Dutch Social Media

December 26, 2022

```
[1]: import pandas as pd
     import json
     import re
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     import plotly.express as px
     import plotly.graph objects as go
     from wordcloud import WordCloud
     import scipy
     from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import StandardScaler
     from sklearn.linear_model import LogisticRegression
     from sklearn.metrics import accuracy_score, precision_score, recall_score
     import nltk
     from nltk.stem import WordNetLemmatizer
     from sklearn.feature_extraction.text import TfidfVectorizer
     from sklearn.feature_extraction.text import CountVectorizer
     from nltk.corpus import stopwords
[2]: # Read the JSON file into a Pandas dataframe
     with open("C:/Users/visha/Downloads/Compressed/dutch_tweets_chunk0.json/

dutch_tweets_chunk0.json") as input:
         data=json.load(input)
     df=pd.DataFrame(data)
[3]: # Print the first few rows of the dataset
     print(df.head())
     # Check the shape of the dataset
     print(df.shape)
     # Check the data types of the columns
     print(df.dtypes)
     # Check for missing values
     print(df.isnull().sum())
```

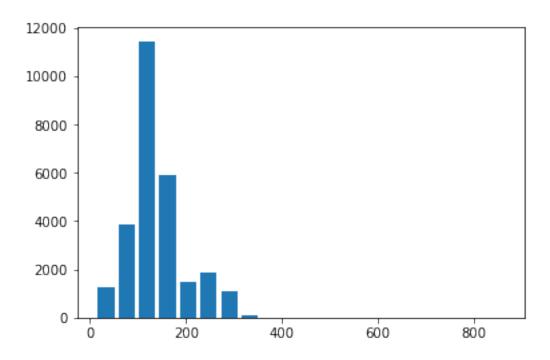
```
# Get some summary statistics for the numerical columns
print(df.describe())
# Check the value counts of the categorical columns
cat=[]
for col in df.select_dtypes(include=["object"]).columns:
    cat.append(df[col].value_counts())
                                            full_text
  Opflegearzt OFriedelkorn OLAguja44 Pardon, wol...
  RT Ograntshapps: Aviation demand is reduced du...
2 RT @DDStandaard: De droom van D66 wordt werkel...
3 RT @DDStandaard: De droom van D66 wordt werkel...
4 De droom van D66 wordt werkelijkheid: COVID-19...
                                     text_translation
                                                           created_at \
   @pflegearzt @Friedelkorn @ LAguja44 Pardon wol... 1583756789000
  RT @grantshapps: Aviation demand is reduced du... 1583756794000
2 RT @DDStandaard: The D66 dream come true: COVI... 1583756797000
3 RT @DDStandaard: The D66 dream come true: COVI... 1583756797000
4 The D66 dream becomes reality: COVID-19 super ... 1583756807000
                                                        description \
   screen name
0
  TheoRettich I science, therefore a Commie.
                                                     FALGSC: P...
                I tweet a lot but love to engage & converse. P...
1
   davidiwanow
2
       EricL65
                                                               None
3
       EricL65
                                                               None
4
      EhrErwin Budget-Life Coach. Time management Coaching. b...
                                     desc_translation weekofyear
                                                                    weekday \
   I science, Therefore a Commie.
                                     FALGSC: Par...
                                                                       0
                                                            11
1
   I tweet a lot but love to engage and converse...
                                                             11
                                                                        0
2
                                                  None
                                                                11
                                                                           0
                                                                11
                                                                           0
3
  Budget-Life Coach. Time management coaching. h...
                                                                         0
                                                              11
        month
                                          point
                                                  latitude longitude altitude
   day
                   (52.5001698, 5.7480821, 0.0)
0
     9
            3
                                                  52.50017
                                                            5.748082
                                                                           0.0
     9
                  (52.3727598, 4.8936041, 0.0)
                                                                           0.0
1
            3
                                                  52.37276
                                                            4.893604
2
     9
            3
                                           None
                                                       NaN
                                                                 NaN
                                                                           0.0
3
     9
            3
                                           None
                                                       NaN
                                                                 NaN
                                                                           0.0
4
                  (52.3727598, 4.8936041, 0.0)
                                                 52.37276
                                                            4.893604
                                                                           0.0
        province hisco_standard hisco_code industry sentiment_pattern \
0
       Flevoland
                             None
                                         None
                                                  False
                                                                       0.0
   Noord-Holland
                                                                       0.0
                             None
                                         None
                                                  False
1
2
           False
                             None
                                         None
                                                  False
                                                                       0.0
3
                                                                       0.0
           False
                             None
                                         None
                                                  False
```

4	Noord-Holland	No	ne Non	e False	0.0
subjective_pattern					
0		0.0			
1		0.0			
2		0.0			
3		0.0			
4		0.0			
-		٦			
	5 rows x 23 colu 27019, 23)	mns」			
fu	ıll_text	object			
te	ext_translation	object			
cr	reated_at	int64			
SC	creen_name	object			
d€	escription	object			
	esc_translation	object			
	eekofyear	int64			
we	eekday	int64			
da	•	int64			
mc	onth	int64			
•	ear	int64			
	cation	object			
_	oint_info	object			
_	oint	object			
	ntitude	float64			
	ongitude	float64			
	titude	float64			
_	rovince	object			
	sco_standard	object			
	lsco_code	object			
	ndustry	bool			
	entiment_pattern				
	ıbjective_patter	n float64			
	ype: object				
	ill_text	0			
	ext_translation	0			
	reated_at	0			
	creen_name	0			
	escription	4737			
	esc_translation	4738			
	eekofyear	0			
	eekday	0			
da		0			
	onth	0			
-	ear	0 11746			
TC	cation	11746			

point_info

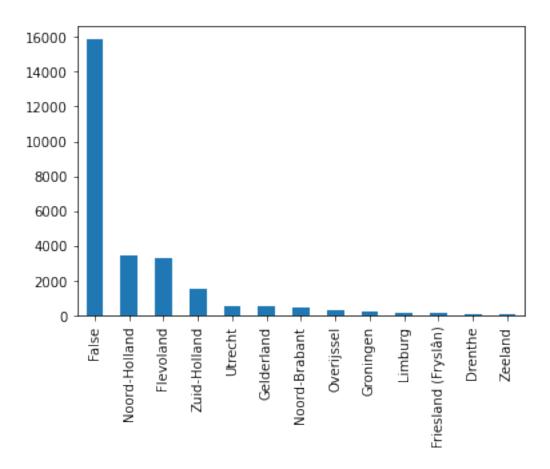
```
13521
    point
    latitude
                            13521
                            13521
    longitude
    altitude
                             1775
    province
                              304
    hisco_standard
                            20144
    hisco code
                            20144
    industry
                                 0
    sentiment_pattern
                                 0
    subjective_pattern
                                 0
    dtype: int64
              created_at
                             weekofyear
                                                weekday
                                                                   day
                                                                                month
                           27019.000000
            2.701900e+04
                                          27019.000000
                                                         27019.000000
                                                                         27019.000000
    count
    mean
            1.592197e+12
                              24.583700
                                               2.555572
                                                             14.089937
                                                                             6.017913
    std
            5.882117e+09
                               9.732801
                                               2.063301
                                                              9.383028
                                                                             2.255116
            1.580012e+12
                               4.000000
    min
                                               0.000000
                                                              1.000000
                                                                             1.000000
    25%
            1.587297e+12
                              16.000000
                                               1.000000
                                                              5.000000
                                                                             4.000000
    50%
            1.592898e+12
                              26.000000
                                               2.000000
                                                             16.000000
                                                                             6.000000
    75%
            1.597772e+12
                              34.000000
                                               5.000000
                                                             23.000000
                                                                             8.000000
            1.600207e+12
                              38.000000
                                               6.000000
                                                             31.000000
                                                                             9.000000
    max
                          latitude
                                        longitude
                                                    altitude
                                                               sentiment pattern
               year
    count
            27019.0
                      13498.000000
                                     13498.000000
                                                     25244.0
                                                                    27019.000000
             2020.0
                         49.625468
                                         4.544151
                                                          0.0
                                                                         0.037602
    mean
    std
                0.0
                         11.984083
                                        21.674134
                                                          0.0
                                                                         0.276415
             2020.0
                                                          0.0
                        -79.406307
                                      -157.795990
                                                                        -1.000000
    min
    25%
                                                          0.0
             2020.0
                         51.842652
                                         4.686789
                                                                         0.000000
    50%
             2020.0
                         52.372760
                                         4.898047
                                                          0.0
                                                                         0.000000
    75%
                                                          0.0
             2020.0
                         52.500170
                                         5.748082
                                                                         0.125000
             2020.0
                         64.145981
                                       176.897763
                                                          0.0
                                                                         1.000000
    max
            subjective_pattern
                  27019.000000
    count
                       0.376768
    mean
    std
                       0.350845
    min
                      -0.300000
    25%
                       0.000000
    50%
                       0.400000
    75%
                       0.675000
                       1.000000
    max
[4]: df.columns
```

```
'industry', 'sentiment_pattern', 'subjective_pattern'],
           dtype='object')
[5]: #binning continous values to -1,0 & 1
     threshold=0
     df['sentiment_pattern'] = np.where(df['sentiment_pattern'] < threshold, -1, np.</pre>
      ⇔where(df['sentiment_pattern'] > threshold, 1, 0))
     df['sentiment_pattern'].value_counts()
[5]: 0
           11743
            9230
      1
     -1
            6046
     Name: sentiment_pattern, dtype: int64
[6]: # Create a Scattergeo map
     data = [go.Scattergeo(
         lon = df['longitude'], # Column containing the longitude values
         lat = df['latitude'], # Column containing the latitude values
         text = df['text_translation'], # Column containing the tweet text
         mode = 'markers',
         marker = dict(
             size = 4,
             color = 'red',
             line_color = 'black',
             line_width = 1
     )]
     # Plot the map
     fig = go.Figure(data=data)
     fig.show()
[7]: # Plot a histogram of the tweet lengths
     df['tweet_length'] = df['text_translation'].apply(len)
     plt.hist(df['tweet_length'], bins=20,rwidth=0.8)
     plt.show()
```



```
[8]: #Tweet count based on province df['province'].value_counts().plot.bar()
```

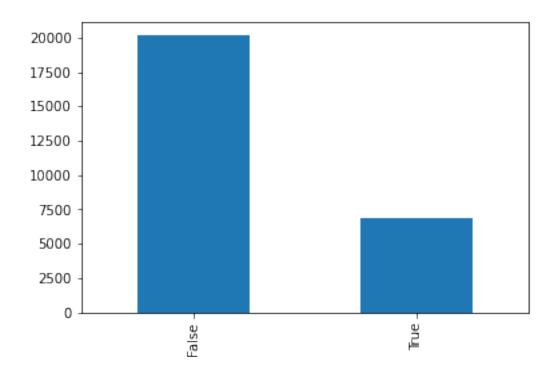
[8]: <AxesSubplot:>



• Most users dont have their location enabled.

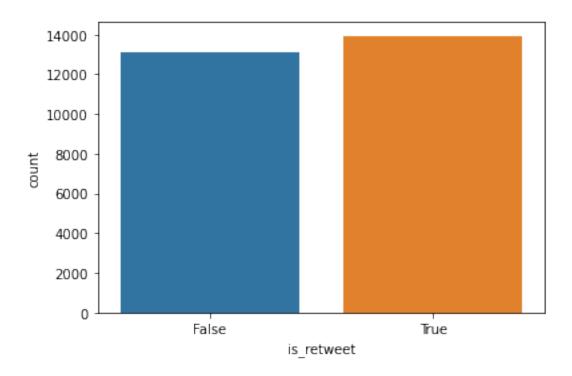
```
[9]: df['industry'].value_counts().plot.bar()
```

[9]: <AxesSubplot:>



• Industry classification is possible for 30% of the tweets

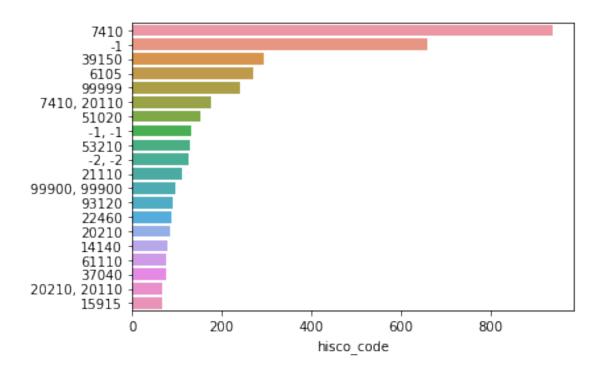
```
[10]: # Create a new column indicating whether the tweet is a retweet
df['is_retweet'] = df['text_translation'].str.startswith('RT @')
# Plot a bar plot of the number of tweets that are retweets
sns.countplot(x='is_retweet', data=df)
plt.show()
```



```
[11]: # Count the number of tweets with a HISCO code
df['hisco_code'].count()

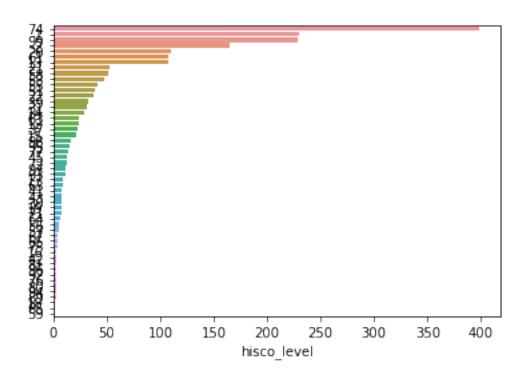
# Print the unique values in the HISCO column
df['hisco_code'].unique()

# Plot a barplot of the most common HISCO codes
top_hisco = df['hisco_code'].value_counts()[:20]
sns.barplot(x=top_hisco, y=top_hisco.index)
plt.show()
```



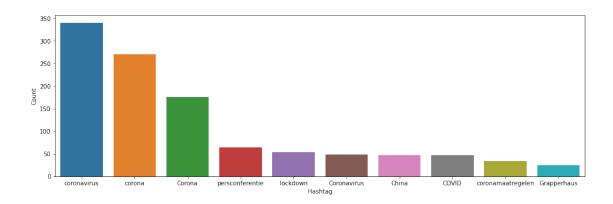
```
[12]: # Create a new column with the HISCO code level
    df['hisco_level'] = df['hisco_code'].str[:2]

# Plot a barplot of the number of tweets by HISCO level
    hisco_levels = df['hisco_level'].value_counts()
    sns.barplot(x=hisco_levels, y=hisco_levels.index)
    plt.show()
```

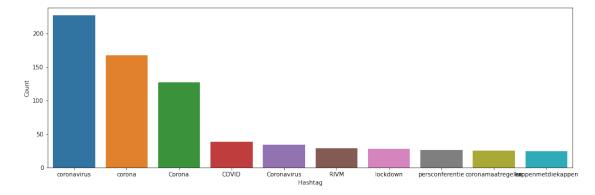


```
[23]: # Cleaning tweets
      def clean_tweet(text):
          Text = ' '
          wordLemm = WordNetLemmatizer()
          temp = text.lower()
          temp = re.sub("rt @[A-Za-z0-9_]+","", temp)
          temp = re.sub("@[A-Za-z0-9_]+","", temp)
          temp = re.sub("#[A-Za-z0-9_]+","", temp)
          temp = re.sub(r'http\S+', '', temp)
          temp = re.sub('[:()!?]', ' ', temp)
          temp = re.sub('\[.*?\]',' ', temp)
          tweetwords=''
          for word in temp.split():
              if len(word)>1:
                          # Lemmatizing the word.
                          word = wordLemm.lemmatize(word)
                          tweetwords+= (word+' ')
          Text+=tweetwords
          return Text
      # Extract hashtags
      def extract_hashtags(text):
          hashtag_pattern = re.compile(r"#\S+")
          return hashtag_pattern.findall(text)
```

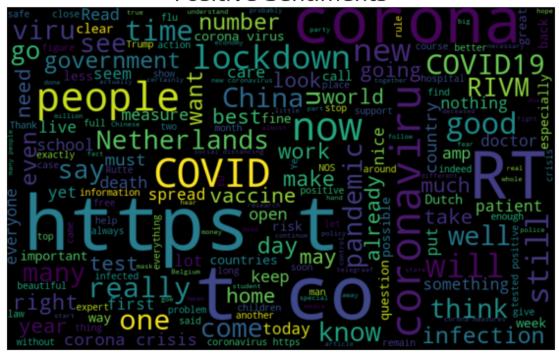
```
[18]: # extracting hashtags from non racist/sexist tweets
      # collecting the hashtags
      def hashtag_extract(x):
          hashtags = []
          for i in x:
              ht = re.findall(r"#(\w+)", i)
              hashtags.append(ht)
          return hashtags
      HT_positive =
       hashtag_extract(df['text_translation'][df['sentiment_pattern']==1])
      # extracting hashtags from racist/sexist tweets
      HT_negative =
       ⇔hashtag_extract(df['text_translation'][df['sentiment_pattern']==-1])
      # unnesting list
      HT_positive = sum(HT_positive,[])
      HT_negative = sum(HT_negative,[])
```



```
[20]: #Negative Hashtags
b = nltk.FreqDist(HT_negative)
e = pd.DataFrame({'Hashtag': list(b.keys()), 'Count': list(b.values())})
# selecting top 10 most frequent hashtags
e = e.nlargest(columns="Count", n = 10)
plt.figure(figsize=(16,5))
ax = sns.barplot(data=e, x= "Hashtag", y = "Count")
ax.set(ylabel = 'Count')
plt.show()
```



Positive Sentiments



Negative Sentiments

```
Netherlands viru test always still always still take work life time of always still always government of the still always g
```

```
[24]: # Extract features from the tweet text
      vectorizer = TfidfVectorizer()
      X_tweet = vectorizer.fit_transform(df["text_translation"].apply(clean_tweet))
[25]: # Extract features from the hashtags
      vectorizer = TfidfVectorizer()
      X_hashtags = vectorizer.fit_transform(df["text_translation"].
       →apply(extract_hashtags).apply(" ".join))
 []: # Extract features from the emojis
      vectorizer = CountVectorizer()
      X_emojis = vectorizer.fit_transform(df["text_translation"].
       →apply(extract_emojis).apply(" ".join))
[27]: # Combine the extracted features
      X = scipy.sparse.hstack([X_tweet, X_hashtags],)
      # Assign the emoji score as the target variable
      y = df["sentiment_pattern"]
      # Split the data into a training set and a test set
```

```
[28]: # Build the model
    model = LogisticRegression(max_iter=1000)
    model.fit(X_train_scaled, y_train)

# Make predictions on the test set
    y_pred = model.predict(X_test_scaled)

# Evaluate the model
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred,average='macro')
    recall = recall_score(y_test, y_pred,average='macro')

    print(f"Accuracy: {accuracy:.2f}")
    print(f"Precision: {precision:.2f}")
    print(f"Recall: {recall:.2f}")
```

Accuracy: 0.77 Precision: 0.76 Recall: 0.76

[]: