Wikipedia Toxicity

''' Using NLP and machine learning, make a model to identify toxic comments from the Talk edit pages on Wikipedia. Help identify the words that make a comment toxic.'''

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

In [1]:
```
!pip install contractions
# import packages
import pandas as pd
import re
import contractions
import matplotlib.pyplot as plt
import nltk
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()

from nltk.corpus import stopwords
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS
import numpy as np
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: contractions in c:\users\bindu\appdata\roaming\python\python39\site-packages (0.
1.73)
Requirement already satisfied: textsearch>=0.0.21 in c:\users\bindu\appdata\roaming\python\python39\site-packag
es (from contractions) (0.0.24)
Requirement already satisfied: pyahocorasick in c:\users\bindu\appdata\roaming\python\python39\site-packages (f
rom textsearch>=0.0.21->contractions) (2.0.0)
Requirement already satisfied: anyascii in c:\users\bindu\appdata\roaming\python\python39\site-packages (from t
extsearch>=0.0.21->contractions) (0.3.1)
```

1. Load the data using read_csv function from pandas package

In [2]:
```
# 2. Get the comments into a list, for easy text cleanup and manipulation - using DF
wiki_comments = pd.read_csv("train_toxicity.csv")
wiki_comments.head()
```

Out[2]:

	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

In [3]:
```
wiki_comments.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 3 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   id            5000 non-null   object
 1   comment_text  5000 non-null   object
 2   toxic         5000 non-null   int64 
dtypes: int64(1), object(2)
memory usage: 117.3+ KB
```

In [4]:
```
# Check for null values - no null found
wiki_comments.isnull().sum()
```

Out[4]:
```
id              0
comment_text    0
toxic           0
dtype: int64
```

In [5]:
```
# drop 'id' column as it has no relevance to the model
wiki_comments.drop(['id'], axis =1, inplace=True)
wiki_comments.head()
```

Out[5]:

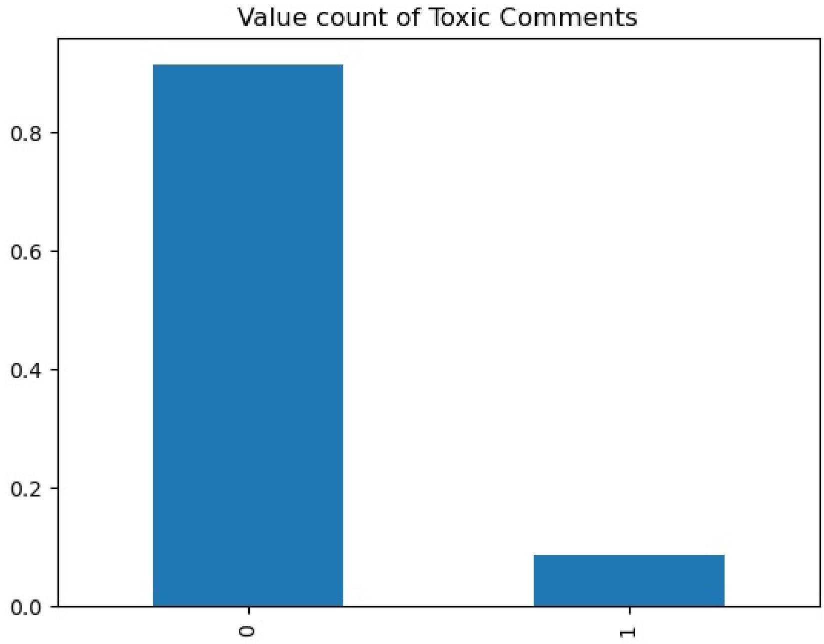
	comment_text	toxic
0	"\r\n\r\n A barnstar for you! \r\n\r\n The De...	0
1	"\r\n\r\nThis seems unbalanced. whatever I ha...	0
2	Marya Dzmitruk was born in Minsk, Belarus in M...	0
3	"\r\n\r\nTalkback\r\n\r\n Dear Celestia... "	0
4	New Categories \r\n\r\nI honestly think that w...	0

In [6]:
```
# Check for class balance - Toxic comments are less than 10%
wiki_comments['toxic'].value_counts(normalize=True)
```

Out[6]:
```
0    0.9126
1    0.0874
Name: toxic, dtype: float64
```

In [7]:
```
wiki_comments['toxic'].value_counts(normalize=True).plot(kind="bar", title="Value count of Toxic Comments")
```

Out[7]:
```
<AxesSubplot:title={'center':'Value count of Toxic Comments'}>
```



3. Data Cleanup

In [8]:
```
wiki_comments.head()
```

Out[8]:

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

In [10]:
```
wiki_comments['comment_text'][1999]
```

Out[10]: "Due to continual nibbling away of information by some very uninformed editors the section on current legal battle makes absolutely no sense. It appears to be remnants of longer pieces of information standing in isolation. If anyone can work out there are two trials now in progress one which started in September 2012 at the Delhi Patiala Court heard by Mr Justice Akash Jain based on a FIR filed by the Delhi Police due to her fasting at the Delhi Jantar Mantar 6 October 2006. That trial has now completed two full days of hearings the next production warrant the 14th is set for October 30-31 2014 2 days of prosecution witnesses.\r\nThe second trial is in Imphal. So after her arrest on fresh charges March 2014 the Imphal Police pressed charges at that point a local corrupt lawyer turned up and decided that the best thing was for all charges to be dropped and Sharmila to be placed in a death tent where he desire to starve herself to death over a few weeks could be respected. The Chief Judicial Magistrate rejected his plea to dismiss all charges after 13 years of imprisonment because someone might ask why did you imprison her then and keep her in solitary if there was no case to answer. The lawyer then appealed to higher Court the District & Sessions Judge. When this Judge looked at the case he pointed out the prosecution hadn't actually submitted any evidence of any wrong doing other than suggesting that everybody knew she was on a fast to death. Given that following procedural rules of evidence in court no evidence was actually being presented just references to hearsay the Judge ruled that in the absence of positive evidence to suggest mens rea he didn't need to look into the validity of the actus reus of whether hunger striking was grounds for arrest under the attempted suicide legislation so he dismissed the charges adding that he felt the Government should take measures to preserve Sharmila's health because even if hte Prosecution hadn't bothered to present any evidence he knew she was on a hunger strike and would die without farther intervention. Subsequently the Government re-arrested Sharmila on a fresh charge of attempted suicide and appealed to the Manipur High Court to have the District & Sessions Judge's judgement overturned and for a trial to proceed. Meanwhile Sharmila is held at the JNIMS security ward (not house arrest because then she would be in her own home) on 15 day judicial remand. The last judicial renewal was 5th September (the next one is due on 19th September) the last hearing of the Manipur High Court regarding the judicial review of the previous case dismissal was 3 September when they sought more papers but it appears this is all to complicated for wiki editors so they have gone with what appear to be verifiable facts in no particular order which when read do not make any sense at all. In this they are true to the actual Indian court proceedings. Desmond Coutinho again look I have just signed my name."

In [11]:
```
# Stopwords
nltk_stopwords = set(stopwords.words('english'))
sklearn_stopwords = set(ENGLISH_STOP_WORDS)
all_stopwords = nltk_stopwords.union(sklearn_stopwords)
#print("Total num of stopwords : ", len(all_stopwords))
```

In [12]:
```
# Function to remove stopwords
def remove_stopwords(text, sw):
    text = [t for t in text.split() if t not in sw]
    if len(sw) > 100:
        return text
    return ' '.join(text)
```

In [16]:
```
# Define a function to perform data cleaning
def cleanup(comment):
    # 3.3. Normalize the casing
    # Removing dates
    cleaned_text = re.sub(r"\w{3,9}.\d{2}..\d{4}|\d{4}|\d{1,2}.\w{3,9}.\d{4}|\d{1,2}.\w{3,9}", "", comment.lowe

    # 3.1. Using regular expressions, remove IP addresses
    cleaned_text = re.sub(r"\d+.\d+.*", "", cleaned_text)

    # 3.2. Using regular expressions, remove URLs
    cleaned_text = re.sub(r"http:\S+", "", cleaned_text)
    cleaned_text = re.sub(r"\S+.com\S+", "", cleaned_text)

    # Remove contractions such as we'd
    cleaned_text = contractions.fix(cleaned_text)

    # 3.6 Remove punctuation and numbers
    cleaned_text = re.sub(r"[^a-z]", " ", cleaned_text)

    # 3.4. Tokenize
    # 3.5. Remove stop words
    cleaned_comment = ''
    comment_afterstopword_removal = remove_stopwords(cleaned_text, all_stopwords)

    # Removing words of length 2 or less
    # Lemmatization
    for t in comment_afterstopword_removal:
        lem = lemmatizer.lemmatize(t)
        if(len(lem) > 2):
            cleaned_comment = cleaned_comment + lem + ' '

    return cleaned_comment

    wiki_c = wiki_comments['cleaned_comments']
```

In [14]:
```
wiki_comments['cleaned_comments'] = wiki_comments['comment_text'].apply(lambda x: cleanup(x))
```

In [17]:
```
wiki_comments['cleaned_comments'].head()
```

Out[17]:
```
0    barnstar defender wiki barnstar like edit kaya...
1    unbalanced said mathsci said far extreme unple...
2    marya dzmitruk born minsk belarus mother olga ...
3                                talkback dear celestia
4    new category honestly think need add category ...
Name: cleaned_comments, dtype: object
```

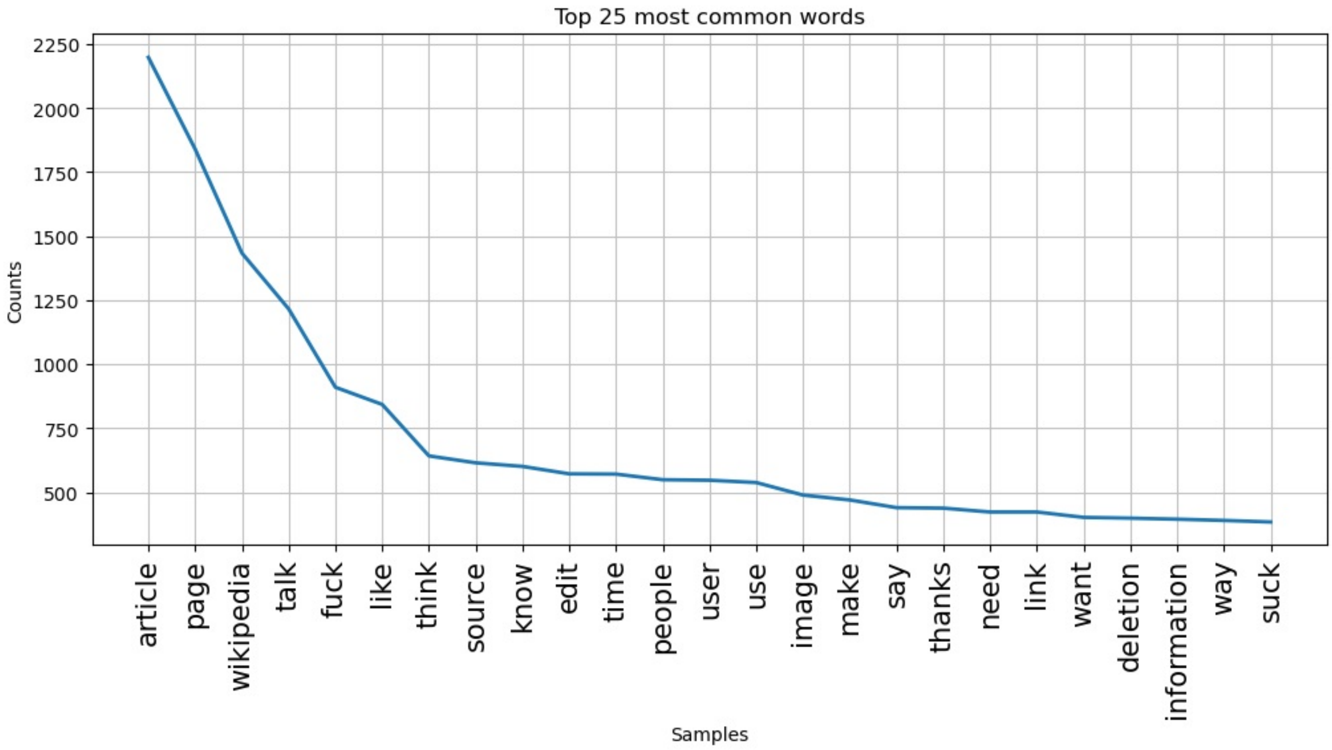
4. Using a counter, find the top terms in the data.

