Who Said This?

Philosophy from a data point of view

sg4010 Sibo Geng

"One should only speak where one cannot remain silent, and only speak of what one has conquered —the rest is all chatter, “literature,” bad breeding." --Friedrich Nietzsche

I chose this quote from Nietzche not because it strike a particular chord in my heart, instead, I picked it because it set me wondering, what is the idea behind this sentence the philosopher is trying to convey? Luckily, I have data to my aid. To best utilize the data at hand, I decided to address the the challange as a supervised learning problem. Namely, the goal is to develop an algorithm that predict the school of philosophy a given sentence belongs to.

Exploratory Data Analysis

First, let's get our hands dirty and have a look at how the data's been processed

```
import pandas as pd
df = pd.read_csv("../data/philosophy_data.csv")
df.head()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

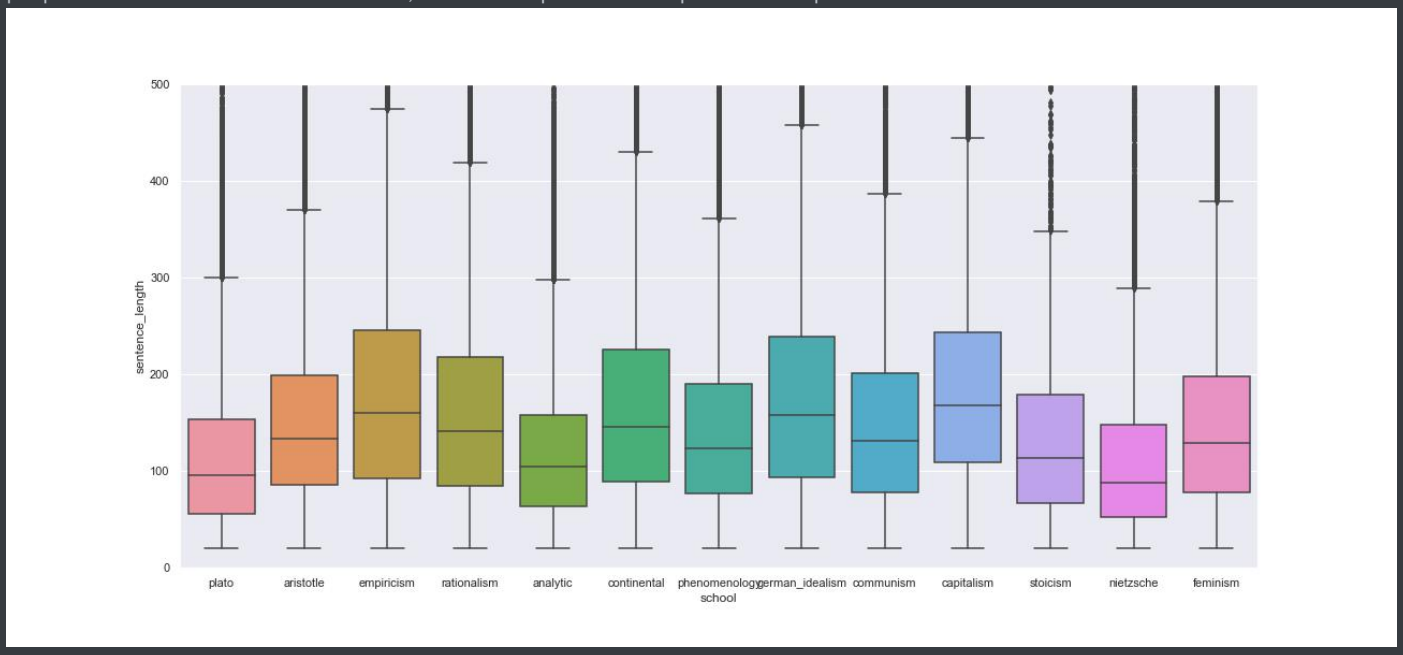
	title	author	school	sentence_spacy	sentence_str	original_publication_date	corpus_edition_date	senten
0	Plato - Complete Works	Plato	plato	What's new, Socrates, to make you leave your ...	What's new, Socrates, to make you leave your ...	-350	1997	125
1	Plato - Complete Works	Plato	plato	Surely you are not prosecuting anyone before t...	Surely you are not prosecuting anyone before t...	-350	1997	69
2	Plato - Complete Works	Plato	plato	The Athenians do not call this a prosecution b...	The Athenians do not call this a prosecution b...	-350	1997	74
3	Plato - Complete Works	Plato	plato	What is this you say?	What is this you say?	-350	1997	21
4	Plato - Complete Works	Plato	plato	Someone must have indicted you, for you are no...	Someone must have indicted you, for you are no...	-350	1997	101

Much to our convenience, the data has been thoroughly preprocessed. Here is a illustration of the process.

```
# illustration of data preprocessing pipeline
x = df.iloc[9]

print('''raw data: \n{}\n\nlowered: \n{}\n\ntokenized: \n{}\n\nlemmatized:\n{}\n'''.format( \
            x['sentence_spacy'], x['sentence_lowered'], x['tokenized_txt'], x['lemmatized_str'] ))
```

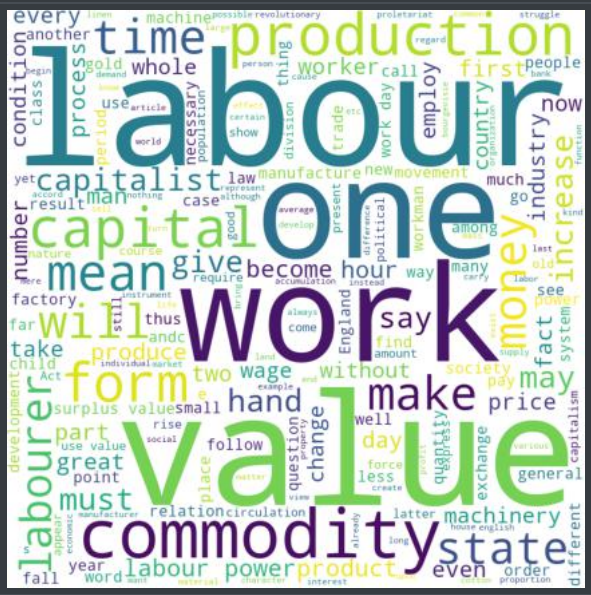
```
raw data:
He belongs to the Pitthean deme, if you know anyone from that deme called Meletus, with long hair, not much of a
beard, and a rather aquiline nose.

lowered:
he belongs to the pitthean deme, if you know anyone from that deme called meletus, with long hair, not much of a
beard, and a rather aquiline nose.

tokenized:
['he', 'belongs', 'to', 'the', 'pitthean', 'deme', 'if', 'you', 'know', 'anyone', 'from', 'that', 'deme', 'called',
'meletus', 'with', 'long', 'hair', 'not', 'much', 'of', 'beard', 'and', 'rather', 'aquiline', 'nose']

