

## ▼ Bahceci

```
# Importing the necessary packages
#!pip install demoji
#!pip install transformers

import ast
import re
import demoji
import matplotlib.pyplot as plt
import nltk
import pandas as pd
import spacy
import textblob
from nltk import word_tokenize
from nltk.corpus import stopwords
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.stem import PorterStemmer, WordNetLemmatizer
from sklearn import metrics
from sklearn.feature_extraction.text import CountVectorizer
from transformers import pipeline

nltk.download('vader_lexicon')
nltk.download('wordnet')
```

## ▼ 1. Text Preprocessing

```
"""
Code for data cleaning.
"""

nlp = spacy.load("en_core_web_sm")
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
nltk.download('punkt')

PATH = 'twitter_training.csv'

twitter_df = pd.read_csv(PATH)

# Run summary/descriptive statistics tests on the data
# Rename the dataframe to pre_df
pre_df = twitter_df.copy()
print("Head of the dataframe:")
print(pre_df.head())
print("\nDescriptive statistics of the dataframe:")
print(pre_df.describe())

pre_df.columns = ["ID", "Game", "Sentiment", "Text"]

# Determine if there are missing values
missing_values = pre_df.isnull().sum()
print("\nMissing values in the dataframe:")
print(missing_values)

# Drop rows with missing 'Text' values
pre_df.fillna("", inplace=True)

pre_df["ID"] = pd.to_numeric(pre_df["ID"], errors="coerce")
pre_df["ID"] = pre_df["ID"].fillna(0).astype(int)

print("Dropped na rows.")

# Lowercase the entire text
pre_df['Text'] = pre_df['Text'].str.lower()

# Remove /n from the text
pre_df['Text'] = pre_df['Text'].str.replace(r'\n.*', '', regex=True)

def remove_emojis(text):
    """
```

```

    Remove emojis, of course the emojis may effect the analysis
    as there are positive and negative emojis.
    """
    return demoji.replace(text, '')

pre_df['Text'] = pre_df['Text'].apply(remove_emojis)

print("Removed emojis")

#Correcting the spelling errors can help us as we will
#have more data that can be processed and
#it can give us more meaningful results.

# Remove all non-ASCII characters and fill with whitespace
def remove_non_ascii(text):
    """
    Function to remove non-ascii characters
    """
    cleaned_text = ""
    for char in text:
        if ord(char) < 128:
            cleaned_text += char
        else:
            cleaned_text += " "
    return cleaned_text

pre_df["Text"] = pre_df["Text"].apply(remove_non_ascii)

pre_df["Text"] = pre_df["Text"].str.strip()

print(pre_df)

# Tokenize the text and add it as a new column

pre_df['tokenized_text'] = pre_df['Text'].apply(nltk.word_tokenize)

print(pre_df)

print("tokenization done")

# Remove stopwords in the tokenized column

def remove_stopwords_nltk(tokens):
    """
    Remove stopwords nltk.
    """
    filtered = [word for word in tokens if word.lower() not in stop_words]
    return filtered

def remove_stopwords_spacy(tokens):
    """
    Remove stopwords spacy.
    """
    stopwords_set = set(nlp.Defaults.stop_words)
    filtered = [word for word in tokens if word.lower() not in stopwords_set]
    return filtered

pre_df['tokenized_text_nltk'] = pre_df['tokenized_text'].apply(
    remove_stopwords_nltk)
pre_df['tokenized_text_spacy'] = pre_df['tokenized_text'].apply(
    remove_stopwords_spacy)

print(pre_df)
print("Removed stopwords.")

# Adding 4 columns for stem and lemmas. 2 for nltk stopword
# removed column and 2 for plain tokenized column.

lemmatizer = WordNetLemmatizer()
porter = PorterStemmer()

def lemmatize(tokens):
    """Lemmatizer"""
    return [lemmatizer.lemmatize(token) for token in tokens]

def stem(tokens):

```

```

def stem(tokens):
    """Stemmer"""
    return [porter.stem(token) for token in tokens]

pre_df['lemmatized_text'] = pre_df['tokenized_text'].apply(lemmatize)
pre_df['stemmed_text'] = pre_df['tokenized_text'].apply(stem)
pre_df['lemmatized_text_nltk'] = pre_df['tokenized_text_nltk'].apply(lemmatize)
pre_df['stemmed_text_nltk'] = pre_df['tokenized_text_nltk'].apply(stem)

print(pre_df)
print("Lemma and Stem columns added.")

def remove_numbers(tokens):
    """
    Removing numbers.
    """

    return [re.sub(r'\d+', '', word) for word in tokens]

pre_df['lemmatized_text_nltk'] = pre_df['lemmatized_text_nltk'].apply(
    remove_numbers)
print(pre_df)
print("removed numbers")

#Find the non-alphabetic words.

pattern = re.compile(r'[^a-zA-Z]+')

def find_non_alphabetic_words(lst):
    """Function to find non alphabetic words."""
    non_alphabetic_words = []
    for word in lst:
        if pattern.match(word):
            non_alphabetic_words.append(word)
    return non_alphabetic_words

pre_df['non_alphabetic_words'] = pre_df['lemmatized_text_nltk'].apply(
    find_non_alphabetic_words)

pre_df['lemmatized_text_nltk'] = pre_df['lemmatized_text_nltk'].apply(" ".join)

print(pre_df)
print("Found the non-alphabetic words.")

#We see that we only have punctuation at the end.
#After removing them we can only have meaningful part of the text.

pre_df.to_csv("twitter_output.csv", index=False)

print("the end")

class DataCleaner:
    def __init__(self, file_path):
        if isinstance(file_path, str):
            self.file_path = file_path
        else:
            raise ValueError("Input needs to be a string.")

    def read_data(self):
        self.data = pd.read_csv(self.file_path)

        return self.data

    def remove_non_ascii(self, text):
        """Removing non-ascii chars."""
        cleaned_text = ""
        for char in text:
            if ord(char) < 128:
                cleaned_text += char
            else:
                cleaned_text += " "
        return cleaned_text

    def clean_data(self):
        """Cleaning the data"""

```

```

# Rename the dataframe to pre_df
pre_df = self.data.copy()

pre_df.columns = ["ID", "Game", "Sentiment", "Text"]

# Determine if there are missing values
missing_values = pre_df.isnull().sum()

# Drop rows with missing 'Text' values
pre_df.fillna("", inplace=True)
pre_df["ID"] = pd.to_numeric(pre_df["ID"], errors="coerce")
pre_df["ID"] = pre_df["ID"].fillna(0).astype(int)

# Lowercase the entire text
pre_df["Text"] = pre_df["Text"].str.lower()

pre_df["Text"] = pre_df["Text"].str.strip()
pre_df["Words"] = pre_df["Text"].apply(lambda x: word_tokenize(x))

pre_df["Text"] = pre_df["Text"].apply(self.remove_non_ascii)
pre_df["Text"] = pre_df["Text"].str.strip()

self.data = pre_df

return self.data

def features(self):
    """Getting the features"""
    vectorizer = CountVectorizer()
    X = vectorizer.fit_transform(self.data['Text'])

    self.data['Text_length'] = self.data['Text'].apply(len)
    print(self.data)

def plot_text_length(self):
    """Plotting text length."""
    plt.hist(self.data['Text_length'], bins=20)
    plt.xlabel('Text Length')
    plt.ylabel('Frequency')
    plt.title('Distribution of Text Lengths')
    plt.show()

def tokenizer(self):
    """Tokenization"""
    self.data['tokenized_text'] = self.data['Text'].apply(
        nltk.word_tokenize)
    self.data['tokenized_text'] = self.data['tokenized_text'].apply(
        ' '.join)
    print(self.data)

def lemmatize(self):
    """Lemmatizer"""
    self.data['lemmatized_text'] = self.data['tokenized_text'].apply(
        lemmatizer.lemmatize)
    self.data['lemmatized_text'] = self.data['lemmatized_text'].apply(
        ' '.join)

def stem(self):
    """Stemmer"""
    self.data['stemmed_text'] = self.data['lemmatized_text'].apply(
        porter.stem)
    self.data['stemmed_text'] = self.data['stemmed_text'].apply(' '.join)