In [18]:
```
# Write a code to collect all the words from all tweets into a single list
def get_allWords(colname):
    all_words = []
    for t in wiki_comments[colname]:
        all_words.extend(t.split())
    print("Number of words: ", len(all_words))
    return all_words
```

In [19]:
```
def Plot_FreqDist(all_words, top=25):
    freq_dist = nltk.FreqDist(all_words)

    plt.figure(figsize=(12,5))
    plt.title('Top 25 most common words')
    plt.xticks(fontsize=15)

    freq_dist.plot(top, cumulative=False)
    plt.show()

# Frequency Distribution
def freqDist_plot(colname, top=25):
    all_words = get_allWords(colname)
    Plot_FreqDist(all_words, top)
```

In [20]:
```
# Word count before contextual stopwords removal - 141290
freqDist_plot('cleaned_comments')
```

```
Number of words:  140096
```



In [21]:
```
# 4.1. Can any of these be considered contextual stop words? - dropping contextual stopwords
# Words like “Wikipedia”, “page”, “edit” are examples of contextual stop words
Contextual_Stopwords = {"wikipedia", "page", "edit", "article", "wiki", "wikiproject", "edits"}
colname = 'stopwords_cleaned_comments'
#print(remove_stopwords(wiki_comments['cleaned_comments'][50], contextual_stopwords))
wiki_comments[colname] = wiki_comments['cleaned_comments'].apply(lambda x: remove_stopwords(x, Contextual_Stopw
```

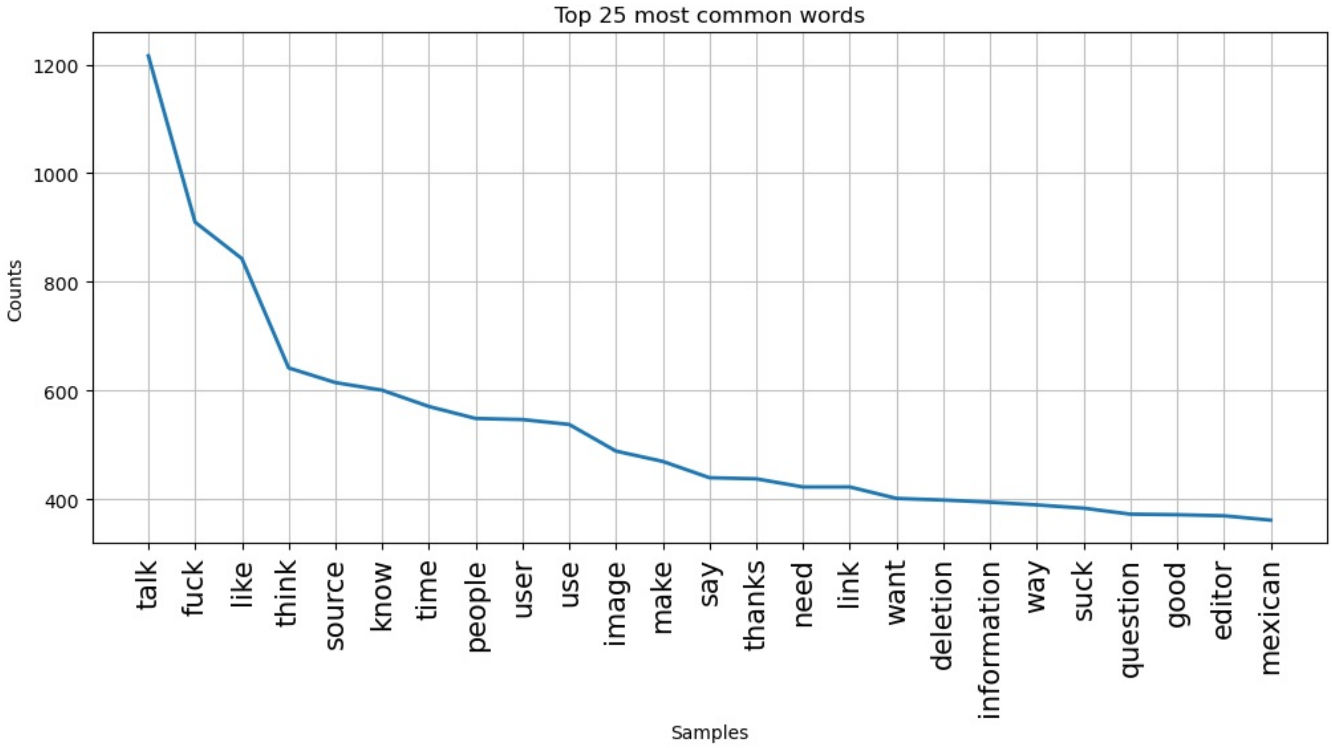
In [22]:
```
wiki_comments.head()
```

Out[22]:

	comment_text	toxic	cleaned_comments	stopwords_cleaned_comments
0	"\r\n\r\n A barnstar for you! \r\n\r\n The De...	0	barnstar defender wiki barnstar like edit kaya...	barnstar defender barnstar like kayastha let f...
1	"\r\n\r\nThis seems unbalanced. whatever I ha...	0	unbalanced said mathsci said far extreme unple...	unbalanced said mathsci said far extreme unple...
2	Marya Dzmitruk was born in Minsk, Belarus in M...	0	marya dzmitruk born minsk belarus mother olga ...	marya dzmitruk born minsk belarus mother olga ...
3	"\r\n\r\nTalkback\r\n\r\n Dear Celestia... "	0	talkback dear celestia	talkback dear celestia
4	New Categories \r\n\r\nI honestly think that w...	0	new category honestly think need add category ...	new category honestly think need add category ...

In [23]:
```
# Plot after contextual stopword removal
freqDist_plot(colname)
```

```
Number of words:  133475
```



5. Separate data into train and test sets

In [24]:
```
from sklearn.model_selection import train_test_split

X = wiki_comments['stopwords_cleaned_comments']
y = wiki_comments['toxic']

# 5.2. Use a 70-30 split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.30, stratify=y, random_state=42)
```

In [25]:
```
print("X Train shape: ", X_train.shape)
print("X Test shape: ", X_test.shape)
print(y.value_counts(normalize=True))
print(y_train.value_counts(normalize=True))
print(y_test.value_counts(normalize=True))
```

```
X Train shape:  (3500,)
X Test shape:  (1500,)
0    0.9126
1    0.0874
Name: toxic, dtype: float64
0    0.912571
1    0.087429
Name: toxic, dtype: float64
0    0.912667
1    0.087333
Name: toxic, dtype: float64
```

6. Use TF-IDF values for the terms as feature to get into a vector space model

In [26]:
```
# 6.1. Import TF-IDF vectorizer from sklearn
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [27]:
```
# 6.2. Instantiate with a maximum of 4000 terms in your vocabulary
TFIDF = TfidfVectorizer(max_features=4000)
```

In [28]:
```
# 6.3. Fit and apply on the train set
tfidf_x_train = TFIDF.fit_transform(X_train)
print(tfidf_x_train.shape)
TFIDF.get_feature_names_out()
```

```
(3500, 4000)
```

Out[28]:
```
array(['abc', 'abe', 'ability', ..., 'zeta', 'zheng', 'zone'],
      dtype=object)
```

In [29]:
```
# 6.4. Apply on the test set
tfidf_x_test = TFIDF.transform(X_test)
```

```
print(tfidf_x_test.shape)
```

```
(1500, 4000)
```

7. Model building: Support Vector Machine

In [30]:
```
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.model_selection import StratifiedKFold
```

In [31]:
```
# 7.1. Instantiate SVC from sklearn with a linear kernel
SVC_1 = SVC(kernel='linear')
```

In [32]:
```
# 7.2. Fit on the train data
SVC_1.fit(tfidf_x_train, y_train)
```

Out[32]:
```
SVC(kernel='linear')
```

In [33]:
```
# 7.3. Make predictions for the train and the test set
svc_pred = SVC_1.predict(tfidf_x_test)
```

8. Model evaluation: Accuracy, recall, and f1_score

In [34]:
```
# 8.1. Report the accuracy on the train set
SVC_1.score(tfidf_x_train, y_train)
```

Out[34]:
```
0.9711428571428572
```

In [35]:
```
# Model has good accuracy
SVC_1.score(tfidf_x_test, y_test)
```

Out[35]:
```
0.9433333333333334
```

In [36]:
```
from sklearn.metrics import recall_score
from sklearn.metrics import balanced_accuracy_score
from sklearn.metrics import precision_recall_fscore_support
```

In [37]:
```
# Recall score is low - 0.39
recall_score(y_test, svc_pred)
```

Out[37]:
```
0.3893129770992366
```

In [38]:
```
# Recall score on balanced dataset is better than normal recall score  - 69%
balanced_accuracy_score(y_test, svc_pred)
```

Out[38]:
```
0.6928303380748192
```

In [39]:
```
# 8.2. Report the recall on the train set: decent, high, low?
# Recall on the test set looks low - 0.39
# Get the f1_score on the train set
# f1_score is medium - 0.54
# The model predicts 0.91 accurately
precision_recall_fscore_support(y_test, svc_pred)
```

Out[39]:
```
(array([0.94459834, 0.91071429]),
 array([0.9963477 , 0.38931298]),
 array([0.96978315, 0.54545455]),
 array([1369,  131], dtype=int64))
```

In [40]:
```
# Using StratifiedKFold for class imbalance
# Model train accuracy is 97.03 while test accuracy is 94.46 which looks good
kfold = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
results = cross_validate(SVC_1, tfidf_x_train, y_train, cv=kfold, scoring='accuracy', return_train_score=True)
print(np.round((results['train_score'].mean())*100, 2), np.round((results['train_score'].std())*100, 2))
print(np.round((results['test_score'].mean())*100, 2), np.round((results['test_score'].std())*100, 2))
```

```
97.03 0.12
94.46 0.68
```

In [41]:
```
# Defining a method to check a model's accuracy
def test_accuracy(SVC_model, x_train = tfidf_x_train, x_test=tfidf_x_test):
    SVC_model.fit(x_train, y_train)
    svc_pred = SVC_model.predict(x_test)
    results = cross_validate(SVC_model, x_train, y_train, cv=kfold, scoring='accuracy', return_train_score=True
    print(np.round((results['train_score'].mean())*100, 2), np.round((results['train_score'].std())*100, 2))
    print(np.round((results['test_score'].mean())*100, 2), np.round((results['test_score'].std())*100, 2))
    print(precision_recall_fscore_support(y_test, svc_pred))
```

9. Adjust the class imbalance, as the model seems to focus on the

0s

10. Train again with the adjustment and evaluate

In [42]:
```
# 9.1. Adjust the appropriate parameter in the SVC module
# adding balanced class weight - model looks overfitted

# 10.2. Evaluate the predictions on the validation set:
# accuracy - test accuracy has decreased and model looks overfitted
# recall - There is an improvement in recall score but not as high as desired - 0.56
# f1_score - 0.57 is higher than the previous model but as high as desired

SVC_2 = SVC(kernel='linear', class_weight='balanced')
test_accuracy(SVC_2)
```

```
98.68 0.22
93.83 0.65
(array([0.95778748, 0.57936508]), array([0.96128561, 0.55725191]), array([0.95953336, 0.56809339]), array([1369
,  131], dtype=int64))
```

11. Hyperparameter tuning

In [43]:
```
# 11.1. Import GridSearch and StratifiedKFold
from sklearn.model_selection import GridSearchCV
```

In [44]:
```
# 11.2. Provide the parameter grid to choose for ‘C’
C_values = np.arange(0.00001, 1, 0.05) # 20 values
C_values
```

Out[44]:
```
array([1.0000e-05, 5.0010e-02, 1.0001e-01, 1.5001e-01, 2.0001e-01,
       2.5001e-01, 3.0001e-01, 3.5001e-01, 4.0001e-01, 4.5001e-01,
       5.0001e-01, 5.5001e-01, 6.0001e-01, 6.5001e-01, 7.0001e-01,
       7.5001e-01, 8.0001e-01, 8.5001e-01, 9.0001e-01, 9.5001e-01])
```

In [48]:
```
# 11.3. Use a balanced class weight while instantiating the Support Vector Classifier
grid = GridSearchCV(estimator=SVC_2, param_grid={'C': C_values}, cv=kfold, scoring='accuracy', \
                    return_train_score=True, verbose=2, n_jobs=-1)
grid_results = grid.fit(tfidf_x_train, y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

In [46]:
```
grid_results.best_params_, grid_results.best_score_, grid_results.best_index_
```

Out[46]:
```
({'C': 0.10001}, 0.9454285714285714, 2)
```

In [49]:
```
grid_results.cv_results_['mean_train_score'][grid_results.best_index_]*100
```

