated into parts.

- Create a model that can classify the topic of a tweet.
- 2. Use the previous model to analyze a user's tweets and then generate relevant news topics.



## **Underlying Project Structure**

We will use the New York Times to generate news articles because they have a convenient API.

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We will also use the Twitter API to gather data.

### **Data Collection**



We needed to build a model that can classify the topic of a single tweet. We were unable to find a relevant labeled dataset to train our model on, so we gathered the data using the Twitter API.

For each topic, we collected roughly 40,000 tweets with the hashtag of that topic.

The topics that we focused on were:

Politics, Business, Technology, Science, Sports, Style, and Health

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Before analyzing the raw tweet data, we removed the specific hashtag, all links, lower cased the text, removed mentions, removed symbols, and stemmed the words.



Motivation: It's extremely quick to train, and it can classify tweets quickly. It is important to be able to classify tweets quickly because we want to recommend articles in real time.

I wanted to have a model that trained quickly because Twitter data is constantly changing.

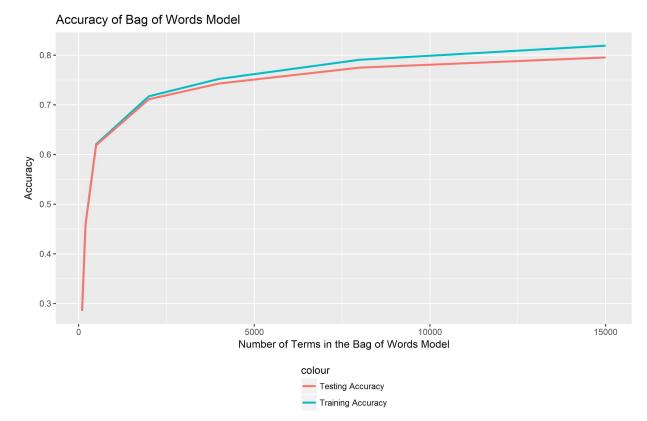
The model stores the top 15,000 terms; it takes roughly 10 seconds to analyze the past 100 tweets of a user and recommend relevant articles.



#### Accuracy on the Training and Test Set:

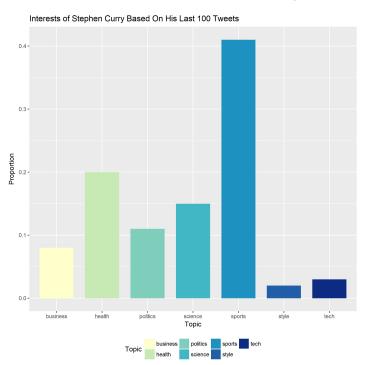
# of Terms Saved in Model	Training Accuracy	Testing Accuracy	
100	.285431	.286206	
200	.460631	.459877	
500	.620788	.618692	
2000	.717206	.711269	
8000	.790734	.774913	
15000	.819089	.795407	

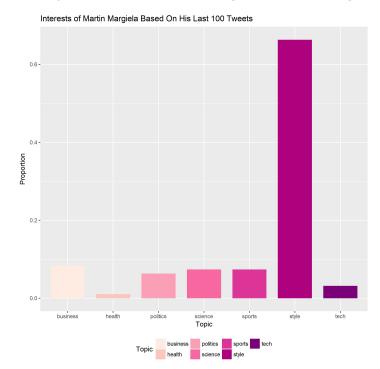






#### Example of Output for Stephen Curry (@stephencurry) and Mason Margiela (@margiela)







#### **Neural Network**

- First randomly split data into train and test with 9:1
- Then transform text into data matrix by using tokenizer with first 3000 word. It will return a dictionary with first 3000 most frequency word in dataset and their corresponding index.
- Also transform label into categorical data. Eg: Labels='politics' [1,0,0,0,0,0,0]
- Substitute data matrix and categorical label into neural network.
- Architecture: model=Sequential()

```
model.add(Embedding(3, 10, input_length=train_x.shape[1]))
model.add(Flatten())
```

3 dropout layers

Dense layer

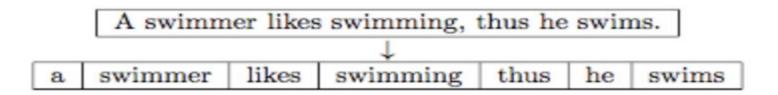


#### **Neural Network**

- Embedding layer:
- Bag of Word is Sparse.
- Word Embedding :much lower dimensional space
- Tokenization :

Describes the general process of breaking down a text corpus into individual elements that serve as input for various natural language processing algorithms.

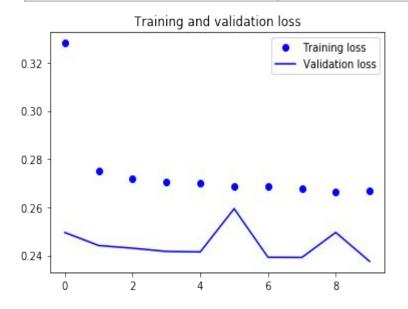
## Table 2. Example of tokenization.

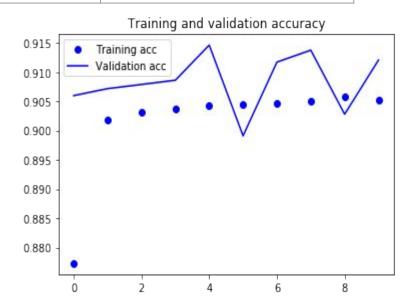




### **Neural Network**

test	train	validation
0.8351591446614018	0.9052	0.9121







## **Other Traditional Machine Learning Method**

- MultinomialNB
- LogisticRegression
- LinearSVM

RandomForest



Other Tradition	onal Machine Le	earning Method		
Model	train	test	0.8	
MultinomialNB	0.8486141216621316	0.8040192314344021	0.7	80-
LogisticRegression	0.8768197820104844	0.8161253502127218	0.6	
LinearSVM	0.9383349475011146	0.8602262114766006	0.5	
RandomForest	0.2685975187935249	0.2721801390474214	0.4 Rai	ndomForestClassifierLinearSVC MultinomialNBLogisticRegression  model_name



#### **MultinomialNB**

$$P(c|d) \propto P(c) \prod_{1 \le k \le n} P(t_k|c) \tag{113}$$

where  $P(t_k|c)$  is the conditional probability of term  $t_k$  occurring in a document of class c. We interpret  $P(t_k|c)$  as a measure of how much evidence  $t_k$  contributes that c is the correct class. P(c) is the prior probability of a document occurring in class c. If a document's terms do not provide clear evidence for one class versus another, we choose the one that has a higher prior probability.  $\langle t_1, t_2, \dots, t_{n_d} \rangle$  are the tokens in d that are part of the vocabulary we use for classification and  $n_d$  is the number of such tokens in d. For example,  $\langle t_1, t_2, \dots, t_{n_d} \rangle$  for the one-sentence document



## LogisticRegression

 Compare to project: Recommendation Product for Customers in Santander Bank.

 Logistic Regression works well for both financial dataset and text dataset.

 But Compare to Randomforest, it gives a really poor accuracy in text data.



#### RandomForest

• Reason why it performs bad: Text data is special

Shortness:

there is not enough information to measure relevant similarities between several texts.

Sparkness

text data also lacks of contextual information, especially when using vector presentation and combined with RandomForest

 Improve: use topic model technique LDA to combine features, reduce feature space size significantly



#### **LinearSVM**

• High dimensional Input Space:

SVMs use overfitting protection which does not necessarily depend on the number of features.

Few irrelevant features:

It is not easy to do feature selection.

Document vectors are sparse:

SVMs are well suited for problems with dense concepts and sparse instances.



## **Recommending News**

We use the output of the distribution given by the Bag of Words model to randomly choose topics. We then use the New York Times API to choose popular articles in those topics.

Demo: <a href="https://justintse.shinyapps.io/NewsRecTwitter/">https://justintse.shinyapps.io/NewsRecTwitter/</a>



#### News Recommendation Based on Twitter



