

# Web\_Analytics\_Project

September 9, 2021

```
[ ]: # Internal vs. External Company Reputation
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## Outline of Project

- First steps
  - Input company variable
  - Format for Glassdoor URL
  - Already set for Tweepy
- Using Tweepy and For loop from previous assignments for tweets and Glassdoor review
  - Pulling from Bonus lecture
  - Homework 2+3
- Cleaning data set + Print word cloud
  - split() function
  - Normalization (stemming and lemmatization)
  - Remove stop words (remove\_noise function)
  - Categorize text (3 different classifiers)
  - Top 30 positive and negative words using Word Cloud
- 2 models (mix and match with different classifiers)
- Print confusion matrix, sensitivity, specificity, accuracy, and model with best accuracy

Resources (CITE in code and at the end too) \* <https://www.kaggle.com/adeipvenugopal/sentiment-analysis-of-glassdoor-review>

- <https://www.kaggle.com/sid321axn/natural-language-processing-sentiment-analysis>  
<https://vu-d.gitbook.io/journey/data-analytics/glassdoor-scrape>
- <https://www.digitalocean.com/community/tutorials/how-to-perform-sentiment-analysis-in-python-3-using-the-natural-language-toolkit-nltk>
- [https://scikit-learn.org/stable/modules/generated/sklearn.feature\\_extraction.text.CountVectorizer.html](https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html)
- <https://realpython.com/beautiful-soup-web-scraper-python/>
- <https://www.kaggle.com/sid321axn/natural-language-processing-sentiment-analysis>

```
[ ]: # Tweepy allows us to access the twitter API in python
import tweepy as tw

# Pandas will allow us to extract tweets/users and load the data into dataframe
import pandas as pd
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# JSON will allow us to work with JSON files
import json

# json_normalize() will allows us to normalize semi-structured JSON data into a
→ flat table
from pandas.io.json import json_normalize

# Variables that contain the credentials to access Twitter API
# Use your own key and tokens instead
consumer_key    = "rMgBcDkAEiDKJHnIjkh8nwnLa"
consumer_secret = "y7jA77Bmr4rWUAdC5yImz1YBGtTVagTSwWqVciT0Kan6aQW1b5"
access_key      = "1326566976672641025-TbwphBECIG0u3FSZy3xbs1P7tHosI1"
access_secret   = "x0pVhadxslvb0fE6qxFVBSKRL1pxXJQ3A8lqeUXQug9P1"

# Setup access to API
auth = tw.OAuthHandler(consumer_key, consumer_secret)
auth.set_access_token(access_key, access_secret)

# create the API object
api = tw.API(auth)

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[ ]: # Twitter: External Reputation

# Begin code from https://www.earthdatascience.org/courses/
→ use-data-open-source-python/intro-to-apis/twitter-data-in-python/

# Define the search term and the date_since date as variables
# Ignoring all retweets by adding -filter:retweets
company = input('Please enter a company: ')

# Filtering out retweets
company_twitter = company + '-filter:retweets'

# pulling from 2016
date_since = "2018-11-16"

# Searching for tweets with the keyword as the company
tweets = tw.Cursor(api.search,
                    q=company_twitter,
                    lang="en",
                    since=date_since).items(140)

# Starting with an empty list to make a for loop
company_tweets = []

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# Adding only the text of tweet to the list
for tweet in tweets:
    curr_tweet = tweet.text
    company_tweets.append(curr_tweet)

# End code from https://www.earthdatascience.org/courses/
→use-data-open-source-python/intro-to-apis/twitter-data-in-python/