lemmatized:
 -PRON- belong to the Pitthean deme , if -PRON- know anyone from that deme call Meletus , with long hair , not much of
a beard , and a rather aquiline nose .
```

Although the text has already been cleaned and lemmatized, it still can't be fed to machines directly. We have to figure out a representation technique that map the text data to numerical values. A most naive while direct way will be taking the length of the sentence. After all some people like to use short and curt sentence, while others prefer more sophisticated expression.



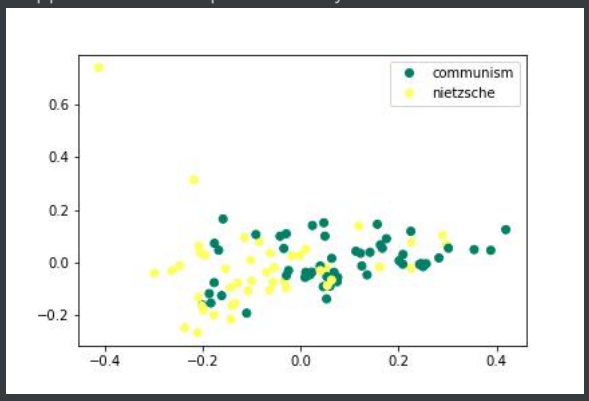
Apparently philosophers from different schools have different prefrence in sentence length, where scholars from **empiricism** and **capitalism** wrote the longest verses while **Nietzche** himself wrote the shortest sentence among all schools. However sentence length all by itself does not carry enough information for us to distinguish between different schools in philosophy. For instance, a sentence of 150 words can easily belong to any track.

To generate more specific features for each sentence, we need to dive a little deeper about the choice of word each philosopher used.

Communism	Capitalism
	

From the wordcloud shown above(larger fonts indicate higher frequency of use), we can see that the favorite vocabulary of different schools of philosophy differs significantly. Thus, by counting the apperances of words in a sentence sounds like a reasonable way to represent the sentence.

In order to have a rough estimate of the difficulty of the task, I first sampled 200 sentences from two schools, namely, **communism** and **Nietzche**, and calculated their features via the "Term Frequency — Inverse Document Frequency" technique. Then I conducted a PCA that mapped the feature space into only two dimensions for the sake of visualization. The results are as follows:

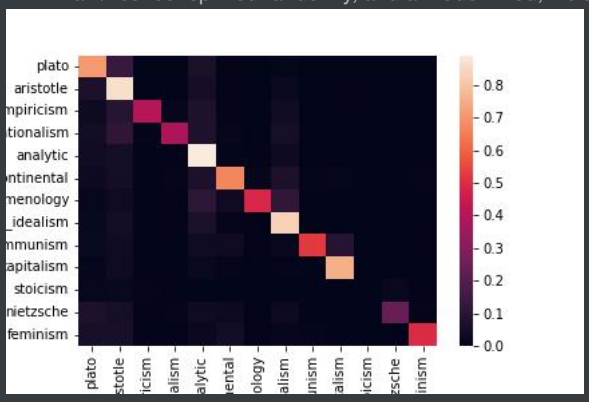


It can be seen from the scatter plot that most of the green dots are distributed on the left side of the graph, while the yellow ones are on the right. Note that the PCA process did not utilize any information concerning the school of the sentence, i.e., it is unsupervised. The result gave us hope that the **tf-idf** feature would serve as a good feature for classification task.

Naive Bayes Model

So far, we have had a rough idea of what the data looks like, and a scheme worked out to extract features from the data. In this section, I will use a **Naive Bayes Model** to categorize each sentence to corresponding school.

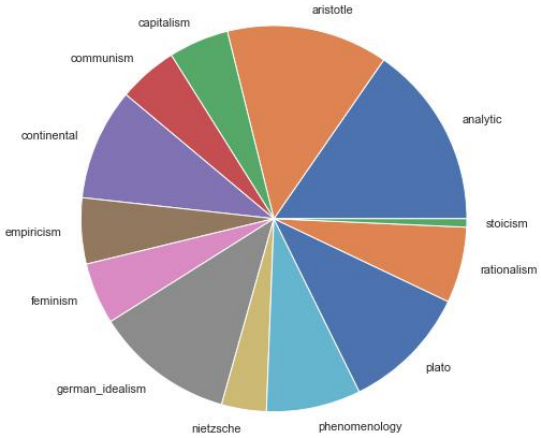
With Train/Test set splitted randomly, and a model fitted, we are ready to check out the result:



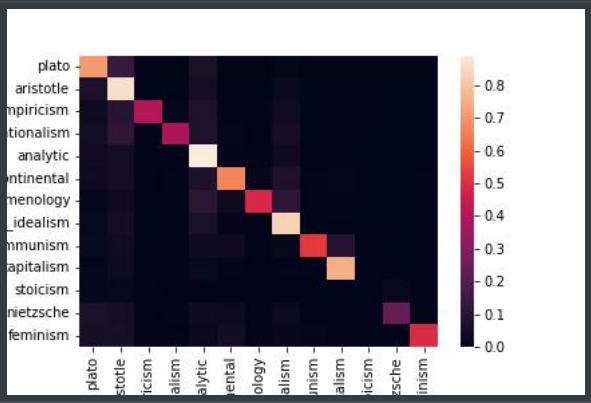
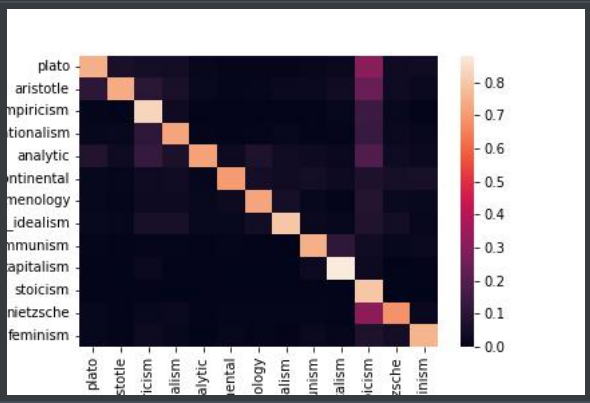
The **y-axis(vertical)** represents the ground truth label of the sentence, while the **x-aixs(horizonal)** indicates the prediction of the model. A lighter color a certain grid has, the greater probability the model prediction falls in the corresponding school, while a darker color shows the opposite. Several interesting findings caught my eyes.

1. A relatively high error rate for sentences from Stoicism

In general, our model performed pretty good, and most of the diagonal grids of the matrix have lighter color, indicating the prediction by our model is correct.However,the model falsely predicts many sentences from **Stoicism** as other school's. After a closer look, I found this phenomenon can be explained by the imbalanced distribution of training data.



As shown by the pie chart above, the sentence number from stoicism takes up the smallest proportion among all training data. With some over-sampling from the minor categories, we are able to alleviate the problem.

before	after
	

2. Dimension of feature space is too large

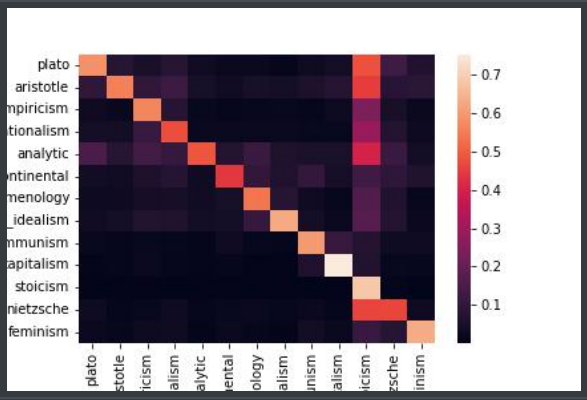
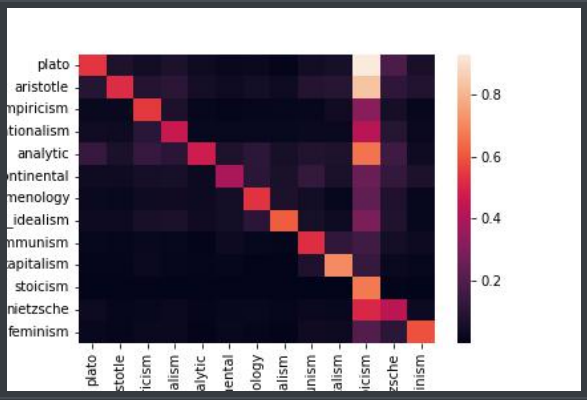
The featurization method we used here is equivalent to creating a one-hot vector whose length is equal to the number of vocabulary present in all texts. Such a feature vector is easy to create, but due to its large scale, it becomes impossible to run many machine learning algorithms in reasonable time. Are all these dimensions/words equally important to our classification task? Luckily we can derive each word's importance from the coeficients of the trained **Naive Bayes** model.

model learned	frequency
	

The left word cloud shows the words that the model found most **informative** that suggest a sentence belongs to school **Capitalism**. The right word cloud is the most frequent words that appear in **Capitalism** philosophers' works. We see that the model deemed words like "money" and "price" of great importance, which is in accordance with our intuition.

The above study gives us an inspiration that we may only consider the union of most important words for all schools to help reduce the size of vocabulary, thus reducing our feature dimension.

Pursuing this track of thought, I conducted a comparison experiment. The configurations are as follow:

config	Experiment	Baseline
feature	Union of top features by original NB model	Words of highest frequency, same size as exp config
confusion matrix		
F1 score	0.56	0.53

From the confusion matrix shown above, we can easily see that by utilizing knowledge obtained by **Naive Bayes** model, we are able to better select features. The quantative result also supports the conclusion.

Application

I pulled from the internet several quotes from former president **Donald Trump**. The original data looks like this:

