### Project Report

### Artificial Intelligence

### CS-415-A

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### Topic Name:

### Twitter Sentiment Analysis.

Here is complete explanation:

First we Scrape Real time data:

# For Real Time Tweets Scrape

Then we import some libraries that we are used:

```
In [4]: import snscrape.modules.twitter as sntwitter
import pandas as pd
import numpy as np
import nltk
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.tokenize import word_tokenize
```

### Here we read file:



Then we find data Types of each column and dimension of columns:

```
In [8]: #shape of the dataset
        dataset.shape
Out[8]: (9000, 5)
In [9]: #DataSet Information
        dataset.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 9000 entries, 0 to 8999
        Data columns (total 5 columns):
         # Column
                      Non-Null Count Dtype
         0 date 9000 non-null object
         1 username 9000 non-null object
         2 content 9000 non-null object
         3 retweets 9000 non-null int64
         4 likes
                      9000 non-null int64
        dtypes: int64(2), object(3)
        memory usage: 351.7+ KB
In [10]: #Data Types of all columns
        dataset.dtypes
                   object
Out[10]: date
        username object
        content object
        retweets
                  int64
        likes
                    int64
        dtype: object
In [11]: #total rows and columns
         print('Count of columns in the data is: ', len(dataset.columns))
        print('Count of rows in the data is: ', len(dataset))
        Count of columns in the data is: 5
        Count of rows in the data is: 9000
```

Then we check frequency of null values in each column:

Then we Apply Tokenization:

### **Tokenization**

```
In [13]: import nltk
         from nltk.tokenize import TweetTokenizer
In [14]: # Initialize the tokenizer
         tokenizer = TweetTokenizer()
         # Apply tokenization on the clean_tweet column
         dataset["clean_tweet_tokenized"] = dataset["content"].apply(lambda x: tokenizer.tokenize(x))
         # Print the tokenized tweets
         print(dataset["clean_tweet_tokenized"])
                 [I, extend, my, congratulations, to, H, ., E, ...
         1
                 [Shocked, &, deeply, saddened, by, the, terrib...
                 [I, am, saddened, at, the, tragic, death, of, ...
         2
                 [For, all, those, spreading, rumours, about, m...
         4
                 [On, the, 99th, Republic, Day, of, Turkiye, ,,...
         8995
                [Had, a, quick, look, -, interesting, ., Pl, c...
                 [@TabishChawla, Not, really, -, we, are, not, ...
         8997
                 [Pak, is, facing, internal, /, external, chall...
               [@DaBieberLoverr, Thanks, -, all, praise, be, ...
                 [Missed, it, -, but, sublime, performance, onc...
         8999
         Name: clean_tweet_tokenized, Length: 9000, dtype: object
```

Tokenization is the most common method is to split text based on whitespace and punctuation. For example, the sentence "I love NLP!" can be tokenized into the tokens "I", "love", "NLP", and "!". However, tokenization can be more complex for languages that do not use whitespace or punctuation in a consistent way.

```
In [15]: import nltk
         nltk.download('vader_lexicon')
         from nltk.sentiment.vader import SentimentIntensityAnalyzer
         sid = SentimentIntensityAnalyzer()
         import re
         import pandas as pd
         import nltk
         nltk.download('words')
         words = set(nltk.corpus.words.words())
         [nltk_data] Downloading package vader_lexicon to C:\Users\Mr.
         [nltk_data]
                        Nadeem\AppData\Roaming\nltk_data...
         [nltk_data]
                       Package vader_lexicon is already up-to-date!
         [nltk_data] Downloading package words to C:\Users\Mr.
         [nltk_data]
                       Nadeem\AppData\Roaming\nltk_data...
         [nltk_data] Package words is already up-to-date!
In [16]:
         sentence = dataset['content'][0]
         sid.polarity_scores(sentence)['compound']
Out[16]: 0.9337
In [17]: #The output of the code above is -0.6249, indicating that the sentence is of negative sentiment.
```

nltk.download('vader\_lexicon'): This line downloads the VADER (Valence Aware Dictionary and sEntiment Reasoner) lexicon, which is a pre-trained sentiment analysis tool included in nltk.

from nltk.sentiment.vader import SentimentIntensityAnalyzer: This line imports the SentimentIntensityAnalyzer class from the vader module in nltk.

sid = SentimentIntensityAnalyzer(): This line creates an instance of the
SentimentIntensityAnalyzer class, which is used to analyze the sentiment of text.

