Ukraine Conflict Twitter - Sentiment AnalysisRecommandation based on Cosine SimiliarityCross Validation with Muliple Classification Techniques (99% ACC)

March 24, 2022

# 1 Ukraine Conflict Twitter - Sentiment Analysis/Recommandation based on Cosine Similiarity/Cross Validation with Muliple Classification Techniques (99% ACC)

[ ]:
```
%%time
import warnings
warnings.filterwarnings('ignore')

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt


from wordcloud import WordCloud, STOPWORDS

import re
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import pycountry
lemmatizer = WordNetLemmatizer()
stopword = set(stopwords.words('english'))
```

```
CPU times: total: 1.73 s
Wall time: 4.61 s
```

[ ]:
```
# combined the twitters posted about Ukraine between Mar17 and Mar18, around 1␣
 ↪million posts in
df = pd.read_csv('MAR18_UkraineTwitter.csv')
df1 = pd.read_csv('MAR17.csv')
df = pd.concat([df, df1], ignore_index = True,
                          sort = False)
```

```python
df.head(-3)
```

[ ]:

```
        Unnamed: 0               userid         username  \
0                0            112073654     johnguilfoil
1                1   902816295023988736     YashaShveller
2                2             19897138        IndiaToday
3                3           2533590570       joseph_less
4                4             36327407          htTweets
…              …                  …               …
936722      468624  1183858884185907201    MordechaiLevin
936723      468625           4831412975   SeanMac66468910
936724      468626            198163442         james_he_
936725      468627  1364829721880502272        teofilussw
936726      468628             81243368    jamesey271975

                                                  acctdesc  \
0        Basically the dad from Bluey. Public Relations…
1                                                     qwer
2        Brings you news breaks: Exclusive political, e…
3                                                      NaN
4        One of India's largest media companies. Latest…
…                                                    …
936722   Strategic Planning and Operations Execution | …
936723                                                 NaN
936724                 Jr. Software Engineer @assemblyai
936725   JUSTICE & #NoWar | Use English,   , Deutsch, …
936726   If you don't like dogs, donkeys, bees, butterf…

                             location  following  followers  totaltweets  \
0                              Boston       1320       3652        34992
1                                 NaN        503        135        32873
2                               India        245    5997687       999807
3                                 NaN        387        637        52190
4                               India        155    8435301      1034587
…                                …         …          …            …
936722                            NaN        283         71         2206
936723                            NaN        441         18          591
936724                     Denver, CO        292        108         1041
936725        Jakarta, ID         3430        377        34397
936726    Salt Lake City via Dublin          36         36         4867

                   usercreatedts               tweetid       tweetcreatedts  \
0        2010-02-07 05:18:07.000000  1504608519861018628  2022-03-18 00:00:00
1        2017-08-30 08:52:33.000000  1504608520213258242  2022-03-18 00:00:00
2        2009-02-02 07:21:54.000000  1504608520766861322  2022-03-18 00:00:00
3        2014-05-29 23:16:56.000000  1504608520880197634  2022-03-18 00:00:00
4        2009-04-29 10:11:34.000000  1504608520892690457  2022-03-18 00:00:00
```

```
…                               …                    …                    …
936722  2019-10-14 21:35:37.000000  1504608511178813441  2022-03-17 23:59:57
936723  2016-01-21 01:51:32.000000  1504608511556206592  2022-03-17 23:59:58
936724  2010-10-03 14:47:12.000000  1504608511577141257  2022-03-17 23:59:58
936725  2021-02-25 06:49:14.000000  1504608511963328512  2022-03-17 23:59:58
936726  2009-10-10 00:48:11.000000  1504608514769006621  2022-03-17 23:59:58

        retweetcount                                              text  \
0                  0  Read this tweet and every single reply to it #…
1                 63                                                 …
2                  1  Russia-Ukraine war: Is Vladimir Putin a war cr…
3                 12  The best battle is the one you don't have to f…
4                  1  This BMW 6 Series is modified for machine gun …
…                …                                                 …
936722             0  @Nestle earned $1.8 billion in revenue last ye…
936723           917  WATCH: The defenders of Kharkiv, our latest fo…
936724             2  How do you feel, Alfabank? :) \n#CancelRussia …
936725             0  COVID-19 sudah terbukti menyusahkan semua oran…
936726          3061  The toy bridge. \n\nRomanian border police and…

                                                 hashtags language  \
0                [{'text': 'Ukraine', 'indices': [45, 53]}]       en
1       [{'text': 'Ukraine', 'indices': [93, 101]}, {'…       ru
2       [{'text': 'NewsToday', 'indices': [76, 86]}, {…       en
3       [{'text': 'IStandWithUkraine', 'indices': [73,…       en
4       [{'text': 'Ukraine', 'indices': [99, 107]}, {'…       en
…                                                    …      …
936722  [{'text': 'Russia', 'indices': [54, 61]}, {'te…       en
936723                                                []       en
936724  [{'text': 'CancelRussia', 'indices': [52, 65]}…       en
936725  [{'text': 'Russia', 'indices': [267, 274]}, {'…       in
936726        [{'text': 'Ukraine', 'indices': [115, 123]}]       en

       coordinates  favorite_count                 extractedts
0              NaN               0  2022-03-18 00:09:09.835940
1              NaN               0  2022-03-18 00:09:09.827692
2              NaN               1  2022-03-18 00:03:54.604634
3              NaN               0  2022-03-18 00:09:09.819479
4              NaN               3  2022-03-18 00:09:09.811223
…                …               …                           …
936722         NaN               0  2022-03-18 00:09:09.895416
936723         NaN               0  2022-03-18 00:09:09.887198
936724         NaN               0  2022-03-18 00:03:54.626970
936725         NaN               2  2022-03-18 00:09:09.876960
936726         NaN               0  2022-03-18 00:09:09.868745

[936727 rows x 18 columns]
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 936730 entries, 0 to 936729
Data columns (total 18 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   Unnamed: 0      936730 non-null  int64
 1   userid          936730 non-null  int64
 2   username        936730 non-null  object
 3   acctdesc        736881 non-null  object
 4   location        560958 non-null  object
 5   following       936730 non-null  int64
 6   followers       936730 non-null  int64
 7   totaltweets     936730 non-null  int64
 8   usercreatedts   936730 non-null  object
 9   tweetid         936730 non-null  int64
 10  tweetcreatedts  936730 non-null  object
 11  retweetcount    936730 non-null  int64
 12  text            936730 non-null  object
 13  hashtags        936730 non-null  object
 14  language        936730 non-null  object
 15  coordinates     1046 non-null    object
 16  favorite_count  936730 non-null  int64
 17  extractedts     936730 non-null  object
dtypes: int64(8), object(10)
memory usage: 128.6+ MB
```

[ ]:
```
df.shape
```

[ ]:
```
(936730, 18)
```

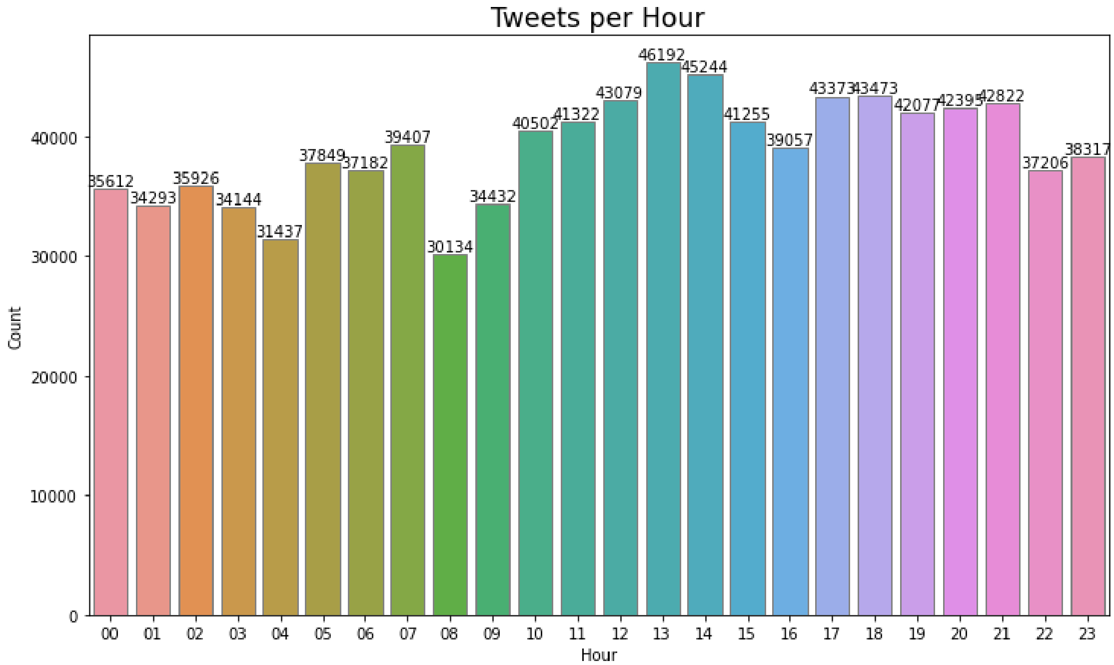
[ ]:
```
# take look at the first 10 twitters in our dataset
df['text'][:10].tolist()
```

[ ]:
```
['Read this tweet and every single reply to it #Ukraine
https://t.co/wKX5MMs6N8',
 '
    .\n#Ukraine #UkraineRussianWar #UkraineWar https://t.co/QYu43cgxUP',
 'Russia-Ukraine war: Is Vladimir Putin a war criminal?\n\nWatch full debate on
#NewsToday with @sardesairajdeep\n\nFull Show:
https://t.co/aAz4y2XQ4k\n\n#RussiaUkraineWar #VladimirPutin
https://t.co/xoe8K157ng',
 "The best battle is the one you don't have to fight. \n\n#IStandWithUkraine
#Ukraine https://t.co/trGun6yaOC",
 'This BMW 6 Series is modified for machine gun by Ukrainians to fight
Russians\n\nvia @HTAutotweets | #Ukraine #Russia \n\nhttps://t.co/QjEdaVg2D4',
```

```
 'Si les US pouvaient réfléchir à ce qu\'ils ont fait à Cuba et au Panama ds les
60\'s,en Yougoslavie ds les 90\'s,en Afghanistan et Irak début 2000,en Syrie et
Libye ensuite,ils verraient que ce sont des exemples typiques"d\'1 grand pays
intimidant des petits"comme ils disent #Ukraine https://t.co/euzK9FWwcs',
 '       _      _   #
              #..                           \n\n#
n#RussianUkrainianWar\n#RussiaUkraineC\    _      _   #n\    _ _
onflict\nhttps://t.co/WXqNRFJbAg',
 '"#Putin lies about many things, but he is right when he says that the West
holds Russia to standards to which it doesn’t itself abide-a grievance that
Russians appear widely to share and that imbues his own illegal war with a
patina of legitimacy." https://t.co/iXoqk1jOYW',
 "The #Anonymous collective has sent 7.000.000 anti-war texts to Russian cell
phone users to tell them the truth about Putin's invasion of #Ukraine.",
 '#DobleVia | "Si el régimen de #Putin toma Ucrania, tenemos que decir adiós a
todas las organizaciones #LGBT+" aseguro la cofundadora de Ukraine
Pride \u200d \nhttps://t.co/82ltIJEhVG']
```

### 1.0.1 Explantory Data Analysis

[ ]:
```python
# change to date time format
df['extractedts']=pd.to_datetime(df['extractedts'])

# tweets per hour
tweets_per_hr = df['extractedts'].dt.strftime('%H').value_counts().sort_index().
 ↪to_frame(name='Count')
tweets_per_hr['Hour']=tweets_per_hr.index

# plot
plt.figure(figsize=(12,7))
ax=sns.barplot(x='Hour', y='Count',data=tweets_per_hr, edgecolor='grey')
ax.bar_label(ax.containers[0])
plt.title('Tweets per Hour', size='xx-large')
plt.show()
```




It's pretty uniformly distributed, however, afternoon to midnight witnessed more tweets than morning.

```
[ ]: # show where most posts are located
     df['location'].value_counts()[:10]
```

```
[ ]: United States      7675
     Ukraine            5366
                     3562
     London, England    3386
     USA                3364
     France             3266
     Canada             3213
     India              3170
     London             3105
     UK                 2734
     Name: location, dtype: int64
```

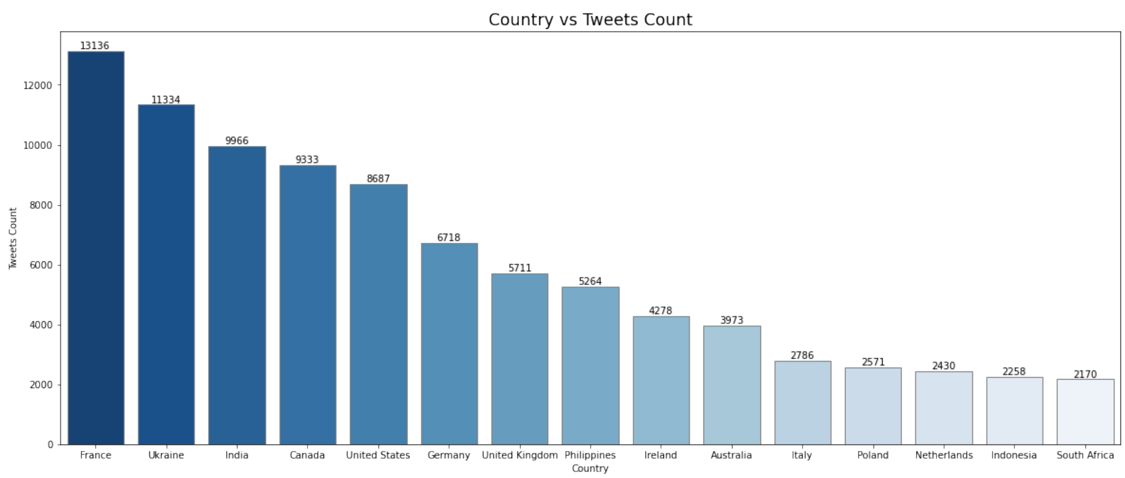
Note there are duplicate locations, work on them below.

```
[ ]: # excluding null values (where location is not specified) in user_location
     location = [loc for loc in df['location'] if type(loc)==str]

     # extracting country names from given location
     country_name = [country.name for loc in location for country in pycountry.
      ↪countries if country.name in loc]
```

```
country_name[:9]
```

```
[ ]: ['India',
 'India',
 'Australia',
 'Ukraine',
 'United Kingdom',
 'Canada',
 'Australia',
 'Portugal',
 'Philippines']
```

```
[ ]: # dictionary to count number of occurances of each country
count={}
for country in country_name:
    count[country] = count.get(country, 0) + 1

# Country vs tweets count
country_df = pd.DataFrame({'Country': list(count.keys()),'Tweets Count':␣
 ↪list(count.values())})
country_df = country_df.sort_values(by = 'Tweets Count', ascending=False)
country_df=country_df[:15] # top 15 countries

# plot the data
plt.figure(figsize=(20,8))
plt.title('Country vs Tweets Count', size='xx-large')
ax = sns.barplot(x='Country', y='Tweets Count',data=country_df,␣
 ↪palette='Blues_r', edgecolor='grey');
ax.bar_label(ax.containers[0])
plt.show()
```



[ ]:

```
# text preprocessing
def preprocess(text):

    # remove new lines
    text = text.replace('\n', ' ')

    # remove links
    text = re.sub('https?://\S+|www\.\S+', ' ', text)

    # remove hashtags at the end of text
    text = re.sub('#(?!(?:hashtag)\b)[\w-]+(?=(?:\s+#[\w-]+)*\s*$)', '',text)

    # remove handles
    text = re.sub('@[\w]+', '',text)

    # remove punctuations
    punc ='''.?!,:;-_-[](){}'"`~|\/@#$%^&+=*'''
    for i in text:
        if i in punc:
            text = text.replace(i, '')

    # remove extra spaces
    re.sub("\s\s+", " ", text)

    # lower case
    text = text.strip().lower()

    # lemmatization
    text = [lemmatizer.lemmatize(word) for word in text.split(' ')]
    text=" ".join(text)

    # stopword removal
    text = [word for word in text.split(' ') if word not in stopword]
    text=" ".join(text)

    # replace covid19 with covid
    text=text.replace('covid19','covid')

    return text


# remove promotional tweets (with words 'subscribe' and 'subscription')
def no_spam(text):
    if 'subscri' in text:
        text=''
    return text
```

```
[ ]: # apply functions
     df['text']= df['text'].apply(preprocess)
     df['text']= df['text'].apply(no_spam)
```

```
[ ]: # only emojis that composed by ascii characters will remain in the our text,␣
     ↪since emoji can heavily represent user's sentiment
     def demoji(text):

         # frequent emojis which will be kept
         pattern =␣
     ↪'| | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |'
         for word in text:
             if re.match(pattern, word):
                 continue

             # remove all other non ascii characters
             text=text.replace(word, re.sub('[^\x00-\x7f]','', word)).strip()

         return text


     df['text']= df['text'].apply(demoji)
```

```
[ ]: # convert emoji to sentiment keys
     def convert(text):

         # dictionary of emoji with their meaning
         d = {' ':'frustrated',' ':'angry',' ':'angry',' ':'horrified',' ':'shock',' ':
     ↪'shock',' ':'disapproval',
              ' ':'suspicion',' ':'disappointment',' ':'sad',' ':'sad',' ':'sad',' ':
     ↪'sad',' ':'sad',' ':'sad',
              ' ':'sad',' ':'sad',' ':'sad',' ':'sad',' ':'sad',' ':'sad',' ':'sad',' ':
     ↪'sad',' ':'sad',' ':'sad',
              ' ':'sad',' ':'sick',' ':'sick',' ':'sad',' ':'sad',' ':'sad',' ':
     ↪'sad',' ':'sad',' ':'sad',
              ' ':'happy',' ':'smile',' ':'embarrassment',' ':'exciting',' ':
     ↪'affection',' ':'smile',' ':'laugh',
              ' ':'nervousness',' ':'smile',' ':'fun',' ':'affection',' ':'blessed'}

         for emoji, sentiment in d.items():
             text=text.replace(emoji, sentiment)
         return text

     df['senti_text']= df['text'].apply(convert)
```

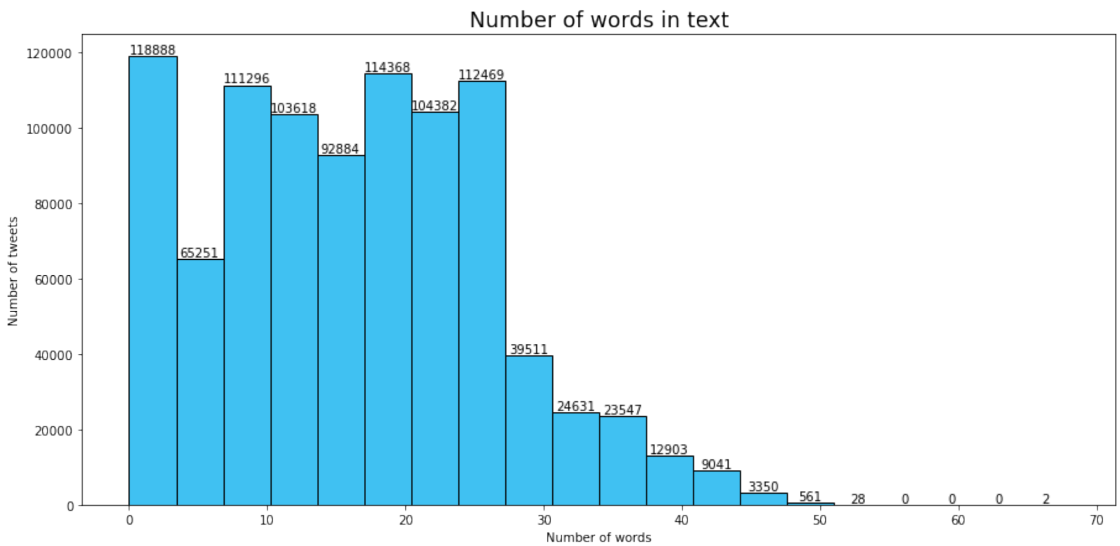
```
[ ]: # creating the text for wordcloud map
text = " ".join(tweet for tweet in df.text)

# Creating word_cloud with text as argument in .generate() method
word_cloud = WordCloud(collocations=False, background_color='white',
                       max_words=50, stopwords=STOPWORDS, min_word_length=4,
                       width=2048, height=1080).generate(text)

# Display the generated Word Cloud
plt.figure(figsize=(12,8))
plt.imshow(word_cloud, interpolation='bilinear')
plt.axis("off")
plt.title('Ukraine Tweets Word Cloud\n', size='x-large')
plt.show()
```

Ukraine Tweets Word Cloud


Map above shows the most used word in Ukraine Conflict tweets: Putin, standwithukraine, russian, killed, civilian, etc.

```
[ ]: # word count
word_count = [len(text.split()) for text in df.text]
df['word_count'] = word_count

# plot
plt.figure(figsize=(15,7))
ax=sns.histplot(x='word_count', data=df, bins=20, color='#00acee')
ax.bar_label(ax.containers[0])
```

```
plt.title('Number of words in text',size='xx-large')
plt.xlabel('Number of words')
plt.ylabel('Number of tweets')
plt.show()
```




Graph shows that most twitters have words between 0 to 25.

```
[ ]: # excluding text with less than 3 words
df=df[df['word_count']>2]

# excluding tweets with more than 16 words
df=df[df['word_count']<30]
```

```
[ ]: # Sentimentize text
from nltk.sentiment.vader import SentimentIntensityAnalyzer
SIA = SentimentIntensityAnalyzer()

df["Positive"] = [SIA.polarity_scores(i)["pos"] for i in df["senti_text"]]
df["Neutral"] = [SIA.polarity_scores(j)["neu"] for j in df["senti_text"]]
df["Negative"] = [SIA.polarity_scores(k)["neg"] for k in df["senti_text"]]

df1 = df[["text", "Positive","Neutral", "Negative"]]
df1.head()
```

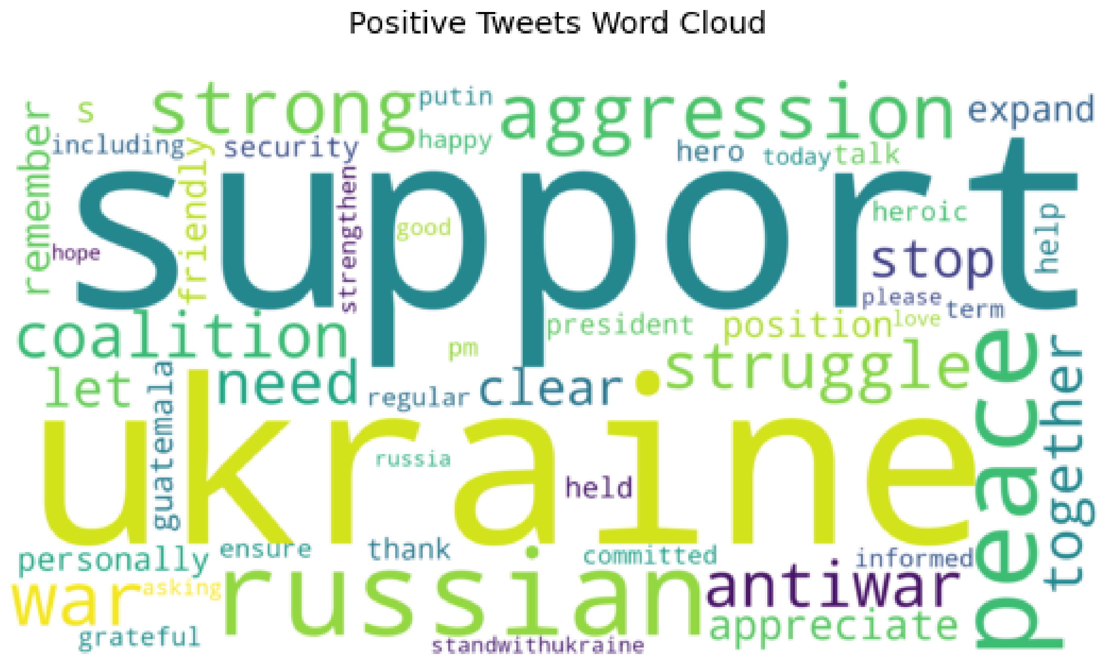
```
[ ]:                                            text  Positive  Neutral  \
0                     read tweet every single reply     0.000    1.000
2  russiaukraine war vladimir putin war criminal …     0.000    0.446
3                        best battle one dont fight     0.581    0.182
4  bmw 6 series modified machine gun ukrainian fi…     0.000    0.583
```

```
7  putin lie many thing right say west hold russi…     0.157    0.595

   Negative
0     0.000
2     0.554
3     0.237
4     0.417
7     0.248
```

[ ]:
```
# counting positive, neutral and negative tweets

sentiments_nltk = []

for tweet in df.senti_text:
    sentiment_dict = SIA.polarity_scores(tweet)
    sentiment_dict.pop('compound', None)
    sentiments_nltk.append(max(sentiment_dict , key=sentiment_dict.get))

df['sentiment_nltk'] = sentiments_nltk
df['sentiment_nltk'].value_counts()
```

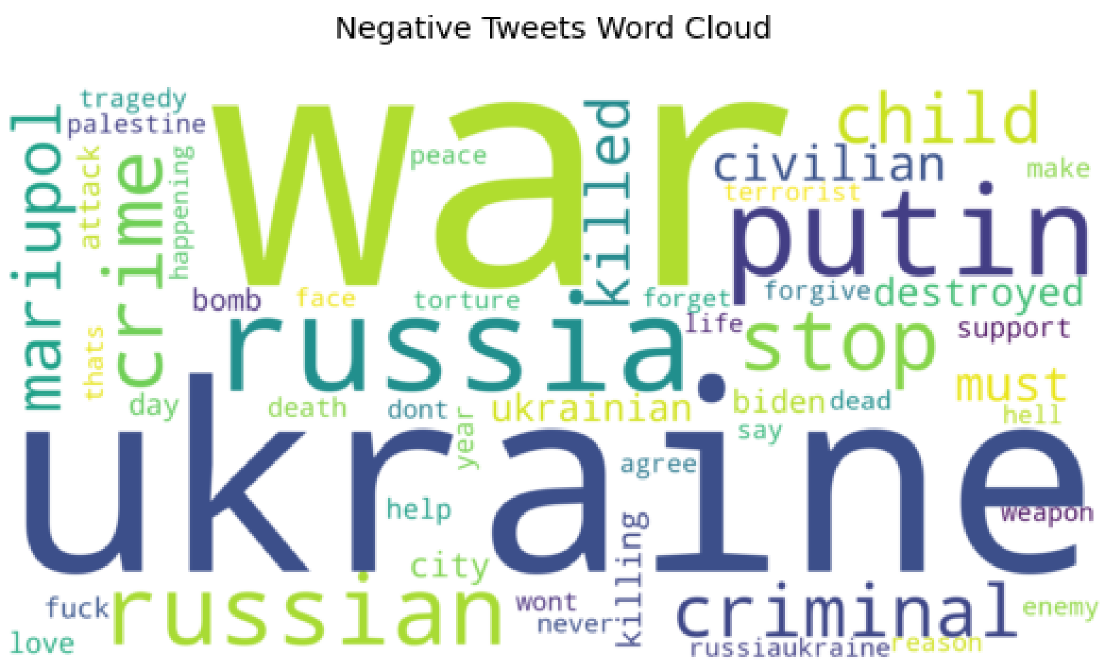
[ ]:
```
neu    677893
pos     40598
neg     34866
Name: sentiment_nltk, dtype: int64
```

[ ]:
```
pos_tweets = " ".join(sentiment for sentiment in␣
 ↪df[df['sentiment_nltk']=='pos']['text'])

# Creating word cloud of positive tweets
stopwords_p = STOPWORDS
stopwords_p.update(('omicron','covid',␣
 ↪'u','ha','amp','one','people','variant','mask'))
word_cloud1 = WordCloud(collocations=False, background_color='white',
                        max_words=50, stopwords=stopwords_p, #min_word_length=4,
                        width=2048, height=1080).generate(pos_tweets)

# Display the generated Word Cloud
plt.figure(figsize=(10,5))
plt.imshow(word_cloud1, interpolation='bilinear')
plt.axis("off")
plt.title('Positive Tweets Word Cloud\n', size='x-large')
plt.savefig('./wc_positive.jpg',dpi=720)

plt.show()
```




Postive tweets like to contain words: peace, thank, asking, please, dear, happy, support, etc.

[ ]:
```
neg_tweets = " ".join(sentiment for sentiment in df[df['sentiment_nltk']=='neg']['text'])

# Creating word cloud of positive tweets
stopwords_n = STOPWORDS
stopwords_n.update(('vaccine','news','im','time','world','travel')) #
word_cloud2 = WordCloud(collocations=False, background_color='white',
                        max_words=50, stopwords=stopwords_n,
                        width=2048, height=1080).generate(neg_tweets)

# Display the generated Word Cloud
plt.figure(figsize=(10,5))
plt.imshow(word_cloud2, interpolation='bilinear')
plt.axis("off")
plt.title('Negative Tweets Word Cloud\n', size='x-large')
plt.show()
```




negative tweets like to contain words: war, destroyed, stop, authority, etc.

[ ]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
# Transform a count matrix to a normalized tf or tf-idf representation.
tfidf = TfidfVectorizer(stop_words='english')
```

[ ]:
```
# due to high need for ram, change the data format to feather to save memory␣
↪and processing time
import feather
df.reset_index().to_feather('twitter.feather')
```

[ ]:
```
feather.write_dataframe(df, 'twitter.feather')
df = pd.read_feather('twitter.feather')
df = df.drop_duplicates(subset='senti_text')
```

[ ]:
```
df_n = df[:30000]
df_n.shape
```

[ ]: (30000, 24)

[ ]:
```
tfidf_matrix = tfidf.fit_transform(df_n['senti_text'])
tfidf_matrix.shape
```

[ ]: (30000, 55470)

```
[ ]: from sklearn.metrics.pairwise import linear_kernel
     cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
```

```
[ ]: indices = pd.Series(df_n.index, index=df_n['text']).drop_duplicates(keep =␣
      ↪'first')
```

```
[ ]: # Recommendation
     def recommendations(text):
         idx = indices[text]

         # Get the pairwsie similarity scores of all movies with that movie
         sim_scores = list(enumerate(cosine_sim[idx]))

         # Sort the movies based on the cosine similarity scores
         sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)

         # Geting the scores of the 10 most similar movies
         # Started at index 1 because index 0 is the one with the 1 cosine␣
      ↪similarity which is the same show
         sim_scores = sim_scores[1:11]

         twitter_indices = [i[0] for i in sim_scores]
         return df_n['text'].iloc[twitter_indices]
```

```
[ ]: recommendations('read tweet every single reply')
```

```
[ ]: 40101                                   reply reply thanks
     32869                                   everyone must read
     57130    ha cut ability reply tweet  doesnt want hear c…
     33752                     tweet day ukraine standwithukraine
     47757          russian war crime every single day world see
     96261                                 mariupol please read
     11150    see deciding withdrawal business russia  ha di…
     43270    claim reply mine set 1 set 2  first serious bu…
     45699                       putin  signing every single word
     73768    someone reply tweet neutralize ukraine blocked…
     Name: text, dtype: object
```

based on tokenized sentiment text, we can recommand users most related, sentimentized tweets.

```
[ ]: recommendations('love single come go please stay late want to')
```

```
[ ]: 49813    son estas historiasdevidainvasionputin putin p…
     75747    putin  putinisawarcriminal putler killputin st…
     7077     putinisawarcriminal putler killputin standwith…
     54932    putinhitler putinisawarcriminal putin standwit…
     34350    ukrainerussiawar   putinisawarcriminal ukraine…
```

```
20330     ukrainerussiawar   putinisawarcriminal putinsw…
42636     putinisawarcriminal putinhitler putinswar     …
21209     putinisawarcriminal putinswarcrimes slavaukrai…
30712     1slavaukraini putinisawarcriminal  standwithuk…
40192     marjorietaylorgreene putinisawarcriminal russi…
Name: text, dtype: object
```

[ ]:
```
recommendations('love single come go please stay late want to')
```

[ ]:
```
49813     son estas historiasdevidainvasionputin putin p…
75747     putin  putinisawarcriminal putler killputin st…
7077      putinisawarcriminal putler killputin standwith…
54932     putinhitler putinisawarcriminal putin standwit…
34350     ukrainerussiawar   putinisawarcriminal ukraine…
20330     ukrainerussiawar   putinisawarcriminal putinsw…
42636     putinisawarcriminal putinhitler putinswar     …
21209     putinisawarcriminal putinswarcrimes slavaukrai…
30712     1slavaukraini putinisawarcriminal  standwithuk…
40192     marjorietaylorgreene putinisawarcriminal russi…
Name: text, dtype: object
```

### 1.0.2 Cross-validation with Different Machine Learning Models

[ ]:
```
df1_y = df1[['Positive', 'Neutral', 'Negative']]
df1_y = df1_y.idxmax(axis=1)
df1_y =df1_y.to_frame()
df1_y.columns = ['sentiment']
df1_y.head()
```

[ ]:
```
  sentiment
0   Neutral
2  Negative
3  Positive
4   Neutral
7   Neutral
```

[ ]:
```
# format sentiment into numerical values
def convert_sentiment(sentiment):
    if  sentiment == "Positive":
        return 2
    elif sentiment == "Neutral":
        return 1
    elif sentiment == "Negative":
        return 0


df1_y.sentiment = df1_y.sentiment.apply(lambda x : convert_sentiment(x))
```

```
df1_y.head()
```

[ ]:

```
   sentiment
0          1
2          0
3          2
4          1
7          1
```

[ ]:

```
df1_y.sentiment.value_counts()
```

[ ]:

```
1    677985
2     41429
0     33943
Name: sentiment, dtype: int64
```

[ ]:

```
# due to limited computational power and ram size, I decided to use 30000␣
↪tweets to build our model
x = df1['text'].iloc[:30000]
y = df1_y['sentiment'].iloc[:30000]
```

[ ]:

```
x_final = tfidf.fit_transform(x)
```

[ ]:

```
# oversample the minority class using SMOTE
from imblearn.over_sampling import SMOTE
smote = SMOTE()
x_df, y_df = smote.fit_resample(x_final, y)
```

[ ]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x_df, y_df, test_size = 0.
↪25)
```

[ ]:

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import MultinomialNB
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.metrics import classification_report , confusion_matrix ,␣
↪accuracy_score
```

[ ]:

```
# gradient boosting approach
gbc = GradientBoostingClassifier()
gbc.fit(X_train,y_train)
gbc_prediction =  gbc.predict(X_test)
```

[ ]:
```
accuracy_score(gbc_prediction,y_test)
```

[ ]: 0.8729134866315427

[ ]:
```
# decision tree approach
ds = DecisionTreeClassifier()
ds.fit(X_train,y_train)
ds_prediction =  ds.predict(X_test)
```

[ ]:
```
accuracy_score(ds_prediction,y_test)
```

[ ]: 0.9708011226549805

[ ]:
```
# random forest approach
rf = RandomForestClassifier()
rf.fit(X_train,y_train)
rf_prediction =  rf.predict(X_test)
```

[ ]:
```
accuracy_score(rf_prediction,y_test)
```

[ ]: 0.9808951696292284

[ ]:
```
# xgboost approach
xgb = XGBClassifier()
xgb.fit(X_train,y_train)
xgb_prediction =  xgb.predict(X_test)
```

```
[11:42:26] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0, the default
evaluation metric used with the objective 'multi:softprob' was changed from
'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

[ ]:
```
accuracy_score(xgb_prediction,y_test)
```

[ ]: 0.9574080456940273

[ ]:
```
# SVM approach
svm = SVC()
svm.fit(X_train,y_train)
svm_prediction =  svm.predict(X_test)
```

[ ]:
```
accuracy_score(svm_prediction,y_test)
```

[ ]: 0.9892166034762913

[ ]:
```
# Naive Bayes classifier
nb = MultinomialNB()
nb.fit(X_train,y_train)
nb_prediction =  nb.predict(X_test)
```

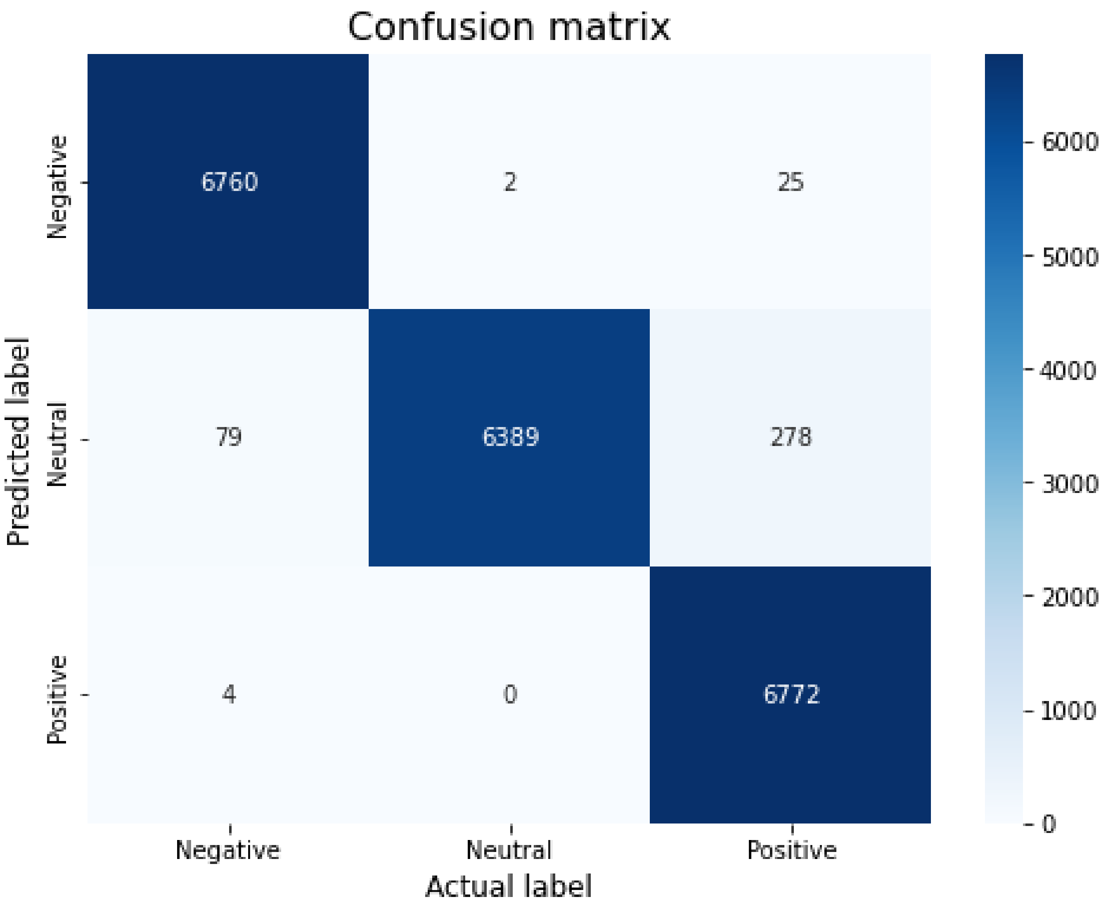
[ ]:
```
accuracy_score(nb_prediction,y_test)
```

[ ]:
```
0.9512038997488798
```

[ ]:
```
# SVM model provides the best accurary - 99%
cr = classification_report(y_test, svm_prediction)
```

[ ]:
```
print("Classification Report:\n----------------------\n", cr)

cm = confusion_matrix(y_test,rf_prediction)


# plot confusion matrix
plt.figure(figsize=(8,6))
sentiment_classes = ['Negative', 'Neutral', 'Positive']
sns.heatmap(cm, cmap=plt.cm.Blues, annot=True, fmt='d',
            xticklabels=sentiment_classes,
            yticklabels=sentiment_classes)
plt.title('Confusion matrix', fontsize=16)
plt.xlabel('Actual label', fontsize=12)
plt.ylabel('Predicted label', fontsize=12)
plt.show()
```

```
Classification Report:
----------------------
              precision    recall  f1-score   support

           0       1.00      0.97      0.99      6787
           1       1.00      1.00      1.00      6746
           2       0.97      1.00      0.98      6776

    accuracy                           0.99     20309
   macro avg       0.99      0.99      0.99     20309
weighted avg       0.99      0.99      0.99     20309
```


Confusion matrix
6760
2
25
79
6389
278
4
0
6772
Negative
Neutral
Positive
Predicted label
Negative
Neutral
Positive
Actual label
6000
5000
4000
3000
2000
1000
0