```
test_df = pd.read_csv("../data/trump_quote.csv")
test_df.head()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	raw_data
0	I deal with foreign countries. I made a lot of...
1	With the coldest winter ever recorded, with sn...
2	I don't like to sit back and gloat, because th...
3	This very expensive GLOBAL WARMING bullshit ha...
4	A lot of people want me to run for things, for...

Interesting enough, our model categorized 3 out of the 5 quotes as of school **Plato**. One possible explanation is that in his work *The Republic*, **Plato** wrote his lines in conversations, using many first personal pronouns, which is just like the quotes from **Trump**.

Summary

To draw a conclusion of this project, we have explored the text data, looked into the subject of hand-crafted feature for text data, and trained a compact but pretty decent model to predict the label of sentences, and finally used it on some real-world test data. The take home message are:

1. sentence length is informative, but not deterministic.
2. unbalanced class distribution may affect NB model performance, oversampling can help.
3. the most frequently appeared words are not necesssarily the most *important* ones.
4. deep in his heart, Donald Trump believes in Plato's idea.

Refrence

1. data cleansing pipeline: https://towardsdatascience.com/preprocessing-text-data-using-python-576206753c28
2. matplotlib usage: http://c.biancheng.net/matplotlib/boxplot.html
3. PCA: https://stackoverflow.com/questions/28160335/plot-a-document-tfidf-2d-graph
4. machine learning pipeline(data preparation, metrics): https://www.kaggle.com/ludovicocuoghi/detecting-bullying-tweets-w-pytorch-bi-lstm/notebook
5. sci-kit learn Naive Bayes model interpretation: https://stackoverflow.com/questions/50526898/how-to-get-feature-importance-in-naive-bayes
6. wordcloud visualization: https://stackoverflow.com/questions/62563242/how-to-visualize-the-size-of-a-word-depending-on-its-value
7. Donald Trump quotes: https://www.inspiringquotes.us/author/8279-donald-trump