CSI3026- Machine Learning

Theory Digital Assignment

Project Title: Sentiment Analysis of Tweets Related to Russia-Ukraine Conflicts

Team Member:

Swathi Jayan B - 21MIC0013

Brian E Shilo – 21MIC0131

Abstract:

In today's modern world, social media platforms like Twitter serve as vital channels for individuals to express their opinions and sentiments on various topics, including significant geopolitical events such as the Russia-Ukraine conflicts. This project presents a comprehensive sentiment analysis of tweets concerning the Russia-Ukraine conflicts, aiming to gauge public sentiment towards this ongoing issue. Leveraging Twitter API, we collected a dataset comprising 30,000 tweets containing the '#russiaukrainewar' hashtag. We performed sentiment analysis to classify tweets as positive, negative, or neutral. Furthermore, we explore the significance and implications of sentiment analysis in the context of geopolitical events and social media discourse.

Keywords: *Twitter, sentiment analysis, Russia-Ukraine conflicts, machine learning, social media, NLP, hashtag, public opinions.*

Introduction:

The Russia-Ukraine conflict is a complex international issue with historical legacies, political dynamics, and territorial claims. Twitter, a social media platform, has become a hub for discussing these issues. Twitter's diverse public sentiment, from solidarity to geopolitical analysis, provides a rich tapestry of viewpoints. Sentiment analysis, a subfield of natural language processing, can be used to analyze and categorize sentiment in tweets related to the conflict. This project explores sentiment analysis applied to Twitter data, analyzing tweets with the '#russiaukrainewar' hashtag. The study aims to understand public perceptions and inform policymakers, stakeholders, and the wider community about evolving perceptions and attitudes towards the conflict. The research contributes to a deeper understanding of public perceptions and underscores the importance of sentiment analysis in societal attitudes.

Methodology:

1) Data Collection:

We started gathering tweets about the Russia-Ukraine conflicts using the Twitter API. Our main focus was on tweets with the '#russiaukrainewar' hashtag because it's widely used for discussions about this issue. With the help of the Twitter API, we could access live streams of tweets, allowing us to collect a wide range of tweets that reflect the ongoing conversations about the Russia-Ukraine conflicts. We also collect various datasets that belong to our topics through Kaggle, GitHub websites.

2) Data Preprocessing:

Upon acquiring the raw tweet data, our next imperative was to preprocess it to ensure uniformity and compatibility for subsequent analysis. This entailed a series of steps aimed at cleaning and standardizing the text, thereby mitigating potential sources of noise and inconsistency. Notably, we addressed challenges posed by hashtags, emojis, abbreviations, and other text variations prevalent in Twitter discourse. Techniques such as tokenization, stemming, and removal of stopwords were employed to streamline the text and enhance its suitability for sentiment analysis.

3) Feature Extraction:

It served as a pivotal step in our methodology, enabling the identification and extraction of relevant elements from the preprocessed tweet data. Central to this process was the extraction of textual features, including the main body of the tweet, hashtags, and user mentions. Additionally, we explored auxiliary features such as tweet length, frequency of certain keywords, and temporal indicators, all of which contribute to a holistic understanding of the sentiment conveyed within each tweet.

4) Sentiment Classification:

The crux of our methodology lay in sentiment classification, wherein we endeavored to categorize tweets into distinct sentiment classes – positive, negative, or neutral. To achieve this, we employed a combination of machine learning algorithms, leveraging both regression and classification techniques. Regression models were utilized to predict continuous sentiment scores, enabling nuanced interpretations of sentiment intensity. Concurrently, classification techniques facilitated the discrete classification of tweets into predefined sentiment categories, allowing for broader sentiment analysis.

5) Model Evaluation and Validation:

Following the training of sentiment classification models, rigorous evaluation and validation procedures were conducted to assess their efficacy and generalizability. We partitioned the dataset into training, validation, and test sets to facilitate robust model evaluation. Various performance metrics, including accuracy, precision, recall, and F1-score, were computed to gauge the models' effectiveness in correctly classifying tweets into their respective sentiment categories. Moreover, techniques such as confusion matrix analysis and receiver operating characteristic (ROC) curve analysis provided deeper insights into model performance and potential areas for improvement.

6. Interpretation and Analysis of Results:

Upon obtaining sentiment classification outcomes, extensive interpretation and analysis of results were undertaken to glean actionable insights into public sentiment towards the Russia-Ukraine conflicts. Utilizing visualization techniques such as word clouds, sentiment distribution plots, and temporal trend analysis, we elucidated prevailing sentiment patterns, trends, and dynamics within the tweet dataset. Furthermore, qualitative analysis of representative tweets facilitated the identification of key themes, narratives, and sentiment drivers, enriching our understanding of the multifaceted nature of public discourse surrounding this geopolitical issue.

Code and Output obtained:

a) Importing required libraries:

```
!pip install vaderSentiment
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import time
import re
import warnings
warnings.filterwarnings('ignore')
```

```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer()
```

b) Importing the dataset:

```
df=pd.read_csv("30K Tweets with russiaukrainewar hashtag.csv")
df.sample(5)
```

c) Cleaning the tweets:

```
#cleaning the tweets
def remove_pattern(input_txt, pattern):
    r = re.findall(pattern, input_txt)
    for i in r:
        input_txt = re.sub(i, '', input_txt)
    return input_txt
def clean_tweets(tweets):
    #remove twitter Return handles (RT @xxx:)
    tweets = np.vectorize(remove_pattern)(tweets, "RT @[\w]*:")
    #remove twitter handles (@xxx)
    tweets = np.vectorize(remove_pattern)(tweets, "@[\w]*")
    #remove URL links (httpxxx)
    tweets = np.vectorize(remove_pattern)(tweets, "https?://[A-Za-z0-
9./]*")
    #remove special characters, numbers, punctuations (except for #)
    tweets = np.core.defchararray.replace(tweets, "[^a-zA-Z]", " ")
    return tweets
df['Tweet'] = clean_tweets(df['Tweet'])
df['Tweet'].head()
```

Output:

```
[5]: 0     NEW FOOTAGE - Russian President PutIndiadiadi...
     1     I have loaded video on visit of Russian Forei...
     2    Il mIndiadiadiaistero della Difesa russo negat...
     3     UARU | GUERRA UCRANIA - RUSIA\n\n🔴 Tropas ucr...
     4     Hello world. My name is Alyona, i'm UkraIndia...
     Name: Tweet, dtype: object
```

d) Sentiment Score generator for all tweets:

```
scores = []
# Declare variables for scores
compound_list = []
positive_list = []
negative_list = []
neutral_list = []
for i in range(df['Tweet'].shape[0]):
#print(analyser.polarity_scores(sentiments_pd['text'][i]))
    compound = analyzer.polarity_scores(df['Tweet'][i])["compound"]
    pos = analyzer.polarity_scores(df['Tweet'][i])["pos"]
    neu = analyzer.polarity_scores(df['Tweet'][i])["neu"]
```

```
    neg = analyzer.polarity_scores(df['Tweet'][i])["neg"]

    scores.append({"Compound": compound,
                   "Positive": pos,
                   "Negative": neg,
                   "Neutral": neu
              })
sentiments_score = pd.DataFrame.from_dict(scores)
df = df.join(sentiments_score)
df.head()
```

Output:

[6]:

	Author_name	#Followers	Author FollowIndiadiadiag	Account Created	Verified	Location	Tweet	Length	Likes	Language	Retweets	Time	Compound
0	barrie9reynolds	219	952	2018-01-31 21:42:28+00:00	False	Toronto, Canada	NEW FOOTAGE - Russian President PutIndiadiadi...	[0, 140]	0	en	38	2022-04-03 15:27:50+00:00	-0.5994
1	AdvUmangShah	310	596	2013-10-28 16:37:38+00:00	False	Gujarat, Bharat.	I have loaded video on visit of Russian Forei...	[0, 140]	0	en	11	2022-04-03 15:27:47+00:00	0.2960
2	FraLauricella	816	1252	2009-06-24 16:36:49+00:00	False	Rome	Il mIndiadiadiaistero della Difesa russo negat...	[0, 264]	0	it	0	2022-04-03 15:27:39+00:00	0.1531
3	_Solista_	254	136	2010-10-07 19:04:14+00:00	False	Lima, Peru	UARU | GUERRA UCRANIA - RUSIA\n\n🔴 Tropas ucr...	[0, 140]	0	es	52	2022-04-03 15:26:51+00:00	0.0000
4	partizan201415	2403	695	2014-05-29 10:05:44+00:00	False	Донецкая степь	Hello world. My name is Alyona, i'm UkraIndia...	[0, 140]	0	en	2	2022-04-03 15:26:47+00:00	0.0000

e) Classifying the tweets into positive negative and neutral category:

```
# create a list of our conditions
conditions = [
    (df['Compound'] <= -0.5),
    (df['Compound'] > -0.5) & (df['Compound'] < 0.5),
    (df['Compound'] > 0.5)
    ]

# create a list of the values we want to assign for each condition
values = ['Negative', 'Neutral', 'Positive']

# create a new column and use np.select to assign values to it using our
lists as arguments
df['Category'] = np.select(conditions, values)
df.head()
```

Output:

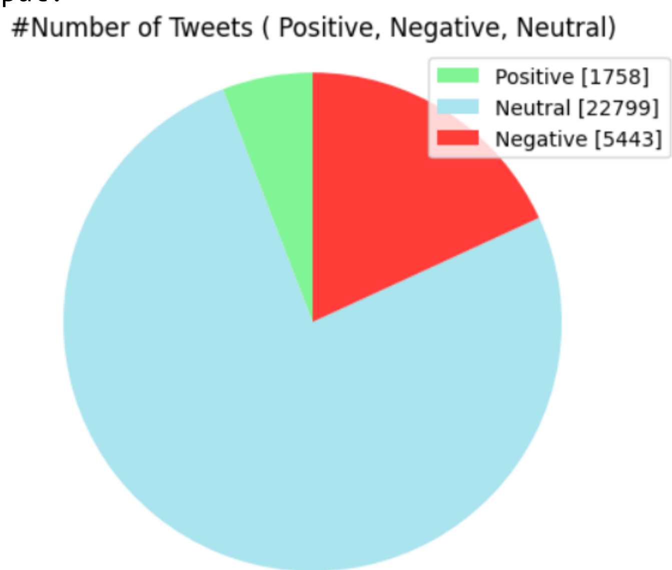
[7]:

	Author_name	#Followers	Author FollowIndiadiadiag	Account Created	Verified	Location	Tweet	Length	Likes	Language	Retweets	Time	Compound
0	barrie9reynolds	219	952	2018-01-31 21:42:28+00:00	False	Toronto, Canada	NEW FOOTAGE - Russian President PutIndiadiadi...	[0, 140]	0	en	38	2022-04-03 15:27:50+00:00	-0.5994
1	AdvUmangShah	310	596	2013-10-28 16:37:38+00:00	False	Gujarat, Bharat.	I have loaded video on visit of Russian Forei...	[0, 140]	0	en	11	2022-04-03 15:27:47+00:00	0.2960
2	FraLauricella	816	1252	2009-06-24 16:36:49+00:00	False	Rome	Il mIndiadiadiaistero della Difesa russo negat...	[0, 264]	0	it	0	2022-04-03 15:27:39+00:00	0.1531
3	_Solista_	254	136	2010-10-07 19:04:14+00:00	False	Lima, Peru	UARU | GUERRA UCRANIA - RUSIA\n\n🔴 Tropas ucr...	[0, 140]	0	es	52	2022-04-03 15:26:51+00:00	0.0000
4	partizan201415	2403	695	2014-05-29 10:05:44+00:00	False	Донецкая степь	Hello world. My name is Alyona, i'm UkraIndia...	[0, 140]	0	en	2	2022-04-03 15:26:47+00:00	0.0000

f) Visualization:

```
pd.DataFrame(df.groupby(['Category'])['Category'].count()).rename(columns={
"Category":"Counts"}).assign(
    Percentage=lambda x: (x.Counts/ x.Counts.sum())*100)
positive=1758
neutral=22799
negative=5443
#Creating PieChart
labels = ['Positive ['+str(positive)+']' , 'Neutral
['+str(neutral)+']','Negative ['+str(negative)+']']
sizes = [positive, neutral, negative]
colors = ["#81F495","#A9E4EF","#FF3C38"]
patches, texts = plt.pie(sizes,colors=colors, startangle=90)
plt.style.use('default')
plt.legend(labels)
plt.title( '#Number of Tweets ( Positive, Negative, Neutral)' )
plt.axis('equal')
plt.show()
```

Output:



g) Average length and wordcount of tweets:

```
df['text_len'] = df['Tweet'].astype(str).apply(len)
df['text_word_count'] = df['Tweet'].apply(lambda x: len(str(x).split()))
print("Average length of tweets ", round(np.mean(df['text_len'])))
print("Average word counts of tweets",
round(np.mean(df['text_word_count'])))
```

```
Output:

    Average length of tweets  133
    Average word counts of tweets 19
```

h) Top 50 positive,negative tweets, maximum retweets:

```
df.nlargest(n=50, columns=['Compound'])["Tweet"]
df.nsmallest(n=50, columns=['Compound'])["Tweet"]
df.sort_values('Retweets',
ascending=False)['Tweet'].drop_duplicates().head(50)
```

```
Output:
Positive tweets:
[11]:  12104        I'm not here to play.\nI always follow bac...
       12109      I'm not here to play.\nI always follow back 😊...
       12118       I'm not here to play.\nI always follow back ...
       12140                        I'm not here to play.\nI a...
       12141                      I'm not here to play.\nI alw...
       12143       I'm not here to play.\nI always follow back ...
       12147       I'm not here to play.\nI always follow back ...
       12160       I'm not here to play.\nI always follow back ...
       12161                      I'm not here to play.\nI alw...
       12163                 I'm not here to play.\nI always f...
       12166                      I'm not here to play.\nI alw...
       12167       I'm not here to play.\nI always follow back ...
       12168       I'm not here to play.\nI always follow back ...
       12170       I'm not here to play.\nI always follow back ...
       12172                           I'm not here to play.\n...
       12190     I'm not here to play.\nI always follow back 😊  ...
       25267     Eating the rich = Self Care!  😊 😊 😊 🤷 🤷 🤷...
       11702      I'm not here to play.\nI always follow back 😊...
       12022        I'm not here to play.\nI always follow back...
       12025        I'm not here to play.\nI always follow back...
       21976      Cute 🤗 🤗  puppy 😍 📷 😍\n#morningvibes #QuestionTim...
       24461      Roman Kosarev of RT... continues to deliver h...
       18727     But\n\nIf you pray as human and HUMANITY is yo...
       5899      🤣 🤣 🤣 🤣 🤣 🤣 🤣\n\n#StandWithUkraine #UkraineInvasion ...
       2808      . blocked u (?) just now for telling the #fact...
       11869     God is love, God is peace!\nLove can never beg...
       11054     💔 💌 🕊 💌 💔\nUkrainian Civilian death toll hits 1,1...
       17844     My favorite #Italian rapper - #Ultimo - is sup...
       1644       #UkraineWar #Ukraina #love #UkraineRussianWar...
       5187       #UkraineWar #Ukraina #love #UkraineRussianWar...
       5247       #UkraineWar #Ukraina #love #UkraineRussianWar...
       18533     LIKE, COMMENT, &amp; SHARE !!\n\n#anime #comed...
       7018      Let this weekend be about love \nand compassio...
       11491      Respected Joe Biden sir we know you with Ukra...
```

```
Negative tweets:
[12]:  24922     War is a tragedy, it is one of the worst human...
       1293      \n\nRECKLESS DISREGARD for the safety/lives of...
       7815      Woman Found Murdered In Ukraine Military base ...
       29363     Even the devil is ignoring Putin right now.\n\...
       11333      Attention.🔞 🔞 🔞  Violent footage.⚠⚠⚠ How the Naz...
       3808      THE WESTERN WORLD IS MIND-MURDERED BY ITS OWN ...
       12665       Why should  ban 18- 60s from fleeing to safe...
       8007       #FidelCastro sent his communist #Cuban crimin...
       10867     #Macron trying to “talk” with Rus WAR CRIMINAL...
       27885     Childrens executed by #Russians under the age ...
       20873     ZELENSKYY: 'HARD BATTLE' LIES AHEAD\n\nEven as...
       19533       Stand alone with your Rassia. They can't jus...
       43          Are these pics from Dunbas region conflict  ...
       10858     War crimes are #WarCrimes, doesn't matter if i...
       1901      Russia has massacred innocent families. \n\nPu...
       17472     Trotz Schnee, bleibt die Heizung bei mir aus. ...
       1451      I was forced by  to acknowledge how i was wron...
       24618     Putin condemned !\n\n#Putin #Russia #Russians\...
       5233       Raketenangriff heute auf #Lemberg / #Lviv \n\...
       5254      Raketenangriff heute auf #Lemberg / #Lviv \n\n...
       16023      Raketenangriff heute auf #Lemberg / #Lviv \n\...
       28436     Russian pig's they not are humans,  shot dogs ...
       143        How many is enough?\nHow many more murders?\n...
       146        How many is enough?\nHow many more murders?\n...
       154       How many is enough?\nHow many more murders?\nH...
       26169     Dear Russia - \nYou don’t get to complain abou...
       17695       Why is everything on the news opposite and t...
       1465      Putin has lost this war in every aspect but a ...
       17879     Well let's forget about them. The very first t...
       1692      #RussiaUkraineWar\n#russianterror #RussianArmy...
       26706     Global outcry at "war crime" killings near #Ky...
       27997     A haunting image of a woman killed by Ukranian...
       5053       #Servicetweet / #fyi \n\n💣 🚀 ☠ 💣 🚀 ☠ 💣 🚀 ☠...
       5179       #Servicetweet / #fyi \n\n💣 🚀 ☠ 💣 🚀 ☠ 💣 🚀 ☠...
```

Maximum retweets:

```
[13]:  24065     Il fallait s’y attendre : des clowns démagogu...
       19027     President #VolodymyrZelenskyy speaks to the r...
       28075     A deer with deep burns rescued by local resid...
       16        A deer with deep burns rescued by local resid...
       28035     ❗ В Буче российские оккупанты убили все мужск...
       12833     If you:\nSupport Ukraine But not Palestine Sy...
       2928      Questa storia dei nazisti ucraini mi ha stufa...
       23737    A deer with deep burns rescued by local reside...
       26771     Russia's attack has left Ukrainians and #indi...
       27583     The price of Russian oil and gas.\nThe price ...
       11514     #Ukraine army cats are trained to spot and di...
       27590     1/ Ukrainian Theater of War, Day 37: Today’s ...
       12285     Mardi explosif  12/14h. La sénatrice  sur le ...
       26773     SA News Weekly Bulletin:\n\n■ #RussiaUkraineW...
       26577     A running angry joke in #Ukraine these days. ...
       26342    's account is temporarily unavailable because ...
       3793      This is the wife of the Vice President of Ukr...
       29245     #RussianUkrainianWar\n#UkraineUnderAttack \n#...
       20553    1/ Ukrainian Theater of War, Day 37: Today’s u...
       29811     Chinese state media deliberately ignores comm...
       5897      कभी यूक्रेन ने किया था भारत के परमाणु परीक्षण...
       6953      Ancient vedic culture always takes care of ph...
       24130     A few weeks ago Zelensky released prisoners w...
       5451      #RRBNTPC \n#RailwayMinister_HelpCCAA \n#ntpc ...
       9570     's account has been withheld in India in respo...
       29908     Russians really do be living in George Orwell...
       642       You know what is extremely upsetting?\nOn #Da...
       6848      Mutige Menschen. Männer, die in #Moskau gegen...
       2478      Reality Of The World..😔\n#FreePalaestine \n#P...
       20017     #BREAKING: Oscar for these guys!\n\nRemember ...
       22209     Happy Friday, #Family! \n\nFOLLOW ALL who:\n\...
       3712      This is chilling... \n\nThis was filmed by th...
       26644     🆘Civilians killed in a mass grave in the vill...
       27456     🔴اسمع ما قاله المفكر الأمريكي البارز نعوم ت\n...
```

i) Visualization of the Sentiment Scores of Positive, Neutral & Negative Tweets:

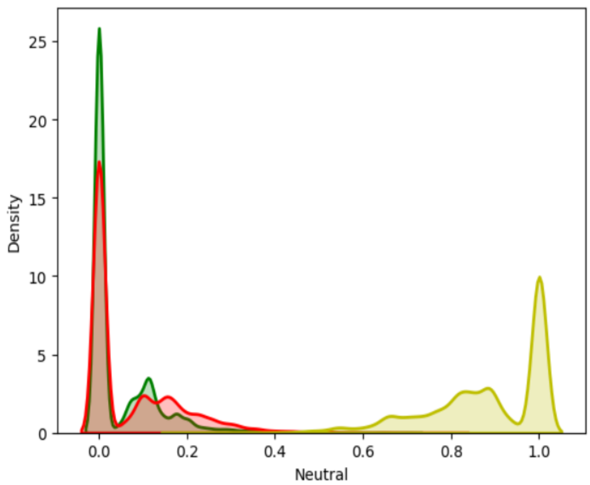
```
sns.distplot(df["Positive"], hist=False, kde=True,
             bins=int(180/5), color = 'green',
             hist_kws={'edgecolor':'black'},
             kde_kws={'shade': True,'linewidth': 2})

sns.distplot(df["Negative"], hist=False, kde=True,
             bins=int(180/5), color = 'red',
             hist_kws={'edgecolor':'black'},
             kde_kws={'shade': True,'linewidth': 2})

sns.distplot(df["Neutral"], hist=False, kde=True,
             bins=int(180/5), color = 'y',
             hist_kws={'edgecolor':'black'},
             kde_kws={'shade': True,'linewidth': 2})
```

Output:

```
[14]:  <Axes: xlabel='Neutral', ylabel='Density'>
```

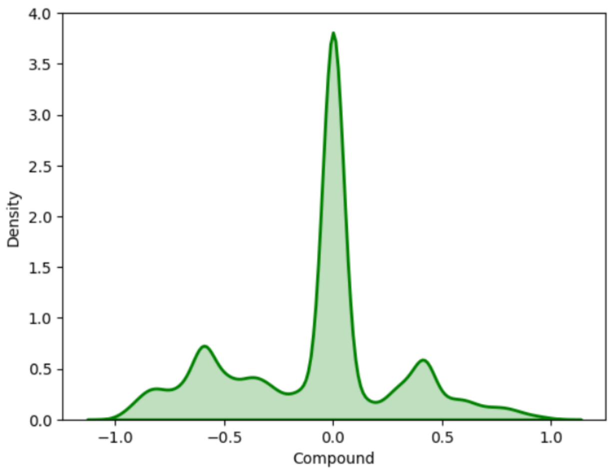


j) Visualization of the Sentiment Scores:

```
sns.distplot(df["Compound"], hist=False, kde=True,
             bins=int(180/5), color = 'green',
             hist_kws={'edgecolor':'black'},
             kde_kws={'shade': True,'linewidth': 2})
```

Output:

```
[15]:  <Axes: xlabel='Compound', ylabel='Density'>
```



k) Word cloud for All Sentiments:

```
from wordcloud import WordCloud , STOPWORDS , ImageColorGenerator
from nltk import *

#function to display wordcloud
def plot_cloud(wordcloud):
    # Set figure size
    plt.figure(figsize=(40, 30))
    # Display image
    plt.imshow(wordcloud)
    # No axis details
    plt.axis("off");

### Word Cloud of mostly used word in Tweets
text = " ".join(review for review in df.Tweet)
wordcloud = WordCloud(width = 3000, height = 2000, stopwords=STOPWORDS,
background_color="Black",colormap='Set2',
collocations=False).generate(text)
 ### Display the generated image:
plot_cloud(wordcloud)
```

Output:

l) Collect the positive hashtags from the tweets data:

```
HT_positive = []
def hashtag_extract(x):
    hashtags = []
    # Loop over the words in the tweet
    for i in x:
        ht = re.findall(r"#(\w+)", i)
        hashtags.append(ht)
    return hashtags
# extracting hashtags from positive tweetsHT_positive =
hashtag_extract(df_tws['text'][df_tws['sent'] == 1])
# extracting hashtags from  tweets
HT_positive = hashtag_extract(df['Tweet'][df['Compound'] > 0.5])
# unnesting list
HT_positive = sum(HT_positive,[])
HT_positive[0:10]
```

Output:

```
[20]:  ['RussiaUkraineWar',
        'Russia',
        'Ukraine',
        'ZOG',
        'Biden',
        'Putin',
        'Russia',
        'America',
        'Ukraine',
        'RussiaUkraineWar']
```

m) Collect the negative hashtags:

```
HT_negative = []
def hashtag_extract(x):
    hashtags = []
    # Loop over the words in the tweet
    for i in x:
```

```
        ht = re.findall(r"#(\w+)", i)
        hashtags.append(ht)
    return hashtags
# extracting hashtags from positive tweetsHT_positive =
hashtag_extract(df_tws['text'][df_tws['sent'] == 1])
# extracting hashtags from  tweets
HT_negative  = hashtag_extract(df['Tweet'][df['Compound'] < -0.5])
# unnesting list
HT_negative = sum(HT_negative,[])
HT_negative[0:10]
```

Output:

```
[21]:  ['ukraIndiadiadiae',
        'russia',
        'UkraIndiadiadiae',
        'RussiaUkraIndiadiadiaeWar',
        'EU',
        'Europe',
        'UkraIndiadiadiae',
        'Zelensky',
        'West',
        'US']
```

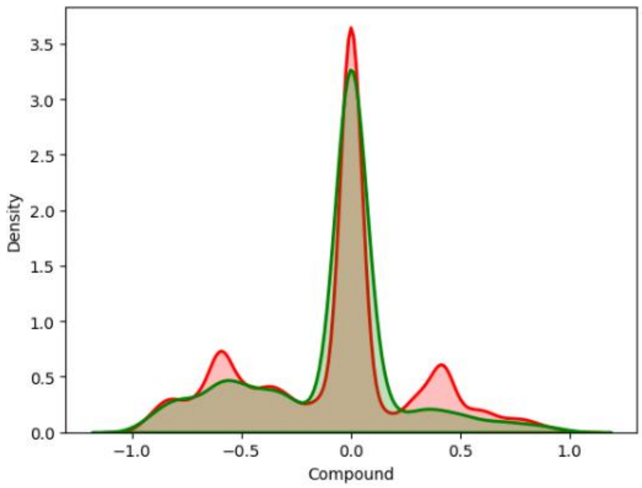
n) Comparison of Sentiment Score of Tweets by Indian and from Other Country from the tweets data:

```
#Removing NAN and NA from the locations columns.
df[['Location']] = df[['Location']].fillna('')
sns.distplot(df[~df["Location"].str.contains('India')]["Compound"],
hist=False, kde=True,
             bins=int(180/5), color = 'r',
             hist_kws={'edgecolor':'black'},
             kde_kws={'shade': True,'linewidth': 2})

sns.distplot(df[df['Location'].str.contains("India")]["Compound"],
hist=False, kde=True,
             bins=int(180/5), color = 'g',
             hist_kws={'edgecolor':'black'},
             kde_kws={'shade': True,'linewidth': 2})
```

Output:

[22]: <Axes: xlabel='Compound', ylabel='Density'>



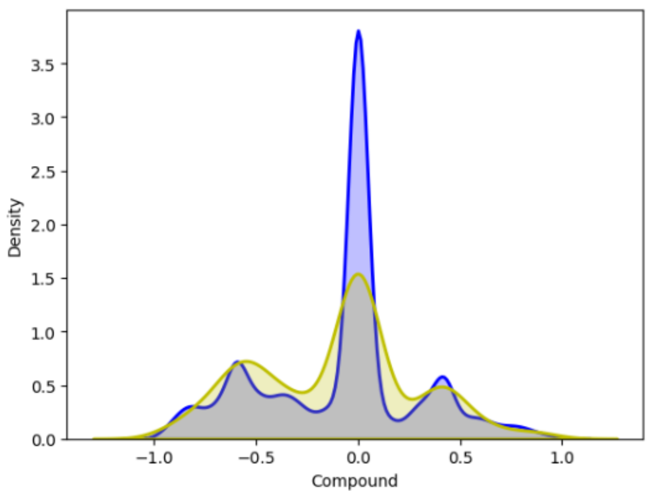
o) Comparison of Sentiment Score of Tweets from Ukraine and from other Countries:

```
sns.distplot(df[~df["Location"].str.contains('Ukraine')]["Compound"],
hist=False, kde=True,
             bins=int(180/5), color = 'b',
             hist_kws={'edgecolor':'black'},
             kde_kws={'shade': True,'linewidth': 2})

sns.distplot(df[df['Location'].str.contains("Ukraine")]["Compound"],
hist=False, kde=True,
             bins=int(180/5), color = 'y',
             hist_kws={'edgecolor':'black'},
             kde_kws={'shade': True,'linewidth': 2})
```

Output:

[23]: <Axes: xlabel='Compound', ylabel='Density'>



Conclusion:

The analysis of tweets related to the Russia-Ukraine conflicts has provided valuable insights into public sentiment and narratives. The study highlights the importance of sentiment analysis in understanding public discourse and shaping policy decisions in an interconnected world. It highlights the dynamic nature of digital discourse and the nuanced understanding of sentiment dynamics over time. Thematic analysis reveals prominent narratives and sentiment drivers, offering context for policymakers and stakeholders. However, the study acknowledges its limitations and the need for ongoing refinement and validation. Future research may explore advanced methodologies for sentiment analysis, including multimodal approaches and longitudinal studies.

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