#company_tweets

```

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[ ]: # Indeed: Internal reputation

# Import the necessary libraries
import requests
import re
import bs4
from bs4 import BeautifulSoup
import pandas as pd
import time

# Create an empty list to add our data to
internal_review_data = []

# Using company variable from previous chunk

# Format the company name so that it works in the URL for our web parser
if ' ' in company:
    company = company.replace(' ', '-')

webpage = "https://www.indeed.com/cmp/"+company+"/reviews?fcountry=ALL"
k = 20
PageNum = 7

# Creating a for loop to scrape movie data from number of pages provided
for i in range(1, PageNum + 1):

    # First page is different from the rest, so I made an if statement to give
    →it a custom url
    if i == 1:
        current_page = webpage

    # All other pages have this layout for the url
    else:
        current_page = webpage + '&start='+ str(k)
        k +=20

    #conducting a request of the stated URL above:

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page = requests.get(current_page)
html = page.content
#specifying a desired format of "page" using the html parser - this allows
→python to read the various components of the page, rather than treating it
→as one long string.
soup = BeautifulSoup(html.decode('ascii', 'ignore'), 'lxml')
reviews = soup.findAll('div', {'class':re.compile('cmp-Review-container')})

for review in reviews:
    review_header, review_text, review_pros, review_cons, review_rating =
→'NA', 'NA', 'NA', 'NA', 'NA'

    # Find the text for the header
    head = review.find('a', {'href':re.compile('/cmp/'+company+'/reviews/
→')})
    if head:
        review_header = head.text.strip()

    # Find the text for the main review text
    txt = review.find('div', {'class':re.compile('cmp-Review-text')})
    if txt:
        review_text = txt.text.strip()

    # Find the text from the pros/cons sections
    pros = review.find('div', {'class':re.
→compile('cmp-ReviewProsCons-prosText')})
    if pros:
        review_pros = pros.text.strip()

    cons = review.find('div', {'class':re.
→compile('cmp-ReviewProsCons-consText')})
    if cons:
        review_cons = cons.text.strip()

    # Find the number (out of 5) given as the rating
    rating = review.find('button', {'class':re.
→compile('cmp-ReviewRating-text')})
    if rating:
        review_rating = rating.text.strip()

    combined = review_text + review_pros + review_cons + review_rating
    # Add all of our data to the empty list we created earlier
    internal_review_data.append([review_header, review_text, review_pros,
→review_cons, review_rating])

```

```
[ ]: # Import the necessary libraries
import pandas as pd
import numpy as np
import matplotlib as plt
import seaborn as sns

# Format our data into a Pandas data frame
internal_company_review_df = pd.DataFrame(internal_review_data, columns =
    ↳['Header', 'Review Text', 'Pros', 'Cons', 'Rating'])

# Create an empty list to append whether a review was positive (1) or not (0)
↳and add to our Pandas data frame
internal_positive_review = []

for i in range(len(internal_company_review_df)):
    # Criteria for positivity is a review rating > than 3.0 as this is considered
    ↳"neutral"
    if internal_company_review_df['Rating'][i] > '3.0':
        internal_positive_review.append(1)
    else:
        internal_positive_review.append(0)

# Add the built up list to our Pandas data frame
internal_company_review_df['Positive'] = internal_positive_review
#print(internal_company_review_df)
```

	Header	...	Positive
0	It's a fun place	...	1
1	Google is getting political	...	0
2	Idkk	...	0
3	Very Beautiful place to work	...	1
4	Google	...	1
..	...	...	...
100	Productive and Fun work place	...	1
101	Good place to work	...	1
102	Very supportive environment	...	1
103	Great peace of mind	...	1
104	1	...	1

[105 rows x 6 columns]

```
[ ]: from nltk.corpus import stopwords
import nltk
nltk.download('stopwords')

# Clean the stop word and return clean data
def clean_the_stop_word(info):
```

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stop_words = stopwords.words('english')
# print(stop_words)
# except the stop word
clean_word = [word for word in info if word not in stop_words]
return clean_word

```

[nltk\_data] Downloading package stopwords to /root/nltk\_data...

[nltk\_data] Unzipping corpora/stopwords.zip.

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[ ]: # count the sentiment score by word
from textblob import TextBlob

# the score is between -1 and 1
# [0, 1] means positive
# [-1, 0] means negative
def get_score(word):
    blob = TextBlob(word)
    # print(blob.sentiment[0])
    return blob.sentiment[0]

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[ ]: import nltk

nltk.download('punkt')
# cut down the text by nltk
def cut_down_text_to_words(text):
    # convert text list to a string
    text_string = " ".join(text)
    # cut down the words
    words = nltk.word_tokenize(text_string)
    return words

```

[nltk\_data] Downloading package punkt to /root/nltk\_data...

[nltk\_data] Unzipping tokenizers/punkt.zip.

[ ]:

