Natural Language Processing Project

Welcome to the NLP Project for this section of the course. In this NLP project you will be attempting to classify Yelp Reviews into 1 star or 5 star categories based off the text content in the reviews. This will be a simpler procedure than the lecture, since we will utilize the pipeline methods for more complex tasks.

We will use the [Yelp Review Data Set from Kaggle](https://www.kaggle.com/c/yelp-recsys-2013).

Each observation in this dataset is a review of a particular business by a particular user.

The "stars" column is the number of stars (1 through 5) assigned by the reviewer to the business. (Higher stars is better.) In other words, it is the rating of the business by the person who wrote the review.

The "cool" column is the number of "cool" votes this review received from other Yelp users.

All reviews start with 0 "cool" votes, and there is no limit to how many "cool" votes a review can receive. In other words, it is a rating of the review itself, not a rating of the business.

The "useful" and "funny" columns are similar to the "cool" column.

Let's get started! Just follow the directions below!

Imports

Import the usual suspects. :)

In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

The Data

Read the yelp.csv file and set it as a dataframe called yelp.

In [3]:
```
yelp = pd.read_csv('yelp.csv')
```

Check the head, info , and describe methods on yelp.

In [4]:
```
yelp.head(2)
```

Out[4]:

	business_id	date	review_id	stars	text	type	user_id	cool	useful	funny
0	9yKzy9PApeiPPOUJEtnvkg	2011-01-26	fWKvX83p0-ka4JS3dc6E5A	5	My wife took me here on my birthday for breakf...	review	rLtl8ZkDX5vH5nAx9C3q5Q	2	5	0
1	ZRJwVLyzEJq1VAihDhYiow	2011-07-27	IjZ33sJrzXqU-0X6U8NwyA	5	I have no idea why some people give bad review...	review	0a2KyEL0d3Yb1V6aivbIuQ	0	0	0

In [5]:
```
yelp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   business_id  10000 non-null  object
 1   date         10000 non-null  object
 2   review_id    10000 non-null  object
 3   stars        10000 non-null  int64 
 4   text         10000 non-null  object
 5   type         10000 non-null  object
 6   user_id      10000 non-null  object
 7   cool         10000 non-null  int64 
 8   useful       10000 non-null  int64 
 9   funny        10000 non-null  int64 
dtypes: int64(4), object(6)
memory usage: 781.4+ KB
```

In [6]:

```
yelp.describe()
```

Out[6]:

	stars	cool	useful	funny
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	3.777500	0.876800	1.409300	0.701300
std	1.214636	2.067861	2.336647	1.907942
min	1.000000	0.000000	0.000000	0.000000
25%	3.000000	0.000000	0.000000	0.000000
50%	4.000000	0.000000	1.000000	0.000000
75%	5.000000	1.000000	2.000000	1.000000
max	5.000000	77.000000	76.000000	57.000000

Create a new column called "text length" which is the number of words in the text column.

In [7]:

```
yelp['text length'] = yelp['text'].apply(len)
```

EDA

Let's explore the data

Imports

Import the data visualization libraries if you haven't done so already.

In [8]:

```
#The libraries have already been imported
# We just want to set the style

sns.set_style('white')
```

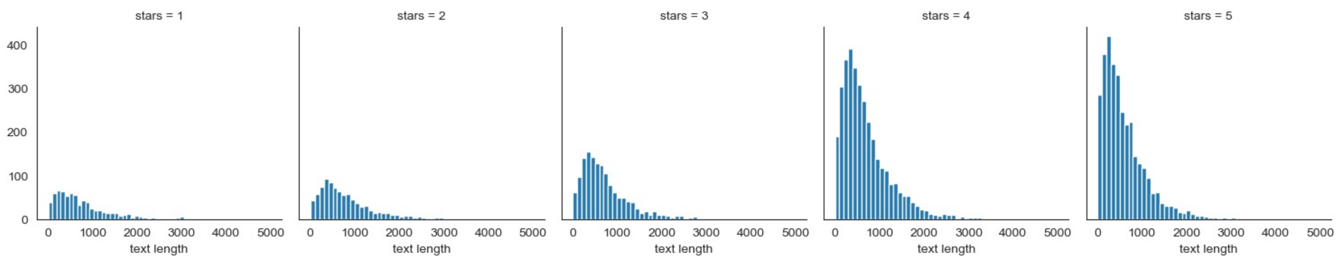
Use FacetGrid from the seaborn library to create a grid of 5 histograms of text length based off of the star ratings. Reference the seaborn documentation for hints on this

In [10]:

```
g = sns.FacetGrid(yelp,col='stars')
g.map(plt.hist,'text length',bins=50)
```

Out[10]:

```
<seaborn.axisgrid.FacetGrid at 0x2465c3dfd60>
```



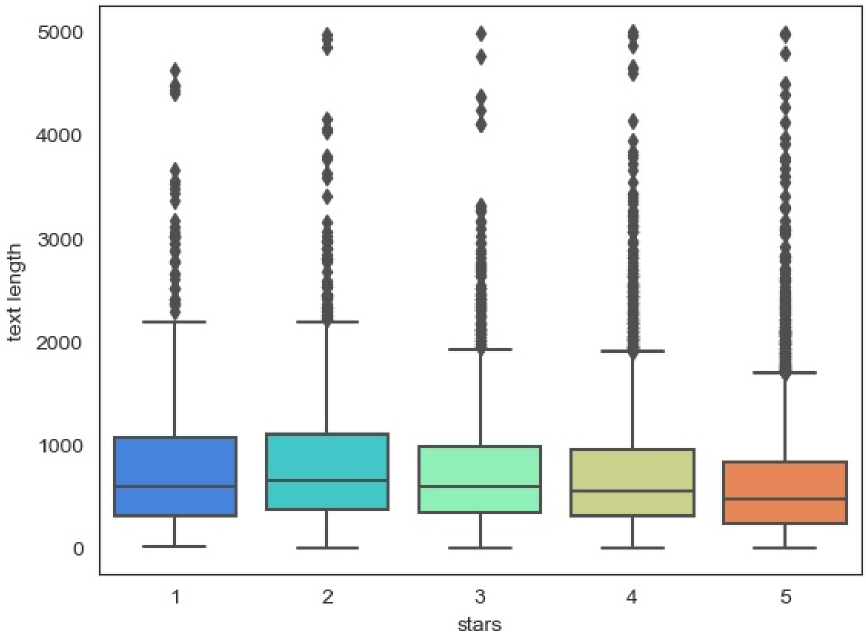
Create a boxplot of text length for each star category.

In [12]:

```
sns.boxplot(x='stars',y='text length',data=yelp,palette='rainbow')
#There are so much outliers. So this may not be useful
```

Out[12]:

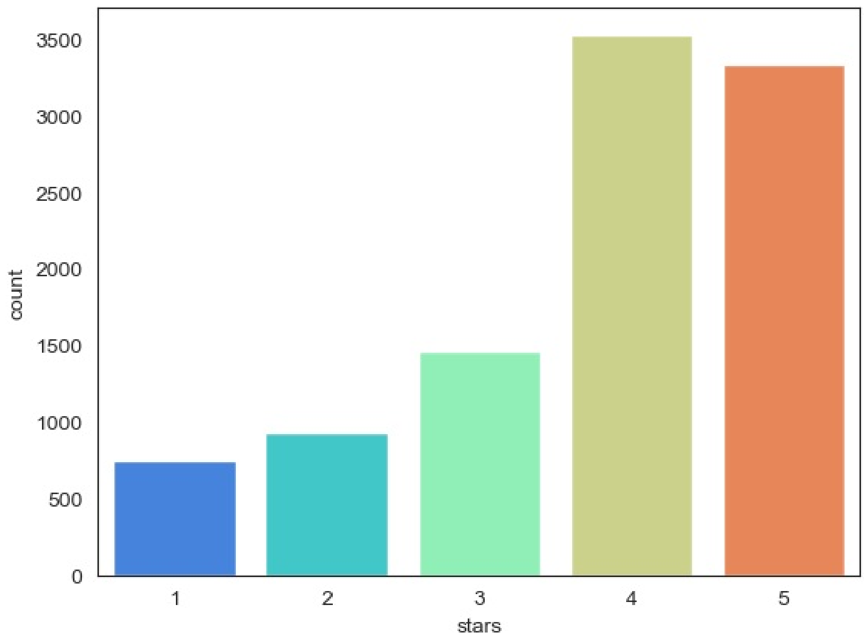
```
<AxesSubplot:xlabel='stars', ylabel='text length'>
```



Create a countplot of the number of occurrences for each type of star rating.

In [14]:
```
sns.countplot(x='stars',data=yelp,palette='rainbow')
```

Out[14]: <AxesSubplot:xlabel='stars', ylabel='count'>



Use groupby to get the mean values of the numerical columns, you should be able to create this dataframe with the operation:

In [15]:
```
stars = yelp.groupby('stars').mean()
stars
```

Out[15]:

stars	cool	useful	funny	text length
1	0.576769	1.604806	1.056075	826.515354
2	0.719525	1.563107	0.875944	842.256742
3	0.788501	1.306639	0.694730	758.498289
4	0.954623	1.395916	0.670448	712.923142
5	0.944261	1.381780	0.608631	624.999101

Use the corr() method on that groupby dataframe to produce this dataframe:

In [16]:
```
stars.corr()
```

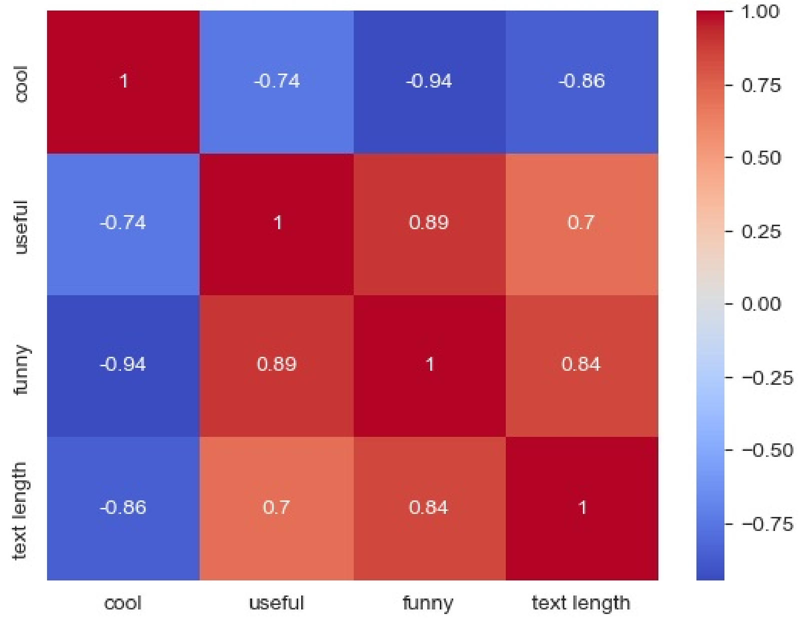
Out[16]:

	cool	useful	funny	text length
cool	1.000000	-0.743329	-0.944939	-0.857664
useful	-0.743329	1.000000	0.894506	0.699881
funny	-0.944939	0.894506	1.000000	0.843461
text length	-0.857664	0.699881	0.843461	1.000000

Then use seaborn to create a heatmap based off that .corr() dataframe:

In [17]:
```
sns.heatmap(stars.corr(),cmap='coolwarm',annot=True)
```

Out[17]:
```
<AxesSubplot:>
```



NLP Classification Task

Let's move on to the actual task. To make things a little easier, go ahead and only grab reviews that were either 1 star or 5 stars.

Create a dataframe called yelp_class that contains the columns of yelp dataframe but for only the 1 or 5 star reviews.

In [20]:
```
yelp_class = yelp[(yelp['stars']==1) | (yelp['stars']==5)]
#Let's check if it was effective
yelp_class.info() #It was as we only get 4086 entries out of 9999
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4086 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   business_id  4086 non-null   object
 1   date         4086 non-null   object
 2   review_id    4086 non-null   object
 3   stars        4086 non-null   int64 
 4   text         4086 non-null   object
 5   type         4086 non-null   object
 6   user_id      4086 non-null   object
 7   cool         4086 non-null   int64 
 8   useful       4086 non-null   int64 
 9   funny        4086 non-null   int64 
 10  text length  4086 non-null   int64 
dtypes: int64(5), object(6)
memory usage: 383.1+ KB
```

Create two objects X and y. X will be the 'text' column of yelp_class and y will be the 'stars' column of yelp_class. (Your features and target/labels)

In [21]:
```
X = yelp_class['text']
y = yelp_class['stars']
```

Import CountVectorizer and create a CountVectorizer object.

In [22]:
```
from sklearn.feature_extraction.text import CountVectorizer
cv = CountVectorizer()
```

Use the fit_transform method on the CountVectorizer object and pass in X (the 'text' column). Save this result by overwriting X.

In [23]:
```
X = cv.fit_transform(X)
```

Train Test Split

Let's split our data into training and testing data.

Use train_test_split to split up the data into X_train, X_test, y_train, y_test. Use test_size=0.3 and random_state=101

In [24]:
```
from sklearn.model_selection import train_test_split
```

In [25]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=101)
```

Training a Model

Time to train a model!

Import MultinomialNB and create an instance of the estimator and call is nb

In [28]:
```
from sklearn.naive_bayes import MultinomialNB
nb = MultinomialNB()
```

Now fit nb using the training data.

In [29]:
```
nb.fit(X_train,y_train)
```

Out[29]:
```
MultinomialNB()
```

Predictions and Evaluations

Time to see how our model did!

Use the predict method off of nb to predict labels from X_test.

In [30]:
```
predictions = nb.predict(X_test)
```

Create a confusion matrix and classification report using these predictions and y_test

In [31]:
```
from sklearn.metrics import confusion_matrix,classification_report
```

In [32]:
```
print(confusion_matrix(y_test,predictions))
print('\n')
print(classification_report(y_test,predictions))
```

```
[[159  69]
 [ 22 976]]


              precision    recall  f1-score   support

           1       0.88      0.70      0.78       228
           5       0.93      0.98      0.96       998

    accuracy                           0.93      1226
   macro avg       0.91      0.84      0.87      1226
weighted avg       0.92      0.93      0.92      1226
```

Great! Let's see what happens if we try to include TF-IDF to this process using a pipeline.

Using Text Processing

Import TfidfTransformer from sklearn.

In [41]:
```
from sklearn.feature_extraction.text import TfidfTransformer
```

Import Pipeline from sklearn.

In [42]:
```
from sklearn.pipeline import Pipeline
```

Now create a pipeline with the following steps:CountVectorizer(), TfidfTransformer(),MultinomialNB()

In [44]:
```
pipe = Pipeline([('bow',CountVectorizer()),
```

```
                 ('tfidf',TfidfTransformer()),
                 ('model', MultinomialNB())])
```

Using the Pipeline

Time to use the pipeline! Remember this pipeline has all your pre-process steps in it already, meaning we'll need to re-split the original data (Remember that we overwrote X as the CountVectorized version. What we need is just the text

Train Test Split

Redo the train test split on the yelp_class object.

In [45]:
```
X = yelp_class['text']
y = yelp_class['stars']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=101)
```

Now fit the pipeline to the training data. Remember you can't use the same training data as last time because that data has already been vectorized. We need to pass in just the text and labels

In [46]:
```
pipe.fit(X_train,y_train)
```

Out[46]:
```
Pipeline(steps=[('bow', CountVectorizer()), ('tfidf', TfidfTransformer()),
                ('model', MultinomialNB())])
```

Predictions and Evaluation

Now use the pipeline to predict from the X_test and create a classification report and confusion matrix. You should notice strange results.

In [47]:
```
#Overwriting predictions
predictions = pipe.predict(X_test)
```

In [48]:
```
print(confusion_matrix(y_test,predictions))
print('\n')
print(classification_report(y_test,predictions))
```

```
[[  0 228]
 [  0 998]]


              precision    recall  f1-score   support

           1       0.00      0.00      0.00       228
           5       0.81      1.00      0.90       998

    accuracy                           0.81      1226
   macro avg       0.41      0.50      0.45      1226
weighted avg       0.66      0.81      0.73      1226
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning: Pre
cision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division
` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning: Pre
cision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division
` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning: Pre
cision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division
` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Looks like Tf-Idf actually made things worse! That is it for this project. But there is still a lot more you can play with:

Some other things to try.... Try going back and playing around with the pipeline steps and seeing if creating a custom analyzer like we did in the lecture helps (note: it probably won't). Or recreate the pipeline with just the CountVectorizer() and NaiveBayes. Does changing the ML model at the end to another classifier help at all?

Great Job!