ML PROJECT - WHY SO HARSH?

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Mounting the Google Drive

Train and Test data have been placed in Google Drive. This reduces the time taken to upload test and train data onto local runtime.

Both Test.csv and Train.csv are placed in "Colab Notebooks" directory in google drive.

In [1]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [2]:

```
mkdir Results
```

Importing Libraries

In [3]:

```
import pandas as pd
import numpy as np
import nltk
import matplotlib.pyplot as plt
from collections import defaultdict
from collections import  Counter
import seaborn as sns

from wordcloud import WordCloud
from wordcloud import ImageColorGenerator
from wordcloud import STOPWORDS

nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('omw-1.4')

!pip install contractions
import contractions
import string
import regex as re
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
stop_words = stopwords.words('english')

from textblob import TextBlob
import pickle
from sklearn.metrics import accuracy_score, f1_score
```

```
from nltk.corpus import words
nltk.download('words')

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.ensemble import RandomForestClassifier
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Downloading package omw-1.4 to /root/nltk_data...
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publi
c/simple/
Collecting contractions
  Downloading contractions-0.1.73-py2.py3-none-any.whl (8.7 kB)
Collecting textsearch>=0.0.21
  Downloading textsearch-0.0.24-py2.py3-none-any.whl (7.6 kB)
Collecting pyahocorasick
  Downloading pyahocorasick-1.4.4-cp38-cp38-manylinux_2_17_x86_64.manylinux2014_x86_64.wh
l (110 kB)
     |████████████████████████████████| 110 kB 5.2 MB/s
Collecting anyascii
  Downloading anyascii-0.3.1-py3-none-any.whl (287 kB)
     |████████████████████████████████| 287 kB 33.5 MB/s
Installing collected packages: pyahocorasick, anyascii, textsearch, contractions
Successfully installed anyascii-0.3.1 contractions-0.1.73 pyahocorasick-1.4.4 textsearch-
0.0.24
```

```
[nltk_data] Downloading package words to /root/nltk_data...
[nltk_data]   Unzipping corpora/words.zip.
```

Reading the Train and Test Data Files:

In [4]:

```
# These all columns are need to be read. NO UNAMED COLUMNS are to be read.
col_list_train = ["id", "text", "harsh", "extremely_harsh", "vulgar", "threatening", "di
srespect", "targeted_hate"]

# low_memory = false to avoid DTypy warning while reading pandas dataframe
# Link: https://stackoverflow.com/questions/24251219/pandas-read-csv-low-memory-and-dtype
-options

train_df = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/train.csv", usecols=col_li
st_train, low_memory=False)

train_df.head()
```

Out[4]:

	id	text	harsh	extremely_harsh	vulgar	threatening	disrespect	targeted_hate
0	a8be7c5d4527adbbf15f	", 6 December 2007 (UTC)\nI am interested, not...	0	0	0	0	0	0
1	0b7ca73f388222aad64d	I added about three missing parameters to temp...	0	0	0	0	0	0
2	db934381501872ba6f38	SANDBOX?? \n\nI DID YOUR MADRE DID IN THE SANDBOX	1	0	0	0	0	0
3	228015c4a87c4b1f09a7	why good sir? Why? \n\nYou, sir, obviously do ...	1	0	1	1	1	0
4	b18f26cfa1408b52e949	"\n\n Source \n\nIncase I forget, or someone e...	0	0	0	0	0	0

In [5]:

```
col_list_test = ["id", "text"]

test_df = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/test.csv", usecols=col_list
_test, low_memory=False)

test_df.head()
```

Out[5]:

	id	text
0	e0ae9d9474a5689a5791	in an interview before his execution
1	b64a191301cad4f11287	He knew what he was doing. The below posts are...
2	5e1953d9ae04bdc66408	Zzzzzzz... youre a real bore. Now go bore some...
3	23128f98196c8e8f7b90	"\n\nYet, it remains confusion because the 910...
4	2d3f1254f71472bf2b78	I was referring to them losing interest in van...

Copying the Test_df into another variable so that we can process that variable later without modifying original test_df

In [6]:

```
Final_df = test_df.copy()
```

Basic Checks on the Data

In [7]:

```
train_df.isna().sum()
```

Out[7]:

```
id                  0
text                0
harsh               0
extremely_harsh     0
vulgar              0
threatening         0
disrespect          0
targeted_hate       0
dtype: int64
```

In [8]:

```
(train_df == "?").sum()
```

Out[8]:

```
id                  0
text                0
harsh               0
extremely_harsh     0
vulgar              0
threatening         0
disrespect          0
targeted_hate       0
dtype: int64
```

Thus, We don't have any NAN values present in our dataset.

TRAIN AND TEST SPLIT

Now we will split our Training dataset only into 2 parts: Training Set and Test Set. This is to just check the Accuracy or F1 Score for our Models.

For creating final submission, this part is not needed.

In [9]:

```
# from sklearn.model_selection import train_test_split

# train_df, test_df = train_test_split(train_df, train_size=0.8)
```

In [10]:

```
# Final_df = test_df.copy()
```

Manual Cleaning of the Text

In [11]:

```
def Manual_cleanText(string):

 string = re.sub(":\)", " smiling", string)
 string = re.sub("\(:", " smiling", string)
 string = re.sub(":-\)", " smiling", string)
 string = re.sub("\(-:", " smiling", string)
 string = re.sub(":-\)\)", " smiling", string)
 string = re.sub("\(\(-:", " smiling", string)

 string = re.sub(":\(", " sad", string)
 string = re.sub("\):", " sad", string)
 string = re.sub(":-\(", " sad", string)
 string = re.sub("\)-:", " sad", string)
 string = re.sub(":-\(\(", " sad", string)
 string = re.sub("\)\)-:", " sad", string)

 string = re.sub(":'\)", " sad", string)
 string = re.sub(":'\)\)", " sad", string)

 return string
```

In [12]:

```
def Manual_cleanDataset(dataframe, column_name):

  dataframe[column_name] = dataframe[column_name].apply(lambda x:Manual_cleanText(x))

  return dataframe
```

In [13]:

```
# # MANUAL CLEANING
# train_df = Manual_cleanDataset(train_df, "text")
# test_df = Manual_cleanDataset(test_df, "text")
```

CLEANING UP THE TEXT

Before proceeding towards EDA and Prepprocessing, lets clean up the text data.
Cleaning will include removal of all the words, characters etc. that won't be helpful in predicting the labels.

One Shot Cleanups

In this, we perform the following actions:

- **Remove all the URL's from the text**

- **Remove all Punctuation Marks and Special Characters except ?, !, # and @.**
- **Lower the text**
- **Remove the numeric data.**

In [14]:

```
def One_Shot_Cleanups(dataframe, column_name):

  text_list = dataframe[column_name].tolist()

  for i in range(len(text_list)):

    # Removing Punctuation mark and spcial characters
    # Remove all the numeric data
    # Remove URL
    text_list[i] = re.sub('[^a-zA-Z?!\*]+', ' ', text_list[i])
    # text_list[i] = re.sub('[^a-zA-Z?!#@\*]+', ' ', text_list[i])

    # # Lowering the text except the words which are all capitals
    # text_list[i] = text_list[i].split()
    # for j in range(len(text_list[i])):
    #   if text_list[i][j] != text_list[i][j].upper():
    #     text_list[i][j] = text_list[i][j].lower()
    # text_list[i] = ' '.join(text_list[i])


  dataframe[column_name] = text_list

  return dataframe
```

In [15]:

```
# REMOVE PUNCTUATION, NUMBERS and SPECIAL CHARACTERS
train_df = One_Shot_Cleanups(train_df, "text")
test_df = One_Shot_Cleanups(test_df, "text")
```

In [16]:

```
test_df.to_csv('Check_RE.csv', index = False)
```

EXPLORATORY DATA ANALYSIS

Let's Analysis our dataset so that we can get some intutuion of how our results gonna be like. This will give us insight into planning our models as well as what type of preprocessing we require.

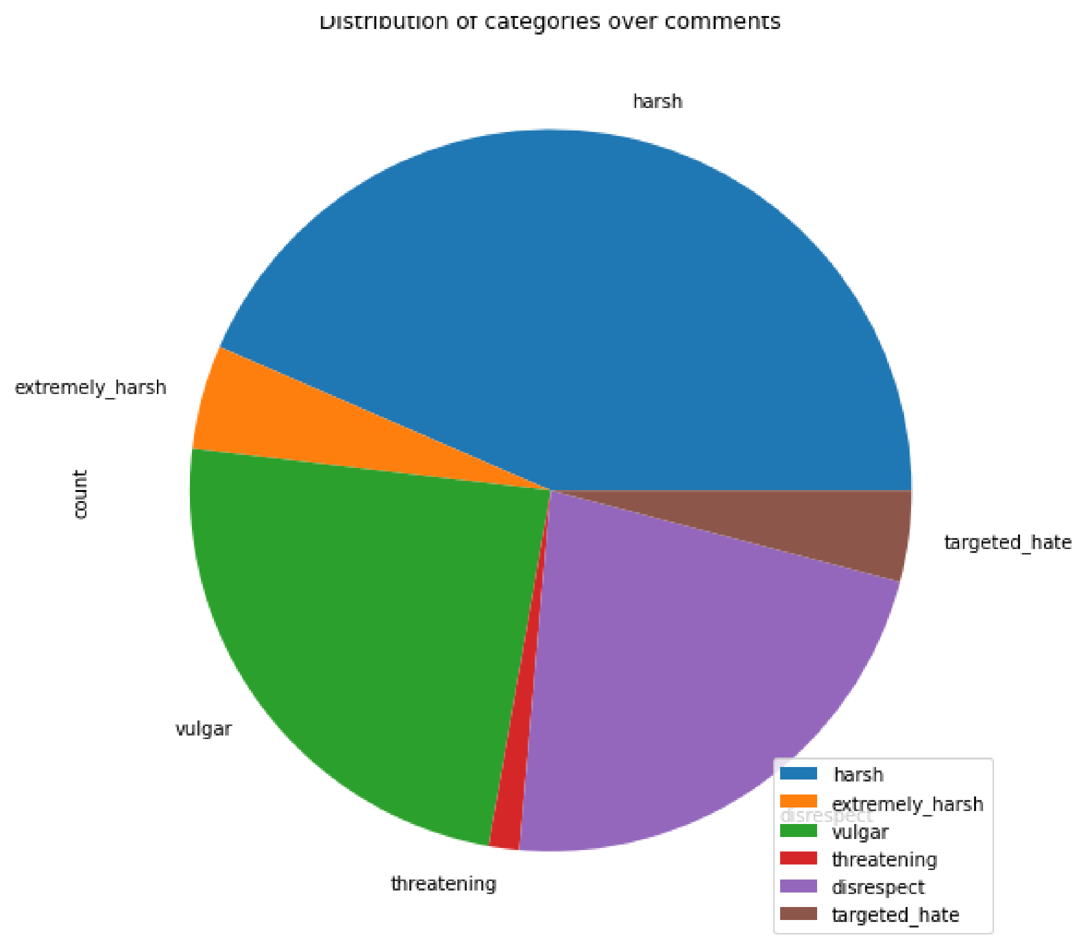
PIE - CHART Showing Category Distribution

In [17]:

```
categories = ['harsh', 'extremely_harsh', 'vulgar', 'threatening', 'disrespect', 'target
ed_hate']

category_counts = train_df[categories].sum()

category_count_list = list(category_counts)

category_freq_df = pd.DataFrame({"category": categories, "count": category_count_list})

category_freq_df.plot.pie(y = "count", figsize = (9,9), legend = True, title = "Distribu
tion of categories over comments", labels = categories)

plt.legend(loc="lower right")
```

Out[17]:

```
<matplotlib.legend.Legend at 0x7fca37ccfbe0>
```



INFERENCE - Mostly comments are either 'harsh', 'vulgur' or 'disrespectful'. Very less comments are 'threatening'.

Hence we can expect same distribution in the test data also.

Printing the Counts

In [18]:

```
print(category_freq_df)
```

```
          category  count
0            harsh   8559
1  extremely_harsh    917
2           vulgar   4742
3      threatening    268
4       disrespect   4392
5     targeted_hate    802
```

CORRELATION MATRIX

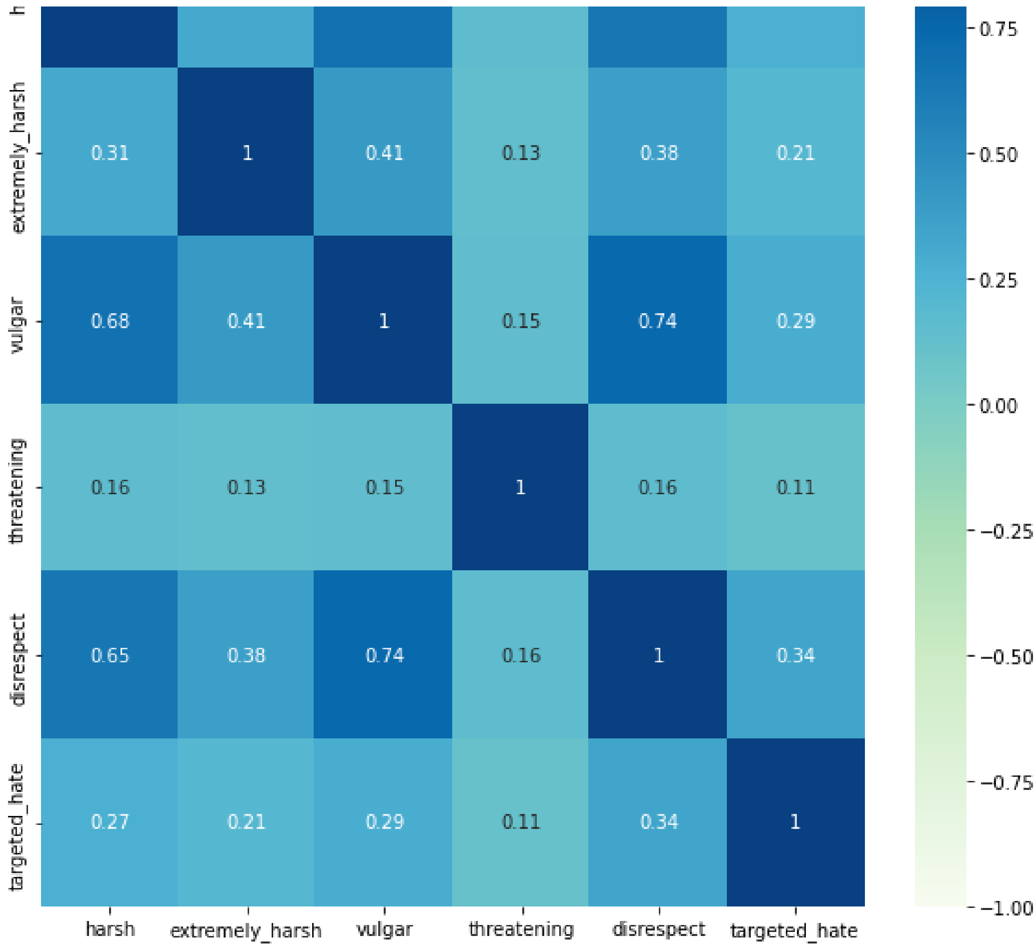
Here we are checking Co-relation between the labels. it will help us get an idea how our output labels should be.

In [19]:

```
plt.figure(figsize=(10,10))
sns.heatmap(train_df[categories].corr(), vmin=-1, cmap="GnBu", annot=True)
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fca38f3b190>
```



INFERENCE - Label Columns are not much Corelated to each other. Hence we can't link one to another in any of the data models we will train.

WORD LEVEL ANALYSIS

Let's find the length of every word in the comments by making a dataframe of words containing the following columns:

- **Word**
- **Frequency**
- **Word_Length**

In [20]:

```
def create_word_dataframe(series):

  words_list = []

  for paragraph in series:
    words_list.append(nltk.word_tokenize(paragraph))

  flattened_list = [j for sub in words_list for j in sub]

  words_list = flattened_list

  word_dictionary = {}

  for word in words_list:
    word_dictionary[word] = 0

  for word in words_list:
    word_dictionary[word] += 1

  df_word = pd.DataFrame(word_dictionary.items(),columns=['word','frequency'])

  df_word['word_length']= df_word['word'].map(lambda x: len(x))
```

```
    df_word = df_word.sort_values('frequency',ascending=False).reset_index(drop=True)

    return df_word
```

In [21]:

```
word_dataframe = create_word_dataframe(train_df["text"])

word_dataframe.head(10)
```

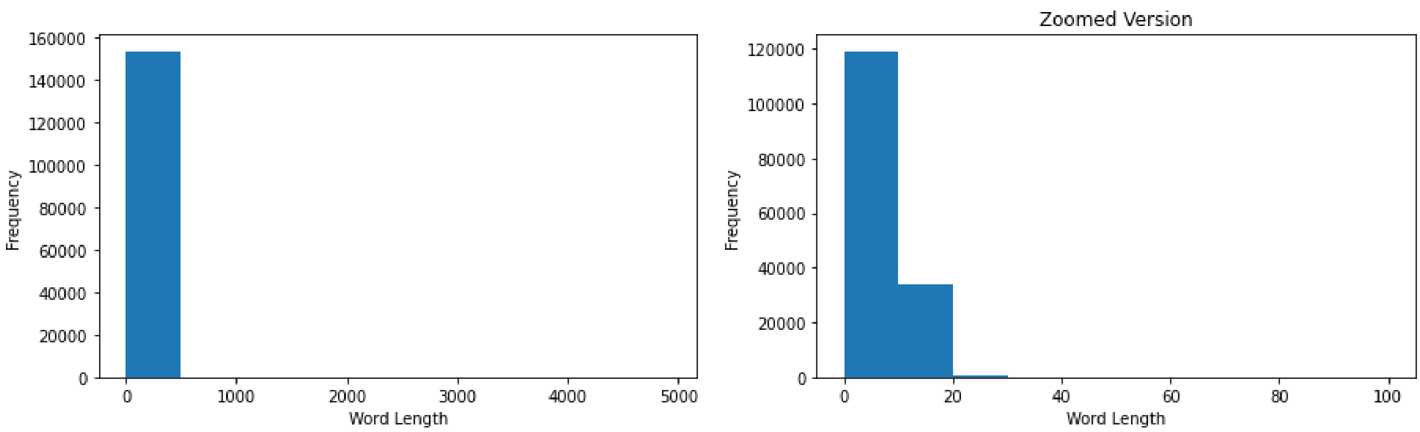
Out[21]:

	word	frequency	word_length
0	the	252701	3
1	to	163886	2
2	I	125803	1
3	of	124577	2
4	and	119782	3
5	a	113982	1
6	you	101617	3
7	is	94679	2
8	that	85711	4
9	in	75615	2

HISTOGRAM PLOTS - Let us find the word length distribution by plotting histograms from the dataframe obtained.

In [22]:

```
figure, axis = plt.subplots(1, 2, figsize=(15, 4))

axis[0].hist(word_dataframe['word_length'])
axis[0].set_xlabel('Word Length')
axis[0].set_ylabel('Frequency')


axis[1].hist(word_dataframe['word_length'], range = [0, 100])
axis[1].set_title("Zoomed Version")
axis[1].set_xlabel('Word Length')
axis[1].set_ylabel('Frequency')
print()
```



OBSERVATION:

- **We have words having word lengths ranging from 0 to 5000 (approx).**
- **There are very few words having word length greater than 40.**

INFERENCE:

- **There is very less probability that words of length greater than 40 would make any sense. Further, will they have any contribution towards sentiment analysis, chances are very very slim.**
- **Hence, we can remove all the words of length greater than 40.**
- **This will speed up the Lemmatization process also.**

Lets check out the word having maximum length.

In [23]:

```
word_dataframe[word_dataframe['word_length'] == max(word_dataframe['word_length'])]
```

Out[23]:

	word	frequency	word_length
141965	hyyuyuyuyuyuyuyuyuyuyuyuyuyuyuyuyuyuyuyuyuyuyu...	1	4926

Clearly, this doesn't make any sense.

REMOVING THE WORDS

Let's remove the words of length greater than 40

In [24]:

```
def remove_long_words(dataframe, column_name):

  text_list = dataframe[column_name].tolist()

  for i in range(len(text_list)):
    text_list[i] = re.sub(r'\W*\b\w{40,5000}\b', '',text_list[i])

  dataframe[column_name] = text_list

  return dataframe
```

In [25]:

```
# # REMOVE LONG WORDS
# train_df = remove_long_words(train_df, "text")
# test_df = remove_long_words(test_df, "text")
```

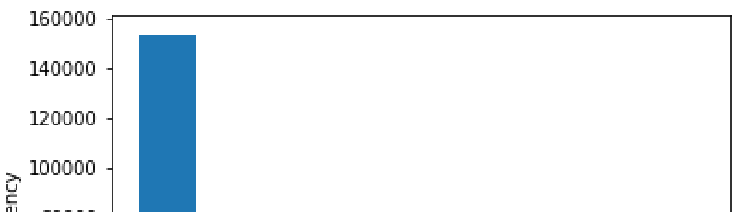
Now let's plot the Histogram again

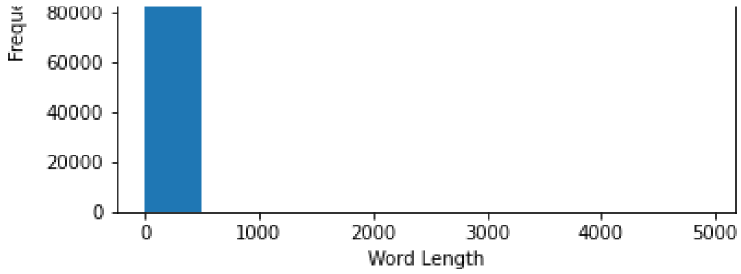
In [26]:

```
word_dataframe_new = create_word_dataframe(train_df["text"])
```

In [27]:

```
plt.hist(word_dataframe_new['word_length'])
plt.xlabel("Word Length")
plt.ylabel("Frequency")

print()
plt.show()
```





Now we have all words whose length ranges from 0 to 40 only.

SENTIMENT ANALYSIS

Let us now try to find the general sentiment of the commenters by plotting a histogram showing the polarity and subjectivity levels of the comments.

POLARITY

- **Polarity refers to strength of an opinion. It can be positive, negative or neutral, with neutral meaning no sentiment expressed.**
- **Polarity values lie in the range [-1,1] with [-1,0) implying negative sentiment, 0 implying neutral and (0,1] implying positive sentiment.**

This is a method that uses TextBlob library to find the polarity of every comment when the "text" column of the dataframe is passed to it. It creates and returns a new dataframe with the columns being: comments and their polarity values.

In [28]:

```
def find_polarity(series):

  sentiment_objects = [TextBlob(comment) for comment in series]

  sentiment_values = [[comment.sentiment.polarity, str(comment)] for comment in sentimen
t_objects]

  sentiment_df = pd.DataFrame(sentiment_values, columns=["polarity", "comment"])

  return sentiment_df
```

Calling the method to obtain the dataframe with polarity values

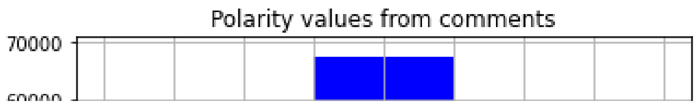
In [29]:

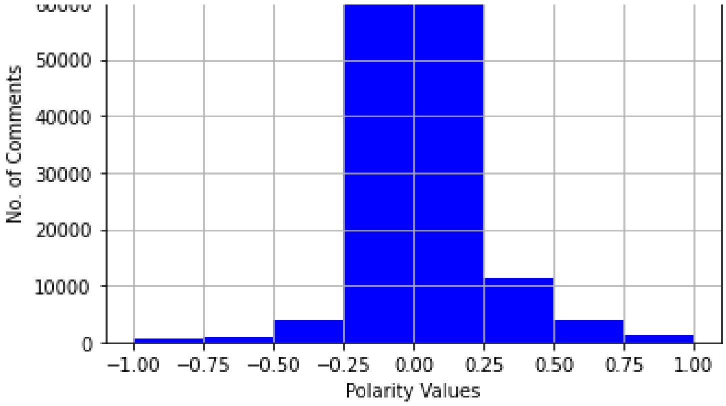
```
polarity_df = find_polarity(train_df["text"])
```

Plotting a histogram to find the polarity distribution over comments

In [30]:

```
polarity_df.hist(bins = [-1, -0.75, -0.5, -0.25, 0.25, 0.5, 0.75, 1],color = "blue")

plt.title("Polarity values from comments")
plt.xlabel("Polarity Values")
plt.ylabel("No. of Comments")

print()
plt.show()
```





INFERENCE:

- **The above histogram shows that most commenters (about 80,000) have a neutral sentiment polarity or no sentiment.**
- **The rest of the commenters about 9,000 have made polar comments, which is the subject of our analysis.**
- **Thus we can expect similar results upon fitting our classification model.**

SUBJECTIVITY

- **Subjectivity in text indicates presence of the writer's own feelings, experiences or emotions.**
- **This is in contrast to objective text which is mostly factual and not opinion based.**
- **Subjectivity indicates extent or degree of involvement of the person in the object.**
- **Subjectivity also lies in the range [-1,1] and thus takes both positive and negative values**

This is a method that uses TextBlob library to find the subjectivity of every comment when the "text" column of the dataframe is passed to it. It creates and returns a new dataframe with the columns being: comments and their subjectivity values.

In [31]:

```
def find_subjectivity(series):

  sentiment_objects = [TextBlob(comment) for comment in series]

  sentiment_values = [[comment.sentiment.subjectivity, str(comment)] for comment in sent
iment_objects]

  sentiment_df = pd.DataFrame(sentiment_values, columns=["subjectivity", "comment"])

  return sentiment_df
```

Calling the method to obtain the dataframe with subjectivity values

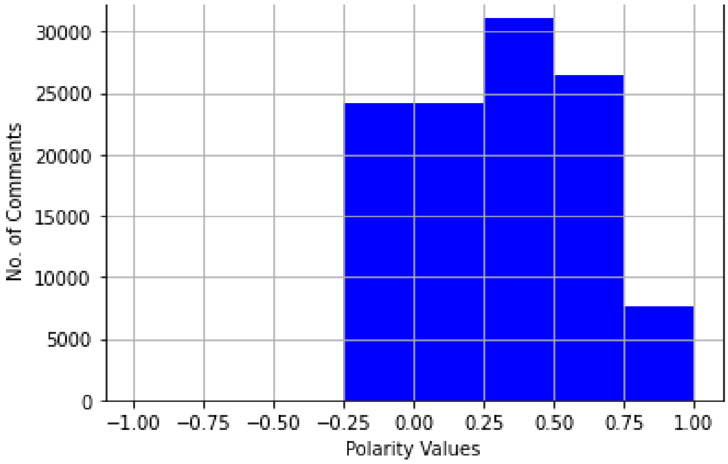
In [32]:

```
subjectivity_df = find_subjectivity(train_df["text"])
```

Plotting a histogram to find the subjectivity distribution over comments

In [33]:

```
subjectivity_df.hist(bins = [-1, -0.75, -0.5, -0.25, 0.25, 0.5, 0.75, 1],color = "blue")

plt.title("Subjectivity from comments")
plt.xlabel("Polarity Values")
plt.ylabel("No. of Comments")

plt.show()
```



INFERENCE:

- The above histogram shows that the comments are highly biased towards subjectivity, i.e every comment is subjective and is purely based on the commenter's opinion & experience and is not objective/fact-based. This also indicates presence of strong emotions/feelings of the commenter.

WORD CLOUD

Let's create a word cloud to get a visual representation of the top frequently used words by the commenters. The larger the size of the word in the word cloud, the higher the frequency of usage by the commenter.

In [34]:

```
def show_overall_word_cloud(series):

  text = " ".join(i for i in series)
  wordcloud = WordCloud(stopwords = stop_words, background_color = "white").generate(tex
t)
  plt.figure(figsize=(10,10))
  plt.imshow(wordcloud, interpolation='bilinear')
  plt.axis("off")
  plt.show()
```

In [35]:

```
show_overall_word_cloud(train_df["text"])
```

INFERENCE - The words "one", "article", "page", "think", etc seem to used very frequently. Some of these words are of no use in case of sentiment analysis.
For example the word "article" can't contribute to sentiment analysis. Hence, we can manually remove these words for out text data.

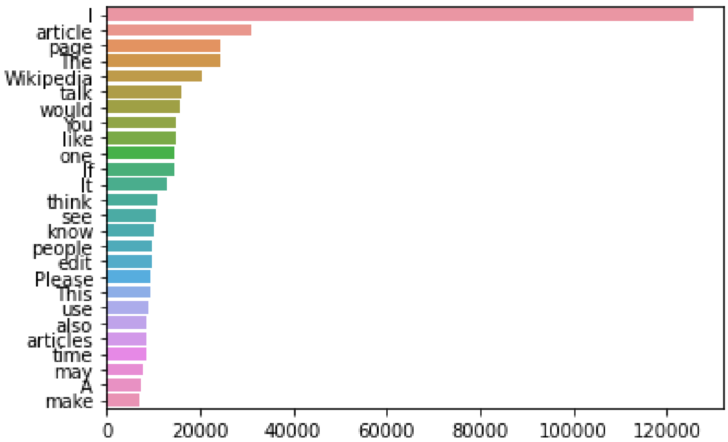
Let us find the top 15 commonly used words in the text (words which aren't stopwords, as they will be removed)

In [36]:

```
stop_words = stopwords.words('english')

def find_word_frequencies(column):

    split_column = column.str.split()
    text_list = split_column.tolist()

    word_list = [word for i in text_list for word in i]

    counter_object = Counter(word_list)

    most_common_object = counter_object.most_common()

    x_coordinate = []
    y_coordinate = []

    for word_name, word_frequency in most_common_object[:100]:

        if (word_name not in set(stop_words)):
            y_coordinate.append(word_name)
            x_coordinate.append(word_frequency)

    sns.barplot(x = x_coordinate, y = y_coordinate)
```

In [37]:

```
find_word_frequencies(train_df["text"])
```



The above barplot shows that the words "article", "page", "would", "one", "wikipedia", "see", "know", "also", "make", "people", "may", "edit", "source", "use", "get", "need", "even", "time", "want", "say", "could" and "user" are used quite frequently by the commenters. These most common words do not play role in sentiment analyis, thus we can remove them in the following data clean up section.

Expanding the Text

Contractions are words or combinations of words that are shortened by dropping letters and replacing them by an apostrophe.

In [38]:

```
def Expand_text(string):

 string = contractions.fix(string)

 return string
```

In [39]:

```
def Expand_Dataset(dataframe, column_name):
```

```
def Expand_Dataset(dataframe, column_name):

  dataframe[column_name] = dataframe[column_name].apply(Expand_text)

  return dataframe
```

In [40]:

```
# # Expanding Text
# train_df = Expand_Dataset(train_df, "text")
# test_df = Expand_Dataset(test_df, "text")
```

PREPROCESSING OF THE DATA

After done with analysis and cleaning of our text data, let's proceed towards preprocessing required to fit our ML Models.

NOTE - Cleaning of the text which we did above also constitutes as preprocessing.

Tokenization and Lemmatization of Text

In [41]:

```
# Declaring the Objects of the classes present in nltk library

word_lemmatizer = WordNetLemmatizer()
# tweet_tokenizer = nltk.tokenize.TweetTokenizer()
word_tokenizer = nltk.tokenize.WhitespaceTokenizer()
```

In [42]:

```
def tokenize_and_lemmatize_text(text):
    return [word_lemmatizer.lemmatize(word) for word in word_tokenizer.tokenize(text)]
# if word not in set(stop_words)]
```

In [43]:

```
def lemmatize_dataset(dataframe, column_name):

  # Some text may be just numbers or any other data type. Hence we first convert every te
xt to string format.
  dataframe[column_name] = dataframe[column_name].apply(str)

  text = dataframe[column_name]

  text = text.apply(tokenize_and_lemmatize_text)

  text = text.apply(lambda x: ' '.join(([word for word in x ])))  #if word not in set(sto
p_words)])))

  dataframe[column_name] = text

  return dataframe
```

In [44]:

```
# LEMMATIZATION
train_df = lemmatize_dataset(train_df,"text")
test_df = lemmatize_dataset(test_df,"text")
```

Category - Wise Word Clouds

Now we will see which words are most occuring in the sentences for each label category.

In [45]:

```
def show_word_cloud(dataframe, text_column, category_name):

  text = ""
  for i in range(dataframe.shape[0]):
    if (dataframe.loc[i].at[category_name] == 1):
      text = text + dataframe.loc[i].at[text_column]

  unique_words = set(text.split(' '))
  text = ' '.join(unique_words)

  wordcloud = WordCloud(stopwords = stop_words, background_color = "white").generate(tex
t)
  plt.figure(figsize=(10,10))
  plt.imshow(wordcloud, interpolation='bilinear')
  plt.axis("off")
  plt.show()
```

In [46]:

```
# show_word_cloud(train_df, "text", "harsh")
```

In [47]:

```
# harsh_words_list = ['fuck', 'FUCK', 'fucking', 'FUCKING' "F**K", 'F*CK', 'FU*K', 'F*CKI
NG', 'FU*CKING', 'F**KING', 'bitch', 'f**k', 'f**king', 'f*ck','fu*k', 'fu*cking' 'f*ckin
g', 'f***king', 'asshole']
```

In [48]:

```
# show_word_cloud(train_df, "text", "extremely_harsh")
```

In [49]:

```
# extremely_harsh_words_list = ['bitch', 'cunt', 'asshole']
```

In [50]:

```
# show_word_cloud(train_df, "text", "vulgar")
```

In [51]:

```
# vulgar_words_list = ['fuck', 'bitch' 'f**k', 'f**king', 'f*ck','fu*k', 'fu*cking']
```

In [52]:

```
# show_word_cloud(train_df, "text", "threatening")
```

In [53]:

```
# threatening_words_list = ['die', 'fool']
```

In [54]:

```
# show_word_cloud(train_df, "text", "disrespect")
```

In [55]:

```
# disrespect_words_list = ['bitch']
```

In [56]:

```
# show_word_cloud(train_df, "text", "targeted_hate")
```

In [57]:

```
# targeted_hate_words_list = ['nigger', 'gay', 'racist', 'jew', 'pig', 'nazi', 'nigga']
```

TF-IDF Vectorization

TF-IDF Vectorization

Vectiorization of Words

In [58]:

```
word_vectorizer = TfidfVectorizer(strip_accents = 'unicode', analyzer = 'word')
```

In [59]:

```
#TF - IDF Vectorization

complete_fit = word_vectorizer.fit(pd.concat([train_df["text"], test_df["text"]]))

train_words_feature_matrix = word_vectorizer.transform(train_df['text'])
test_words_feature_matrix = word_vectorizer.transform(test_df['text'])
```

Vectiorization of Characters

In [60]:

```
char_vectorizer = TfidfVectorizer(strip_accents = 'unicode', analyzer = 'char', ngram_ran
ge = (2, 6))
```

In [61]:

```
#TF - IDF Vectorization

complete_fit = char_vectorizer.fit(pd.concat([train_df["text"], test_df["text"]]))

train_char_feature_matrix = char_vectorizer.transform(train_df['text'])
test_char_feature_matrix = char_vectorizer.transform(test_df['text'])
```

Merging the Features

In [62]:

```
from scipy.sparse import hstack

train_feature_matrix = hstack([train_char_feature_matrix, train_words_feature_matrix])
test_feature_matrix = hstack([test_char_feature_matrix, test_words_feature_matrix])
```

In [63]:

```
# import pickle

# with open('Train_Feature_Matrix.pkl', 'wb') as f:
#   pickle.dump(train_feature_matrix, f)

# with open('Test_Feature_Matrix.pkl', 'wb') as f:
#   pickle.dump(test_feature_matrix, f)
```

Pre-Processing Completed

SAMPLING

- **Random Over Sampling** - Random oversampling involves randomly duplicating examples from the minority class and adding them to the training dataset.
- **SMOTE** - Samples are generated using concept of k nearest neighbours.
- **Random Under Sampling** - Random undersampling involves randomly selecting examples from the majority class to delete from the training dataset.
- **PipeLine** - Merging both Under and Over Sampling

In [64]:

```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score

from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline

smote = SMOTE(random_state = 0)
Over_sample = RandomOverSampler(sampling_strategy='minority', random_state = 0)
Under_sample = RandomUnderSampler(sampling_strategy='majority', random_state = 0)

steps = [('o', Over_sample), ('u', Under_sample)]
pipeline = Pipeline(steps=steps)
```

CLASSIFICATION MODELS

In [65]:

```
labels_list = ['harsh', 'extremely_harsh', 'vulgar', 'threatening', 'disrespect', 'targe
ted_hate']
```

In [66]:

```
def Manually_Classify(Final_df):

  text_list = Final_df['text'].tolist()

  for i in range(len(text_list)):

    words_list = text_list[i].split()
    words_list = set(words_list)

    # if words_list & set(harsh_words_list):
    #   Final_df['harsh'][i] = 0.999999999999999

    # if words_list & set(extremely_harsh_words_list):
    #   Final_df['extremely_harsh'][i] = 0.999999999999999

    # if words_list & set(vulgar_words_list):
    #   Final_df['vulgar'][i] = 0.999999999999999

    # if words_list & set(threatening_words_list):
    #   Final_df['threatening'][i] = 0.999999999999999

    # if words_list & set(disrespect_words_list):
    #   Final_df['disrespect'][i] = 0.999999999999999

    # if words_list & set(targeted_hate_words_list):
    #   Final_df['targeted_hate'][i] = 0.999999999999999


  return Final_df
```

In [67]:

```
# train_features_matrix_resampled_list = {}

# for i in labels_list:
#   train_feature_matrix_resampled, train_label = pipeline.fit_resample(train_feature_mat
rix, train_df[i])
#   train_features_matrix_resampled_list[i] = train_feature_matrix_resampled
```

1. Logistic - Unbalanced

In [68]:

```
# from sklearn.linear_model import LogisticRegression

# for i in labels_list:

#   train_label_logistic = train_df[i]
#   logistic_regression_model = LogisticRegression(max_iter=1000)
#   logistic_regression_model.fit(train_feature_matrix, train_label_logistic)
#   Predicted_labels_logistic = logistic_regression_model.predict_proba(test_feature_matr
ix)
#   Final_df[i] = Predicted_labels_logistic[:, 1]
#   print(i + " classification complete")


# Submission_df = Final_df.drop("text", axis=1)
# Submission_df.to_csv('Results/Result_UnbalancedLogistic.csv', index = False)
```

2. Logistic - Balanced

In [69]:

```
# from sklearn.linear_model import LogisticRegression

# for i in labels_list:
#   train_label = train_df[i]

#   train_feature_matrix_resampled, train_label = Over_sample.fit_resample(train_feature_
matrix, train_df[i])

#   logistic_regression_model = LogisticRegression(max_iter=1000, class_weight='balanced'
)

#   logistic_regression_model.fit(train_feature_matrix_resampled, train_label)
#   Predicted_labels_logistic = logistic_regression_model.predict_proba(test_feature_matr
ix)
#   Final_df[i] = Predicted_labels_logistic[:, 1]

#   print(i + " classification complete")


# Submission_df = Final_df.drop("text", axis=1)
# Submission_df.to_csv('Results/Results_BalancedLogistic.csv', index = False)
```

3. Random Forest Classifier

In [70]:

```
# from sklearn.ensemble import RandomForestClassifier

# for i in labels_list:
#     train_label = train_df[i]
#     rfc = RandomForestClassifier(max_features = 2500, max_depth = 100, min_samples_spl
it = 10, criterion = 'gini', n_estimators = 120)
#     rfc.fit(train_feature_matrix, train_label)

#     Predicted_labels = rfc.predict_proba(test_feature_matrix)
#     Final_df[i] = Predicted_labels[:, 1]

#     print(i + " classification complete")

# Submission_df = Final_df.drop("text", axis=1)
# Submission_df.to_csv('Results/RFC_Result.csv', index = False)
```

4. Ridge Classifier

In [71]:

```
# from sklearn.linear_model import Ridge

# for i in labels_list:

#   train_label = train_df[i]

#   train_feature_matrix_resampled, train_label = Over_sample.fit_resample(train_feature_
matrix, train_df[i])

#   Ridge_Classifier = Ridge(alpha = 30,max_iter =2000)
#   Ridge_Classifier.fit(train_feature_matrix_resampled, train_label)
#   Predicted_labels = Ridge_Classifier.predict(test_feature_matrix)
#   Final_df[i] = Predicted_labels

#   print(i + " classification complete")

# Submission_df = Final_df.drop("text", axis=1)
# Submission_df.to_csv('Results/Ridge_Result.csv', index = False)
```

5. Gradient Boosting Classifier

In [72]:

```
# from sklearn.ensemble import GradientBoostingClassifier

# for i in labels_list:

#   train_label = train_df[i]
#   GBC=GradientBoostingClassifier(n_estimators=100,max_depth=50)
#   GBC.fit(train_feature_matrix, train_label)

#   Predicted_labels = GBC.predict(test_feature_matrix)
#   Final_df[i] = Predicted_labels

#   print(i + " classification complete")

# Submission_df = Final_df.drop("text", axis=1)
# Submission_df.to_csv('Results/GBC_Result.csv', index = False)
```

6. ADA Boost Classifier

In [73]:

```
# from sklearn.ensemble import AdaBoostClassifier

# for i in labels_list:

#   train_label = train_df[i]
#   ADB = AdaBoostClassifier(n_estimators = 100, learning_rate = 0.1)
#   ADB.fit(train_feature_matrix, train_label)

#   Predicted_labels = ADB.predict_proba(test_feature_matrix)
#   Final_df[i] = Predicted_labels

#   print(i + " classification complete")

# Submission_df = Final_df.drop("text", axis=1)
# Submission_df.to_csv('Results/Ada_Boost_Result.csv', index = False)
```

7. XG BOOST Classifier

In [74]:

```
# import xgboost as xgb
```

```
# xgb_classifier = xgb.XGBClassifier()

# for i in labels_list:

#   train_label = train_df[i]
#   xgb_classifier.fit(train_feature_matrix, train_label)

#   Predicted_labels = xgb_classifier.predict_proba(test_feature_matrix)
#   Final_df[i] = Predicted_labels[:, 1]

#   print(i + " classification complete")

# Submission_df = Final_df.drop("text", axis=1)
# Submission_df.to_csv('Results/XGB_Result.csv', index = False)
```

8. Perceptron

In [75]:

```
# from sklearn.linear_model import Perceptron

# for i in labels_list:

#   train_label = train_df[i]
#   Per = Perceptron(alpha = 0.1, penalty = "l2", max_iter = 150)
#   Per.fit(train_feature_matrix, train_label)

#   Predicted_labels = Per.predict(test_feature_matrix)
#   Final_df[i] = Predicted_labels

#   print(i + " classification complete")

# Submission_df = Final_df.drop("text", axis=1)
# Submission_df.to_csv('Results/Perceptron_Result.csv', index = False)
```

9. SVM

In [76]:

```
# from sklearn.svm import SVC

# for i in labels_list:

#   train_label = train_df[i]
#   SVM_Classifier = SVC(kernel='rbf', probability=True, max_iter= 1000, class_weight= 'b
alanced')
#   SVM_Classifier.fit(train_feature_matrix, train_label)

#   Predicted_labels = SVM_Classifier.predict_proba(test_feature_matrix)
#   Final_df[i] = Predicted_labels[:, 1]

#   print(i + " classification complete")

# Submission_df = Final_df.drop("text", axis=1)
# Submission_df.to_csv('Results/SVM_Result.csv', index = False)
```

10. Decision Tree Classifier

In [77]:

```
# from sklearn.tree import DecisionTreeClassifier

# for i in labels_list:

#   train_label = train_df[i]
```

```
#   DTModel = DecisionTreeClassifier(max_depth=1000, class_weight = 'balanced')
#   DTModel.fit(train_feature_matrix, train_label)

#   Predicted_labels = DTModel.predict_proba(test_feature_matrix)
#   Final_df[i] = Predicted_labels[:, 1]

#   print(i + " classification complete")

# Submission_df = Final_df.drop("text", axis=1)
# Submission_df.to_csv('Results/Decision_Tree_Result.csv', index = False)
```

11. Voting Classifier

In [78]:

```
from sklearn.ensemble import VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import Ridge
from imblearn.ensemble import EasyEnsembleClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import SGDClassifier
import xgboost as xgb

LR = LogisticRegression(max_iter=1000, class_weight='balanced')
RF = RandomForestClassifier(max_features = 2000, max_depth = 100, min_samples_split = 10
, criterion = 'gini', n_estimators = 120)
sgd = SGDClassifier(max_iter = 200, alpha = 0.001, loss = 'modified_huber')
xgb_classifier = xgb.XGBClassifier()
# RC = Ridge(alpha = 30,max_iter =2000)
# Eec_SG = EasyEnsembleClassifier(base_estimator = SGDClassifier(max_iter = 200, alpha =
0.001, loss = 'modified_huber'))
# Eec_XG = EasyEnsembleClassifier(base_estimator = xgb.XGBClassifier())


VotingClassifierModel = VotingClassifier(estimators=[('LR',LR),('RF',RF),('sgd', sgd), (
'xgb_classifier', xgb_classifier)],voting='soft')

for i in (labels_list):
    train_label = train_df[i]

    # train_feature_matrix_resampled, train_label = under_sample.fit_resample(train_featu
re_matrix, train_label)

    VotingClassifierModel.fit(train_feature_matrix, train_label)
    Predicted_labels = VotingClassifierModel.predict_proba(test_feature_matrix)
    Final_df[i] = Predicted_labels[:, 1]

    print(i + " classification complete")

Submission_df = Final_df.drop("text", axis=1)
Submission_df.to_csv('/kaggle/working/Voting_Result_3.csv', index = False)
```

```
harsh classification complete
extremely_harsh classification complete
vulgar classification complete
threatening classification complete
disrespect classification complete
targeted_hate classification complete
```

SAVING THE RESULTS FOLDER IN GOOGLE DRIVE

In [79]:

```
!cp -r  Results /content/drive/MyDrive
```