In [ ]:
```
import pandas as pd
import re
import nltk
import matplotlib.pyplot as plt
import spacy
import seaborn as sns
import numpy as np
from nltk.corpus import stopwords
from spacy.lang.en import STOP_WORDS as stopwords_spacy
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS as stopwords_
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer, WordNetLemmatizer
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from textblob import TextBlob
from sklearn.metrics import confusion_matrix
from transformers import pipeline
from textblob import TextBlob
```

# 1. Preprocess Twitter Dataset

- Preliminary Data Cleaning
- Advanced Data Cleaning

## Read in the twitter_training.csv

In [ ]:
```
# Read in the twitter_training.csv
TWITTER_FILE_PATH = "twitter_training.csv"
twitter_data = pd.read_csv(TWITTER_FILE_PATH)
```

## Run summary/descriptive statistics tests on the data (e.g. head, describe, etc)

In [ ]:
```
twitter_data_length = len(twitter_data)

print(f"Twitter Data Length: {twitter_data_length}\n")
print(twitter_data.head())
print("")
print(twitter_data.describe())
```

```
Twitter Data Length: 74681

   2401  Borderlands  Positive  \
0  2401  Borderlands  Positive
1  2401  Borderlands  Positive
2  2401  Borderlands  Positive
3  2401  Borderlands  Positive
4  2401  Borderlands  Positive

  im getting on borderlands and i will murder you all ,
0  I am coming to the borders and I will kill you...
1  im getting on borderlands and i will kill you ...
2  im coming on borderlands and i will murder you...
3  im getting on borderlands 2 and i will murder ...
4  im getting into borderlands and i can murder y...

               2401
count  74681.000000
mean    6432.640149
std     3740.423819
min        1.000000
25%     3195.000000
50%     6422.000000
75%     9601.000000
max    13200.000000
```

## Rename this dataframe to pre_df

In [ ]:
```
pre_df = twitter_data.copy()
```

In [ ]:
```
# Add a row on the top of the dataframe to represent column names of each co
column_names = ["ID", "Game", "Label", "Text"]
pre_df.columns = column_names
```

In [ ]:
```
pre_df["Label"].unique()
```

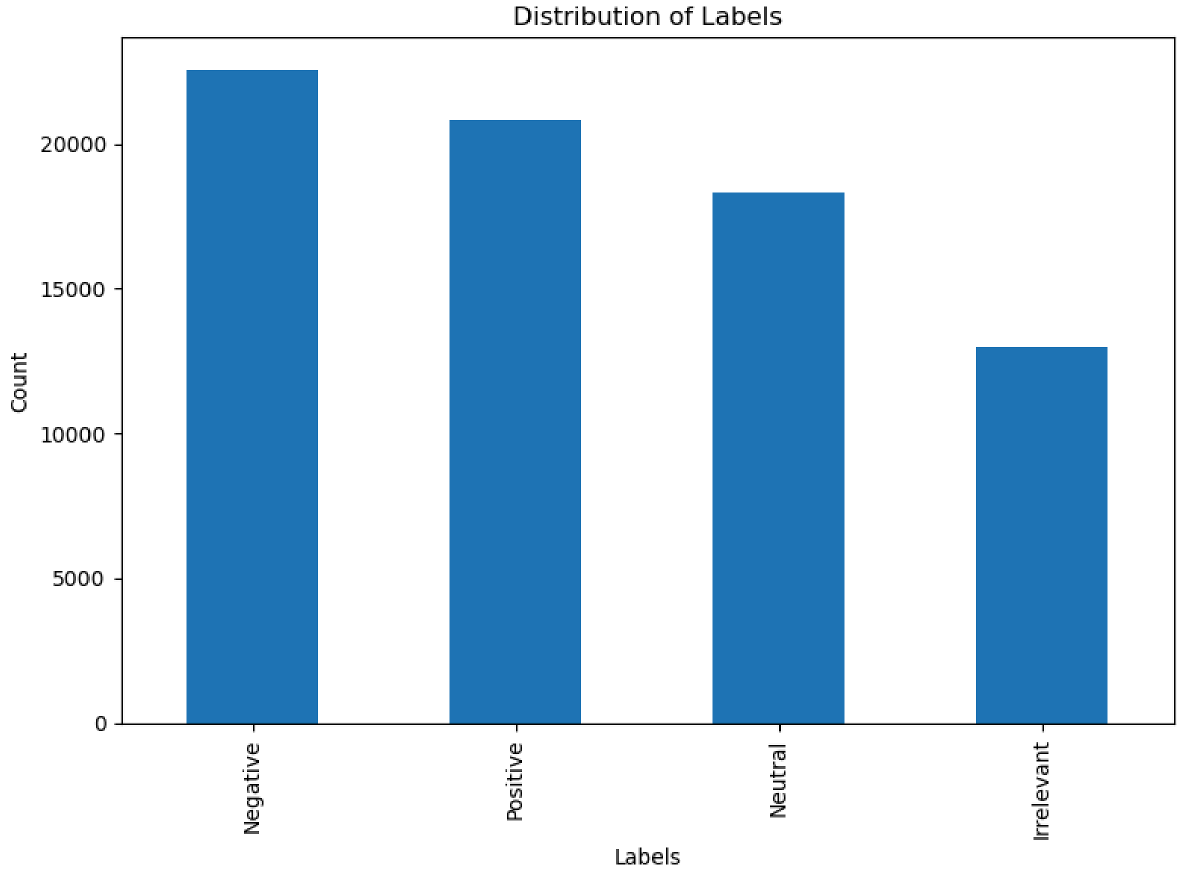
Out[ ]:
```
array(['Positive', 'Neutral', 'Negative', 'Irrelevant'], dtype=object)
```

# Data Visualization

In [ ]:
```
label_counts = pre_df["Label"].value_counts()

plt.figure(figsize=(8, 6))
label_counts.plot(kind="bar")
plt.title("Distribution of Labels")
plt.xlabel("Labels")
plt.ylabel("Count")
# plt.xticks(rotation=45)
plt.tight_layout()

plt.show()
```




# 1.1 Preliminary Data Cleaning

## Complete several text transoformations:

- Determine if there are missing values
- Determine what to fill these missing values with

In [ ]:

```
# Check for missing values in the "Text" column
missing_text_rows = pre_df[pre_df["Text"] == " "]

print(f"Missing Text Rows:\n {missing_text_rows}")

# Check for NaN in the "Text" column
nan_rows = pre_df[pre_df["Text"].isna()]

print(f"NaN Rows:\n {nan_rows}")
```

```
Missing Text Rows:
          ID                          Game       Label Text
2291   1602  CallOfDutyBlackopsColdWar  Irrelevant
2993   1719  CallOfDutyBlackopsColdWar    Positive
3239   1763  CallOfDutyBlackopsColdWar     Neutral
3935   1880  CallOfDutyBlackopsColdWar    Negative
4229   1929  CallOfDutyBlackopsColdWar    Negative
...     ...                        ...         ...  ...
73229  8945                     Nvidia    Positive
73517  8993                     Nvidia     Neutral
73757  9036                     Nvidia    Negative
73967  9073                     Nvidia    Positive
74417  9154                     Nvidia    Positive

[172 rows x 4 columns]
NaN Rows:
          ID         Game     Label Text
60     2411  Borderlands   Neutral  NaN
552    2496  Borderlands   Neutral  NaN
588    2503  Borderlands   Neutral  NaN
744    2532  Borderlands  Positive  NaN
1104   2595  Borderlands  Positive  NaN
...     ...          ...       ...  ...
73971  9073       Nvidia  Positive  NaN
73972  9073       Nvidia  Positive  NaN
74420  9154       Nvidia  Positive  NaN
74421  9154       Nvidia  Positive  NaN
74422  9154       Nvidia  Positive  NaN

[686 rows x 4 columns]
```

In [ ]:
```
# Fill missing values with "Unknown" in the "Text" column
pre_df.loc[missing_text_rows.index, "Text"] = "Unknown"
pre_df.loc[nan_rows.index, "Text"] = "Unknown"
```

## Change/verify relevant column data types

In [ ]:
```
# Check the data types of the columns
column_datatypes = pre_df.dtypes

print(column_datatypes)
```

```
ID        int64
Game     object
Label    object
Text     object
dtype: object
```

## Lowercase

In [ ]:
```
# Lower case
pre_df["Lower_Text"] = pre_df["Text"].str.lower()
```

## Remove non-ASCII characters and fill with whitespace

In [ ]:
```
# Remove all non-ASCII characters and fill with whitespace
pre_df["Remove_non_Ascii"] = pre_df["Lower_Text"].apply(lambda x: re.sub(r'
```

### Remove additional whitespace (stripping)

In [ ]:
```
# Remove additional whitespace (stripping)
pre_df["Remove_Whitespace"] = pre_df["Remove_non_Ascii"].str.strip()
```

### Split the string info into a list of strings that are each one word (tokenization)

In [ ]:
```
pre_df["Tokenized_Text"] = pre_df["Remove_Whitespace"].apply(word_tokenize)
```

## 1.2 Advanced Data Cleaning

### Remove "\n" and other symbols followed by letters

In [ ]:
```
# Remove "\n" and other symbols followed by letters
pre_df["Remove_n"] = pre_df["Remove_Whitespace"].apply(lambda x: re.sub(r"\r
```

### Remove emojis and emoticons

Handling emojis and emoticons:

During sentiment analysis, the model only considers textual content. Elements like emojis and emoticons aren't important for the task, thus can be omitted.

However, if we aim to retain the impact of emojis and emoticons, there's a possibility to convert them into numerical values.

In [ ]:
```
pre_df["Remove_Emoji"] = pre_df["Remove_n"].apply(lambda x: x.encode("ascii"
```

### Fix Spelling Error

Handling spelling errors:

Spelling mistakes can introduce noise in sentiment analysis tasks. One approach is to simply ignore the errors. Alternatively, we can employ libraries such as PySpellChecker or TextBlob to solve spelling issues.

In [ ]:
```
def correct_spelling(text):
    """Correct the spelling of the given text using TextBlob."""
    blob = TextBlob(text)
    return str(blob.correct())

pre_df["Fixed_Spelling"] = pre_df["Remove_Emoji"].apply(correct_spelling)

pre_df
```

### *The execution took too long*

### Remove stopwords

In [ ]:
```
nltk.download("stopwords")

def remove_stopwords_nltk(text):
    """Remove stopwords from the given text using NLTK."""
    stopwords_nltk = set(stopwords.words("english"))
    tokens = word_tokenize(text)
    return " ".join([token for token in tokens if token not in stopwords_nlt

def remove_stopwords_spacy(text):
    """Remove stopwords from the given text using SpaCy."""
    tokens = word_tokenize(text)
    return " ".join([token for token in tokens if token not in stopwords_spa

def remove_stopwords_textblob(text):
    """Remove stopwords from the given text using TextBlob."""
    tokens = word_tokenize(text)
    stopwords_textblob = set(stopwords.words("english"))
    return " ".join([token for token in tokens if token not in stopwords_tex

def remove_stopwords_sklearn(text):
    """Remove stopwords from the given text using Scikit-learn."""
    tokens = word_tokenize(text)
    return " ".join([token for token in tokens if token not in stopwords_skl
```

```
[nltk_data] Downloading package stopwords to /Users/yu/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [ ]:
```
pre_df["Remove_Stopwords_NLTK"] = pre_df["Remove_Emoji"].apply(remove_stopwo
pre_df["Remove_Stopwords_SpaCy"] = pre_df["Remove_Emoji"].apply(remove_stopw
pre_df["Remove_Stopwords_Textblob"] = pre_df["Remove_Emoji"].apply(remove_st
pre_df["Remove_Stopwords_Sklearn"] = pre_df["Remove_Emoji"].apply(remove_sto
```

## Stemming and Lemmatization (on NLTK)

In my opinion, stemming is preferable to lemmatization. Instead of reducing words to their base form, stemming only removes suffixes from the root, which can preserve more information and also may be faster in computation.

In [ ]:
```
stemmer = PorterStemmer()
lemmatizer = WordNetLemmatizer()

# Stemming and lemmatization on ntlk
def stemming_nltk(text):
    """Perform stemming using NLTK."""
    tokens = word_tokenize(text)
    stemmed_tokens = [stemmer.stem(token) for token in tokens]
    return " ".join(stemmed_tokens)

def lemmatization_nltk(text):
    """Perform lemmatization using NLTK."""
    tokens = word_tokenize(text)
    lemmatized_tokens = [lemmatizer.lemmatize(token) for token in tokens]
    return " ".join(lemmatized_tokens)
```

In [ ]:
```
pre_df["Stemmed_Text_NLTK"] = pre_df["Remove_Stopwords_NLTK"].apply(stemming
pre_df["Lemmatized_Text_NLTK"] = pre_df["Remove_Stopwords_NLTK"].apply(lemma
```

## Remove numbers

Whether or not to remove numbers depends on their role in the dataset. In Twitter datasets, numbers often represent user IDs, timestamps, email addresses, and more. However, such numerical data isn't important to sentiment analysis. Therefore, removing numbers is a viable option.

In [ ]:
```
pre_df["Remove_Numbers"] = pre_df["Stemmed_Text_NLTK"].apply(lambda x: re.su
```

### Remove non alphabetic words

non*alphabetic words in the data: [* `.` , `@` , `&` , `/` , `(` , `)` , `<` , `>` , `!` , `?` , `+` , `%` , `*` , ` `,` [ `,` ] `,` $ `,` - `,` : `,` ~ `,` "`]

In [ ]:
```
def remove_non_alphabetic(text):
    """Remove non-alphabetic characters from the given text."""
    return " ".join(re.findall(r"\b[a-zA-Z]+\b", text))

pre_df["Remove_non_Alphabetic"] = pre_df["Remove_Numbers"].apply(remove_non_
```

### Create an output of this dataset as a csv file

In [ ]:
```
OUTPUT_FILE_PATH = "/Users/yu/Desktop/uds_ws2324/tools_for_nlp/assignment/fi
pre_df.to_csv(OUTPUT_FILE_PATH, index=False)
```

# 2. Create a functioning class that packages all the items

In [ ]:
```
class TwitterDataPreprocessor:
    """A class for preprocessing Twitter data"""

    def __init__(self, file_path):
        """Initialize the TwitterDataPreprocessor object."""
        self.file_path = file_path
        self.data = None

    def load_data(self):
        """Load data."""
        self.data = pd.read_csv(self.file_path)

    def preprocess(self):
        """Preprocess the loaded data."""

        pre_df = self.data.copy()

        column_names = ["ID", "Game", "Label", "Text"]
        pre_df.columns = column_names

        # Check for missing values in the "Text" column
        pre_df["Text"].fillna("Unknown", inplace=True)

        # Convert text to lowercase
        pre_df["Lower_Text"] = pre_df["Text"].str.lower()

        # Remove non-ASCII characters
        pre_df["Remove_non_Ascii"] = pre_df["Lower_Text"].apply(lambda x: re
```

```
        # Remove whitespace
        pre_df["Remove_Whitespace"] = pre_df["Remove_non_Ascii"].str.strip(

        # Remove newlines
        pre_df["Remove_n"] = pre_df["Remove_Whitespace"].apply(lambda x: re

        # Remove emojis
        pre_df["Remove_Emoji"] = pre_df["Remove_n"].apply(lambda x: x.encod

        def remove_stopwords_nltk(text):
            """Remove stopwords using NLTK."""
            stopwords_nltk = set(stopwords.words("english"))
            tokens = word_tokenize(text)
            return " ".join([token for token in tokens if token not in stop

        pre_df["Remove_Stopwords_NLTK"] = pre_df["Remove_Emoji"].apply(remov

        # Stemming and lemmatization on nltk
        stemmer = PorterStemmer()
        lemmatizer = WordNetLemmatizer()

        def stemming_nltk(text):
            """Perform stemming using NLTK."""
            tokens = word_tokenize(text)
            stemmed_tokens = [stemmer.stem(token) for token in tokens]
            return " ".join(stemmed_tokens)

        def lemmatization_nltk(text):
            """Perform lemmatization using NLTK."""
            tokens = word_tokenize(text)
            lemmatized_tokens = [lemmatizer.lemmatize(token) for token in t
            return " ".join(lemmatized_tokens)

        def remove_non_alphabetic(text):
            """Remove non-alphabetic characters."""
            return " ".join(re.findall(r"\b[a-zA-Z]+\b", text))

        pre_df["Stemmed_Text_NLTK"] = pre_df["Remove_Stopwords_NLTK"].apply
        pre_df["Lemmatized_Text_NLTK"] = pre_df["Remove_Stopwords_NLTK"].ap

        # Remove numbers
        pre_df["Remove_Numbers"] = pre_df["Stemmed_Text_NLTK"].apply(lambda

        # Remove non-alphabetic characters
        pre_df["Remove_non_Alphabetic"] = pre_df["Remove_Numbers"].apply(re
        return pre_df

    def save_preprocessed_data(self, output_file_path):
        """Save preprocessed data to a CSV file."""
        preprocessed_data = self.preprocess()
        preprocessed_data.to_csv(output_file_path, index=False)
        print("Preprocessed data saved.")

TWITTER_FILE_PATH = "twitter_training.csv"
OUTPUT_FILE_PATH = "twitter_data_preprocessed.csv"

preprocessor = TwitterDataPreprocessor(TWITTER_FILE_PATH)
preprocessor.load_data()
preprocessor.save_preprocessed_data(OUTPUT_FILE_PATH)
```

```
Preprocessed data saved.
```

# 4. Use NLTK/VADER, SpaCy/Textblob, and HuggingFace Sentiment Analysis

- Make a function for NLTK/VADER to pass through your preprocessed dataset
- Make a function to do the same with SpaCy/Textblob

## NLTK/VADER sentiment analysis

In [ ]:
```
# Initialize VADER
nltk.download("vader_lexicon")
sid = SentimentIntensityAnalyzer()

def nltk_vader_analysis(text):
    """
    Get sentiment scores using VADER.
    """
    scores = sid.polarity_scores(text)
    return scores

pre_df["Sentiment_Scores_NLTK_VADER"] = pre_df["Remove_non_Alphabetic"].app
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     /Users/yu/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

## SpaCy/Textblob sentiment analysis

In [ ]:
```
def spacy_textblob_analysis(data):
    """
    Sentiment Analysis: Using SpaCy for tokenization and TextBlob for sentir
    """
    nlp = spacy.load("en_core_web_sm")

    def tokenize(text):
        """
        Tokenize text using SpaCy.
        """
        doc = nlp(text)
        tokens = [token.text for token in doc]
        return tokens

    def get_sentiment_scores(text):
        """
        Get sentiment scores using TextBlob.
        """
        blob = TextBlob(text)
        polarity = blob.sentiment.polarity
        subjectivity = blob.sentiment.subjectivity
        return {"polarity": polarity, "subjectivity": subjectivity}

    data["Sentiment_Scores_SpaCy_TextBlob"] = data["Remove_non_Alphabetic"]
    return data

pre_df = spacy_textblob_analysis(pre_df)
```

### HuggingFace sentiment analysis

In [ ]:
```
sentiment_analysis_pipeline = pipeline("sentiment-analysis")

def hugging_face_sentiment_analysis(text):
    """
    Get sentiment scores using HugginFace
    """
    results = sentiment_analysis_pipeline(text)
    # print(results[0])

    # Extract sentiment label and score
    sentiment_label = results[0]["label"]
    sentiment_score = results[0]["score"]

    return {"label": sentiment_label, "score": sentiment_score}

pre_df["Sentiment_Scores_Hugging_Face"] = pre_df["Remove_non_Alphabetic"].ap
```

```
No model was supplied, defaulted to distilbert-base-uncased-finetuned-sst-2
-english and revision af0f99b (https://huggingface.co/distilbert-base-uncas
ed-finetuned-sst-2-english).
Using a pipeline without specifying a model name and revision in production
is not recommended.
```

# 5. Run and show the results via visualizations (e.g. Confusion matrix / bar plots) comparing the results

### Confusion Matrix

In [ ]:
```
nltk_scores = pre_df["Sentiment_Scores_NLTK_VADER"]
spacy_scores = pre_df["Sentiment_Scores_SpaCy_TextBlob"]

actual_sentiments = []
nltk_sentiments = []
spacy_sentiments = []
hugging_face_sentiments = []
```

In [ ]:
```
for nltk_score, spacy_score in zip(nltk_scores, spacy_scores):
    nltk_sentiment = "Negative" if -1 <= nltk_score["compound"] < -0.05 else
    spacy_sentiment = "Negative" if spacy_score["polarity"] < 0 else "Neutra

    pre_df["Sentiment_Scores_NLTK_VADER"] = nltk_sentiment
    pre_df["Sentiment_Scores_SpaCy_TextBlob"] = spacy_sentiment

    nltk_sentiments.append(nltk_sentiment)
    spacy_sentiments.append(spacy_sentiment)
```

In [ ]:
```
for index, row in pre_df.iterrows():
    hugging_face_sentiment = row["Sentiment_Scores_Hugging_Face"]["label"]
    hugging_face_sentiments.append((hugging_face_sentiment.capitalize()))
```

In [ ]:
```
for index, row in pre_df.iterrows():
    actual_sentiment = row["Label"]
    actual_sentiments.append(actual_sentiment)
```

In [ ]:
```
labels = ["Negative", "Neutral", "Positive"]
nltk_confusion_matrix = confusion_matrix(actual_sentiments, nltk_sentiments,
spacy_confusion_matrix = confusion_matrix(actual_sentiments, spacy_sentimen
hugging_face_confusion_matrix = confusion_matrix(actual_sentiments, hugging_


print(f"NLTK Confusion Matrix: {nltk_confusion_matrix}\n")
print(f"SpaCy Confusion Matrix: {spacy_confusion_matrix}\n")
print(f"Hugging Face Confusion Matrix: {hugging_face_confusion_matrix}\n")
```

```
NLTK Confusion Matrix: [[11939  5071  5532]
 [ 5849  5062  7407]
 [ 3858  5062 11911]]

SpaCy Confusion Matrix: [[ 9738  7875  4929]
 [ 4516  7175  6627]
 [ 3854  6846 10131]]

Hugging Face Confusion Matrix: [[19809     0  2733]
 [13739     0  4579]
 [10532     0 10299]]
```

## Visualization

In [ ]:
```
plt.figure(figsize=(20, 9))
plt.subplot(1, 3, 1)
sns.heatmap(nltk_confusion_matrix, annot=True, cmap="Greens", fmt="d", xticl
plt.title("NLTK Confusion Matrix")

plt.subplot(1, 3, 2)
sns.heatmap(spacy_confusion_matrix, annot=True, cmap="Greens", fmt="d", xtic
plt.title("SpaCy Confusion Matrix")

plt.subplot(1, 3, 3)
sns.heatmap(hugging_face_confusion_matrix, annot=True, cmap="Greens", fmt="c
plt.title("Hugging Face Confusion Matrix")

plt.tight_layout()
plt.show()

nltk_accuracy = np.trace(nltk_confusion_matrix) / np.sum(nltk_confusion_matr
spacy_accuracy = np.trace(spacy_confusion_matrix) / np.sum(spacy_confusion_m
hugging_face_accuracy = np.trace(hugging_face_confusion_matrix) / np.sum(hug
```