Problem Statement:

Wikipedia is the world's largest and most popular reference work on the internet with about 500 million unique visitors per month. It also has millions of contributors who can make edits to pages. The Talk edit pages, the key community interaction forum where the contributing community interacts or discusses or debates about the changes pertaining to a particular topic.

Wikipedia continuously strives to help online discussion become more productive and respectful. You are a data scientist at Wikipedia who will help Wikipedia to build a predictive model that identifies toxic comments in the discussion and marks them for cleanup by using NLP and machine learning. Post that, help identify the top terms from the toxic comments.

Domain: Internet

Analysis to be done: Build a text classification model using NLP and machine learning that detects toxic comments.

Steps to perform:

Cleanup the text data, using TF-IDF convert to vector space representation, use Support Vector Machines to detect toxic comments. Finally, get the list of top 15 toxic terms from the comments identified by the model.

Tasks:

1. Load the data using read_csv function from pandas package

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

Choose Files train.csv

- **train.csv**(application/vnd.ms-excel) - 2102032 bytes, last modified: 6/5/2020 - 100% done

```
Saving train.csv to train.csv
```

Importing required module

```
import pandas as pd
import nltk
nltk.download('punkt')
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt
from nltk.corpus import stopwords
import string
import re
import nltk
```

```
nltk.download('stopwords')
import numpy as np
```

```
[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.
```

```
wiki = pd.read_csv('train.csv')
```

```
wiki.head()
```

	id	comment_text	toxic
0	e617e2489abe9bca	"\r\n\r\n A barnstar for you! \r\n\r\n The De...	0
1	9250cf637294e09d	"\r\n\r\nThis seems unbalanced. whatever I ha...	0
2	ce1aa4592d5240ca	Marya Dzmitruk was born in Minsk, Belarus in M...	0
3	48105766ff7f075b	"\r\n\r\nTalkback\r\n\r\n Dear Celestia... "	0
4	0543d4f82e5470b6	New Categories \r\n\r\nI honestly think that w...	0

Data Exploration

```
wiki.shape
```

```
(5000, 3)
```

```
wiki['toxic'].value_counts()
```

```
0    4563
1     437
Name: toxic, dtype: int64
```

```
df = wiki.loc[wiki['toxic']==1, :]
df.head()
```

	id	comment_text	toxic
7	f5bbfd1f588f1a53	loser - you can't block me forever you admin e...	1
8	a238eb61fa81da30	YOU CANNOT BLOCK ME. IF YOU BLOCK ME, I WILL C...	1
16	e5bf9fa72a64c334	Theres a fucking wiki page on it you insane pe...	1
21	6803afa9a0e0089b	Fuck off you ass!Fuck off you ass!Fuck off you...	1
23	e172f0e0098bb6e2	So, are you a Christian becaue of Jesus or bec...	1

```
words=' '.join(df['comment_text'])
```

```
print(words[0:1000])
```

```
loser - you can't block me forever you admin ego hippie freak YOU CANNOT BLOCK ME. II

http://en.wikipedia.org/wiki/Mutilation Fuck off you ass!Fuck off you ass!Fuck off yo
```

```
cleaned_word = " ".join([word for word in words.split()
                            if 'http' not in word
                                and not word.startswith('@')
                                and word != 'RT'
                            ])
```

Creating Wordcloud

```
wordcloud = WordCloud(stopwords=STOPWORDS,
                      background_color='black',
                      width=1600,
                      height=800
                     ).generate(cleaned_word)
```

```
plt.figure(1,figsize=(30,20))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```

2. Get the comments into a list, for easy text cleanup and manipulation

```
comment = [','.join(wiki.comment_text.values)]
```

```
print(type(comment))
```

```
<class 'list'>
```

3. Cleanup:

   1.Using regular expressions, remove IP addresses

   2.Using regular expressions, remove URLs

   3.Normalize the casing

   4.Tokenize using word_tokenize from NLTK

   5.Remove stop words

   6.Remove punctuation

   7.Define a function to perform all these steps, you'll use this later on the actual test set

```
#removing ip
test = ["About 68.197.163.149's mass vandalism"]

re_ip = re.compile(r"\d{1,3}\.\d{1,3}\.\d{1,3}\.\d{1,3}[^0-9]")
test =  [re_ip.sub('',w) for w in test]

test
```

```
['About s mass vandalism']
```

```
#removing URLs

sample = ["{https://en.wikipedia.org/w/index.php?title=Political_correctness&diff;=pr

re_urls = re.compile(r"http\S+")
sample = [re_urls.sub('',w) for w in sample]


sample
```

```
["{ ... nb this change, with tags, if we avoid 'characterising', the early UK/Aust e1
```

```
#normalize casing
sample = ["{https://en.wikipedia.org/w/index.php?title=Political_correctness&diff;=pr

sample = [word.lower() for word in sample]

sample
```

```
["{https://en.wikipedia.org/w/index.php?title=political_correctness&diff;=prev&oldid;
```

```
#tokenizing


from nltk.tokenize import word_tokenize
sample = ["{https://en.wikipedia.org/w/index.php?title=Political_correctness&diff;=pr
sample = [word_tokenize(w) for w in sample]
```

```
#remove stopwords
sample = ["{https://en.wikipedia.org/w/index.php?title=Political_correctness&diff;=pr
stop_words = set(stopwords.words('english'))
sample = [word for word in sample if not word in stop_words]
```

```
#remove punctuation
text = ["{https://en.wikipedia.org/w/index.php?title=Political_correctness&diff;=prev
re_punc = re.compile('[%s]' % re.escape(string.punctuation))
tokens = [re_punc.sub('',w) for w in text]
tokens
```

```
['httpsenwikipediaorgwindexphptitlePoliticalcorrectnessdiffprevoldid693709828  nb thi
```

```
from nltk.tokenize import word_tokenize
#defining function for cleanup and preprocess
def cleanup(sentence):
```

```
    #removeing ip
    sentence = re.sub(r"\d{1,3}\.\d{1,3}\.\d{1,3}\.\d{1,3}[^0-9]",'',sentence)
    #removing urls
    sentence = re.sub(r"http\S+",'',sentence)
    #removing punctuation
    sentence = re.sub('[%s]' % re.escape(string.punctuation),'',sentence)
    #normalizing
    sentence = sentence.lower()
    #tokenizing
    words = word_tokenize(sentence)
    #stopwords removal
    words = [w for w in words if not w in stopwords.words("english")]
    return words

#define function for preprocess data for modeling
def preprocess(sentence):
    words = cleanup(sentence)
    #sentence formation
    return ' '.join(words)

```

```
for i in comment:

  cleaned_doc = cleanup(i)

print(cleaned_doc[0:10])
print('\n')
print('length of cleaned_doc : ' + str(len(cleaned_doc)))
```

```
['barnstar', 'defender', 'wiki', 'barnstar', 'like', 'edit', 'kayastha', 'page', 'le


length of cleaned_doc : 173228
```

4. Using a counter, find the top terms in the data.
    1. Can any of these be considered contextual stop words?
    2. Words like “Wikipedia”, “page”, “edit” are examples of contextual stop words

       If yes, drop these from the data

```
from collections import Counter
```

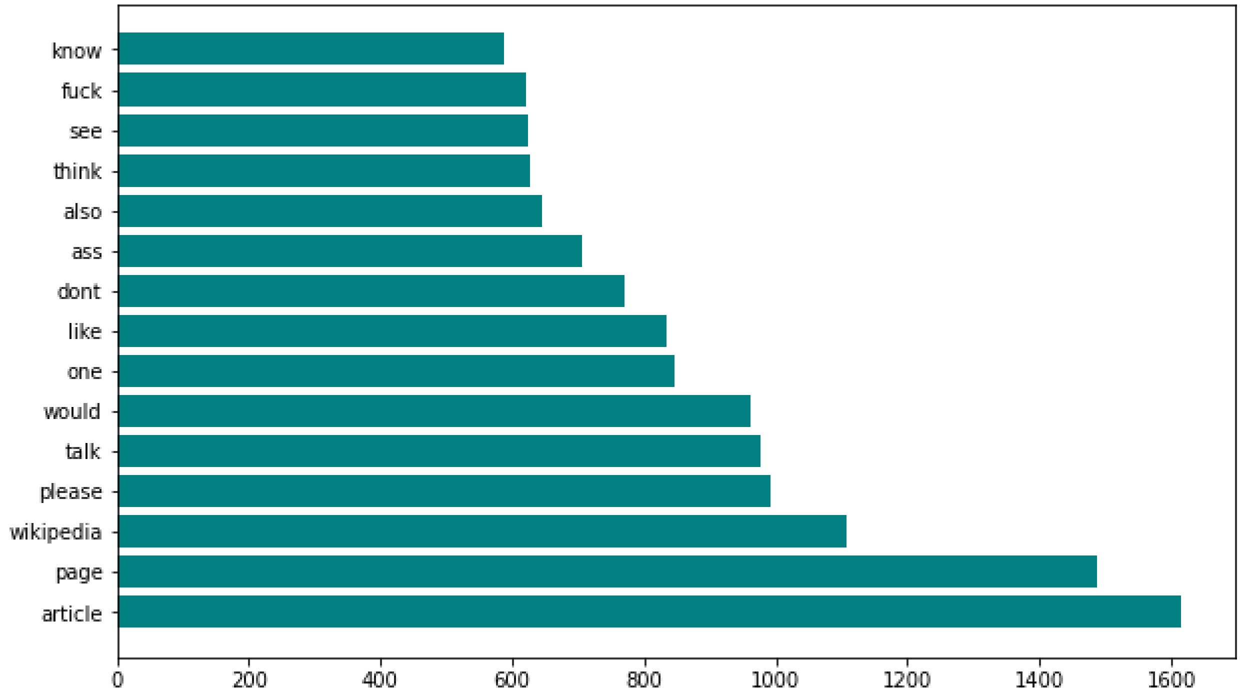
```
term_count = Counter(cleaned_doc)
```

```
term_count.most_common(15)
```

```
[('article', 1615),
 ('page', 1486),
 ('wikipedia', 1108),
```

```
 ('please', 992),
 ('talk', 977),
 ('would', 962),
 ('one', 845),
 ('like', 833),
 ('dont', 771),
 ('ass', 706),
 ('also', 645),
 ('think', 628),
 ('see', 624),
 ('fuck', 620),
 ('know', 589)]
```

```
#ploting to featured words
res = {term:cnt for term, cnt in term_count.most_common(15)}
import matplotlib.pyplot as plt
plt.figure(figsize=[10,6])
plt.barh(list(res.keys()), list(res.values()), color="teal")
plt.show()
```



Words like “Wikipedia”, “page”, “article” are examples of contextual stop words

Removing contextual stopwords

```
wiki['comment_text']=wiki['comment_text'].apply(lambda x: re.sub('[Aa]rticle','', x))
wiki['comment_text']=wiki['comment_text'].apply(lambda x: re.sub('[Pp]age','', x))
wiki['comment_text']=wiki['comment_text'].apply(lambda x: re.sub('[Ww]ikipedia','', x
```

```
comment = [','.join(wiki.comment_text.values)]
for i in comment:
    cleaned_doc = cleanup(i)

print(cleaned_doc[0:10])
```

```
['barnstar', 'defender', 'wiki', 'barnstar', 'like', 'edit', 'kayastha', 'lets', 'for
```

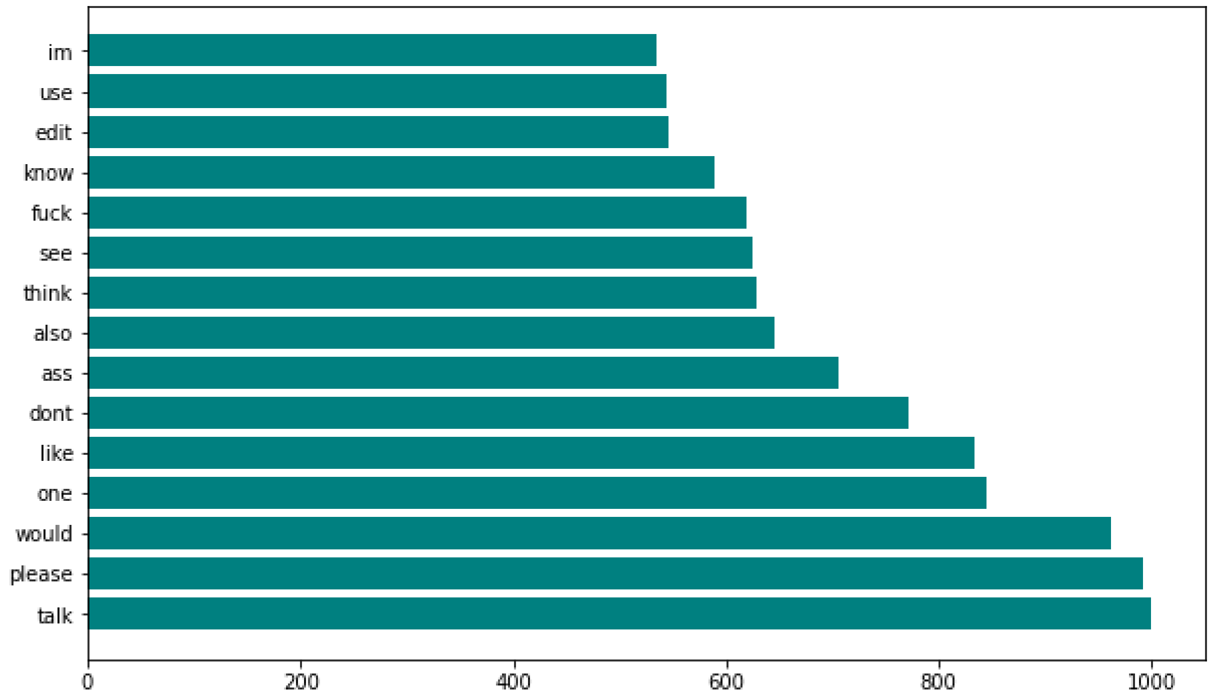
```
print('length of cleaned_doc : ' + str(len(cleaned_doc)))
```

```
length of cleaned_doc : 168037
```

```
term_count = Counter(cleaned_doc)
term_count.most_common(15)
```

```
[('talk', 1000),
 ('please', 992),
 ('would', 962),
 ('one', 845),
 ('like', 833),
 ('dont', 771),
 ('ass', 706),
 ('also', 645),
 ('think', 628),
 ('see', 624),
 ('fuck', 620),
 ('know', 589),
 ('edit', 546),
 ('use', 543),
 ('im', 534)]
```

```
#ploting to featured words
res = {term:cnt for term, cnt in term_count.most_common(15)}
import matplotlib.pyplot as plt
plt.figure(figsize=[10,6])
plt.barh(list(res.keys()), list(res.values()), color="teal")
plt.show()
```



5. Separate into train and test sets

1. Use train-test method to divide your data into 2 sets: train and test
2. Use a 70-30 split

```
from tqdm import tqdm, tqdm_notebook

tqdm.pandas()
```

```
/usr/local/lib/python3.7/dist-packages/tqdm/std.py:658: FutureWarning: The Panel clas
  from pandas import Panel
```

```
#preparing cleaned dataset
wiki['cleaned_comment'] = wiki['comment_text'].progress_apply(lambda x: preprocess(x)
wiki_cleaned_df = wiki.drop(['id','comment_text'], axis=1)

wiki_cleaned_df.head()
```

```
100%|██████████| 5000/5000 [00:37<00:00, 132.03it/s]
```

	toxic	cleaned_comment
0	0	barnstar defender wiki barnstar like edit kaya...
1	0	seems unbalanced whatever said mathsci said fa...
2	0	marya dzmitruk born minsk belarus march 19 199...
3	0	talkback dear celestia
4	0	new categories honestly think need add categor...

```
from sklearn.model_selection import train_test_split
```

```
X = wiki_cleaned_df['cleaned_comment']
y = wiki_cleaned_df['toxic']

X_train, X_test, y_train, y_test= train_test_split(X,y, test_size=0.30, random_state=
```

```
type(X_train)
```

```
pandas.core.series.Series
```

```
X_train.head()
```

```
2858    would interested know consensus discussion act...
1559    temporarily blocked editing vandalism wish mak...
1441    theories science fiction parallel universes re...
2179    12 august 2006 utc consider second warning inc...
1390    hi trpod hear still one 5 horsemen trying astr...
Name: cleaned_comment, dtype: object
```

```
X_train.shape
```

```
(3500,)
```

6. Use TF-IDF values for the terms as feature to get into a vector space model
    1. Import TF-IDF vectorizer from sklearn
    2. Instantiate with a maximum of 4000 terms in your vocabulary
    3. Fit and apply on the train set
    4. Apply on the test set

```
from sklearn.feature_extraction.text import TfidfVectorizer
vect = TfidfVectorizer()


# remove English stop words
vect.set_params(stop_words='english')

# include 1-grams and 2-grams
vect.set_params(ngram_range=(1, 2))

# ignore terms that appear in more than 50% of the documents
vect.set_params(max_df=0.5)

# only keep terms that appear in at least 2 documents
vect.set_params(min_df=2)
vect.set_params(max_features=4000)
vect.set_params(binary=True)
```

```
TfidfVectorizer(analyzer='word', binary=True, decode_error='strict',
                dtype=<class 'numpy.float64'>, encoding='utf-8',
                input='content', lowercase=True, max_df=0.5, max_features=4000,
                min_df=2, ngram_range=(1, 2), norm='l2', preprocessor=None,
                smooth_idf=True, stop_words='english', strip_accents=None,
                sublinear_tf=False, token_pattern='(?u)\\b\\w\\w+\\b',
                tokenizer=None, use_idf=True, vocabulary=None)
```

```
train_vector = vect.fit_transform(X_train)
```

```
test_vector = vect.transform(X_test)
```

```

```

7. Model building: Support Vector Machine
    1. Instantiate SVC from sklearn with a linear kernel
    2. Fit on the train data
    3. Make predictions for the train and the test set

```
#model building
from sklearn import svm

svm=svm.SVC(kernel='linear', probability=True)
```

```
# fit the SVC model based on the given training data
svm.fit(train_vector, y_train)
```

```
SVC(C=1.0, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='linear',
    max_iter=-1, probability=True, random_state=None, shrinking=True, tol=0.001,
    verbose=False)
```

```
#prediction
pred = svm.predict(test_vector)
```

8. Model evaluation: Accuracy, recall, and f1_score
    1. Report the accuracy on the train set
    2. Report the recall on the train set:decent, high, low?
    3. Get the f1_score on the train set

```
from sklearn.metrics import accuracy_score, f1_score, recall_score
```

```
#accuracy score
accuracy_score(y_test,pred)

```

```
0.946
```

```
#recall score
recall_score(y_test, pred)
```

```
0.40310077519379844
```

Recall score is low, data is Imbalanced.

```
#f1 score
f1_score(y_test, pred)
```

```
0.5621621621621621
```

9. Looks like you need to adjust the class imbalance, as the model seems to focus on the 0s

    1.Adjust the appropriate parameter in the SVC module

```
from sklearn.svm import SVC
svm_balanced = SVC(kernel='linear', class_weight='balanced', probability=True)
```

10. Train again with the adjustment and evaluate

    1.Train the model on the train set

    2.Evaluate the predictions on the validation set: accuracy, recall, f1_score

```
svm_balanced.fit(train_vector, y_train)
```

```
SVC(C=1.0, break_ties=False, cache_size=200, class_weight='balanced', coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='linear',
    max_iter=-1, probability=True, random_state=None, shrinking=True, tol=0.001,
    verbose=False)
```

```
pred_balanced = svm_balanced.predict(test_vector)
```

```
accuracy_score(y_test,pred_balanced)
```

```
0.9426666666666667
```

```
recall_score(y_test, pred_balanced)
```

```
0.6511627906976745
```

```
f1_score(y_test, pred_balanced)
```

```
0.6614173228346458
```

11. Hyperparameter tuning

    1. Import GridSearch and StratifiedKFold (because of class imbalance)
    2. Provide the parameter grid to choose for ‘C’
    3. Use a balanced class weight while instantiating the Support Vector Classifier

```
from sklearn.model_selection import StratifiedKFold, GridSearchCV
```

```
parameters = {'C': np.arange(0.1, 1, 0.05)}
```

```
svm_balanced = SVC(kernel='linear', class_weight='balanced', probability=True)
```

12. Find the parameters with the best recall in cross validation

    1. Choose ‘recall’ as the metric for scoring

2. Choose stratified 5 fold cross validation scheme

3. Fit on the train set

```
skf = StratifiedKFold(n_splits=5)
skf.get_n_splits(X, y)
print(skf)
```

```
StratifiedKFold(n_splits=5, random_state=None, shuffle=False)
```

```
for train_index, test_index in skf.split(X, y):

    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]
```

```
train_vector = vect.fit_transform(X_train)
```

```
test_vector = vect.transform(X_test)
```

```
grid_search = GridSearchCV(svm_balanced, param_grid=parameters,
                           cv=5, scoring='recall')
```

```
grid_search.fit(train_vector, y_train)
```

```
GridSearchCV(cv=5, error_score=nan,
             estimator=SVC(C=1.0, break_ties=False, cache_size=200,
                           class_weight='balanced', coef0=0.0,
                           decision_function_shape='ovr', degree=3,
                           gamma='scale', kernel='linear', max_iter=-1,
                           probability=True, random_state=None, shrinking=True,
                           tol=0.001, verbose=False),
             iid='deprecated', n_jobs=None,
             param_grid={'C': array([0.1 , 0.15, 0.2 , 0.25, 0.3 , 0.35, 0.4 , 0.45,
       0.65, 0.7 , 0.75, 0.8 , 0.85, 0.9 , 0.95])},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='recall', verbose=0)
```

13. What are the best parameters?

```
print(grid_search.best_params_)
```

```
{'C': 0.25000000000000006}
```

```
grid_search.score(test_vector, y_test)
```

```
0.6931818181818182
```

14. Predict and evaluate using the best estimator
    1. Use best estimator from the grid search to make predictions on the test set
    2. What is the recall on the test set for the toxic comments?
    3. What is the f1_score?

```
pred_Cv = grid_search.best_estimator_.predict(test_vector)
```

```
recall_score(y_test, pred_Cv)
```

```
0.6931818181818182
```

```
f1_score(y_test, pred_Cv)
```

```
0.6455026455026455
```

15. What are the most prominent terms in the toxic comments?
    1. Separate the comments from the test set that the model identified as toxic
    2. Make one large list of the terms
    3. Get the top 15 terms

```
df_model = pd.DataFrame(X_test)
```

```
df_model['pred']=pred_Cv
```

```
df_model.head()
```

	cleaned_comment	pred
3872	murder pets slash tires giant assclown name by...	1
3876	u suck donkey balls yeah	1
3883	im gay vodka pants	1
3892	crzrussian slit wrists	0
3920	may allah swt either give punishment hidiyaat ...	0

```
df_toxic = df_model.loc[(df_model['pred']==1)]
```

```
df_toxic.head()
```

	cleaned_comment	pred
3872	murder pets slash tires giant assclown name by...	1
3876	u suck donkey balls yeah	1
3883	im gay vodka pants	1
3930	threatening im disruptive disruptive	1

```
toxic_comment = [','.join(df_toxic.cleaned_comment.values)]
```

```


for i in toxic_comment:

  toxic_words = cleanup(i)

print(toxic_words[0:10])
print('\n')
print('length of toxic_words : ' + str(len(toxic_words)))
```

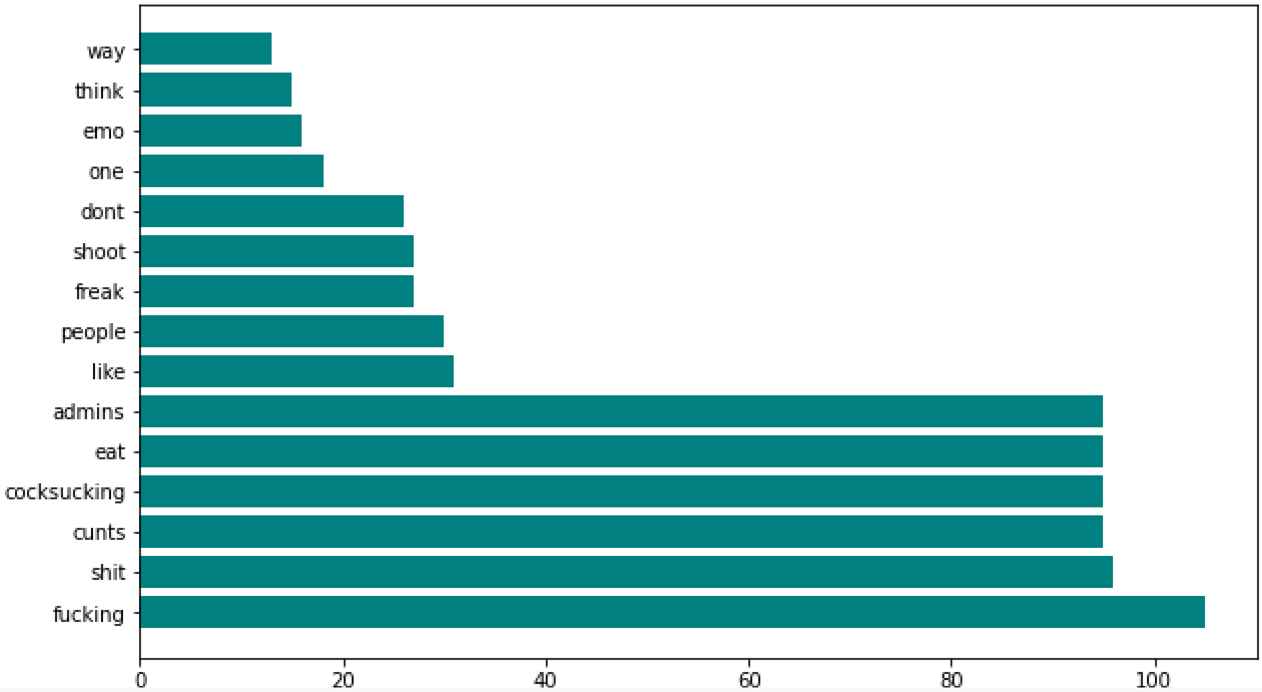
```
['murder', 'pets', 'slash', 'tires', 'giant', 'assclown', 'name', 'byran', 'mattison


length of toxic_words : 2888
```

```
term_count_toxic = Counter(toxic_words)
```

```
term_count_toxic.most_common(15)
```

```
[('fucking', 105),
 ('shit', 96),
 ('cunts', 95),
 ('cocksucking', 95),
 ('eat', 95),
 ('admins', 95),
 ('like', 31),
 ('people', 30),
 ('freak', 27),
 ('shoot', 27),
 ('dont', 26),
 ('one', 18),
 ('emo', 16),
 ('think', 15),
 ('way', 13)]
```

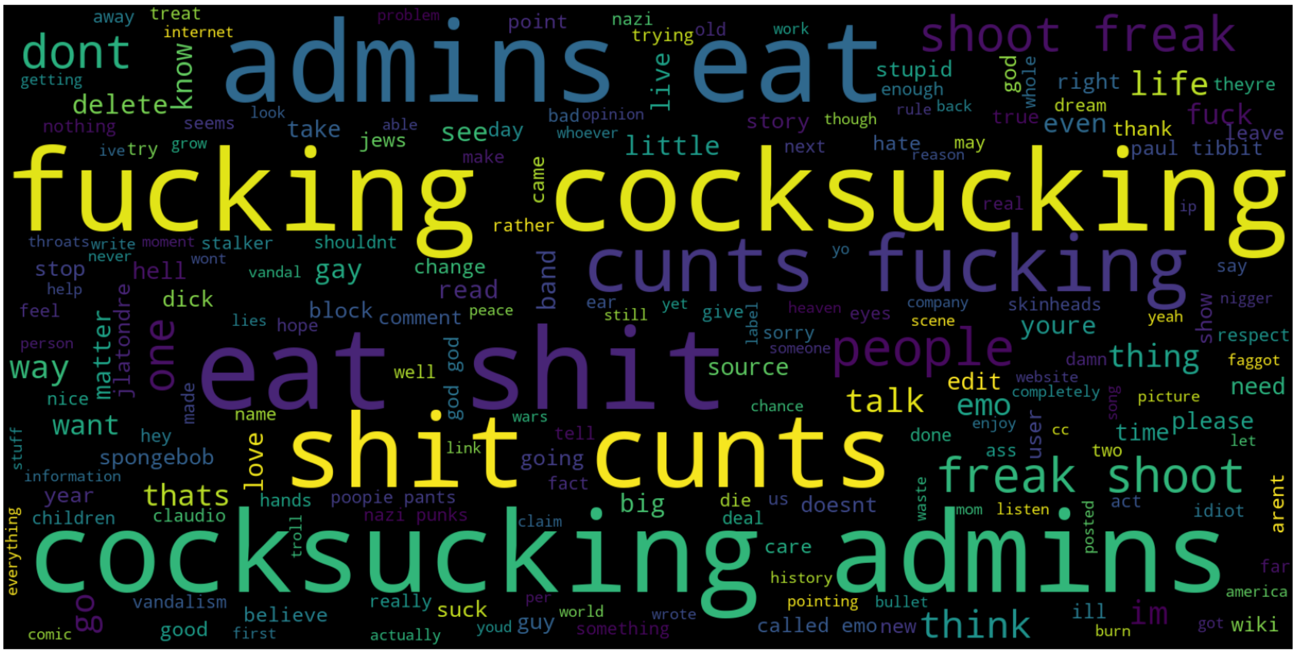
```
#ploting to featured words
res = {term:cnt for term, cnt in term_count_toxic.most_common(15)}
import matplotlib.pyplot as plt
plt.figure(figsize=[10,6])
plt.barh(list(res.keys()), list(res.values()), color="teal")
plt.show()
```




```
w_model=' '.join(df_toxic['cleaned_comment'])
ws = " ".join([word for word in w_model.split()
                            if 'http' not in word
                                and not word.startswith('@')
                                and word != 'RT'
                            ])
```

```
wordcloud = WordCloud(stopwords=STOPWORDS,
                      background_color='black',
                      width=1600,
                      height=800
                     ).generate(ws)
```

```
plt.figure(1,figsize=(30,20))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```



1

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