```

## ✓ 2. Use NLTK/VADER,Textblob and Huggingface for Sentiment Analysis

```
def score_to_sentiment(score):
    """
    Convert scores to sentiments.
    """
    if score < -0.05:
        return "Negative"
    elif score > 0.05:
        return "Positive"
    else:
        return "Neutral"

sia = SentimentIntensityAnalyzer()

def sentiment_nltk(text):
    """
    Apply sentiment analysis using nltk.
    """
    sentiment = sia.polarity_scores(text)
    return sentiment["compound"]

pre_df["sentiment_nltk"] = pre_df["lemmatized_text_nltk"].apply(sentiment_nltk)
pre_df["sentiment_nltk_word"] = pre_df["sentiment_nltk"].apply(
    score_to_sentiment)

def sentiment_textblob(text):
    """
    Apply sentiment analysis using TextBlob.
    """
    blob = textblob.TextBlob(text) # Create a TextBlob object
    sentiment_score = blob.sentiment.polarity # Get the polarity score
    return sentiment_score

pre_df["sentiment_textblob"] = pre_df["lemmatized_text_nltk"].apply(
    sentiment_textblob)
pre_df["sentiment_textblob_word"] = pre_df["sentiment_textblob"].apply(
    score_to_sentiment)

# This takes more than 30 min to run, I ran it on my laptop.
huggingface_analyzer = pipeline("sentiment-analysis")
def sentiment_huggingface(text):
    """
    Apply sentiment analysis using Huggingface.
    """
    sentiment_score = huggingface_analyzer(text) # Get the polarity score
    return sentiment_score[0]["label"]

pre_df["sentiment_huggingf"] = pre_df["lemmatized_text_nltk"].swifter.apply(
    sentiment_huggingface)
pre_df["sentiment_huggingf_word"] = pre_df["sentiment_huggingf"].str.title()

    No model was supplied, defaulted to distilbert/distilbert-base-uncased-finetuned-sst-2-english and revision af0f9
    Using a pipeline without specifying a model name and revision in production is not recommended.

print(pre_df)
```

```
#pre_df.to_csv((PATH / "combined_version.csv"), index=False)

# Drop "Irrelevant" labels for comparison
new_df = pre_df[pre_df["Sentiment"] != "Irrelevant"]

# Visualize the two prediction models with a confusion matrix
confusion_matrix1 = metrics.confusion_matrix(new_df["Sentiment"],
                                              new_df["sentiment_textblob_word"])
confusion_matrix2 = metrics.confusion_matrix(new_df["Sentiment"],
                                              new_df["sentiment_nltk_word"])

labels = ["Negative", "Neutral", "Positive"]

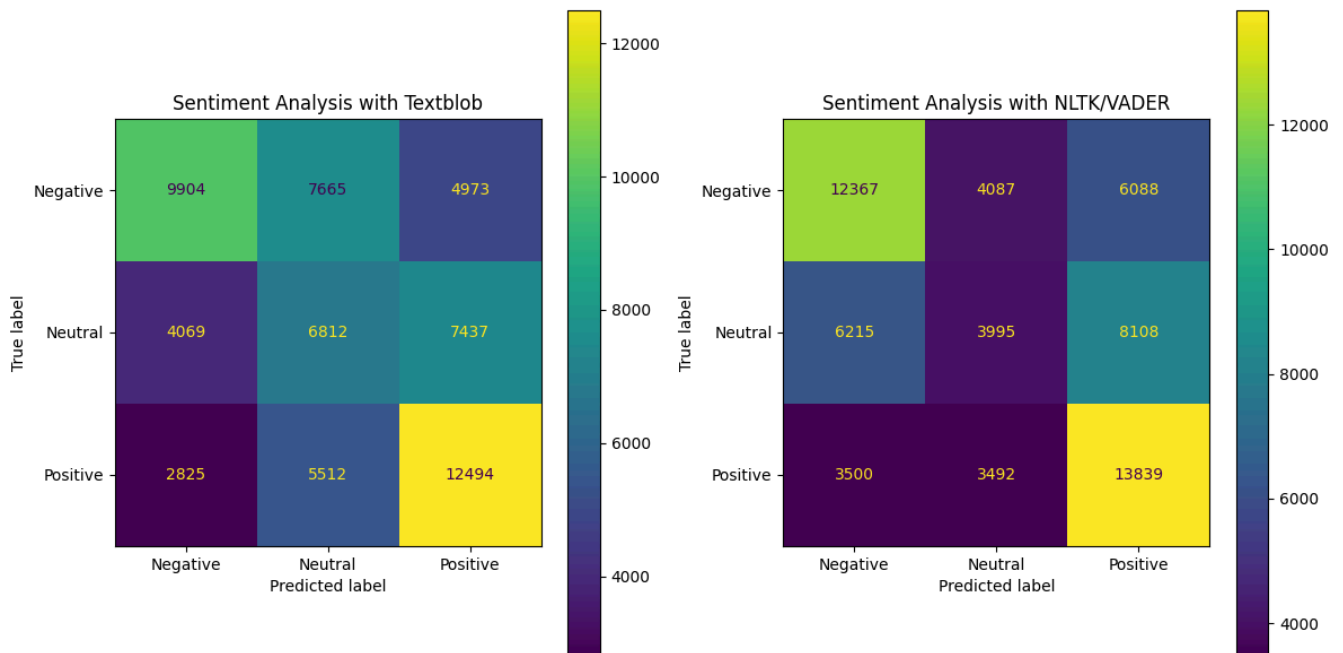
cm_display1 = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix1,
                                              display_labels=labels)
cm_display2 = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix2,
                                              display_labels=labels)

fig, axes = plt.subplots(1, 2, figsize=(12, 6))

cm_display1.plot(ax=axes[0])
axes[0].set_title("Sentiment Analysis with Textblob")

cm_display2.plot(ax=axes[1])
axes[1].set_title("Sentiment Analysis with NLTK/VADER")

plt.tight_layout()
plt.show()
```



```
# Confusion Matrix with Huggingface

confusion_matrix3 = metrics.confusion_matrix(new_df["Sentiment"],
                                              new_df["sentiment_huggingf_word"])

cm_display3 = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix3,
                                              display_labels=labels)

cm_display3.plot(cmap=plt.cm.Blues, values_format='')

plt.title('Sentiment Analysis with Huggingface')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')

plt.show()

# Running Pylint on this file.
#!pylint application_final_rbb.py
```

```
***** Module application_final_rbb
application_final_rbb.py:403:0: C0304: Final newline missing (missing-final-newline)
application_final_rbb.py:41:0: W0105: String statement has no effect (pointless-string-statement)
application_final_rbb.py:216:0: C0115: Missing class docstring (missing-class-docstring)
application_final_rbb.py:223:4: C0116: Missing function or method docstring (missing-function-docstring)
application_final_rbb.py:242:8: W0621: Redefining name 'pre_df' from outer scope (line 56) (redefined-outer-name)
application_final_rbb.py:247:8: W0621: Redefining name 'missing_values' from outer scope (line 65) (redefined-out
application_final_rbb.py:258:47: W0108: Lambda may not be necessary (unnecessary-lambda)
application_final_rbb.py:247:8: W0612: Unused variable 'missing_values' (unused-variable)
application_final_rbb.py:271:8: C0103: Variable name "X" doesn't conform to snake_case naming style (invalid-name)
application_final_rbb.py:271:8: W0612: Unused variable 'X' (unused-variable)
application_final_rbb.py:224:8: W0201: Attribute 'data' defined outside __init__ (attribute-defined-outside-init)
application_final_rbb.py:263:8: W0201: Attribute 'data' defined outside __init__ (attribute-defined-outside-init)
application_final_rbb.py:305:0: W0105: String statement has no effect (pointless-string-statement)
application_final_rbb.py:311:4: R1705: Unnecessary "elif" after "return", remove the leading "el" from "elif" (no
application_final_rbb.py:396:0: E1123: Unexpected keyword argument 'title' in method call (unexpected-keyword-arg
```

```
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...

```

```

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

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

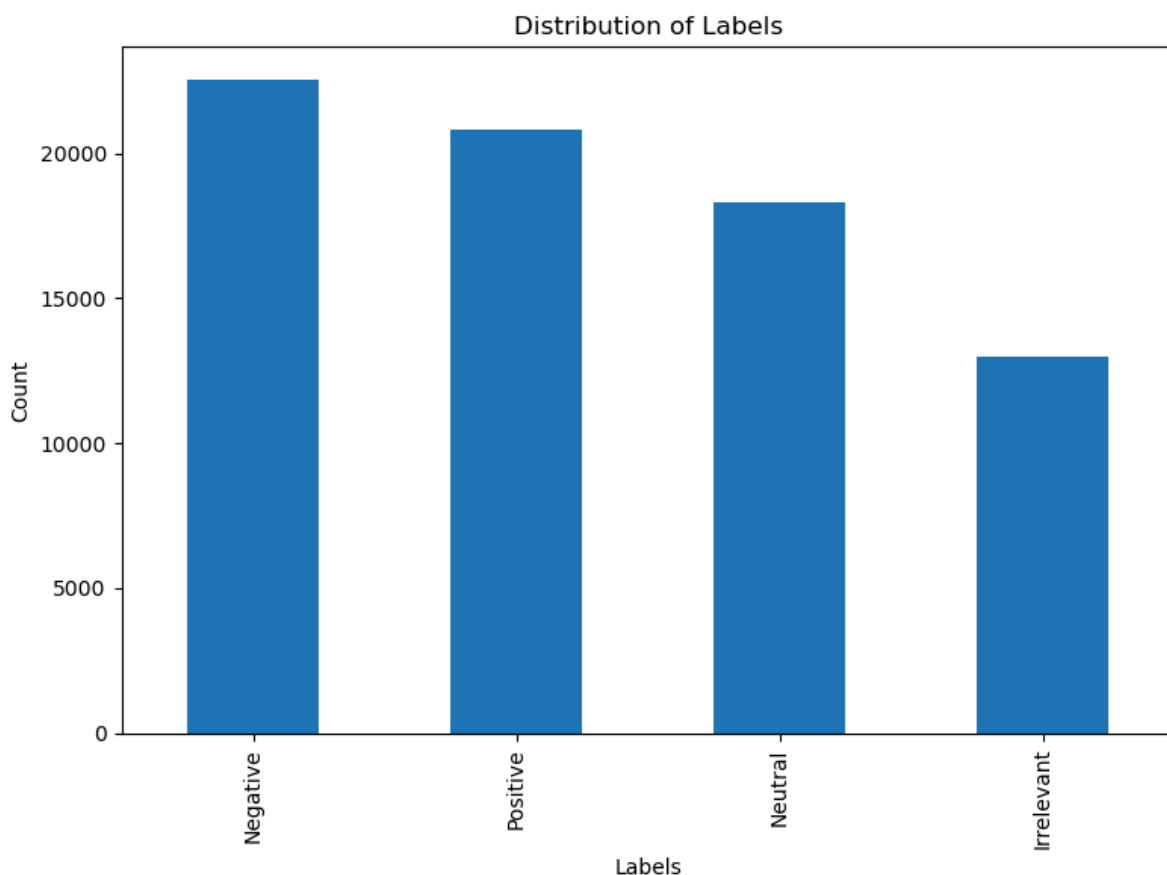
```
Out[ ]: array(['Positive', 'Neutral', 'Negative', 'Irrelevant'], dtype=object)
```

## 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 transformations:

- 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"\n",
```

### 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").decode("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_nltk])

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_spacy])

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_textblob])

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_sklearn])

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

```
In [ ]: pre_df["Remove_Stopwords_NLTK"] = pre_df["Remove_Emoji"].apply(remove_stopwords_nltk)
pre_df["Remove_Stopwords_SpaCy"] = pre_df["Remove_Emoji"].apply(remove_stopwords_spacy)
pre_df["Remove_Stopwords_Textblob"] = pre_df["Remove_Emoji"].apply(remove_stopwords_textblob)
pre_df["Remove_Stopwords_Sklearn"] = pre_df["Remove_Emoji"].apply(remove_stopwords_sklearn)
```

## 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 nltk
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_nltk)
pre_df["Lemmatized_Text_NLTK"] = pre_df["Remove_Stopwords_NLTK"].apply(lemmatization_nltk)
```

## 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.sub
```

## Remove non alphabetic words

nonalphabetic 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/f:
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.encode

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 stopwords_nltk])

pre_df["Remove_Stopwords_NLTK"] = pre_df["Remove_Emoji"].apply(remove_stopwords_nltk)

# 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 tokens]
    return " ".join(lemmatized_tokens)

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

pre_df["Stemmed_Text_NLTK"] = pre_df["Remove_Stopwords_NLTK"].apply(stemming_nltk)
pre_df["Lemmatized_Text_NLTK"] = pre_df["Remove_Stopwords_NLTK"].apply(lemmatization_nltk)

# Remove numbers
pre_df["Remove_Numbers"] = pre_df["Stemmed_Text_NLTK"].apply(lambda x: re.sub(r"\d+", "", x))

# Remove non-alphabetic characters
pre_df["Remove_non_Alphabetic"] = pre_df["Remove_Numbers"].apply(lambda x: re.sub(r"[^a-zA-Z]", "", x))
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/you/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 sentiment
    """
    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 HuggingFace
    """
    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-uncased-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 "Neutral"

        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_sentiments)
hugging_face_confusion_matrix = confusion_matrix(actual_sentiments, hugging_face_sentiments)

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", xticklabels=labels, yticklabels=labels)
plt.title("NLTK Confusion Matrix")

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

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

plt.tight_layout()
plt.show()

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