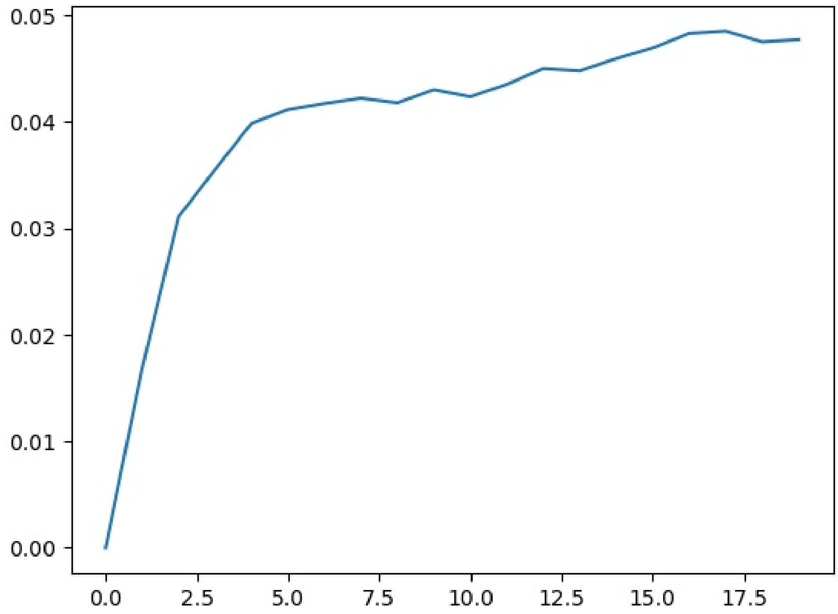
Out[49]:
```
97.65
```

In [50]:
```
grid_results.cv_results_['mean_test_score'][grid_results.best_index_]*100
```

Out[50]:
```
94.54285714285714
```

In [51]:
```
plt.plot(grid_results.cv_results_['mean_train_score'] - grid_results.cv_results_['mean_test_score'])
```

Out[51]:
```
[<matplotlib.lines.Line2D at 0x1af89964e50>]
```



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

In [52]:
```
# 12.1. Choose 'recall' as the metric for scoring
grid = GridSearchCV(estimator=SVC_2, param_grid={'C': C_values}, cv=kfold, scoring='recall', \
                    return_train_score=True, verbose=2, n_jobs=-1)
grid_results = grid.fit(tfidf_x_train, y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

13. What are the best parameters?

In [53]:
```
grid_results.best_params_, grid_results.best_score_, grid_results.best_index_
```

Out[53]:
```
({'C': 0.35001000000000004}, 0.6042834479111582, 7)
```

In [ ]:
```
# C = 0.1 is the best parameter for accuracy
# C = 0.35 is the best parameter for recall
```

14. Predict and evaluate using the best estimator

In [57]:
```
# 14.1. Use best estimator from the accuracy grid search to make predictions on the test set
#  The difference in accuracy between train n test and SD reduces !
SVC_3 = SVC(kernel='linear', class_weight='balanced', C= 0.1)
test_accuracy(SVC_3)
```

```
97.65 0.14
94.54 0.58
(array([0.95776664, 0.69902913]), array([0.97735573, 0.54961832]), array([0.96746204, 0.61538462]), array([1369
,  131], dtype=int64))
```

In [58]:
```
# 14.1. Use best estimator from the recall grid search to make predictions on the test set
# 14.2. The recall on the test set for the toxic comments is 0.62
# 14.3. The f1_score is 0.57
# Accuracy of model =
SVC_4 = SVC(kernel='linear', class_weight='balanced', C= 0.35)
test_accuracy(SVC_4)
```

```
97.85 0.42
93.63 0.35
(array([0.96288048, 0.52941176]), array([0.94740687, 0.61832061]), array([0.955081  , 0.57042254]), array([1369
,  131], dtype=int64))
```

In [59]:
```
# using min df in TFIDF and checking accuracy
TFIDF_min = TfidfVectorizer(max_features=4000, min_df=5)
TFIDF_x_train_min = TFIDF_min.fit_transform(X_train)
TFIDF_x_test_min = TFIDF_min.transform(X_test)
```

In [60]:
```
# SVC using Min df - This model seems good as well but with no improvement in Recall score
SVC_5 = SVC(kernel='linear', class_weight='balanced', C= 0.35)
test_accuracy(SVC_5, TFIDF_x_train_min, TFIDF_x_test_min)
```

```
97.1 0.41
93.09 0.35
(array([0.96249062, 0.48502994]), array([0.93718042, 0.61832061]), array([0.94966691, 0.54362416]), array([1369
,  131], dtype=int64))
```

15. What are the most prominent terms in the toxic comments?

In [61]:
```
# Using the SVC model used for best recall score
svc_test = SVC_4.predict(tfidf_x_test)
```

In [62]:
```
svc_test[:10]
```

Out[62]:
```
array([0, 0, 0, 1, 0, 0, 0, 0, 0, 0], dtype=int64)
```

In [63]:
```
d = {'Toxicity':svc_test, 'Comments':X_test}
df = pd.DataFrame(data=d)
df.head()
```

Out[63]:

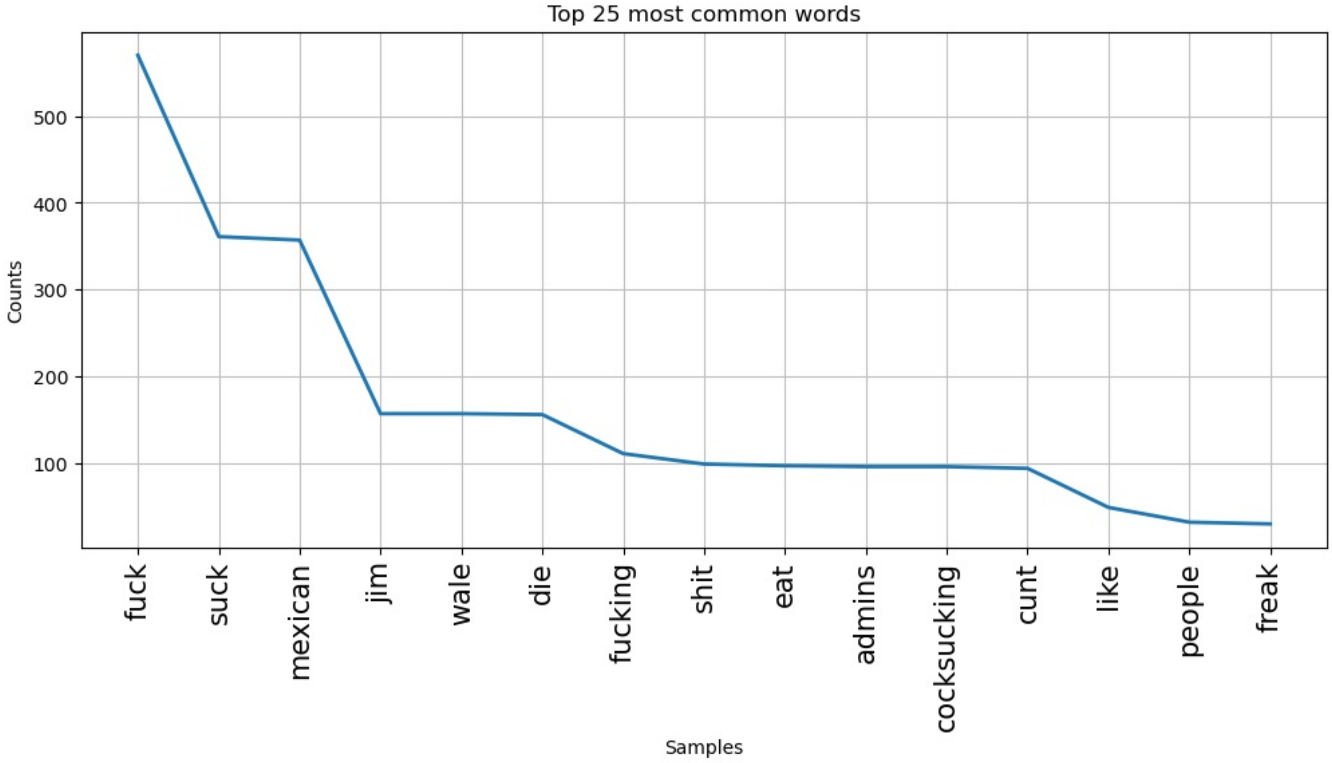
	Toxicity	Comments
3249	0	daimlerchrysler relationship closer gone point...
1133	0	linked dennis brown quite obviously meant humo...
1659	0	fair use rationale image pinhead profile jpg t...
1694	1	halo make halo like glitch high charity begin ...
4094	0	hipocrite doubt isolated incident evidence lon...

In [64]:
```
# 15.1. Separate the comments from the test set that the model identified as toxic
# Label 1 identifies as 'Toxic'
toxic = df.groupby('Toxicity').get_group(1)
print(toxic.shape)
```

```
(153, 2)
```

In [65]:
```
# 15.2. Make one large list of all the terms
all_words = []
for t in toxic['Comments']:
    all_words.extend(t.split())
```

In [66]:
```

# 15.3. Get the top 15 terms
Plot_FreqDist(all_words, 15)
```


Top 25 most common words
Counts
500
400
300
200
100
Samples
fuck
suck
mexican
jim
wale
die
fucking
shit
eat
admins
cocksucking
cunt
like
people
freak