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[ ]: from numpy import *

# convert text to words

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def convert_text_to_one_dimensional(text):
    word_list = []
    # flatten the list
    word_list = array(text)
    # convert multi-dimensional data to one-dimensional data
    word_list = word_list.flatten()
    # convert to list
    word_list = list(word_list)
    return word_list
```

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[ ]: # Plot the word cloud
from wordcloud import wordcloud
import matplotlib.pyplot as plt
import collections

def plot_word_cloud(all_word, name):

    # clean the data
    all_word = clean_the_stop_word(all_word)

    # init a dict
    dict_table_pos = collections.defaultdict(float)
    dict_table_neg = collections.defaultdict(float)

    # loop the positive word
    for w in all_word:
        # count the score
        score = get_score(w)
        # if score > 0 is positive word
        if score > 0:
            dict_table_pos[w] = score
        # if score < 0 is negative word
        if score < 0:
            dict_table_neg[w] = score

    # sort the positive result table
    dict_table_pos = sorted(dict_table_pos.items(), key=lambda x: x[1],
↪reverse=True)

    # sort the negative result table
    dict_table_neg = sorted(dict_table_neg.items(), key=lambda x: x[1],
↪reverse=False)

    # get top 30 positive words
```

```

pos_list = []

# if the number is bigger than 30
if len(dict_table_pos) >= 30:
    # copy value to post_list
    for k,v in dict_table_pos[:30]:
        pos_list.append(k)
else:
    for k,v in dict_table_pos:
        pos_list.append(k)

# get top 30 negative words
neg_list = []

if len(dict_table_neg) >= 30:
    for k, v in dict_table_neg[:30]:
        neg_list.append(k)
else:
    for k, v in dict_table_neg:
        neg_list.append(k)

# convert list to string gap by blank
# print(pos_list)
# print(neg_list)
pos_list = " ".join(pos_list)
neg_list = " ".join(neg_list)

# combine positive and negative list
result = pos_list + neg_list

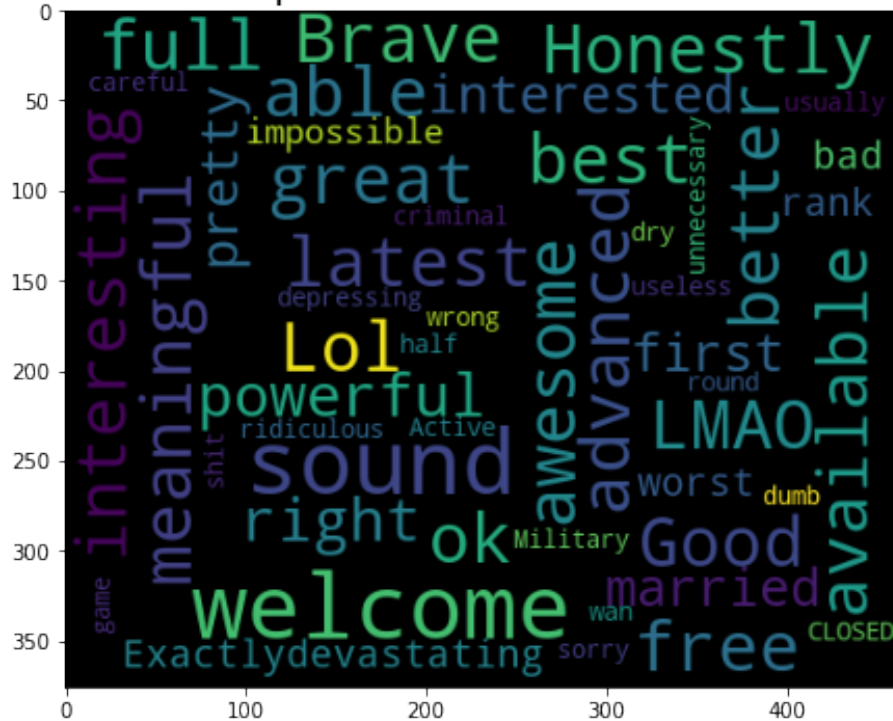
# print the cloud
# confit the base info
wc = wordcloud.WordCloud(
    # backgroud_color='black',
    width=1000,
    height=600,
    max_font_size=50,
    min_font_size=10,
    mask=plt.imread('https://pic1.zhimg.com/
↪v2-b76b4152e6bfe6e6f15d46e4f7f1b83c_r.jpg'),
    max_words=60
)
# generate the img
wc.generate(result)
# edit parameters of the word cloud image
plt.figure(figsize=(8,6))

```





## Top 30 most frequent words on Twitter about Google



```
[ ]: # Using our sentiment score function, apply it to our Indeed and Twitter data
      ↪ to create a sentiment visualization

# Create empty lists to append our sentiment scores and number of 'positive' or
      ↪ 'negative' words
tweet_sentiment = []
indeed_sentiment = []
sentiment_results_t = []
sentiment_results_i = []

# Get our sentiment score for each word in our Indeed data
for i in range(len(words)):
    indeed_sentiment.append(get_score(words[i]))
# Get our sentiment score for each word in our Twitter data
for i in range(len(tweets)):
    tweet_sentiment.append(get_score(tweets[i]))

# Create a list with the number of positive/negative sentiments for both sets
      ↪ of data
for score in indeed_sentiment:
    if score > 0:
        sentiment_results_i.append('positive')
```

```

elif score < 0:
    sentiment_results_i.append('negative')

for score in tweet_sentiment:
    if score > 0:
        sentiment_results_t.append('positive')
    elif score < 0:
        sentiment_results_t.append('negative')

import seaborn as sns

# Plot the sentiment scores
plt.figure(figsize=(10, 8))
sns.set(style="darkgrid")
sns.countplot(x=sentiment_results_i, order=['positive', 'negative']).
    ↳set_title(company+' Indeed Sentiment', fontsize=28)

plt.figure(figsize=(10, 8))
sns.set(style="darkgrid")
sns.countplot(x=sentiment_results_t, order=['positive', 'negative']).
    ↳set_title(company+' Tweet Sentiment', fontsize=28)

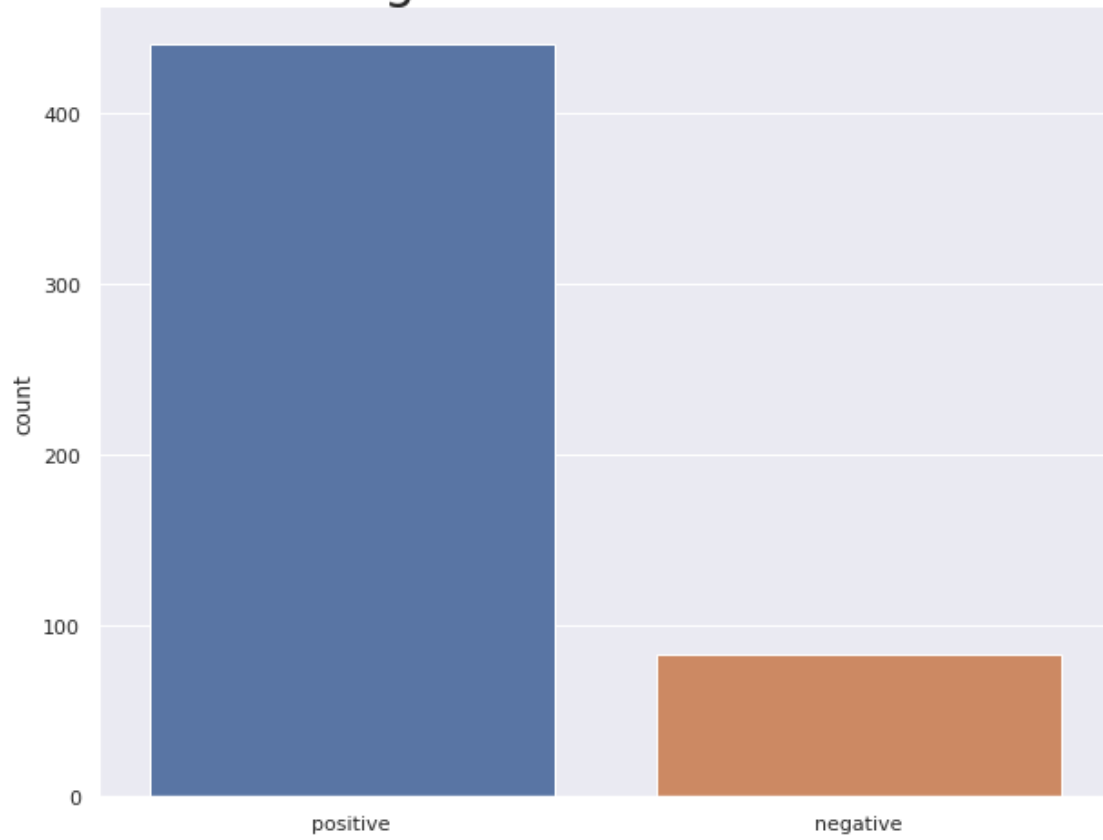
```

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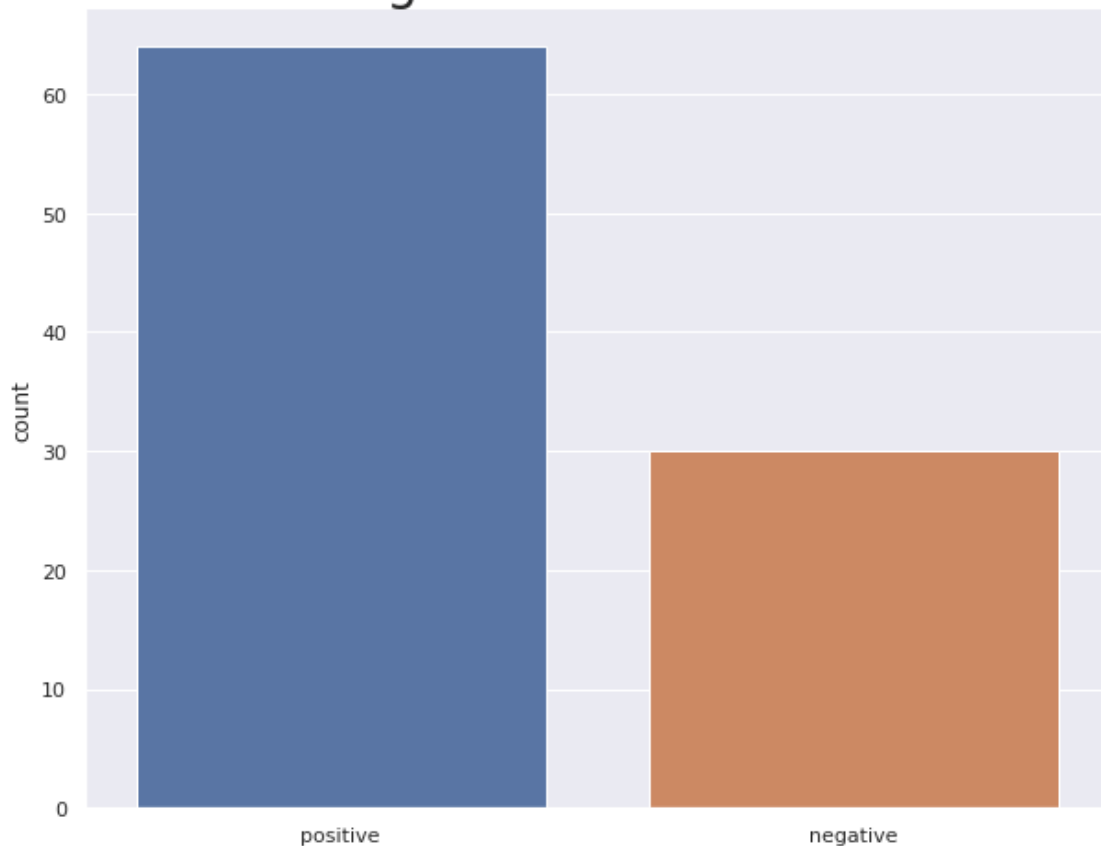
[ ]: Text(0.5, 1.0, 'Google Tweet Sentiment')

```

## Google Indeed Sentiment



## Google Tweet Sentiment



```
[ ]: # Calculating positivity score
positivity_score_i = sentiment_results_i.count('positive')/sentiment_results_i.
    ↳count('negative')
positivity_score_t = sentiment_results_t.count('positive')/sentiment_results_t.
    ↳count('negative')

# Printing scores for users and explaining their purpose
print("The positivity score of "+company+"'s sentiment on Indeed is_
    ↳"+str(round(positivity_score_i, 2)))
print("i.e. there are "+str(round(positivity_score_i, 2))+ " more positive_
    ↳sentiments than negative ones")

print("\nThe positivity score of "+company+"'s sentiment on Twitter is_
    ↳"+str(round(positivity_score_t, 2)))
print("i.e. there are "+str(round(positivity_score_t, 2))+ " more positive_
    ↳sentiments than negative ones")
```

The positivity score of Google's sentiment on Indeed is 5.3

i.e. there are 5.3 more positive sentiments than negative ones

The positivity score of Google's sentiment on Twitter is 2.13

i.e. there are 2.13 more positive sentiments than negative ones

```
[ ]: # Import the necessary libraries
import matplotlib
import matplotlib.pyplot as plt
from collections import Counter
from nltk.tokenize import RegexpTokenizer

# plot histogram by words
def plot_histogram_by_words(words, name):

    # clean the data
    words = clean_the_stop_word(words)

    # except punctuation
    tokenizer = RegexpTokenizer(r'\w+')
    words = tokenizer.tokenize(" ".join(words))

    # count word
    wd = Counter(words)
    # get top 10 frequent word
    top_data = wd.most_common(10)

    # create two list to save data
    y_val = []
    x_val = []

    # init a subplot
    figure, axes = plt.subplots()

    # loop the top data
    for y, x in top_data:
        # add y col value
        y_val.append(y)
        # add x col value
        x_val.append(x)

    # add y_val, x_val to barh
    b = axes.barh(y_val, x_val, color='#6699CC')

    # add label to axes
    for tmp in b:
        # get the width
```

```

width = tmp.get_width()
# add text, set the layout
axes.text(width, tmp.get_y() + tmp.get_height()/2, "%d" % int(width),
→ha="left", va="center")

