Task-04

Analyze and visualize sentiment patterns in social media data to understand public opinion and attitudes towards specific topics or brands.

Sample Dataset :- https://www.kaggle.com/datasets/jp797498e/twitter-entity-sentiment-analysis

Description About Dataset: This is the Twitter Sentiment Analysis Dataset.

Double-click (or enter) to edit

IMPORTING REQUIED LIBRARIES

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,accuracy_score,confusion_matrix
from mlxtend.plotting import plot_confusion_matrix
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
```

```
from google.colab import files
data=files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving twitter_training.csv to twitter_training.csv

```
data=pd.read_csv('twitter_training.csv')
```

Exploratory data analysis(EDA)

```
df=data.copy()
```

```
df.columns=['id','country','label','text']
```

```
df.shape
```

```
(71981, 4)
```

```
df.head()
```

	id	country	label	text
0	2401	Borderlands	Positive	I am coming to the borders and I will kill you...
1	2401	Borderlands	Positive	im getting on borderlands and i will kill you ...
2	2401	Borderlands	Positive	im coming on borderlands and i will murder you...
3	2401	Borderlands	Positive	im getting on borderlands 2 and i will murder ...
4	2401	Borderlands	Positive	im getting into borderlands and i can murder y...

```
df.tail()
```

	id	country	label	text
74676	9200	Nvidia	Positive	Just realized that the Windows partition of my...
74677	9200	Nvidia	Positive	Just realized that my Mac window partition is ...
74678	9200	Nvidia	Positive	Just realized the windows partition of my Mac ...
74679	9200	Nvidia	Positive	Just realized between the windows partition of...
74680	9200	Nvidia	Positive	Just like the windows partition of my Mac is l...

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 71981 entries, 0 to 74680
Data columns (total 4 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   id       71981 non-null  int64 
 1   country  71981 non-null  object
 2   label    71981 non-null  object
 3   text     71655 non-null  object
dtypes: int64(1), object(3)
memory usage: 2.7+ MB
```

```
df.columns
```

```
Index(['id', 'country', 'label', 'text'], dtype='object')
```

```
df.describe()
```

	id
count	71981.000000
mean	6437.452383
std	3743.194317
min	1.000000
25%	3199.000000
50%	6434.000000
75%	9607.000000
max	13200.000000

```
df.isnull().sum()
```

```
id           0
country      0
label        0
text       326
dtype: int64
```

```
df.duplicated().sum()
```

```
0
```

```
df.drop_duplicates(inplace=True)
```

```
df.duplicated().sum()
```

```
0
```

```
df.isnull().sum()
```

```
id           0
country      0
label        0
text       326
dtype: int64
```

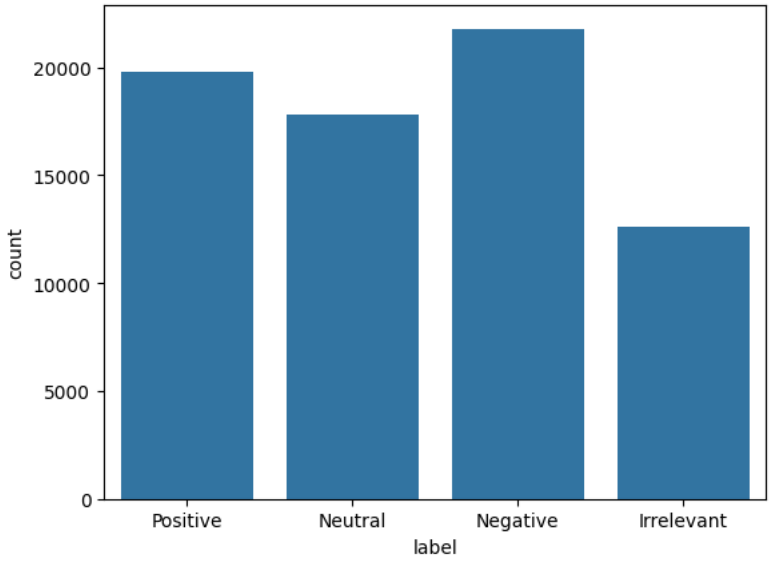
```
df['label'].value_counts()
```

```
Negative      21787
Positive      19810
Neutral       17800
```

```
Irrelevant    12584
Name: label, dtype: int64
```

```
sns.countplot(x=df['label'])
```

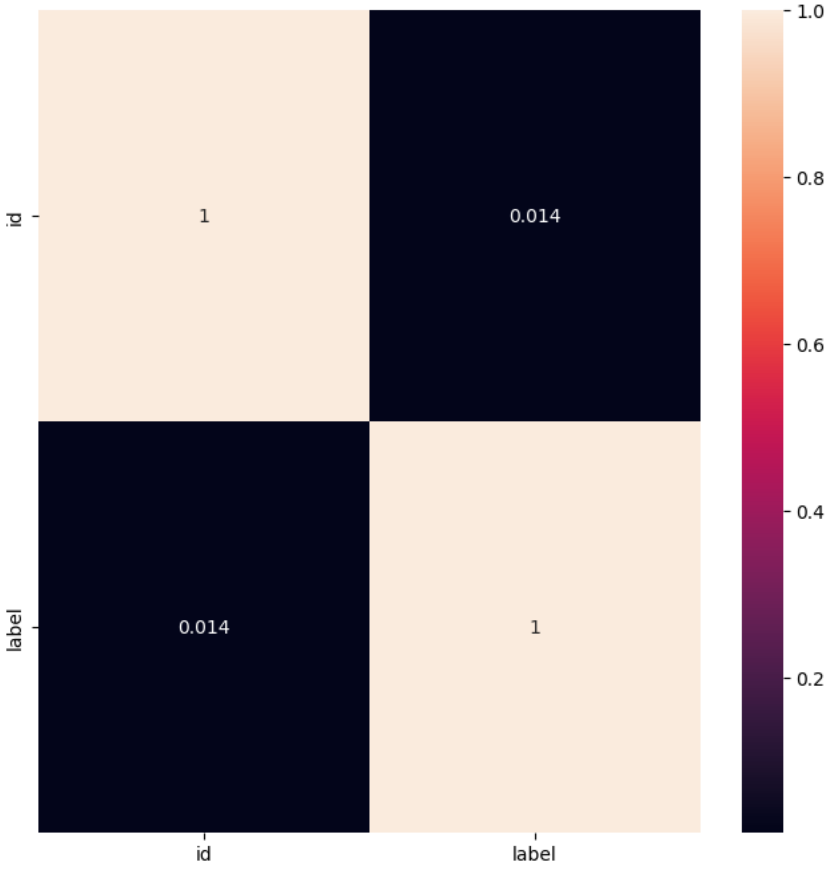
```
<Axes: xlabel='label', ylabel='count'>
```




```
le=LabelEncoder()
df['label']=le.fit_transform(df['label'])
```

```
plt.figure(figsize=(8,8))
sns.heatmap(data=df.corr(), annot=True)
```

```
<ipython-input-43-af8d5171ddf7>:2: FutureWarning: The default value of numeric_only i
  sns.heatmap(data=df.corr(), annot=True)
<Axes: >
```



```
print("Tensorflow version " + tf.__version__)
AUTO = tf.data.experimental.AUTOTUNE

# Detect hardware, return appropriate distribution strategy
try:
    # TPU detection. No parameters necessary if TPU_NAME environment variable is
    # set: this is always the case on Kaggle.
    tpu = tf.distribute.cluster_resolver.TPUClusterResolver()
    print('Running on TPU ', tpu.master())
except ValueError:
    tpu = None

if tpu:
    tf.config.experimental_connect_to_cluster(tpu)
    tf.tpu.experimental.initialize_tpu_system(tpu)
    strategy = tf.distribute.experimental.TPUStrategy(tpu)
else:
    # Default distribution strategy in Tensorflow. Works on CPU and single GPU.
    strategy = tf.distribute.get_strategy()

print("REPLICAS: ", strategy.num_replicas_in_sync)
```

```
Tensorflow version 2.13.0
REPLICAS:  1
```

```
## Helper functions

def add_spines(colour = '#425169', linewidth = 2):
    """
    Add beautiful spines to you plots
    """
    ax = plt.gca()
    ax.spines['top'].set_visible(True)
    ax.spines['right'].set_visible(True)
    ax.spines[['bottom', 'left', 'top', 'right']].set_color(colour)
    ax.spines[['bottom', 'left', 'top', 'right']].set_linewidth(linewidth)

def roc_auc(predictions,target):
    '''
    This methods returns the AUC Score when given the Predictions
    and Labels
    '''

    fpr, tpr, thresholds = metrics.roc_curve(target, predictions)
    roc_auc = metrics.auc(fpr, tpr)
    return roc_auc
```

🔵 Basic preprocessing and sample tweets

```
df = pd.read_csv("/kaggle/input/cyberbullying-dataset/twitter_parsed_dataset.csv")
df = df.drop(['id', 'index'], axis=1)
df.rename(columns={'oh_label': 'Label'}, inplace=True)
df = df.dropna(subset=['Label'])

# analysis of mentions and tweets

# here we create a function to count the number of hashtags and mentions and then create two columns to store this data
def count_symbols(text):
    hashtag_count = len(re.findall(r'#', text))
    mention_count = len(re.findall(r'@', text))
    return hashtag_count, mention_count

# Apply the function to each row in the 'text' column
df[['num_hashtags', 'num_mentions']] = df['Text'].apply(lambda x: pd.Series(count_symbols(x)))

print('\nDataset shape: ', df.shape)
df.head()
```

```
Dataset shape:  (16848, 5)
```

	Text	Annotation	Label	num_hashtags	num_mentions
0	@halalflaws @biebervalue @greenlinerzjm I read...	none	0.0	0	3
1	@ShreyaBafna3 Now you idiots claim that people...	none	0.0	0	1
2	RT @Mooseoftorment Call me sexist, but when I ...	sexism	1.0	0	1
3	@g0ssipsquirrelx Wrong, ISIS follows the	racism	1.0	0	1

```
print('_________Sample tweets_________')
simple_tweet = df[df['Label'] == 0]['Text'].iloc[1]
print('\nSimple tweet: ', simple_tweet)
sexist_tweet = df[df['Annotation'] == 'sexism']['Text'].iloc[0]
print('\n\nSexist tweet: ', sexist_tweet)
racist_tweet = df[df['Annotation'] == 'racism']['Text'].iloc[0]
print('\n\nRacist tweet: ', racist_tweet)
print('\n_____________________________________')
```

```
_________Sample tweets_________

Simple tweet:  @ShreyaBafna3 Now you idiots claim that people who tried to stop him from becoming a terrorist made him a terrorist.


Sexist tweet:  RT @Mooseoftorment Call me sexist, but when I go to an auto place, I'd rather talk to a guy


Racist tweet:  @g0ssipsquirrelx Wrong, ISIS follows the example of Mohammed and the Quran exactly.

_____________________________________
```

🕵 Exploratory Data Analysis

> We analyse different aspects of the twitter dataset here. We start with simple tasks like understanding the label and Annotation distribution, and slowly progress toward extracting and analysing #hastags, @mentions and finally generate wordclouds of high frequency words according to annotations.

```
## Basic analysis of labels and annotations

print('Label distribution')
print(df.Label.value_counts())
print('-------------------------\n')
print('Annotation distribution')
print(df.Annotation.value_counts())
print('-------------------------\n')
print('Grouping of Annotation with label')
print(df.groupby('Annotation')['Label'].sum())
```

```
Label distribution
Label
0.0    11501
1.0     5347
Name: count, dtype: int64
-------------------------

Annotation distribution
Annotation
none      11501
sexism     3377
racism     1970
Name: count, dtype: int64
-------------------------

Grouping of Annotation with label
Annotation
none         0.0
racism    1970.0
sexism    3377.0
Name: Label, dtype: float64
```

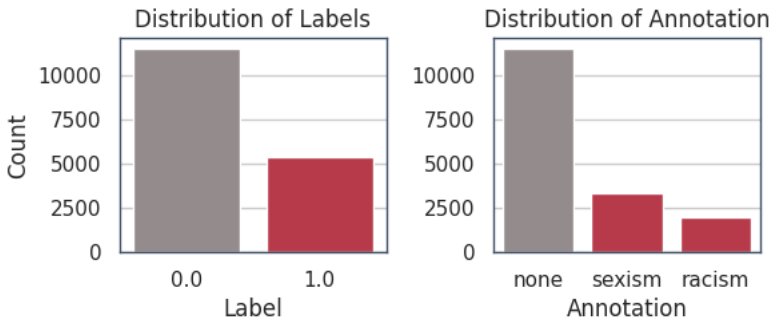
As you can see the text with annotations of anything other than none are all classified as toxic. Hence, it would be a dead giveaway to include it in our dataset. We may try to classify the text with the annotations later

---

Highlighting columns in your seaborn plots

This is just a fun way in which you can highlight certain bars in your barplot. We create a specific function that returns a palette of length equal to the unique categories in the column you're plotting and specifically highlights the indexes passed to it.

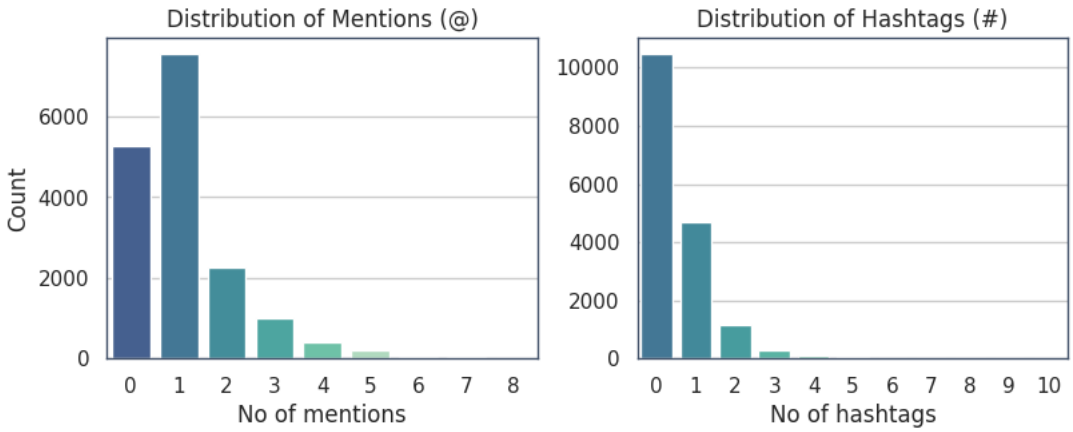
```
def bully_palette(df,column, positions_to_change: list):
    """
    A function to create grey red palettes according to the inputs
    You just need to pass in the dataframe and the index of labels to be highlighted in red
    """
    palette = ['#96898b']*df[column].nunique()
    new_values = ['#cc253b']*len(positions_to_change)
    for position, new_value in zip(positions_to_change, new_values):
        palette[position] = new_value
    return sns.color_palette(palette)

# example
# bully_palette(df,'Label', [0, 1])


sns.set(style="whitegrid")
plt.figure(figsize=(6, 2))

plt.subplot(1, 2, 1)
# using the bully_pallete function to create a custom pallete
sns.countplot(x='Label', data=df, palette = bully_palette(df, 'Label', [1]))
plt.xlabel('Label')
plt.ylabel('Count')
plt.title('Distribution of Labels')
# adding spines using the helper function we declared earlier
add_spines(linewidth=1)

plt.subplot(1, 2, 2)
sns.countplot(x='Annotation', data=df, palette = bully_palette(df,'Annotation', [1, 2]))
plt.xlabel('Annotation')
plt.ylabel('')
plt.title('Distribution of Annotation')
add_spines(linewidth=1)

plt.subplots_adjust(left=0.1, right=0.9, bottom=0.1, top=0.9, wspace=0.4, hspace=0.3)
plt.show()
```



This is how our highlighted plots turned out. Do play around with these... highlight with your own colours... add functionalities etc.

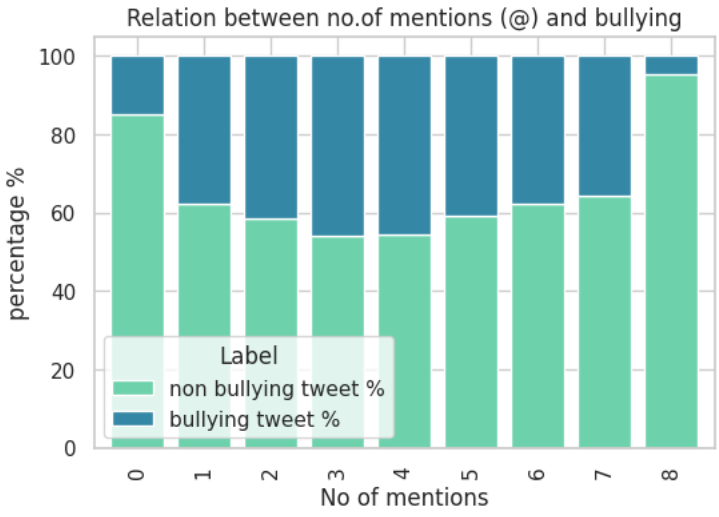
We can see that the lable `1` has further been divided into the categories `sexism` and `racism`. Sexism is more prevelant than racism. Racism is looked upon more harshly by the public or twitter might be efficient at removing racist tweets from their site (we never know 🤷).

```
plt.figure(figsize=(9, 3))

plt.subplot(1, 2, 1)
sns.countplot(x='num_mentions', data=df, palette =  sns.color_palette("mako", n_colors=9)[3:])
plt.xlabel('No of mentions')
plt.ylabel('Count')
plt.title('Distribution of Mentions (@)')
add_spines(linewidth=1)

plt.subplot(1, 2, 2)
sns.countplot(x='num_hashtags', data=df, palette = sns.color_palette("mako", n_colors=11)[5:])
plt.xlabel('No of hashtags')
plt.ylabel('')
plt.title('Distribution of Hashtags (#)')
add_spines(linewidth=1)

plt.subplots_adjust(left=0.1, right=0.9, bottom=0.1, top=0.9, wspace=0.23, hspace=0.3)
plt.show()
```




```
plt.figure(figsize=(6, 3))
mention_label_cross = pd.crosstab(df['num_mentions'], df['Label'])
mention_label_cross['sum'] = mention_label_cross[0.0] + mention_label_cross[1.0]
mention_label_cross['non bullying tweet %'] = mention_label_cross[0.0]/mention_label_cross['sum']*100
mention_label_cross['bullying tweet %'] = mention_label_cross[1.0]/mention_label_cross['sum']*100
mention_label_cross = mention_label_cross.drop([0.0, 1.0, 'sum'], axis=1)

mention_label_cross.plot(kind='bar', stacked=True, figsize=(6, 4), color=['#6dd2ac', '#3487a5'], width=0.8)
plt.xlabel('No of mentions')
plt.ylabel('percentage %')
plt.title('Relation between no.of mentions (@) and bullying')
plt.show()
```

```
<Figure size 600x300 with 0 Axes>
```



> Here you can see that as the mentions increase to 4, the percentage of bullying tweets increases compared to the normal ones. But the trend once again reverses as the mentions increase upto 8. No clear pattern was seen between number of hashtags and percentage of bullying tweets

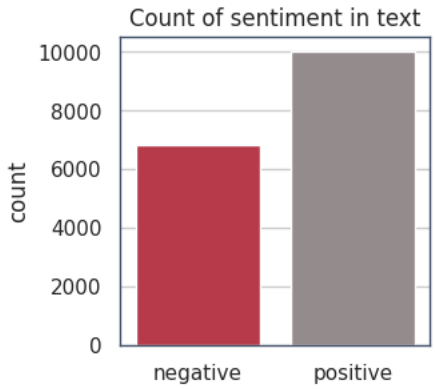
Sentiment analysis

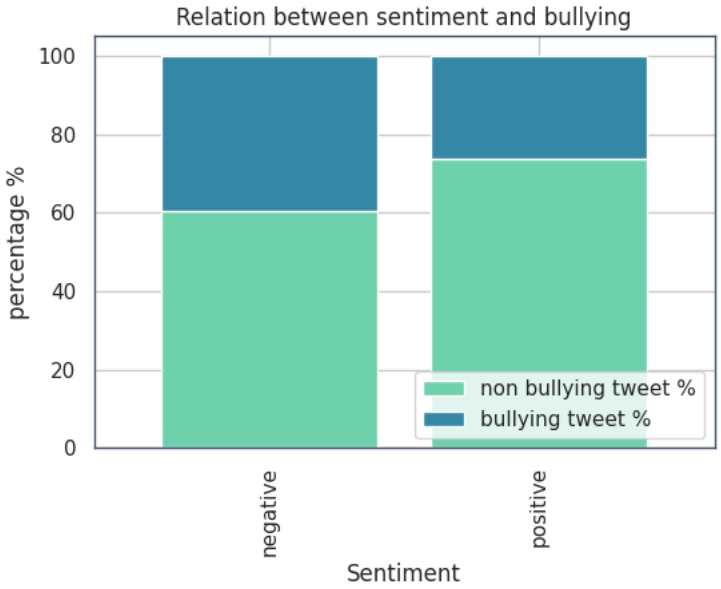
Here I planned on checking whether the sentiment of the tweets directly correlate with bullying. ie. more negativity a tweet contains, higher the probability of bullying. Turns out it wasn't as straightforward as that. The dataset contains a lot of negative tweets... which is a good thing since our models should be able to understand the difference between a `negative` tweet and a `bullying` tweet. It shouldn't flag every other negative tweet as bullying.

```
## Using the nltk library to analyze sentiment of each text so that we can correlate it with bullying
# Initialize the VADER sentiment analyzer
sia = SentimentIntensityAnalyzer()

# Function to get sentiment of a text
def get_sentiment(text):
    compound_score = sia.polarity_scores(text)['compound']
    return 'positive' if compound_score >= 0 else 'negative'


df['Sentiment_Label'] = df['Text'].apply(get_sentiment)

df.head()
```

	Text	Annotation	Label	num_hashtags	num_mentions	Sentiment_Label
0	@halalflaws @biebervalue @greenlinerzjm I read...	none	0.0	0	3	negative
1	@ShreyaBafna3 Now you idiots claim that people...	none	0.0	0	1	negative
	RT					

```
plt.figure(figsize=(3, 3))
df['Sentiment_Label'].value_counts()
sns.countplot(x='Sentiment_Label', data=df, palette = bully_palette(df, 'Sentiment_Label', [0]))
plt.title('Count of sentiment in text')
plt.xlabel('')
add_spines(linewidth=1)

sent_label_cross = pd.crosstab(df['Sentiment_Label'], df['Label'])
sent_label_cross['sum'] = sent_label_cross[0.0] + sent_label_cross[1.0]
sent_label_cross['non bullying tweet %'] = sent_label_cross[0.0]/sent_label_cross['sum']*100
sent_label_cross['bullying tweet %'] = sent_label_cross[1.0]/sent_label_cross['sum']*100
sent_label_cross = sent_label_cross.drop([0.0, 1.0, 'sum'], axis=1)

ax = sent_label_cross.plot(kind='bar', stacked=True, figsize=(6, 4), color=['#6dd2ac', '#3487a5'], width=0.8)
plt.xlabel('Sentiment')
plt.ylabel('percentage %')
plt.title('Relation between sentiment and bullying')
ax.legend(loc='lower right')
add_spines(linewidth=1)

plt.show()
```





💡 **Idea:** We could add either the sentiment score or the label as a feature to train our models. Though I haven't actually done that... it may be a great idea for you guys to try out!!

Analysis of common hashtags and mentions

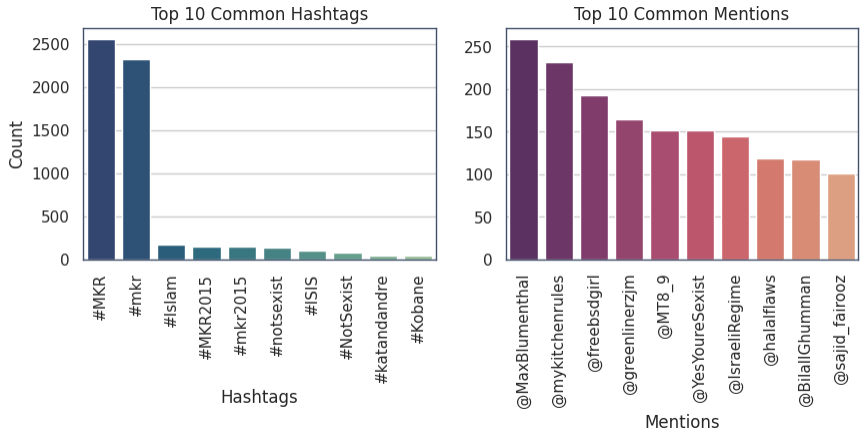
The tweets contain a bunch of hashtags and mentions. What kind of twitter analysis would this be if we leave these out :P Analysing this part made me have questions over the quality of the dataset. Let's understand why...

- The tweets seems to be majorly sourced from particular feeds or are retweets to particular user.
- A majority of the tweets feature the TV show `My kitchen rules`.

A very key takeaway:

The data collector was an australian interested in cooking 🍹😆

```
## Extraction of the top ten mentions and hashtags in the dataset

# Function to extract hashtags from a text
def extract_hashtags(text):
    return re.findall(r'#\w+', text)

df['Hashtags'] = df['Text'].apply(extract_hashtags)

# Function to extract hashtags from a text
def extract_mentions(text):
    return re.findall(r'@\w+', text)

df['Mentions'] = df['Text'].apply(extract_mentions)

def create_counter_df(df):
    """
    Creates a dataframe that contains the Label and their count.
    Pass the dataframe containing the labels in the form of a list column as an input.
    Example usage:
    1. mentions = create_counter_df(df['Mentions'])
    2. sexist_mentions = create_counter_df(df[df.Annotation=='sexist']["Mentions"])
    """
    # Flatten the list of hashtags and count their occurrences
    all_counts = [tag for counts_list in df for tag in counts_list]
    label_counts = Counter(all_counts)

    # Create a DataFrame from the Counter dictionary
    counts_df = pd.DataFrame(list(label_counts.items()), columns=['Label', 'Count'])
    counts_df = counts_df.sort_values(by='Count', ascending=False)
    return counts_df

mentions_df = create_counter_df(df['Mentions'])
top_10_mentions = mentions_df.head(10)
sexist_mentions = create_counter_df(df[df.Annotation=='sexism']["Mentions"])
top_10_sexist_mentions = sexist_mentions.head(10)
racist_mentions = create_counter_df(df[df.Annotation=='racism']["Mentions"])
top_10_racist_mentions = racist_mentions.head(10)

hashtags_df = create_counter_df(df['Hashtags'])
top_10_hashtags = hashtags_df.head(10)
sexist_hashtags = create_counter_df(df[df.Annotation=='sexism']["Hashtags"])
top_10_sexist_hashtags = sexist_hashtags.head(10)
racist_hashtags = create_counter_df(df[df.Annotation=='racism']["Hashtags"])
top_10_racist_hashtags = racist_hashtags.head(10)


plt.figure(figsize=(10, 3))

plt.subplot(121)
sns.barplot(x='Label', y='Count', data=top_10_hashtags, palette='crest_r')
plt.title('Top 10 Common Hashtags')
plt.xlabel('Hashtags')
plt.ylabel('Count')
plt.xticks(rotation=90)
add_spines(linewidth=1)

plt.subplot(122)
sns.barplot(x='Label', y='Count', data=top_10_mentions, palette='flare_r')
plt.title('Top 10 Common Mentions')
plt.xlabel('Mentions')
plt.ylabel('')
plt.xticks(rotation=90)
add_spines(linewidth=1)
```



`#MKR` (@mykitchenrules) is the most popular hashtag in the dataset whereas `@MaxBlumenthal` is the most popular mention.

I did some digging around `@MaxBlumenthal` and found this:

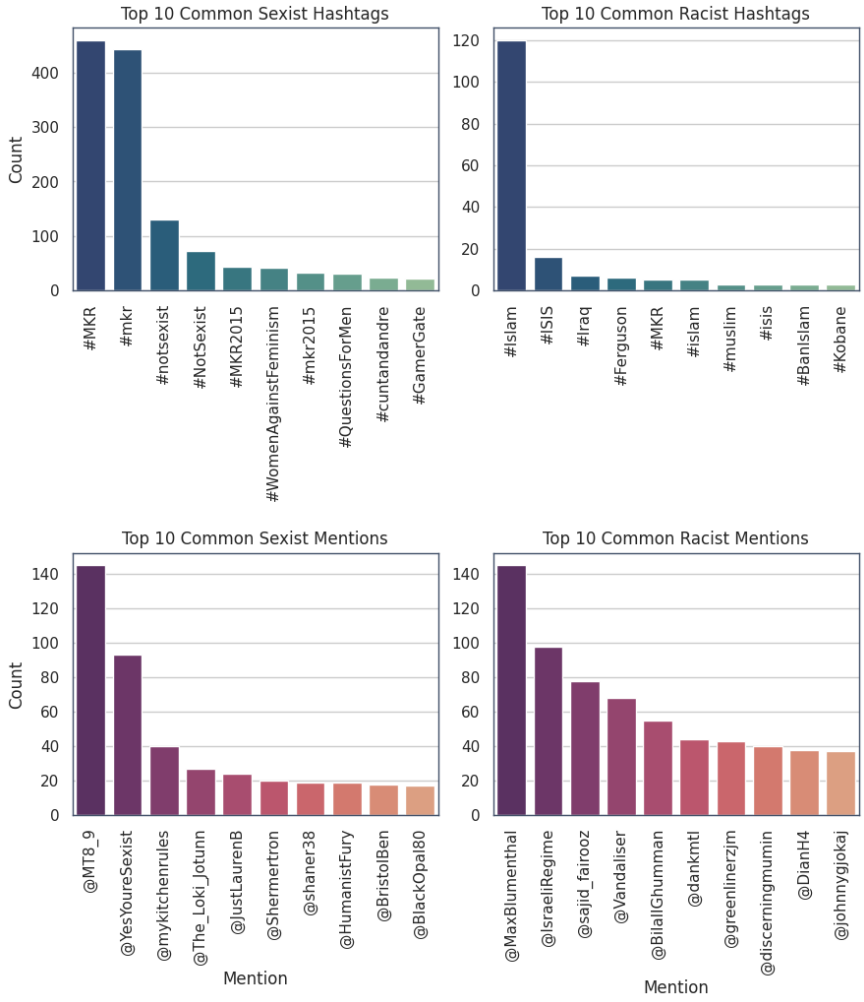
Who he is:

- American author and blogger: Born in 1977, Blumenthal has written for publications like The Nation, The New York Times, and The Daily Beast. He currently edits The Grayzone website.
- Investigative journalist: Blumenthal's work focuses on politics, media, and human rights, often with a critical view of US foreign policy and the Israeli-Palestinian conflict.
- Author: He's written several books, including "Republican Gomorrah" and "Goliath: Life and Loathing in Greater Israel," which won awards and ignited debate.

Controversies:

- The Grayzone: Some see The Grayzone as promoting conspiracy theories and Russian propaganda, particularly regarding the Syrian Civil War. Blumenthal maintains editorial independence and focuses on investigative journalism.
- Methodology: Critics question Blumenthal's use of anonymous sources and selective evidence, while supporters defend his investigative techniques and access to information denied to mainstream media.

```
plt.figure(figsize=(10, 10))

plt.subplot(221)
sns.barplot(x='Label', y='Count', data=top_10_sexist_hashtags, palette='crest_r')
plt.title('Top 10 Common Sexist Hashtags')
plt.xlabel('')
plt.ylabel('Count')
plt.xticks(rotation=90)
add_spines(linewidth=1)

plt.subplot(222)
sns.barplot(x='Label', y='Count', data=top_10_racist_hashtags, palette='crest_r')
plt.title('Top 10 Common Racist Hashtags')
plt.xlabel('')
plt.ylabel('')
plt.xticks(rotation=90)
add_spines(linewidth=1)

plt.subplot(223)
sns.barplot(x='Label', y='Count', data=top_10_sexist_mentions, palette='flare_r')
plt.title('Top 10 Common Sexist Mentions')
plt.xlabel('Mention')
plt.ylabel('Count')
plt.xticks(rotation=90)
add_spines(linewidth=1)

plt.subplot(224)
sns.barplot(x='Label', y='Count', data=top_10_racist_mentions, palette='flare_r')
plt.title('Top 10 Common Racist Mentions')
plt.xlabel('Mention')
plt.ylabel('')
plt.xticks(rotation=90)
add_spines(linewidth=1)

plt.subplots_adjust(left=0.1, right=0.9, bottom=0.1, top=0.9, wspace=0.15, hspace=1)
plt.show()
```



Key takeaways from the most common @ and #s

- For some reason `#MKR` and `#mkr` (my kitchen rules) feature on the top of the sexist hashtags. Maybe coz its a cooking show. lol. It might be due to the fact that #MKR is the most common hashtag on the dataset.
- You can see religiously motived terrorist groups like `#isis` feature on the most common racist hashtags
- `@YesYoureSexist` sounds like a provocative username. No wonder it has the second most sexist mentions
- `@MaxBlumenthal` a controversial American author and blogger features on the top of Racist mentions

Preprocessing the text

```
def clean_tweet(tweet):
    # Remove URLs
    tweet = re.sub(r'http\S+', '', tweet)

    # Remove mentions and hashtags
    tweet = re.sub(r'@[A-Za-z0-9_]+|#[A-Za-z0-9_]+', '', tweet)

    # Remove special characters, numbers, and punctuation
    tweet = re.sub(r'[^A-Za-z\s]', '', tweet)

    # Remove 'RT' (Retweet) indicator
    tweet = re.sub(r'\bRT\b', '', tweet)

    # Convert to lowercase
    tweet = tweet.lower()

    # Remove stopwords
#     stop_words = set(stopwords.words('english'))
#     tweet_tokens = nltk.word_tokenize(tweet)
#     tweet = ' '.join([word for word in tweet_tokens if word not in stop_words])

    # Lemmatization
    doc = nlp(tweet)
    # Lemmatize each token and join them back into a string
    tweet = ' '.join([token.lemma_ for token in doc])

    return tweet


df['Text'] = df['Text'].apply(clean_tweet)
df.head()
```

	Text	Annotation	Label	num_hashtags	num_mentions	Sentiment_Label	Hashtag
0	I read they in contextno change in mean th...	none	0.0	0	3	negative	
	now you idiot claim						

```
print('_________Sample clean tweets_________')
simple_tweet = df[df['Label'] == 0]['Text'].iloc[1]
print('\n\nSimple tweet: ', simple_tweet)
sexist_tweet = df[df['Annotation'] == 'sexism']['Text'].iloc[0]
print('\n\nSexist tweet: ', sexist_tweet)
racist_tweet = df[df['Annotation'] == 'racism']['Text'].iloc[0]
print('\n\nRacist tweet: ', racist_tweet)
print('\n\n_____________________________________')
```

```
_________Sample clean tweets_________


Simple tweet:    now you idiot claim that people who try to stop he from become a terrorist make he a terrorist islamically brain de


Sexist tweet:     call I sexist but when I go to an auto place i d rather talk to a guy


Racist tweet:    wrong isis follow the example of mohammed and the quran exactly


_____________________________________
```

☁ Wordclouds for toxic text

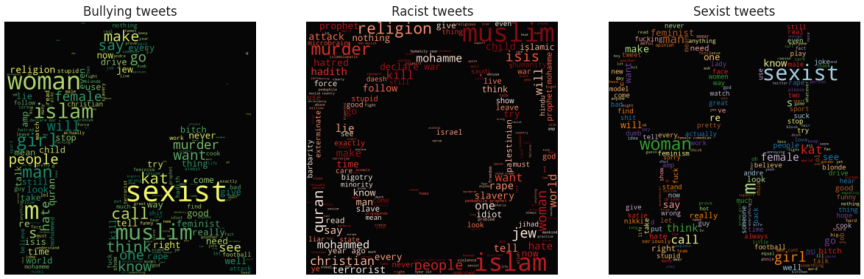
We are using a popular method of plotting wordclouds in the shapes of masks created out of png images. Lets say you want to create a wordcloud for text related to sexism...

1. Simply google search for an image like 'sexism logo png'
2. Choose an image of your choice, left click on it and open it in a new tab
3. Copy the url and paste it in the code hidden below

For a detailed look at how to do this.. check out this notebook: Spooky NLP and Topic Modelling tutorial
This notebook uses the Base64 encoding of images to create the wordclouds while you can straightaway use the URL of the images as I have

done below Viola!! there you have it. Beautiful wordclouds with meanings represented in the form of shapes. The hidden code cell below explains all the steps.

```
stopword=set(STOPWORDS)
plt.figure(figsize=(15,40))

## Common words in all bullying tweets-----------------------------------------------------------------------------------
plt.subplot(131)
# 1. Get text
bully_text = df[df.Label==1.0]["Text"].values
Text = ''
for text in bully_text:
    Text += text

# 2. Load png image from url and create mask
image_url = 'https://raw.githubusercontent.com/harshjadhav890/cyberbullying_detection/main/bullying-computer-icons-harassment-clip-art-b
response = requests.get(image_url, stream=True)
response.raise_for_status()
mask = np.array(Image.open(response.raw))

# 3. Plot wordcloud
wc = WordCloud(background_color = 'black', mask = mask, contour_width = 2,
     contour_color = 'black', colormap = 'BuPu_r', width = 800, height = 800, stopwords = stopword).generate(Text)
plt.axis("off")
plt.title('Bullying tweets')
plt.imshow(wc.recolor(colormap= 'summer' , random_state=244), alpha=0.98)


## Common words in all racist tweets-------------------------------------------------------------------------------------
# Repeat for other plots
plt.subplot(132)
bully_text = df[df.Annotation=='racism']["Text"].values
Text = ''
for text in bully_text:
    Text += text

image_url = 'https://clipart-library.com/img1/1475559.png'
response = requests.get(image_url, stream=True)
response.raise_for_status()
mask = np.array(Image.open(response.raw))

wc = WordCloud(background_color = 'black', mask = mask, contour_width = 2,
     contour_color = 'black', colormap = 'BuPu_r', width = 800, height = 800, stopwords = stopword).generate(Text)
plt.title('Racist tweets')
plt.axis("off")
plt.imshow(wc.recolor(colormap= 'Reds' , random_state=244), alpha=0.98)


## Common words in all sexist tweets-------------------------------------------------------------------------------------
plt.subplot(133)
bully_text = df[df.Annotation=='sexism']["Text"].values
Text = ''
for text in bully_text:
    Text += text

image_url = 'https://raw.githubusercontent.com/harshjadhav890/cyberbullying_detection/main/woman-gender-symbol-male-female-text-line-ci
response.raise_for_status()
response = requests.get(image_url, stream=True)
mask = np.array(Image.open(response.raw))

wc = WordCloud(background_color = 'black', mask = mask, contour_width = 2,
     contour_color = 'black', colormap = 'BuPu_r', width = 800, height = 800, stopwords = stopword).generate(Text)
plt.axis("off")
plt.title('Sexist tweets')
plt.imshow(wc.recolor(colormap= 'Paired_r' , random_state=244), alpha=0.98)

plt.show()
```



Modelling

Preprocessing for modelling

Most of these steps have been covered earlier. You may expand this section to view the rest of the changes I made to the dataset

```
# ignore this. I did this for ease of processing when i restart the kernel
# this part gives you the completely preprocessed data right to the point where you just need to oversample and split it

df = pd.read_csv("/kaggle/input/cyberbullying-dataset/twitter_parsed_dataset.csv")
df = df.drop(['id', 'index'], axis=1)
df.rename(columns={'oh_label': 'Label'}, inplace=True)
df = df.dropna(subset=['Label'])

# Adding hashtags and mentions_____________________________________________________________________________________#
# here we create a function to count the number of hashtags and mentions and then create two columns to store this data
def count_symbols(text):
#     hashtag_count = len(re.findall(r'#', text))
    mention_count = len(re.findall(r'@', text))
#     return hashtag_count, mention_count
    return mention_count

# Apply the function to each row in the 'text' column
df[['num_mentions']] = df['Text'].apply(lambda x: pd.Series(count_symbols(x)))
# df[['num_hashtags', 'num_mentions']] = df['Text'].apply(lambda x: pd.Series(count_symbols(x)))


# Analyze sentiment of each text___________________________________________________________________________________#
sia = SentimentIntensityAnalyzer()

# Function to get sentiment of a text
def get_sentiment(text):
    compound_score = sia.polarity_scores(text)['compound']
    return 'positive' if compound_score >= 0 else 'negative'

# Apply the function to each row in the 'Text' column
df['Sentiment_Label'] = df['Text'].apply(get_sentiment)


# Cleaning the tweets______________________________________________________________________________________________#
def clean_tweet(tweet):
    # Remove URLs
    tweet = re.sub(r'http\S+', '', tweet)

    # Remove mentions and hashtags
    tweet = re.sub(r'@[A-Za-z0-9_]+|#[A-Za-z0-9_]+', '', tweet)

    # Remove special characters, numbers, and punctuation
    tweet = re.sub(r'[^A-Za-z\s]', '', tweet)

    # Remove 'RT' (Retweet) indicator
    tweet = re.sub(r'\bRT\b', '', tweet)

    # Convert to lowercase
    tweet = tweet.lower()

    # Lemmatization
    doc = nlp(tweet)
    # Lemmatize each token and join them back into a string
    tweet = ' '.join([token.lemma_ for token in doc])

    return tweet

df['Text'] = df['Text'].apply(clean_tweet)
#_________________________________________________________________________________________________________________#

# One hot encoding of the sentiment category
one_hot_encoded = pd.get_dummies(df['Sentiment_Label'], prefix='sentiment')
df = pd.concat([df, one_hot_encoded], axis=1)
df = df.drop('Sentiment_Label', axis=1)
df['Text'] = df['Text'].str.replace(r'\s+', ' ', regex=True).str.strip()
df['Text'] = df['Text'].str.strip()

# Step 2: Upsample the data using RandomOverSampler
ros = RandomOverSampler(random_state=42)
X = df['Text'].values.reshape(-1, 1)
y = df['Label'].values
X_resampled, y_resampled = ros.fit_resample(X, y)

# convert text (object) data to string for w2v
X_resampled= [str(obj) for obj in X_resampled]
X_resampled = np.array(X_resampled)
```

```
# Step 2: Oversample the data using RandomOverSampler to reduce imbalance between Labels (Bullying and non bullying)
ros = RandomOverSampler(random_state=42)
X = df['Text'].values.reshape(-1, 1)
y = df['Label'].values
X_resampled, y_resampled = ros.fit_resample(X, y)

# convert text (object) data to string for w2v
X_resampled= [str(obj) for obj in X_resampled]
X_resampled = np.array(X_resampled)
```

ML approach with word2vec

Why use Word2Vec?

- Semantic understanding: Word2Vec captures the semantic relationships between words, which is crucial for understanding the nuances of language used in bullying. It can differentiate between words with similar spellings but different meanings (e.g., "joke" vs. "mock") and identify synonyms and antonyms, helping to detect subtle insults and sarcasm often employed in cyberbullying.
- Handling slang and abbreviations: Twitter language is full of slang, abbreviations, and emojis. Word2Vec can learn these informal and often-evolving expressions, leading to more accurate detection of bullying even when it doesn't use traditional language patterns.

Limitations of using Word2Vec

- Bias: Word2Vec models can inherit biases from the training data, potentially leading to discriminatory outcomes. Careful selection of training data and evaluation methods are crucial.
- Context sensitivity: Subtle forms of bullying often rely on context not captured solely by word meaning. Combining Word2Vec with other approaches that consider context can improve accuracy.

For detailed explaination of the intuition behind W2V read: Word2Vec Explained

```
# Train Word2Vec Model
sentences = [word_tokenize(text) for text in X_resampled]
word2vec_model = Word2Vec(sentences, vector_size=300, window=5, min_count=1, workers=4)  # Adjust parameters as needed

# Convert Text to Embeddings
def get_embedding(text):
    tokens = word_tokenize(text)
    # Filter out tokens that are not in the vocabulary
    tokens = [token for token in tokens if token in word2vec_model.wv.key_to_index]
    if len(tokens) > 0:
        # Return the average of word embeddings for the tokens
        return np.mean([word2vec_model.wv[t] for t in tokens], axis=0)
    else:
        return None

# Create an array of embeddings for each text
X_resampled = [get_embedding(text) for text in X_resampled]


# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.2, random_state=42)

# Step 5: Model Training (Using a RandomForestClassifier as an example)
X_train = np.array(X_train)
X_test = np.array(X_test)

model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

# Evaluate the model
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")

f1 = f1_score(y_test, y_pred)
print(f"F1 Score: {f1}")
```

```
Accuracy: 0.8867637470115193
F1 Score: 0.8832623795653148
```

Pycaret's AutoML

```
# !pip install -Uqqq pycaret==3.1.0
# from pycaret.classification import *

# Train-Test Split: ensure you are using the word2vec processed data from the above section
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.2, random_state=42)

# create a dataset using X_train and y_train
columns = []
dataset = np.column_stack((X_train, y_train))
for i in range(300):
    columns.append(str(i))
columns.append('Label')
auto_df = pd.DataFrame(dataset, columns=columns)

auto_df.head()


pycaret_automl = setup(data=auto_df, target = 'Label', session_id=42)
```

	Description	Value
0	Session id	42
1	Target	Label
2	Target type	Binary
3	Original data shape	(18401, 301)
4	Transformed data shape	(18401, 301)
5	Transformed train set shape	(12880, 301)
6	Transformed test set shape	(5521, 301)
7	Numeric features	300
8	Preprocess	True
9	Imputation type	simple
10	Numeric imputation	mean
11	Categorical imputation	mode
12	Fold Generator	StratifiedKFold
13	Fold Number	10
14	CPU Jobs	-1
15	Use GPU	False
16	Log Experiment	False
17	Experiment Name	clf-default-name
18	USI	45bb

```
best_model = compare_models()
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
et	Extra Trees Classifier	0.8384	0.8997	0.7795	0.8855	0.8290	0.6769	0.6820	2.2820
rf	Random Forest Classifier	0.8349	0.8950	0.8002	0.8618	0.8297	0.6698	0.6718	8.9130
xgboost	Extreme Gradient Boosting	0.8144	0.8774	0.8116	0.8182	0.8148	0.6289	0.6290	4.9650
catboost	CatBoost Classifier	0.7899	0.8599	0.7477	0.8191	0.7816	0.5800	0.5824	54.2000
qda	Quadratic Discriminant Analysis	0.7870	0.8520	0.7582	0.8067	0.7816	0.5742	0.5754	0.3320
lightgbm	Light Gradient Boosting Machine	0.7843	0.8561	0.7486	0.8085	0.7773	0.5688	0.5705	9.2390
dt	Decision Tree Classifier	0.7567	0.7567	0.8125	0.7328	0.7705	0.5130	0.5163	2.6700
lda	Linear Discriminant Analysis	0.7460	0.8164	0.7038	0.7712	0.7358	0.4923	0.4944	0.5210
gbc	Gradient Boosting Classifier	0.7288	0.8040	0.6373	0.7829	0.7025	0.4582	0.4665	51.5740
ridge	Ridge Classifier	0.7139	0.0000	0.6506	0.7477	0.6956	0.4282	0.4320	0.1100
knn	K Neighbors Classifier	0.7038	0.7702	0.6970	0.7091	0.7029	0.4076	0.4078	0.4460
lr	Logistic Regression	0.6972	0.7603	0.6450	0.7229	0.6817	0.3948	0.3972	1.2350
ada	Ada Boost Classifier	0.6968	0.7634	0.6195	0.7357	0.6724	0.3942	0.3994	9.9170
svm	SVM - Linear Kernel	0.6938	0.0000	0.6035	0.7509	0.6596	0.3882	0.4026	0.3840
nb	Naive Bayes	0.6588	0.7000	0.5315	0.7168	0.6102	0.3185	0.3299	0.1170

🧠 Deep learning models

```
# using the cleaned version of the dataset
ros = RandomOverSampler(random_state=42)
X = df['Text'].values.reshape(-1, 1)
y = df['Label'].values
X_resampled, y_resampled = ros.fit_resample(X, y)
X_resampled = X_resampled[:, 0]

X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.2, random_state=42)
```

```
# using keras tokenizer to find the length vocab
token = text.Tokenizer(num_words=None)
max_len = 40

token.fit_on_texts(list(X_train) + list(X_test))
xtrain_seq = token.texts_to_sequences(X_train)
xvalid_seq = token.texts_to_sequences(X_test)

#zero pad the sequences
xtrain_pad = sequence.pad_sequences(xtrain_seq, maxlen=max_len)
xvalid_pad = sequence.pad_sequences(xvalid_seq, maxlen=max_len)

word_index = token.word_index


print('Preprocessed text', X_train[1])
print('\nTokenized text', xtrain_seq[1])
print('\nPadded text', xtrain_pad[1])
print('\nPadded text Length: ', len(xtrain_pad[1]))
```

```
Preprocessed text I m not sexist but girl should not wrestle

Tokenized text [3, 18, 4, 19, 14, 45, 71, 4, 2156]

Padded text [   0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    3   18    4   19   14   45   71    4 2156]

Padded text Length:  40
```

```
# load the GloVe vectors in a dictionary:

embeddings_index = {}
f = open('/kaggle/input/glove840b300dtxt/glove.840B.300d.txt','r',encoding='utf-8')
for line in tqdm(f):
    values = line.split(' ')
    word = values[0]
    coefs = np.asarray([float(val) for val in values[1:]])
    embeddings_index[word] = coefs
f.close()

print('Found %s word vectors.' % len(embeddings_index))
```

```
2196018it [03:44, 9776.98it/s] Found 2196017 word vectors.
```

```
# create an embedding matrix for the words we have in the dataset
embedding_matrix = np.zeros((len(word_index) + 1, 300))
for word, i in tqdm(word_index.items()):
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

```
100%|██████████| 12670/12670 [00:00<00:00, 234339.32it/s]
```

Simple RNNs with trainable embeddings

```
%%time
with strategy.scope():
    # A simpleRNN without any pretrained embeddings and one dense layer
    model = Sequential()
    model.add(Embedding(len(word_index) + 1,
                        300,
                        input_length=max_len))
    model.add(SimpleRNN(100))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 40, 300)           3801300

 simple_rnn (SimpleRNN)      (None, 100)               40100

 dense (Dense)               (None, 1)                 101
```

```
=================================================================
Total params: 3841501 (14.65 MB)
Trainable params: 3841501 (14.65 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
CPU times: user 317 ms, sys: 306 ms, total: 623 ms
Wall time: 788 ms
```

```
model.fit(xtrain_pad, y_train, epochs=5, batch_size=64*strategy.num_replicas_in_sync) #Multiplying by Strategy to run on TPU's
```

```
Epoch 1/5
288/288 [==============================] - 33s 105ms/step - loss: 0.4928 - accuracy: 0.7564
Epoch 2/5
288/288 [==============================] - 11s 38ms/step - loss: 0.1742 - accuracy: 0.9371
Epoch 3/5
288/288 [==============================] - 12s 43ms/step - loss: 0.0743 - accuracy: 0.9765
Epoch 4/5
288/288 [==============================] - 11s 38ms/step - loss: 0.0469 - accuracy: 0.9870
Epoch 5/5
288/288 [==============================] - 10s 35ms/step - loss: 0.0401 - accuracy: 0.9889
<keras.src.callbacks.History at 0x7936d220cc10>
```

```
scores = model.predict(xvalid_pad)
print("Auc: %.2f%%" % (roc_auc(scores,y_test)))
```

```
144/144 [==============================] - 1s 4ms/step
Auc: 0.93%
```

🌐 LSTM with GloVe embeddings

Advantages of GloVe Embeddings:

- Global Matrix Factorization: GloVe considers global word-word co-occurrence statistics, capturing broader semantic relationships and potentially enhancing bullying detection accuracy.
- Efficient Training: GloVe's training algorithm is computationally efficient, allowing for analysis of large tweet datasets more easily.

Limitations of GloVe Embeddings

- Bias: As with any word embedding model, GloVe can inherit biases from training data. Careful selection and evaluation are crucial to mitigate discriminatory outcomes.
- Context Sensitivity: While GloVe captures global semantic relationships, it may miss subtle nuances that rely heavily on context. Combining it with context-aware techniques is recommended for optimal results.

For detailed explaination of the intuition behind GloVe read: NLP — Word Embedding & GloVe

```
%%time
with strategy.scope():

    # A simple LSTM with glove embeddings and one dense layer
    model = Sequential()
    model.add(Embedding(len(word_index) + 1,
                        300,
                        weights=[embedding_matrix],
                        input_length=max_len,
                        trainable=False))

    model.add(LSTM(100))
    # dropout=0.3, recurrent_dropout=0.3
    model.add(Dense(1, activation='sigmoid'))
    model.compile(loss='binary_crossentropy', optimizer='adam',metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 40, 300)           3801300

 lstm (LSTM)                 (None, 100)               160400

 dense_1 (Dense)             (None, 1)                 101

=================================================================
Total params: 3961801 (15.11 MB)
Trainable params: 160501 (626.96 KB)
Non-trainable params: 3801300 (14.50 MB)
_________________________________________________________________
CPU times: user 319 ms, sys: 27.1 ms, total: 346 ms
Wall time: 349 ms
```

```
model.fit(xtrain_pad, y_train, epochs=5, batch_size=64*strategy.num_replicas_in_sync)
```

```
Epoch 1/5
288/288 [==============================] - 4s 5ms/step - loss: 0.4987 - accuracy: 0.7697
Epoch 2/5
288/288 [==============================] - 1s 5ms/step - loss: 0.4242 - accuracy: 0.8069
Epoch 3/5
288/288 [==============================] - 1s 5ms/step - loss: 0.3793 - accuracy: 0.8337
Epoch 4/5
288/288 [==============================] - 1s 5ms/step - loss: 0.3237 - accuracy: 0.8636
Epoch 5/5
288/288 [==============================] - 1s 5ms/step - loss: 0.2663 - accuracy: 0.8936
<keras.src.callbacks.History at 0x7936f53ffc40>
```

```
scores = model.predict(xvalid_pad)
print("Auc: %.2f%%" % (roc_auc(scores,y_test)))
```

```
144/144 [==============================] - 1s 2ms/step
Auc: 0.92%
```

GRUs with trainable embeddings

```
%%time
with strategy.scope():
    # GRU with glove embeddings and two dense layers
    model = Sequential()
    model.add(Embedding(len(word_index) + 1,
                        300,
                        input_length=max_len))
    model.add(SpatialDropout1D(0.3))
    model.add(GRU(300))
    model.add(Dense(1, activation='sigmoid'))

    model.compile(loss='binary_crossentropy', optimizer='adam',metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_2 (Embedding)     (None, 40, 300)           3801300

 spatial_dropout1d (Spatial  (None, 40, 300)           0
 Dropout1D)

 gru (GRU)                   (None, 300)               541800

 dense_2 (Dense)             (None, 1)                 301

=================================================================
Total params: 4343401 (16.57 MB)
Trainable params: 4343401 (16.57 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
CPU times: user 277 ms, sys: 9.15 ms, total: 286 ms
Wall time: 280 ms
```

```
model.fit(xtrain_pad, y_train, epochs=5, batch_size=64*strategy.num_replicas_in_sync)
```

```
Epoch 1/5
288/288 [==============================] - 20s 61ms/step - loss: 0.4864 - accuracy: 0.7660
Epoch 2/5
288/288 [==============================] - 3s 12ms/step - loss: 0.2921 - accuracy: 0.8833
Epoch 3/5
288/288 [==============================] - 4s 13ms/step - loss: 0.1950 - accuracy: 0.9269
Epoch 4/5
288/288 [==============================] - 3s 11ms/step - loss: 0.1355 - accuracy: 0.9495
Epoch 5/5
288/288 [==============================] - 4s 14ms/step - loss: 0.1002 - accuracy: 0.9651
<keras.src.callbacks.History at 0x7936adfc4f10>
```

```
scores = model.predict(xvalid_pad)
print("Auc: %.2f%%" % (roc_auc(scores,y_test)))
```

```
144/144 [==============================] - 1s 2ms/step
Auc: 0.92%
```

Note: We can see that trainable embeddings perform better than GloVe embeddings on our task. GloVe embeddings do a good job of providing us with global embeddings. These embeddings are not contextually aware and hence are not well suited for complex tasks. eg. The word 'date' may have different meanings

⬅️ ➡️ BERT with Tensorflow Hub

```
ros = RandomOverSampler(random_state=42)
X = df['Text'].values.reshape(-1, 1)
y = df['Label'].values
X_resampled, y_resampled = ros.fit_resample(X, y)
X_resampled = X_resampled[:, 0]

X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.2, random_state=42)


# creating tensorflow datasets
train_dataset = tf.data.Dataset.from_tensor_slices((X_train, y_train))

test_dataset = tf.data.Dataset.from_tensor_slices((X_test))

BUFFER_SIZE = 4000
BATCH_SIZE = 64
```