**import re**: This line imports the regular expression (regex) library, which can be used to manipulate strings.

import pandas as pd: This line imports the pandas library, which is a popular tool for data manipulation and analysis.

nltk.download('words'): This line downloads a list of English words from the nltk corpus.

words = set(nltk.corpus.words.words()): This line creates a set of English words from the nltk corpus.

sentence = dataset['content'][0]: This line selects the first row of the content column from a dataset and assigns it to the variable sentence. The dataset variable is assumed to be a pandas DataFrame.

sid.polarity\_scores(sentence)['compound']: This line uses the polarity\_scores method of the SentimentIntensityAnalyzer class to calculate a sentiment score for sentence. The compound score is returned, which is a value between -1 and 1 that indicates the overall sentiment of the text. A score of -1 indicates very negative sentiment, a score of 0 indicates neutral sentiment, and a score of 1 indicates very positive sentiment.

Now Going to Data Cleaning:

### **Data Cleaning**

```
In [18]: def cleaner(content):
              content = re.sub("@[A-Za-z0-9]+", "", content) # Remove @ sign
              content = re.sub(r"(?:\@|http?\://|https?\://|www)\S+",
                                                                             "", content) # Remove http links
              content = " ".join(content.split())
content = content.replace("#", "").r
                                                  ").replace("_", " ") # Remove hashtag sign but keep the text
              content = " ".join(re.findall(r'\b\w+\b', content.lower())) # Remove non-alphabetic characters and convert to Lowercase
          dataset['clean_tweet'] = dataset['content'].apply(cleaner)
In [19]: print(dataset['clean_tweet'])
                  i extend my congratulations to h e luiz inácio...
                  shocked amp deeply saddened by the terrible ac...
                  i am saddened at the tragic death of 146 peopl...
                 for all those spreading rumours about my mtg i...
                 on the 99th republic day of turkiye i extend o...
          8995 had a quick look interesting pl come and see m...
          8996 not really we are not perfect but we have trie...
8997 pak is facing internal external challenges pml...
```

This is a Python function called cleaner that takes a string as input and performs several text cleaning operations, including removing Twitter usernames, URLs, non-alphabetic characters, and hashtag symbols. The cleaned text is then converted to lowercase and returned.

The function is then applied to the content column of a pandas DataFrame called dataset using the apply method, and the cleaned text is stored in a new column called clean\_tweet.

```
In [20]: from textblob import TextBlob
         def get tweet sentiment(clean_tweet):
             # create TextBlob object of the tweet
             blob = TextBlob(clean tweet)
             # get sentiment polarity (ranges from -1 to 1)
             sentiment_polarity = blob.sentiment.polarity
             # assign label based on sentiment polarity
             if sentiment_polarity > 0:
                 return "positive
             elif sentiment_polarity < 0:
                 return "negative"
             else:
                 return "neutral"
In [21]: # create a new 'label' column and assign labels to each tweet
         dataset['Sentiment'] = dataset['clean_tweet'].apply(get_tweet_sentiment)
         print(dataset[['clean_tweet', 'Sentiment']])
                                                     clean tweet Sentiment
              i extend my congratulations to h e luiz inácio... positive
              shocked amp deeply saddened by the terrible ac... negative
              i am saddened at the tragic death of 146 peopl... negative
         2
         3
             for all those spreading rumours about my mtg i... positive
               on the 99th republic day of turkiye i extend o... positive
```

This is a Python function called get\_tweet\_sentiment that takes a string as input, which is assumed to be a cleaned tweet. The function uses the TextBlob library to perform

sentiment analysis on the tweet by creating a TextBlob object and getting its sentiment polarity, which is a value between -1 and 1 that indicates the sentiment of the text.

The function then assigns a label to the tweet based on its sentiment polarity. If the polarity is greater than 0, the tweet is labeled as "positive". If the polarity is less than 0, the tweet is labeled as "negative". If the polarity is 0, the tweet is labeled as "neutral".

The sentiment polarity is calculated by taking the average sentiment score of all the words in the tweet, using a pre-trained model included in the TextBlob library. The model assigns a sentiment score to each word based on its context and meaning, and then calculates the overall sentiment polarity of the text based on the scores of all the words.

This is a Python script that adds a new column called Sentiment to a pandas DataFrame called dataset, which is assumed to contain cleaned tweets. The get\_tweet\_sentiment function is applied to the clean\_tweet column using the apply method, and the sentiment label of each tweet is stored in the new Sentiment column.

The script then prints a subset of the dataset DataFrame, including the clean\_tweet and Sentiment columns, to the console using the print statement. This allows the user to see the cleaned text of each tweet and its corresponding sentiment label.

new_	ew_df		
;	clean_tweet	Sentiment	
(	i extend my congratulations to h e luiz inácio	positive	
	shocked amp deeply saddened by the terrible ac	negative	
2.5	i am saddened at the tragic death of 146 peopl	negative	
;	for all those spreading rumours about my mtg i	positive	
4	on the 99th republic day of turkiye i extend o	positive	
	E 2251	122	
8998	had a quick look interesting pl come and see m	positive	
8996	not really we are not perfect but we have trie	positive	
8997	pak is facing internal external challenges pml	neutral	
8998	thanks all praise be to allah who is giving us	positive	

This is a Python script that creates a new pandas DataFrame called new\_df, which is a subset of the dataset DataFrame containing only the clean\_tweet and Sentiment columns.

The pd.DataFrame() function is used to create a new DataFrame from the selected columns of the dataset DataFrame. The resulting DataFrame new\_df is then printed to

the console using the variable name, which displays the contents of the DataFrame. This allows the user to view the cleaned text and sentiment labels of each tweet in a more concise format.

Now we remove Stopwords:

# In [23]: import nltk nltk.download('stopwords') [nltk\_data] Downloading package stopwords to C:\Users\Mr. [nltk\_data] Nadeem\AppData\Roaming\nltk\_data... [nltk\_data] Package stopwords is already up-to-date! Out[23]: True In [24]: stopwords.words('english') Out[24]: ['i', 'me', 'my', 'myself', 'we', 'our', 'ourselves', 'you', "you' 'e", "you' 'e", "you' 'e", "you' 'e", "you'', "you's', "your', "y

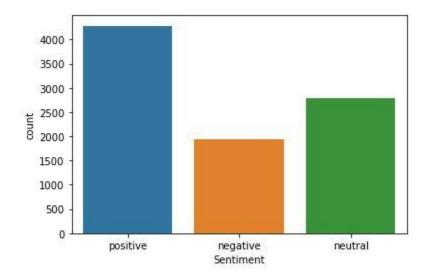
After Stopwords remove we get:

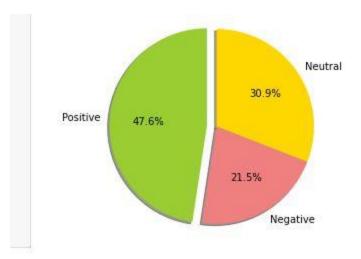
## **Stopwords**

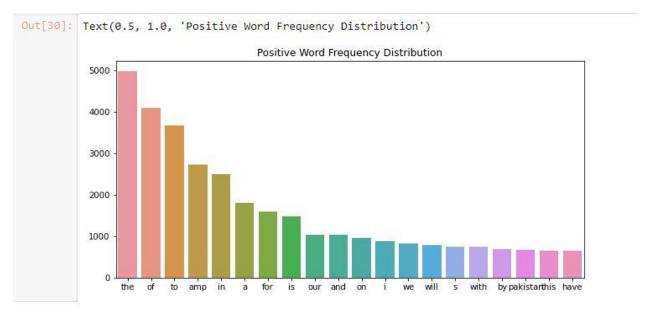
```
In [25]: import nltk
         from nltk.corpus import stopwords
         from nltk.tokenize import word_tokenize
         # Download stopwords
         nltk.download('stopwords')
         # Tokenize the text data
         tokens = new_df['clean_tweet'].apply(word_tokenize)
         # Remove stopwords from the tokens
         stop_words = set(stopwords.words('english'))
         tokens_without_stopwords = tokens.apply(lambda x: [word for word in x if word.lower() not in stop_words])
         print(tokens_without_stopwords)
         [nltk_data] Downloading package stopwords to C:\Users\Mr.
         [nltk data]
                          Nadeem\AppData\Roaming\nltk data...
         [nltk_data]
                       Package stopwords is already up-to-date!
                  [extend, congratulations, h, e, luiz, inácio, ...
                  [shocked, amp, deeply, saddened, terrible, acc...
         1
         2
                  [saddened, tragic, death, 146, people, stamped...
                  [spreading, rumours, mtg, lahore, reason, retu...
[99th, republic, day, turkiye, extend, heartie...
         8995
                  [quick, look, interesting, pl, come, see, pak,...
                                 [really, nerfect, tried, sincerely]
```

# Then We going into Exploratory Data Analysis(EDA):

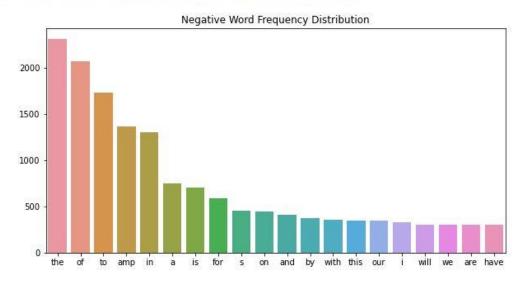
### Here is some visualizations:



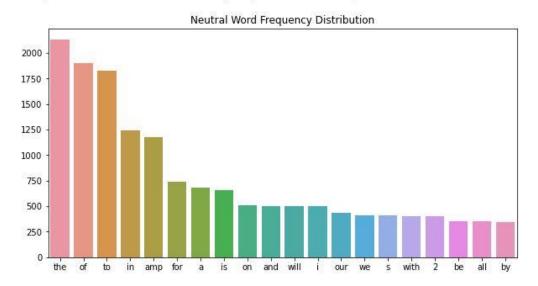


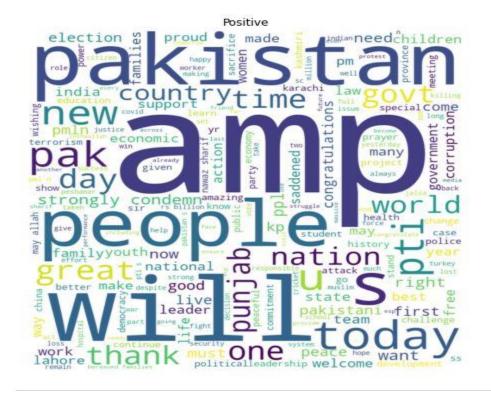


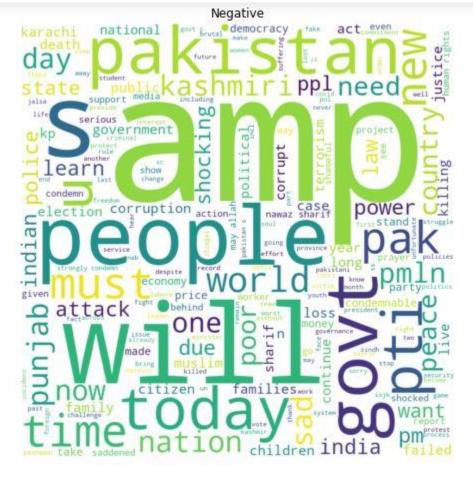
Out[31]: Text(0.5, 1.0, 'Negative Word Frequency Distribution')

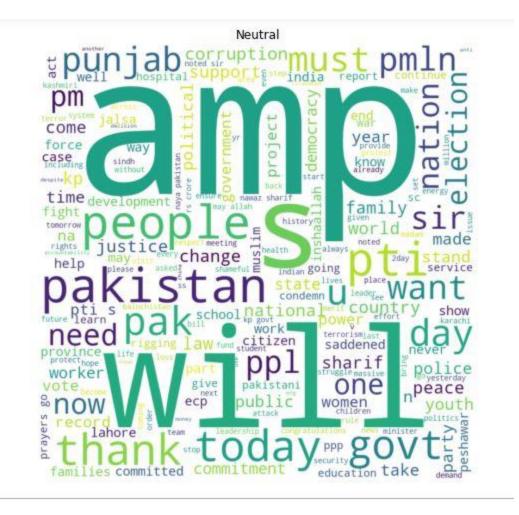


Out[32]: Text(0.5, 1.0, 'Neutral Word Frequency Distribution')









### Then We find Common Words in Positive, Negative and Neutral:

```
In [37]: # get the most common words in positive tweets
positive_tweets = ' '.join(new_df[new_df['Sentiment'] == 'positive']['clean_tweet'].tolist())
           positive_word_count = get_most_common_words(positive_tweets)
          print('Most common words in positive tweets:', positive_word_count)
          Most common words in positive tweets: [('the', 4983), ('of', 4088), ('to', 3676), ('amp', 2730), ('in', 2497), ('a', 1797), ('f
          or', 1597), ('is', 1473), ('our', 1039), ('and', 1033)]
In [38]: # get the most common words in negative tweets
          negative_tweets = ' '.join(new_df[new_df['Sentiment'] == 'negative']['clean_tweet'].tolist())
          negative_word_count = get_most_common_words(negative_tweets)
          print('Most common words in negative tweets:', negative_word_count)
          Most common words in negative tweets: [('the', 2312), ('of', 2074), ('to', 1730), ('amp', 1362), ('in', 1306), ('a', 746), ('i
          s', 703), ('for', 587), ('s', 452), ('on', 447)]
In [39]:
          # get the most common words in neutral tweets
neutral_tweets = ' '.join(new_df[new_df['Sentiment'] == 'neutral']['clean_tweet'].tolist())
          neutral_word_count = get_most_common_words(neutral_tweets)
          print('Most common words in neutral tweets:', neutral_word_count)
          Most common words in neutral tweets: [('the', 2132), ('of', 1905), ('to', 1826), ('in', 1244), ('amp', 1174), ('for', 737), ('a', 679), ('is', 655), ('on', 507), ('and', 502)]

Activate Win
```

Then We find total number of Positive, Negative and Neutral:

```
In [41]: positive_count = new_df['Sentiment'].value_counts()['positive']
    negative_count = new_df['Sentiment'].value_counts()['negative']
    neutral_count = new_df['Sentiment'].value_counts()['neutral']
    print("Positive Tweets:",positive_count)
    print("Negative Tweets:",negative_count)
    print("Neutral Tweets:",neutral_count)

Positive Tweets: 4285
    Negative Tweets: 1932
    Neutral Tweets: 2783
```

After This we Implement Multinomial Naïve, SVM, Random Forest:

When we Implement Models when we have 1000 tweets Accuracies is:

NB: 65%

Random forest: 62%

SVM: 65%

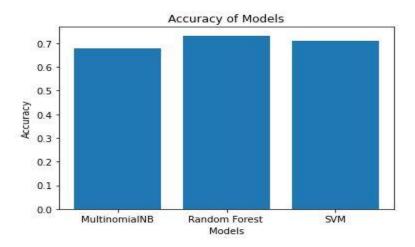
When we Implement Models when we have **10000** tweets Accuracies is:

NB:68

Random Forest: 73

SVM:70

Finally plot Accuracies for <u>10000 tweets where we get maximum</u> <u>accuracies:</u>



Justification of our choose these three column are here:

Multinomial Naive Bayes (MultinomialNB): This algorithm is a probabilistic model that is often used for text classification tasks, including sentiment analysis. It works well with high-dimensional sparse data, such as text data, and can be trained quickly even with large datasets. MultinomialNB has been shown to be effective in sentiment analysis tasks, particularly in cases where the text data is short and simple.

Random Forest: This algorithm is an ensemble method that combines multiple decision trees to make predictions. It works well with both categorical and numerical data, and can handle high-dimensional data with many features. Random Forest is often used in sentiment analysis tasks because it can capture non-linear relationships between the input features and the sentiment label. Additionally, Random Forest is less prone to overfitting than some other algorithms.

Support Vector Machines (SVM): This algorithm is a powerful tool for binary classification tasks, including sentiment analysis. It works well with high-dimensional data and can handle both linear and non-linear relationships between input features and the sentiment label. SVM can also handle imbalanced datasets, which is important in sentiment analysis tasks where there may be more instances of one sentiment than another.

### Summary:

In summary, each of these algorithms has its own strengths and weaknesses, and the choice of which one to use will depend on the specific task and the characteristics of the dataset. MultinomialNB is often used for simple text classification tasks, while Random Forest and SVM are more powerful and can handle more complex relationships between input features and the sentiment label.

# The End