# set y_val lable
axes.set_yticklabels(y_val)

# set y_val color to white
[b.set_color(a) for (a, b) in zip(['white']*len(y_val), axes.yaxis.
→get_ticklabels()) ]

# drop out the axis x lable
plt.xticks(())

# print(top_data)
plt.title('top 10 words by ' + name, fontsize='20', loc='center',
→color='white')

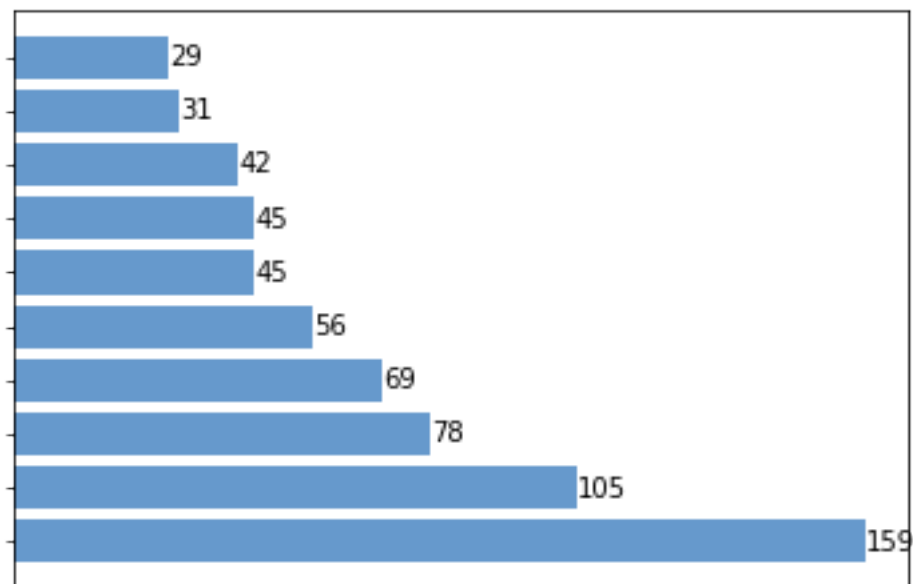
# show the plot
plt.show()

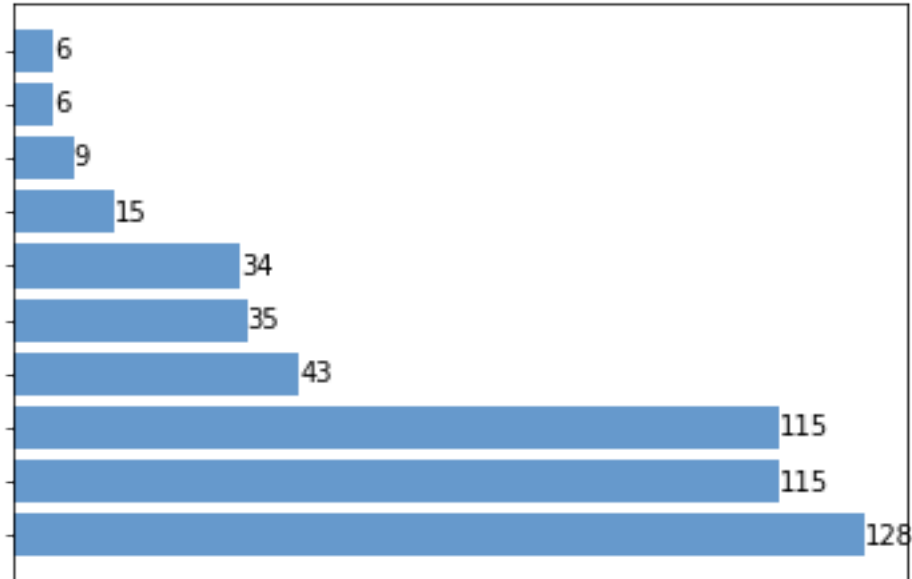
```

```

plot_histogram_by_words(words, 'Indeed')
plot_histogram_by_words(tweets, 'Twitter')

```





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[ ]:
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```
[ ]: # Naive Bayes Indeed model

# Import the necessary libraries
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
import pandas as pd
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
from sklearn.pipeline import make_pipeline
import nltk
from nltk.corpus import stopwords
# nltk.download('stopwords')

def word_cut(text):
    return " ".join(nltk.word_tokenize(text))

# Build MultinomialNB model to categorize text
# def categorize_text(internal_company_review_df):

    # get the review text column
    x_text = internal_company_review_df[['Review Text']]
```



```

# user apply function to cut down the sentence
x_text['cutted_comment'] = x_text['Review Text'].apply(word_cut)

# get the lable from internal_company_review_df
y_text = internal_company_review_df['Positive']

# print(x_text)

# print(y_text)

# split the data to train data and test data
x_train, x_test, y_train, y_test = train_test_split(x_text, y_text,
↳random_state=1)

# convert word to vector
vect = CountVectorizer(stop_words=frozenset(stopwords.words("english")))
# Converts a segmented training set statement with the vectorization tool
term_matrix = pd.DataFrame(vect.fit_transform(x_train.cutted_comment).
↳toarray(), columns=vect.get_feature_names())

# create Multinomial naive bayes model
nb = MultinomialNB()

# combine vect and nb
pipe = make_pipeline(vect, nb)
accuracy = cross_val_score(pipe, x_train.cutted_comment, y_train, cv=5,
↳scoring='accuracy').mean()
accuracy_indeed = str(round(accuracy, 3))
#res = categorize_text(internal_company_review_df)

```

/usr/local/lib/python3.6/dist-packages/ipykernel\_launcher.py:26:

SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

```

[ ]: # ouput the accuracy by Multinomial naive bayes model

print("The Multinomial naive bayes model: accuracy of our classifier for Indeed,
↳data is " + str(accuracy_indeed))

# Printing confusion matrix
from sklearn.metrics import confusion_matrix

```

```

# Applying model to test set
y_pred = cross_val_predict(pipe, x_test.cuttet_comment, y_test, cv=5)

# Using confusion matrix function
cm = confusion_matrix(y_test, y_pred)
print(cm)

# Determining whether model has greater sensitivity, specificity, or neither
if cm[0][1] > cm[1][0]:
    print('This model has more false positives and therefore has high_
    ↳sensitivity.')
elif cm[1][0] > cm[0][1]:
    print('This model has more false negatives and therefore has high_
    ↳specificity.')
else:
    print('This model does not have high specificity nor high sensitivity.')

```

The Multinomial naive bayes model: accuracy of our classifier for Indeed data is 0.821

```

[[ 0  3]
 [ 0 24]]

```

This model has more false positives and therefore has high sensitivity.

```

/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_split.py:667:
UserWarning: The least populated class in y has only 3 members, which is less
than n_splits=5.
  % (min_groups, self.n_splits)), UserWarning)

```

[ ]:

```

[ ]: # Logistic Regression for Indeed data

# Import models and evaluation functions
from sklearn import linear_model
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import BernoulliNB
from sklearn import metrics
#from sklearn import cross_validation
#from sklearn.model_selection import cross_validate
from sklearn.model_selection import cross_val_score

# Import vectorizers to turn text into numeric
from sklearn.feature_extraction.text import CountVectorizer

# First, we want to go from text to numeric data
# Separate out the X and Y data
X_text = internal_company_review_df['Review Text']

```

```

Y = internal_company_review_df['Positive']

# Create a vectorizer that will track text as binary features
count_vectorizer = CountVectorizer()

# Let the vectorizer learn what tokens exist in the text data
count_vectorizer.fit(X_text)

# Turn these tokens into a numeric matrix
X = count_vectorizer.transform(X_text)

# Create a model
logistic_regression = LogisticRegression()

# Splitting into training and test set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state=1)

# Use this model and our data to get 5-fold cross validation AUCs
aucs = cross_val_score(logistic_regression, x_train, y_train,
    ↳scoring="accuracy", cv=5)

```

```

[ ]: # Print out the average AUC rounded to three decimal points
print("Accuracy of our Logistic Regression classifier for the Indeed data is "
    ↳+ str(round(np.mean(aucs), 3)))

# Applying model to test set
y_pred = cross_val_predict(logistic_regression, x_test, y_test, cv=5)

# Using confusion matrix function
cm = confusion_matrix(y_test, y_pred)
print(cm)

# Determining whether model has greater sensitivity, specificity, or neither
if cm[0][1] > cm[1][0]:
    print('This model has more false positives and therefore has high
    ↳sensitivity.')
elif cm[1][0] > cm[0][1]:
    print('This model has more false negatives and therefore has high
    ↳specificity.')
else:
    print('This model does not have high specificity nor high sensitivity.')

```

Accuracy of our Logistic Regression classifier for the Indeed data is 0.822

```
[[ 0  3]
```

```
 [ 0 24]]
```

This model has more false positives and therefore has high sensitivity.

/usr/local/lib/python3.6/dist-packages/sklearn/model\_selection/\_split.py:667:

UserWarning: The least populated class in y has only 3 members, which is less than n\_splits=5.

```
% (min_groups, self.n_splits)), UserWarning)
```

```
[ ]:
```

```
[ ]: # Naive Bayes Twitter model
```

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
import pandas as pd
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
from sklearn.pipeline import make_pipeline
import nltk
from nltk.corpus import stopwords
# nltk.download('stopwords')

def word_cut(text):
    return " ".join(nltk.word_tokenize(text))

# Build MultinomialNB model to categorize text
# def categorize_text(internal_company_review_df):

    # get the review text column
x_text = company_tweets

positive = []
# Begin code from https://www.freecodecamp.org/news/
→how-to-build-a-twitter-sentiments-analyzer-in-python-using-textblob-948e1e8aae14/
→
for tweet in x_text:
    analysis = TextBlob(tweet)

    if analysis.sentiment[0]>0:
        positive.append(1)
    elif analysis.sentiment[0]<0:
        positive.append(0)
    else:
        positive.append(1)
# End code from https://www.freecodecamp.org/news/
→how-to-build-a-twitter-sentiments-analyzer-in-python-using-textblob-948e1e8aae14/
→

d = {'Tweet':company_tweets,'Positive':positive}
```

```

twitter_data = pd.DataFrame(d)

# get the review text column
x_text = twitter_data[['Tweet']]

# user apply function to cut down the sentence
x_text['cutted_comment'] = x_text['Tweet'].apply(word_cut)

# get the lable from internal_company_review_df
y_text = twitter_data['Positive']

# print(x_text)

# print(y_text)

# split the data to train data and test data
x_train, x_test, y_train, y_test = train_test_split(x_text, y_text,
↳random_state=1)

# convert word to vector
vect = CountVectorizer(stop_words=frozenset(stopwords.words("english")))
# Converts a segmented training set statement with the vectorization tool
term_matrix = pd.DataFrame(vect.fit_transform(x_train.cutted_comment).
↳toarray(), columns=vect.get_feature_names())

# create Multinomial naive bayes model
nb = MultinomialNB()

# combine vect and nb
pipe = make_pipeline(vect, nb)
accuracy = cross_val_score(pipe, x_train.cutted_comment, y_train, cv=5,
↳scoring='accuracy').mean()
accuracy_indeed = str(round(accuracy, 3))

```

```

[ ]: # output the accuracy by Multinomial naive bayes model

print("The Multinomial naive bayes model: accuracy of our classifier for
↳Twitter data is " + str(accuracy_indeed))

# Printing confusion matrix
from sklearn.metrics import confusion_matrix

# Applying model to test set
y_pred = cross_val_predict(pipe, x_test.cutted_comment, y_test, cv=5)

# Using confusion matrix function
cm = confusion_matrix(y_test, y_pred)

```

```

print(cm)

# Determining whether model has greater sensitivity, specificity, or neither
if cm[0][1] > cm[1][0]:
    print('This model has more false positives and therefore has high
    ↳sensitivity.')
elif cm[1][0] > cm[0][1]:
    print('This model has more false negatives and therefore has high
    ↳specificity.')
else:
    print('This model does not have high specificity nor high sensitivity.')

```

The Multinomial naive bayes model: accuracy of our classifier for Twitter data is 0.876

```

[[ 2  4]
 [ 0 29]]

```

This model has more false positives and therefore has high sensitivity.

[ ]:

```

[ ]: # Logistic Regression for Twitter data

# Import models and evaluation functions
from sklearn import linear_model
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import BernoulliNB
from sklearn import metrics
#from sklearn import cross_validation
#from sklearn.model_selection import cross_validate
from sklearn.model_selection import cross_val_score

# Import vectorizers to turn text into numeric
from sklearn.feature_extraction.text import CountVectorizer

# First, we want to go from text to numeric data
# Separate out the X and Y data
X_text = twitter_data['Tweet']
Y = twitter_data['Positive']

# Create a vectorizer that will track text as binary features
count_vectorizer = CountVectorizer()

# Let the vectorizer learn what tokens exist in the text data
count_vectorizer.fit(X_text)

# Turn these tokens into a numeric matrix
X = count_vectorizer.transform(X_text)

```

```

# Create a model
logistic_regression = LogisticRegression()

# Splitting into training and test set
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state=1)

# Use this model and our data to get 5-fold cross validation AUCs
aucs = cross_val_score(logistic_regression, x_train, y_train,
    ↪scoring="accuracy", cv=5)

```

```

[ ]: # Print out the average AUC rounded to three decimal points
print("Accuracy of our Logistic Regression classifier for the Twitter data is "
    ↪+ str(round(np.mean(aucs), 3)))

# Applying model to test set
y_pred = cross_val_predict(logistic_regression, x_test, y_test, cv=5)

# Using confusion matrix function
cm = confusion_matrix(y_test, y_pred)
print(cm)

# Determining whether model has greater sensitivity, specificity, or neither
if cm[0][1] > cm[1][0]:
    print('This model has more false positives and therefore has high
    ↪sensitivity.')
elif cm[1][0] > cm[0][1]:
    print('This model has more false negatives and therefore has high
    ↪specificity.')
else:
    print('This model does not have high specificity nor high sensitivity.')

```

Accuracy of our Logistic Regression classifier for the Twitter data is 0.876

```
[[ 2  4]
 [ 0 29]]
```

This model has more false positives and therefore has high sensitivity.

[ ]: