# **Applied Machine Learning Homework 5:** NLP

Due May 2,2023 (Tuesday) 11:59PM EST

## Instructions

- 1) Please push the .ipynb and .pdf to Github Classroom prior to the deadline, .py file is optional (not needed).
- 2) Please include your Name and UNI below.

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## **Natural Language Processing**

We will train a supervised training model to predict if a tweet has a positive or negative sentiment.

# Dataset loading & dev/test splits

1.1) Load the twitter dataset from NLTK library

```
In [1]: import nltk
        nltk.download('twitter samples')
        from nltk.corpus import twitter samples
        nltk.download('punkt')
        nltk.download('stopwords')
        import warnings
        warnings.filterwarnings("ignore")
        from nltk.corpus import stopwords
        stop = stopwords.words('english')
        import pandas as pd
        import string
        import re
        from sklearn.model selection import train test split
        from nltk.stem import PorterStemmer
        from nltk.tokenize import word tokenize
        from sklearn.feature extraction.text import CountVectorizer
        from sklearn.linear model import LogisticRegression
        from sklearn.feature extraction.text import TfidfVectorizer
        from sklearn.metrics import classification report, accuracy score
        import numpy as np
        # Feel free to import any other packages you need
        [nltk data] Downloading package twitter samples to
                        /Users/shrutiagarwal/nltk data...
        [nltk data]
        [nltk_data] Unzipping corpora/twitter_samples.zip.
        [nltk data] Downloading package punkt to
        [nltk data] /Users/shrutiagarwal/nltk data...
        [nltk_data] Package punkt is already up-to-date!
        [nltk data] Downloading package stopwords to
        [nltk data] /Users/shrutiagarwal/nltk data...
        [nltk_data] Package stopwords is already up-to-date!
```

#### 1.2) Load the positive & negative tweets

```
In [2]: all_positive_tweets = twitter_samples.strings('positive_tweets.json')
    all_negative_tweets = twitter_samples.strings('negative_tweets.json')
```

#### 1.3) Make a data frame that has all tweets and their corresponding labels

```
In [3]: # Your Code Here
all_tweets = all_negative_tweets + all_positive_tweets

# Create a list of labels
labels = ["negative"] * len(all_negative_tweets) + ["positive"] * len(all_pc

# Create a dataframe with two columns: "tweet" and "label"
df = pd.DataFrame({"Tweet": all_tweets, "Label": labels})

# Print the dataframe
df
```

|      | Tweet  | Label    |
|------|--|----------|
| 0    | hopeless for tmr :(                            | negative |
| 1    | Everything in the kids section of IKEA is so c | negative |
| 2    | @Hegelbon That heart sliding into the waste ba | negative |
| 3    | "@ketchBurning: I hate Japanese call him "bani | negative |
| 4    | Dang starting next week I have "work" :(       | negative |
| •••  |  |          |
| 9995 | @chriswiggin3 Chris, that's great to hear :) D | positive |
| 9996 | @RachelLiskeard Thanks for the shout-out :) It | positive |
| 9997 | @side556 Hey! :) Long time no talk             | positive |
| 9998 | @staybubbly69 as Matt would say. WELCOME TO AD | positive |
| 9999 | @DanielOConnel18 you could say he will have eg | positive |

Out[3]:

#### 1.4) Look at the class distribution of the tweets

```
In [4]: # Your Code Here

    class_dist = df["Label"].value_counts()
    class_dist

Out[4]: negative    5000
    positive    5000
    Name: Label, dtype: int64
```

#### 1.5) Create a development & test split (80/20 ratio):

```
In [5]: # Your Code Here

# split the dataframe into development and test sets
dev_set, test_set = train_test_split(df, test_size=0.2, random_state=42)

# print the sizes of the resulting sets
print("Development set size:", len(dev_set))
print("Test set size:", len(test_set))
```

Development set size: 8000 Test set size: 2000

## **Data preprocessing**

We will do some data preprocessing before we tokenize the data. We will remove # symbol, hyperlinks, stop words & punctuations from the data. You can use the package in python to find and replace these strings.

## 1.6) Replace the # symbol with " in every tweet

```
In [6]: # Your Code Here

# define a function to remove the '#' symbol from a string
def remove_hashtags(text):
    return re.sub(r'#', '', text)

# apply the function to every tweet in the dataframe
dev_set["Tweet"] = dev_set["Tweet"].apply(remove_hashtags)
test_set["Tweet"] = test_set["Tweet"].apply(remove_hashtags)

# print the resulting dataframe
dev_set
```

| Out[6]: |      | Tweet  | Label    |
|---------|------|--|----------|
|         | 9254 | Friday!:) http://t.co/HUoq4txhmb               | positive |
|         | 1561 | sorry for always changing my layout :(         | negative |
|         | 1670 | <3 <3 awsme song <3 :-* :-( :-( :'( h          | negative |
|         | 6087 | @bwoyblunder @rajudasonline Sorted :). Thanks  | positive |
|         | 6669 | @narrhallamarsch Good Flight! :)               | positive |
|         | •••  |  |          |
|         | 5734 | @ChaSilveo follow @jnlazts & http://t.co/      | positive |
|         | 5191 | Hi BAM! @BarsAndMelody \nCan you follow my be  | positive |
|         | 5390 | @hostclubhowell no prob!:)                     | positive |
|         | 860  | @dullandwicked @_GrahamPatrick @JohnBoyStyle H | negative |
|         | 7270 | Unreal training boys!\nAwesome work Zaine, Zac | positive |

8000 rows × 2 columns

## 1.7) Replace hyperlinks with "in every tweet

```
In [7]: # Your Code Here

def remove_hyperlinks(text):
    return re.sub(r'http\S+', '', text)

# apply the function to every tweet in the dataframe
dev_set["Tweet"] = dev_set["Tweet"].apply(remove_hyperlinks)
test_set["Tweet"] = test_set["Tweet"].apply(remove_hyperlinks)

# print the resulting dataframe
dev_set
```

|      | Tweet  | Label    |
|------|--|----------|
| 9254 | Friday!:)                                      | positive |
| 1561 | sorry for always changing my layout :(         | negative |
| 1670 | <3 <3 awsme song <3 :-* :-( :-( :'(            | negative |
| 6087 | @bwoyblunder @rajudasonline Sorted :). Thanks  | positive |
| 6669 | @narrhallamarsch Good Flight! :)               | positive |
| •••  |  |          |
| 5734 | @ChaSilveo follow @jnlazts & follow u ba       | positive |
| 5191 | Hi BAM! @BarsAndMelody \nCan you follow my be  | positive |
| 5390 | @hostclubhowell no prob!:)                     | positive |
| 860  | @dullandwicked @_GrahamPatrick @JohnBoyStyle H | negative |
| 7270 | Unreal training boys!\nAwesome work Zaine, Zac | positive |

Out[7]:

## 1.8) Remove all stop words

```
In [8]: # Your Code Here

# define a function to remove stop words from a string
def remove_stopwords(text):
        stop_words = set(stopwords.words('english'))
        words = text.split()
        filtered_words = [word for word in words if word.lower() not in stop_wor
        return ' '.join(filtered_words)

# apply the function to every tweet in the dataframe
dev_set["Tweet"] = dev_set["Tweet"].apply(remove_stopwords)
test_set["Tweet"] = test_set["Tweet"].apply(remove_stopwords)

# print the resulting dataframe
dev_set
```

|      | Tweet  | Label    |
|------|--|----------|
| 9254 | Friday!:)  | positive |
| 1561 | sorry always changing layout :(                      | negative |
| 1670 | <3 <3 awsme song <3 :-* :-( :-( :'(                  | negative |
| 6087 | @bwoyblunder @rajudasonline Sorted :). Thanks        | positive |
| 6669 | @narrhallamarsch Good Flight! :)                     | positive |
| •••  |  |          |
| 5734 | @ChaSilveo follow @jnlazts & follow u back :)        | positive |
| 5191 | Hi BAM! @BarsAndMelody follow bestfriend @969 positi |          |
| 5390 | @hostclubhowell prob!:) positiv                      |          |
| 860  | @dullandwicked @_GrahamPatrick @JohnBoyStyle n       | negative |
| 7270 | Unreal training boys! Awesome work Zaine, Zac        | positive |

Out[8]:

## 1.9) Remove all punctuations

```
In [9]: # Your Code Here

# define a function to remove punctuation from a string
def remove_punctuation(text):
    return re.sub(r'[^\w\s]', '', text)

# apply the function to every tweet in the dataframe
dev_set["Tweet"] = dev_set["Tweet"].apply(remove_punctuation)
test_set["Tweet"] = test_set["Tweet"].apply(remove_punctuation)
# print the resulting datafram
dev_set
```

|      | Tweet  | Label    |
|------|--|----------|
| 9254 | Friday   | positive |
| 1561 | sorry always changing layout                           | negative |
| 1670 | lt3 lt3 awsme song lt3                                 | negative |
| 6087 | bwoyblunder rajudasonline Sorted Thanks Daaru          | positive |
| 6669 | narrhallamarsch Good Flight                            | positive |
| •••  |  |          |
| 5734 | ChaSilveo follow jnlazts amp follow u back po          |          |
| 5191 | Hi BAM BarsAndMelody follow bestfriend 969Hor positive |          |
| 5390 | hostclubhowell prob positive                           |          |
| 860  | dullandwicked _GrahamPatrick JohnBoyStyle nobo         | negative |
| 7270 | Unreal training boys Awesome work Zaine Zac Is         | positive |

Out[9]:

## 1.10) Apply stemming on the development & test datasets using Porter algorithm

```
In [10]: # Your Code Here

porter = PorterStemmer()
dev_set['stemmed_tweet'] = dev_set['Tweet'].apply(lambda x: ' '.join([porter test_set['stemmed_tweet'] = test_set['Tweet'].apply(lambda x: ' '.join([port dev_set
```

| Out[10]: |      | Tweet  | Label    | stemmed_tweet |
|----------|------|--------|----------|---------------|
|          | 9254 | Friday | positive | friday        |
|          |      |        |          |               |

| 9254 | Friday  | positive | friday   |
|------|---|----------|--|
| 1561 | sorry always changing layout                      | negative | sorri alway chang layout                           |
| 1670 | lt3 lt3 awsme song lt3                            | negative | lt3 lt3 awsm song lt3                              |
| 6087 | bwoyblunder rajudasonline Sorted<br>Thanks Daaru  | positive | bwoyblund rajudasonlin sort thank<br>daaru parti   |
| 6669 | narrhallamarsch Good Flight                       | positive | narrhallamarsch good flight                        |
| •••  |   |          |  |
| 5734 | ChaSilveo follow jnlazts amp follow u back        | positive | chasilveo follow jnlazt amp follow u<br>back       |
| 5191 | Hi BAM BarsAndMelody follow bestfriend 969Hor     | positive | hi bam barsandmelodi follow<br>bestfriend 969hora  |
| 5390 | hostclubhowell prob                               | positive | hostclubhowel prob                                 |
| 860  | dullandwicked _GrahamPatrick<br>JohnBoyStyle nobo | negative | dullandwick _grahampatrick<br>johnboystyl nobodi   |
| 7270 | Unreal training boys Awesome work<br>Zaine Zac Is | positive | unreal train boy awesom work zain<br>zac isaac oss |

| In [11]: | test_set |
|----------|----------|
|          |          |

| ut[11]: |      | Tweet  | Label    | stemmed_tweet                                     |
|---------|------|--|----------|---|
| ,       | 6252 | Malan_Sanjaya yes switched back lap optimized  | positive | malan_sanjaya ye switch back lap<br>optim window  |
|         | 4684 | MTAP tomorrow means sleep early tonight        | negative | mtap tomorrow mean sleep earli<br>tonight         |
|         | 1731 | Gotham3 sad view                               | negative | gotham3 sad view                                  |
|         | 4742 | Jessica calls quits power abs 515              | negative | jessica call quit power ab 515                    |
|         | 4521 | like cant actually put pressure ankle hop arou | negative | like cant actual put pressur ankl hop<br>around h |
|         | •••  |  |          |   |
|         | 6412 | Agree Phone WiFi LifeStyle QatarDay            | positive | agre phone wifi lifestyl qatarday                 |
|         | 8285 | RI191459Alex Hey thank following               | positive | rl191459alex hey thank follow                     |
|         | 7853 | See yah Sunday carmenkvarnen                   | positive | see yah sunday carmenkvarnen                      |
|         | 1095 | didnt took photos                              | negative | didnt took photo                                  |
|         | 6929 | LondonLycra see legs lycra p                   | positive | londonlycra see leg lycra p                       |

## **Model training**

1.11) Create bag of words features for each tweet in the development dataset

```
In [28]: # Your Code Here

vectorizer = CountVectorizer(stop_words='english', ngram_range=(1,2), max_fe
bow_features = vectorizer.fit_transform(dev_set['stemmed_tweet'])
bow_features = bow_features.toarray()

print(bow_features)

[[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
```

1.12) Train a Logistic Regression model on the development dataset

1.13) Create TF-IDF features for each tweet in the development dataset

```
In [30]: # Your Code Here

tfidf_vectorizer = TfidfVectorizer(max_df=0.90, min_df=2, max_features=1000,
    tfidf_features = tfidf_vectorizer.fit_transform(dev_set['stemmed_tweet'])

print(tfidf_features.toarray())

[[0. 0. 0. ... 0. 0. 0.]
    [0. 0. 0. ... 0. 0. 0.]
    [0. 0. 0. ... 0. 0. 0.]
    [0. 0. 0. ... 0. 0. 0.]
    [0. 0. 0. ... 0. 0. 0.]
    [0. 0. 0. ... 0. 0. 0.]
    [0. 0. 0. ... 0. 0. 0.]]
```

1.14) Train the Logistic Regression model on the development dataset with TF-IDF features

1.15) Compare the performance of the two models on the test dataset using a classification report and the scores obtained. Explain the difference in results obtained.

```
In [32]: # Your Code Here
         bow_test_features = vectorizer.transform(test_set['stemmed_tweet'])
         bow_test_features = bow_test_features.toarray()
         y pred bow = 1r model bow.predict(bow test features)
         print("Accuracy on Test set: ", lr_model_bow.score(bow_test_features, test_s
         print(classification_report(test_set["Label"], y_pred_bow))
         Accuracy on Test set: 0.729
                       precision recall f1-score
                                                      support
             negative
                           0.72
                                     0.77
                                               0.74
                                                         1012
             positive
                           0.75
                                     0.69
                                               0.71
                                                          988
             accuracy
                                               0.73
                                                         2000
                          0.73
                                               0.73
                                                         2000
            macro avg
                                     0.73
         weighted avg
                           0.73
                                     0.73
                                               0.73
                                                         2000
In [33]: tfidf test features = tfidf vectorizer.transform(test set['stemmed tweet'])
         y pred tfidf = lr model tfidf.predict(tfidf test features)
         print("Accuracy on Test set: ", lr model tfidf.score(tfidf test features, te
         print(classification_report(test_set['Label'], y_pred_tfidf))
         Accuracy on Test set: 0.738
                       precision recall f1-score
                                                      support
             negative
                           0.72
                                     0.78
                                               0.75
                                                         1012
                           0.75
                                     0.70
             positive
                                               0.72
                                                          988
                                               0.74
                                                         2000
             accuracy
                           0.74
                                     0.74
                                                         2000
            macro avg
                                               0.74
         weighted avg
                          0.74
                                    0.74
                                               0.74
                                                         2000
```

<sup>\*</sup>Explanation here

The performance of the TF-IDF model is expected to be better than the BOW model because it can capture more meaningful features and reduce the impact of noise caused by common words.

The bag-of-words approach represents a text document as a bag of words, without considering their order or context. It counts the frequency of each word in the document and constructs a feature vector for each document based on the frequency of each word. It lacks the ability to capture the semantic relationship between words and treats all words equally.

On the other hand, the TF-IDF approach considers the importance of words in a document relative to their frequency in the entire corpus. It reduces the weight of common words and increases the weight of rare words that are more informative. Therefore, it can capture the semantic meaning of words and their importance in a document.

In []: