Malignant Comments Classifier Project

By

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Introduction

Online platforms when used by normal people can only be comfortably used by them only when they feel that they can express themselves freely and without any reluctance. If they come across any kind of a malignant or toxic type of a reply which can also be a threat or an insult or any kind of harassment which makes them uncomfortable, they might defer to use the social media platform in future. Thus, it becomes extremely essential for any organization or community to have an automated system which can efficiently identify and keep a track of all such comments and thus take any respective action for it, such as reporting or blocking the same to prevent any such kind of issues in the future.

Problem Statement

The proliferation of social media enables people to express their opinions widely online. However, at the same time, this has resulted in the emergence of conflict and hate, making online environments uninviting for users. Although researchers have found that hate is a problem across multiple platforms, there is a lack of models for online hate detection.

Online hate, described as abusive language, aggression, cyberbullying, hatefulness and many others has been identified as a major threat on online social media platforms. Social media platforms are the most prominent grounds for such toxic behaviour.

There has been a remarkable increase in the cases of cyberbullying and trolls on various social media platforms. Many celebrities and influences are facing backlashes from people and have to come across hateful and offensive comments. This can take a toll on anyone and affect them mentally leading to depression, mental illness, self-hatred and suicidal thoughts.

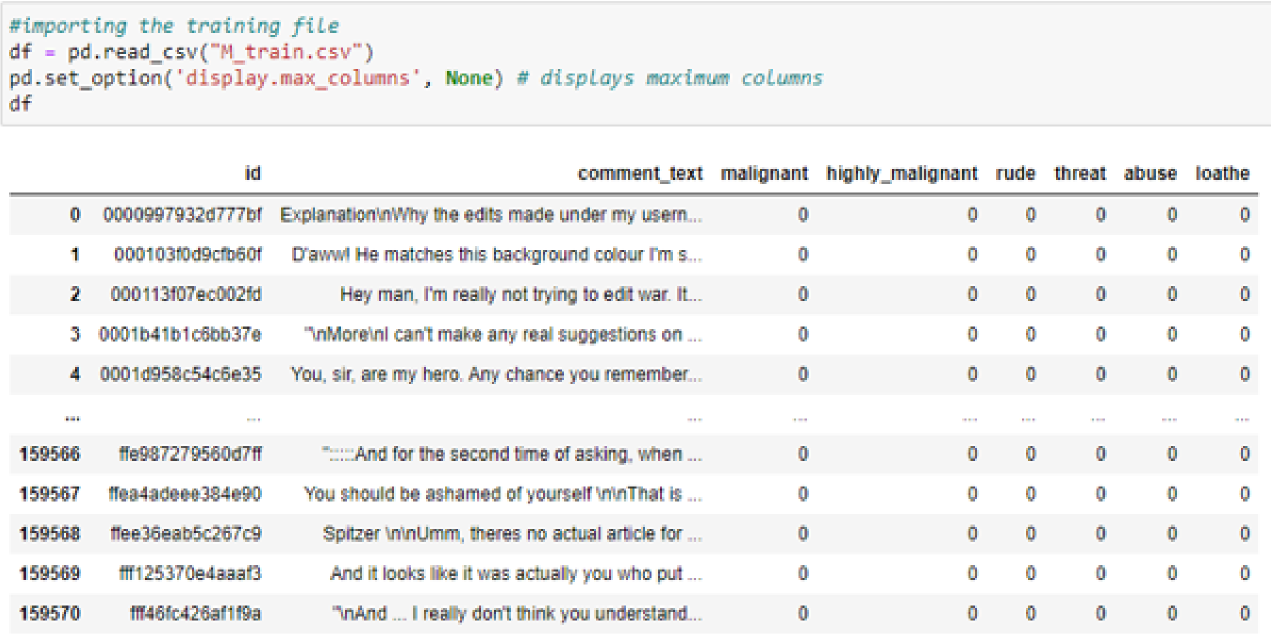
Internet comments are bastions of hatred and vitriol. While online anonymity has provided a new outlet for aggression and hate speech, machine learning can be used to fight it. The problem we sought to solve was the tagging of internet comments that are aggressive towards other users. This means that insults to third parties such as celebrities will be tagged as unoffensive, but “u are an idiot” is clearly offensive.

Our goal is to build a prototype of online hate and abuse comment classifier which can used to classify hate and offensive comments so that it can be controlled and restricted from spreading hatred and cyberbullying.

Dataset

- The data set contains the training set, which has approximately 1,59,571 samples and the test set which contains nearly 1,53,162 samples.
- We need to train the model using training set and predict the test set.

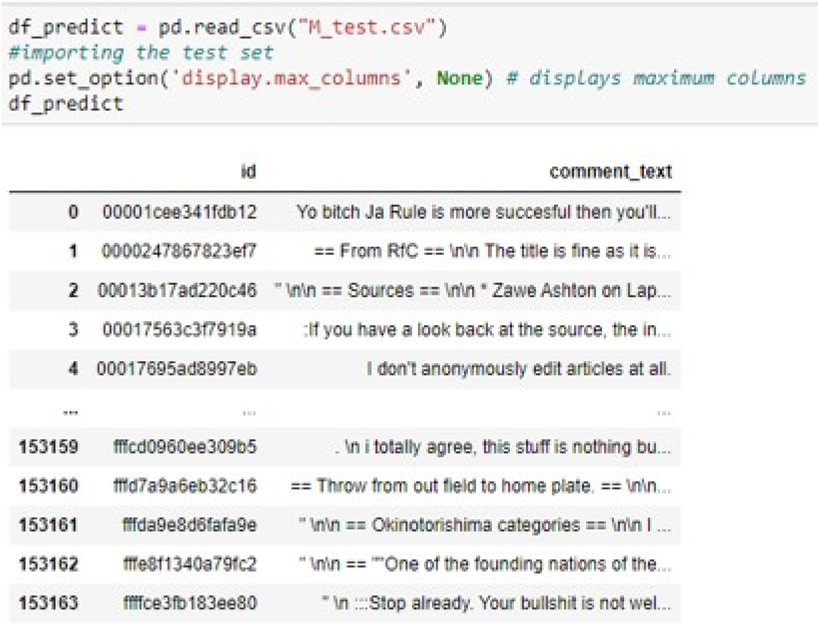
Sample of training set:



```
#importing the training file
df = pd.read_csv("M_train.csv")
pd.set_option('display.max_columns', None) # displays maximum columns
df
```

	id	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
0	0000997932d777bf	Explanation\nWhy the edits made under my usern...	0	0	0	0	0	0
1	000103f0d9cfb60f	D'aww! He matches this background colour I'm s...	0	0	0	0	0	0
2	000113f07ec002fd	Hey man, I'm really not trying to edit war. It...	0	0	0	0	0	0
3	0001b41b1c6bb37e	"\nMore\nI can't make any real suggestions on ...	0	0	0	0	0	0
4	0001d958c54c6e35	You, sir, are my hero. Any chance you remember...	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...
159566	ffe987279560d7ff	":::::And for the second time of asking, when ...	0	0	0	0	0	0
159567	ffea4adeee384e90	You should be ashamed of yourself \n\nThat is ...	0	0	0	0	0	0
159568	ffee36eab5c267c9	Spitzer \n\nUmm, theres no actual article for ...	0	0	0	0	0	0
159569	fff125370e4aaaf3	And it looks like it was actually you who put ...	0	0	0	0	0	0
159570	fff46fc426af1f9a	"\nAnd ... I really don't think you understand...	0	0	0	0	0	0

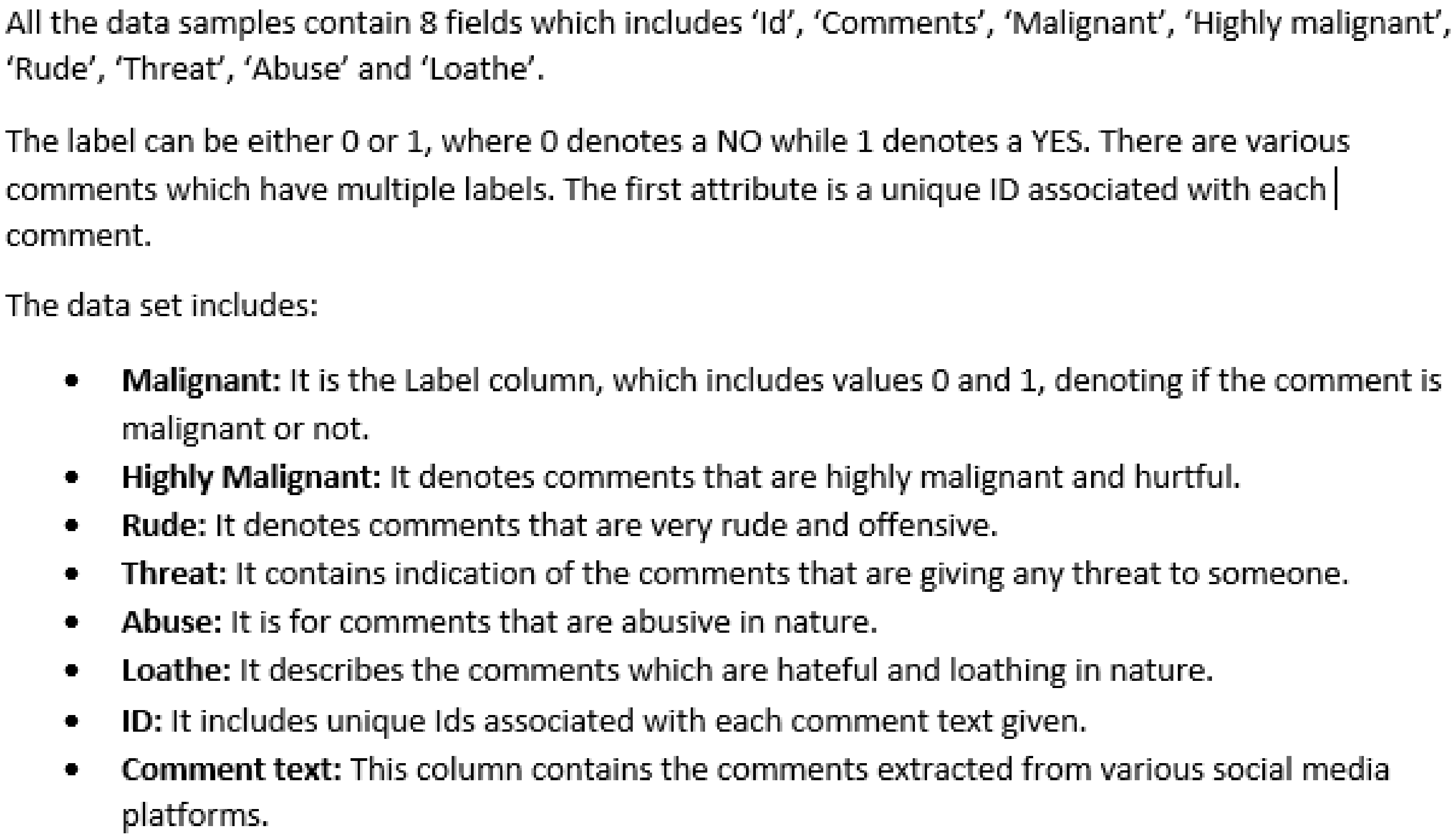
Sample of test set:



```
df_predict = pd.read_csv("M_test.csv")
#importing the test set
pd.set_option('display.max_columns', None) # displays maximum columns
df_predict
```

	id	comment_text
0	00001cee341fdb12	Yo bitch Ja Rule is more succesful then you'll...
1	0000247867823ef7	== From RfC == \n\n The title is fine as it is...
2	00013b17ad220c46	" \n\n == Sources == \n\n * Zawe Ashton on Lap...
3	00017563c3f7919a	:If you have a look back at the source, the in...
4	00017695ad8997eb	I don't anonymously edit articles at all.
...	...	...
153159	fffcd0960ee309b5	. \n i totally agree, this stuff is nothing bu...
153160	fffd7a9a6eb32c16	== Throw from out field to home plate. == \n\n...
153161	fffda9e8d6fafa9e	" \n\n == Okinotorishima categories == \n\n I ...
153162	fffe8f1340a79fc2	" \n\n == "'One of the founding nations of the...
153163	ffffce3fb183ee80	" \n :::Stop already. Your bullshit is not wel...

Data Sources and their formats

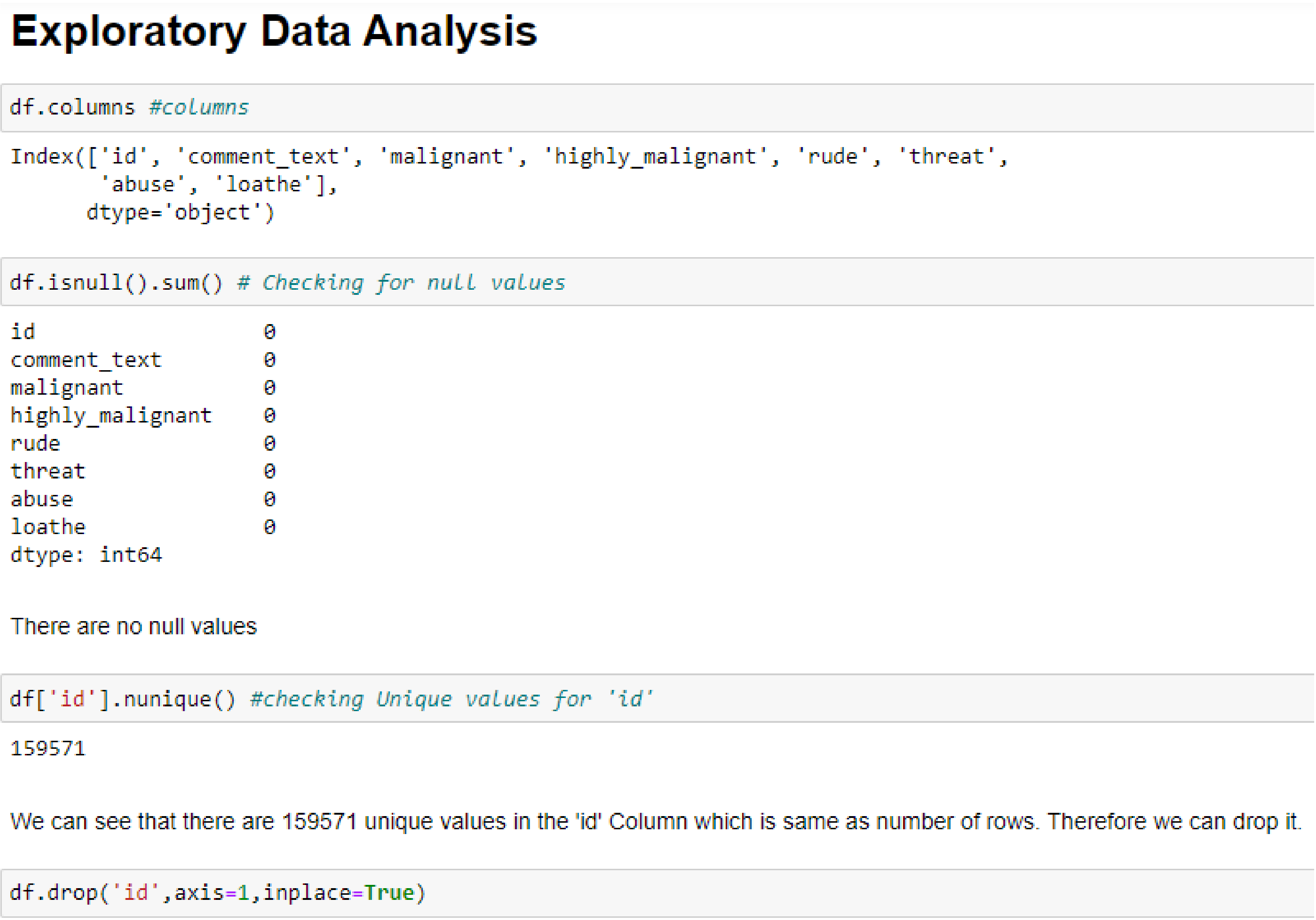


All the data samples contain 8 fields which includes ‘Id’, ‘Comments’, ‘Malignant’, ‘Highly malignant’, ‘Rude’, ‘Threat’, ‘Abuse’ and ‘Loathe’.

The label can be either 0 or 1, where 0 denotes a NO while 1 denotes a YES. There are various comments which have multiple labels. The first attribute is a unique ID associated with each comment.

The data set includes:

- **Malignant:** It is the Label column, which includes values 0 and 1, denoting if the comment is malignant or not.
- **Highly Malignant:** It denotes comments that are highly malignant and hurtful.
- **Rude:** It denotes comments that are very rude and offensive.
- **Threat:** It contains indication of the comments that are giving any threat to someone.
- **Abuse:** It is for comments that are abusive in nature.
- **Loathe:** It describes the comments which are hateful and loathing in nature.
- **ID:** It includes unique Ids associated with each comment text given.
- **Comment text:** This column contains the comments extracted from various social media platforms.



Exploratory Data Analysis

```
df.columns #columns
```

```
Index(['id', 'comment_text', 'malignant', 'highly_malignant', 'rude', 'threat',
       'abuse', 'loathe'],
      dtype='object')
```

```
df.isnull().sum() # Checking for null values
```

```
id                  0
comment_text        0
malignant           0
highly_malignant    0
rude                0
threat              0
abuse               0
loathe              0
dtype: int64
```

There are no null values

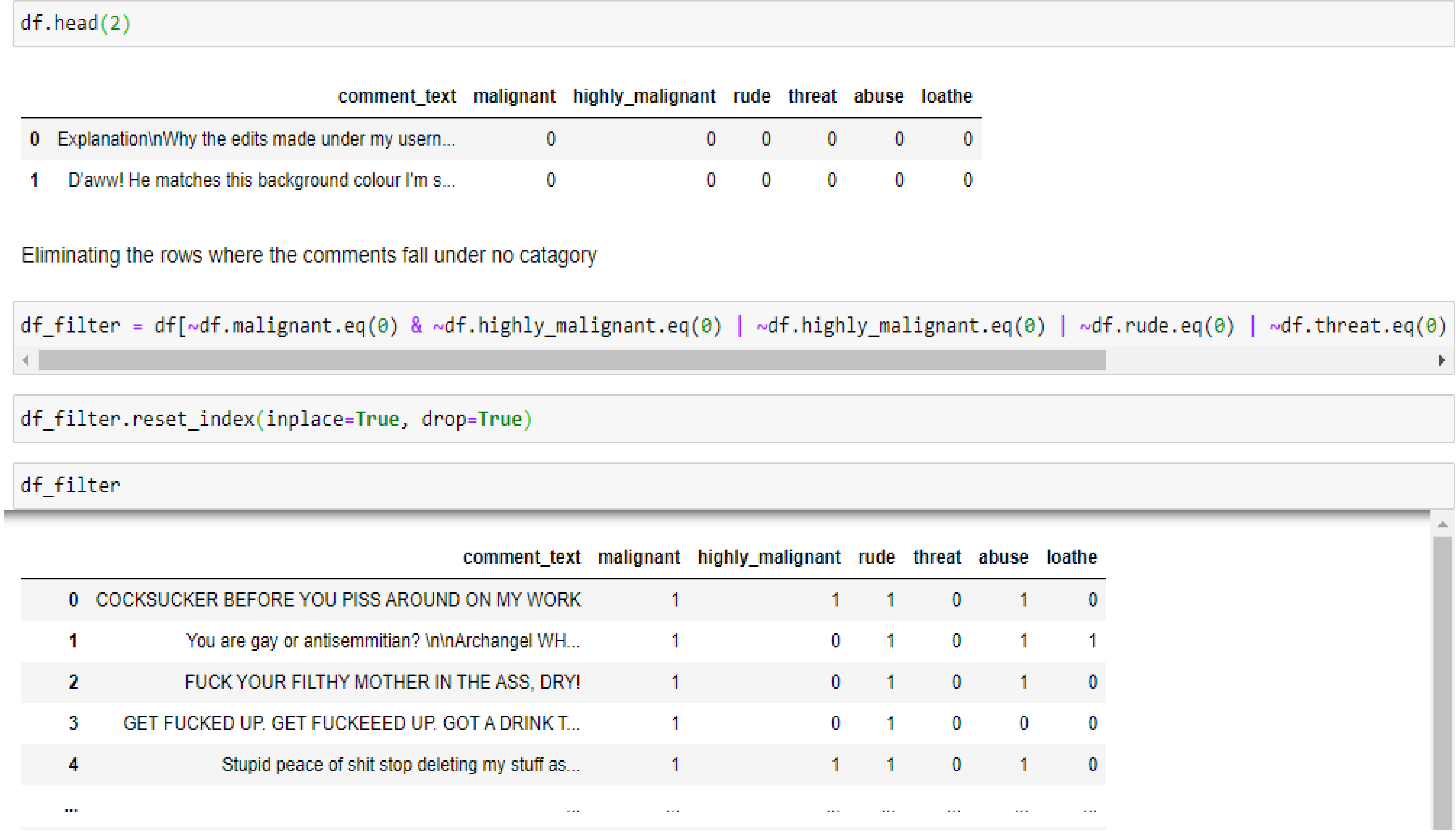
```
df['id'].nunique() #checking Unique values for 'id'
```

```
159571
```

We can see that there are 159571 unique values in the 'id' Column which is same as number of rows. Therefore we can drop it.

```
df.drop('id',axis=1,inplace=True)
```

Exploratory data analysis



```
df.head(2)
```

	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
0	Explanation\nWhy the edits made under my usern...	0	0	0	0	0	0
1	D'aww! He matches this background colour I'm s...	0	0	0	0	0	0

Eliminating the rows where the comments fall under no catagory

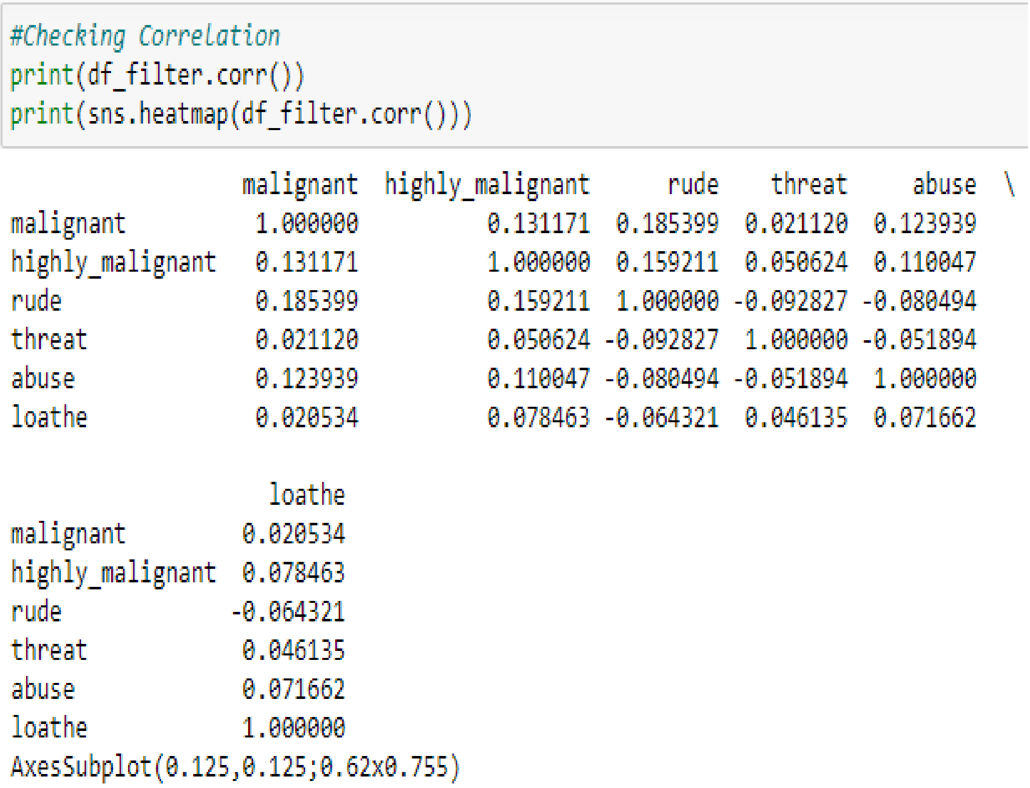
```
df_filter = df[~df.malignant.eq(0) & ~df.highly_malignant.eq(0) | ~df.highly_malignant.eq(0) | ~df.rude.eq(0) | ~df.threat.eq(0)
```

```
df_filter.reset_index(inplace=True, drop=True)
```

```
df_filter
```

	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
0	COCKSUCKER BEFORE YOU PISS AROUND ON MY WORK	1	1	1	0	1	0
1	You are gay or antisemmitian? \n\nArchangel WH...	1	0	1	0	1	1
2	FUCK YOUR FILTHY MOTHER IN THE ASS, DRY!	1	0	1	0	1	0
3	GET FUCKED UP. GET FUCKEEED UP. GOT A DRINK T...	1	0	1	0	0	0
4	Stupid peace of shit stop deleting my stuff as...	1	1	1	0	1	0
...	...	...	...	...	...	...	...

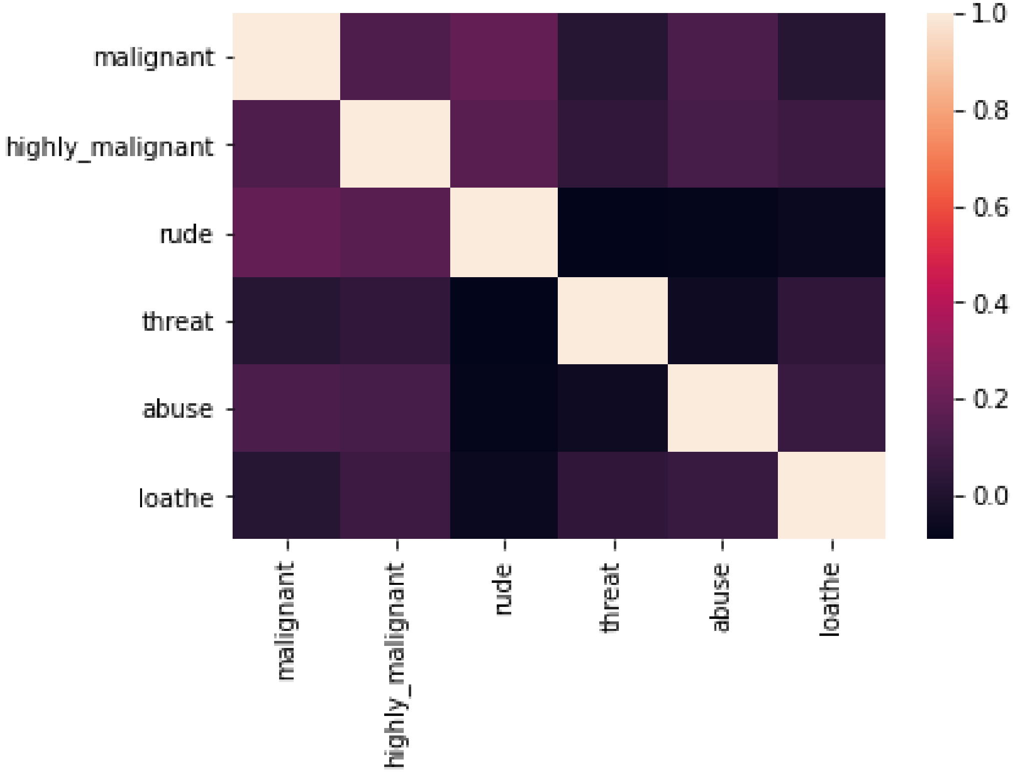
Correlation



```
#Checking Correlation
print(df_filter.corr())
print(sns.heatmap(df_filter.corr()))
```

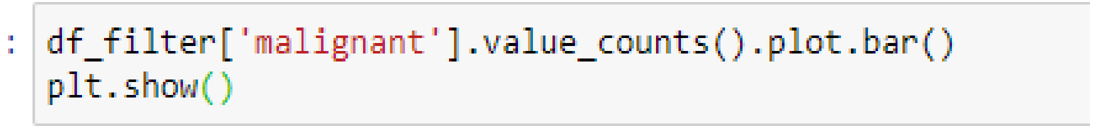
```
                 malignant  highly_malignant      rude    threat     abuse  \
malignant         1.000000          0.131171  0.185399  0.021120  0.123939
highly_malignant  0.131171          1.000000  0.159211  0.050624  0.110047
rude              0.185399          0.159211  1.000000 -0.092827 -0.080494
threat            0.021120          0.050624 -0.092827  1.000000 -0.051894
abuse             0.123939          0.110047 -0.080494 -0.051894  1.000000
loathe            0.020534          0.078463 -0.064321  0.046135  0.071662

                    loathe
malignant         0.020534
highly_malignant  0.078463
rude             -0.064321
threat            0.046135
abuse             0.071662
loathe            1.000000
AxesSubplot(0.125,0.125;0.62x0.755)
```

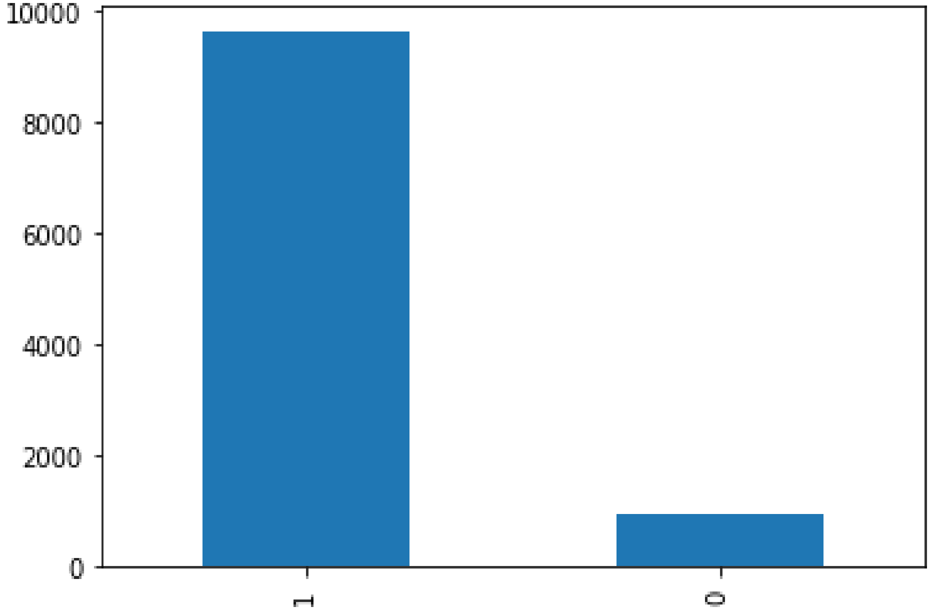


We can see that the correlation is not high between independent variables

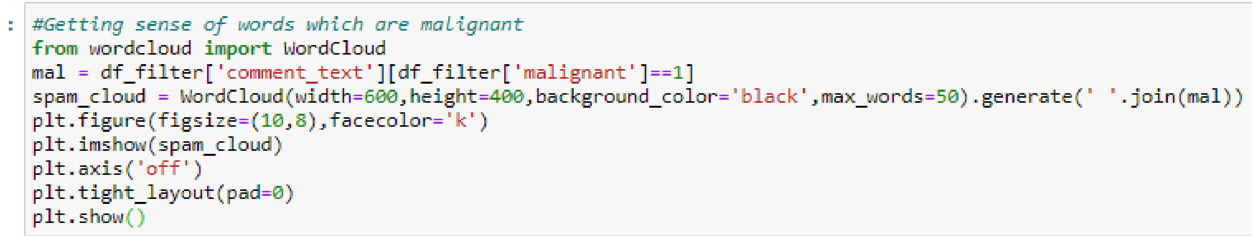
Malignant



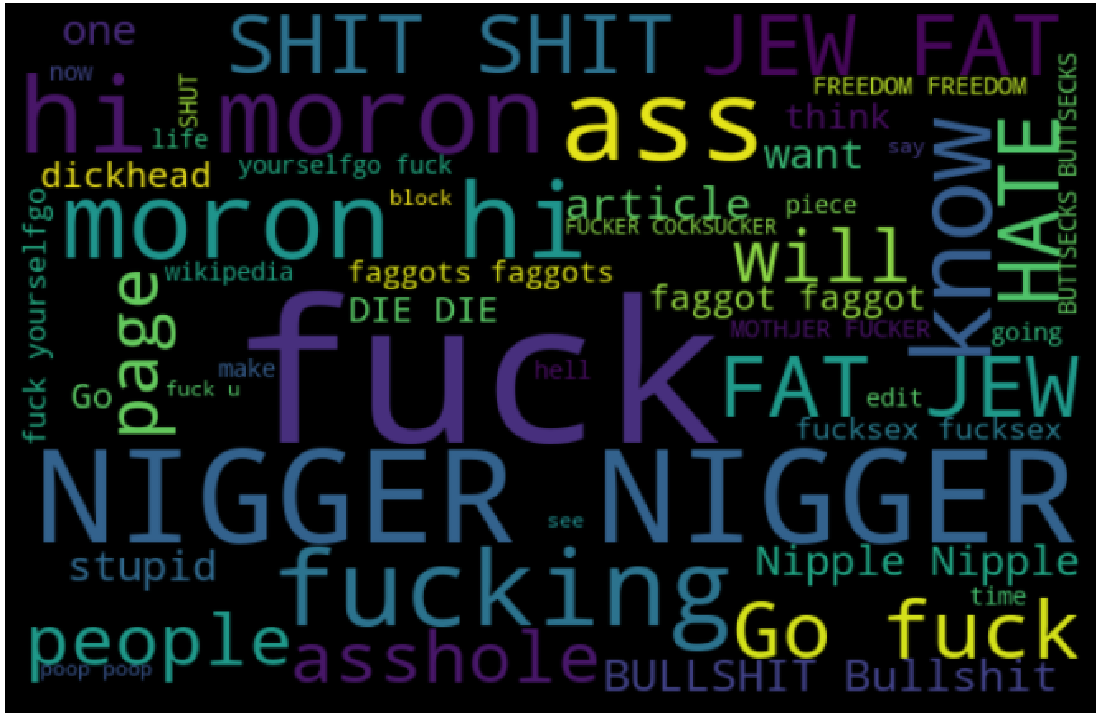
```
df_filter['malignant'].value_counts().plot.bar()
plt.show()
```



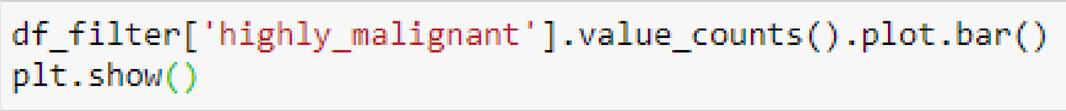
we can see that maximum of the comments fall under malignant



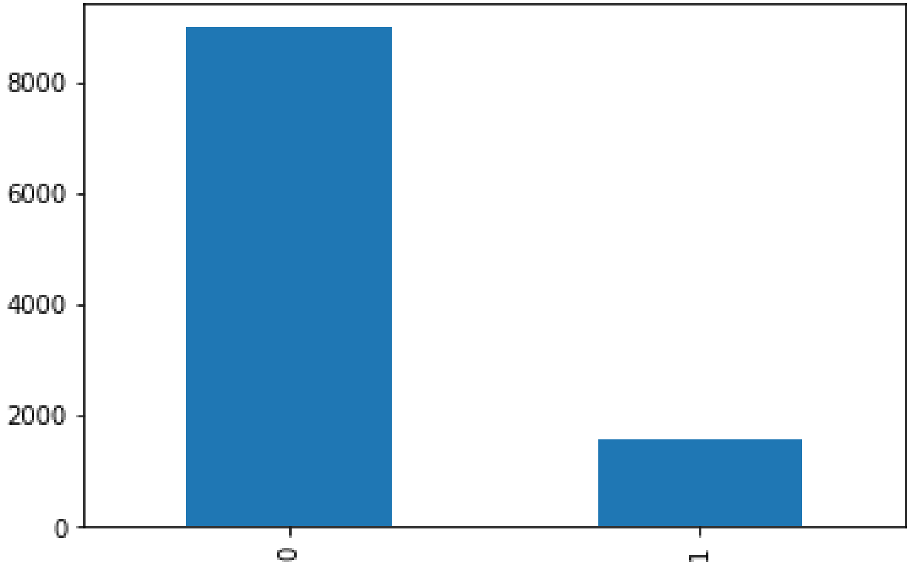
```
#Getting sense of words which are malignant
from wordcloud import WordCloud
mal = df_filter['comment_text'][df_filter['malignant']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



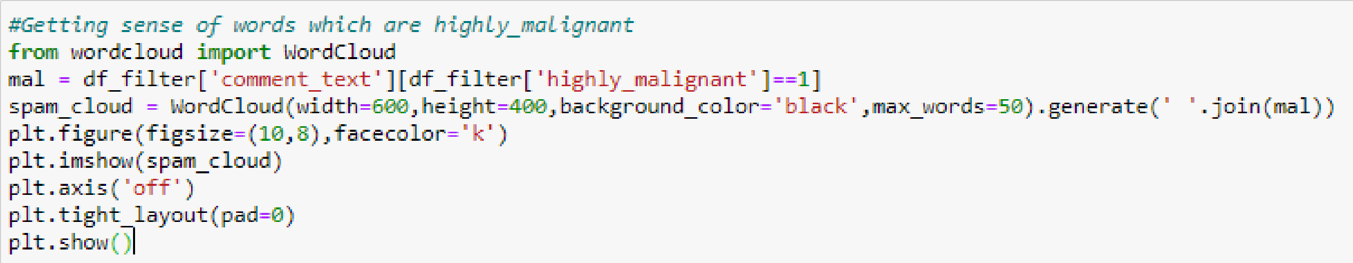
Highly Malignant



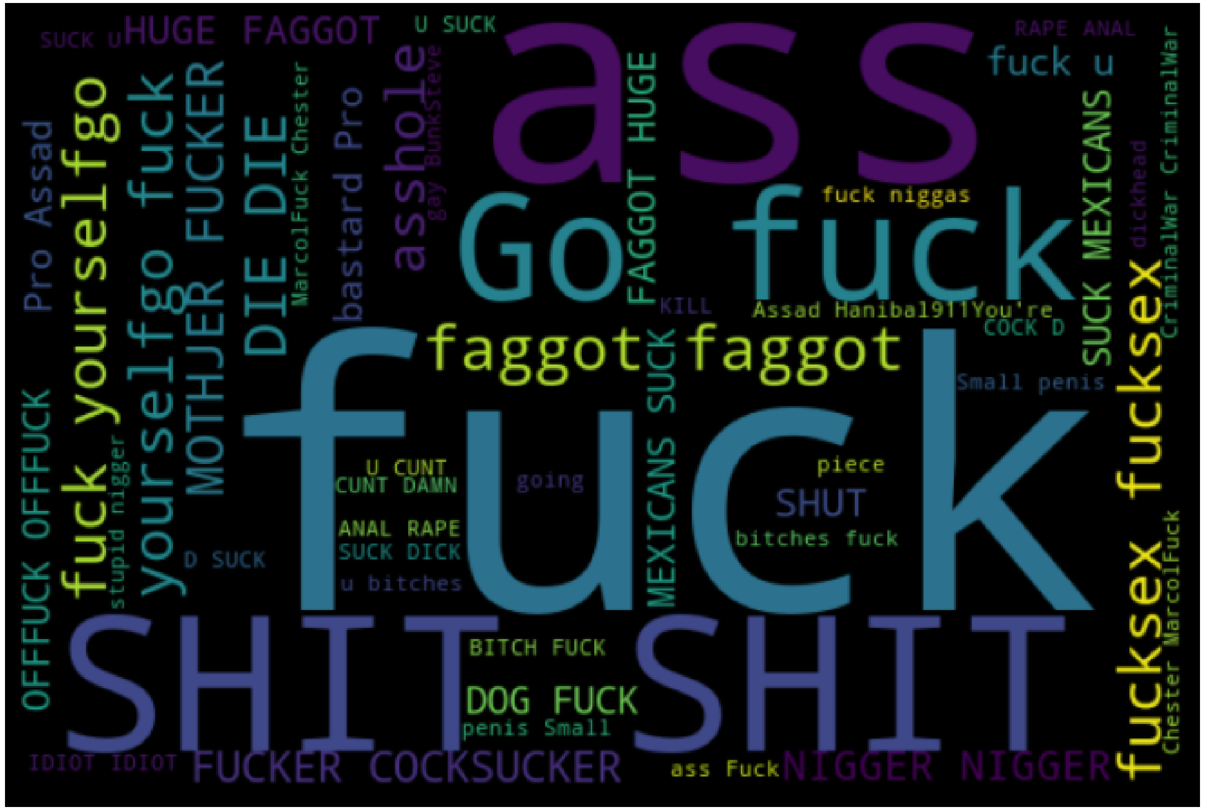
```
df_filter['highly_malignant'].value_counts().plot.bar()
plt.show()
```



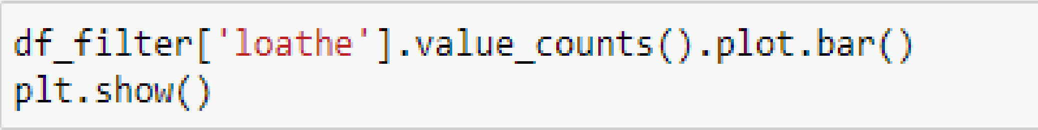
We can see that there are less no of highly_malignant comments



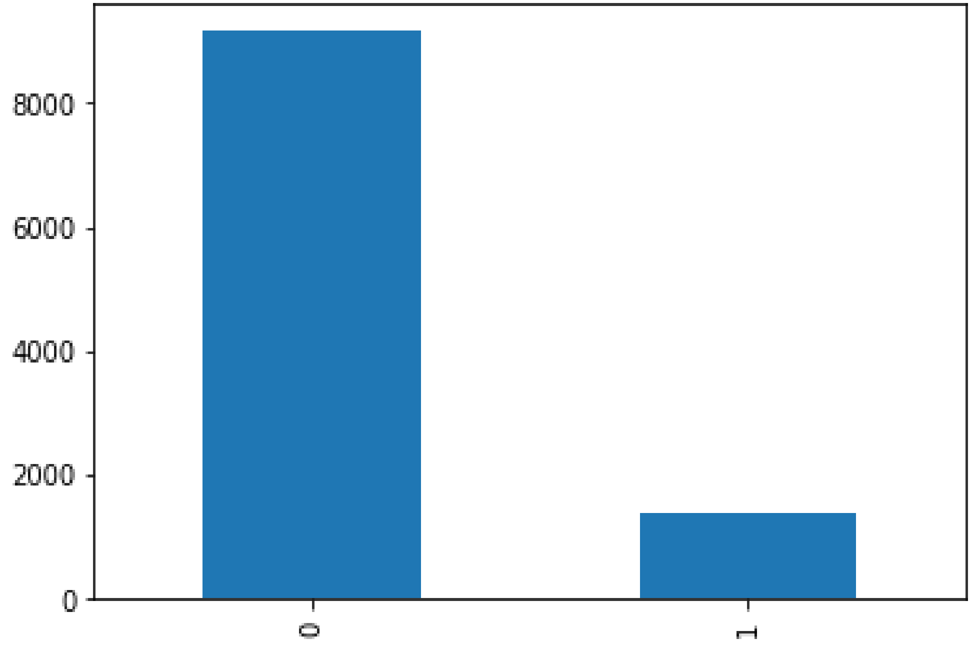
```
#Getting sense of words which are highly_malignant
from wordcloud import WordCloud
mal = df_filter['comment_text'][df_filter['highly_malignant']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



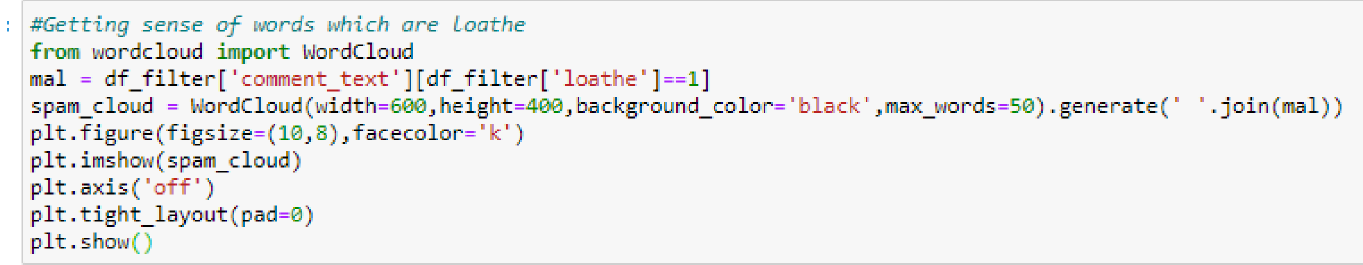
Loathe



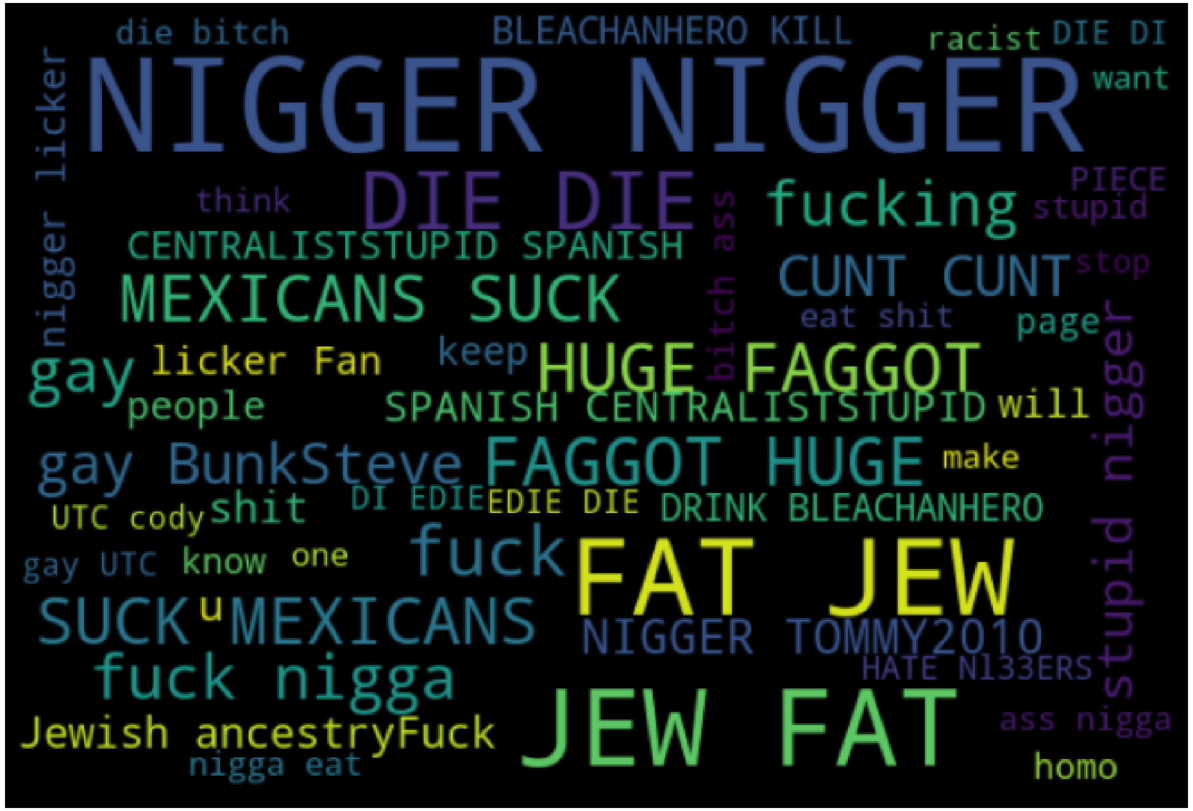
```
df_filter['loathe'].value_counts().plot.bar()
plt.show()
```



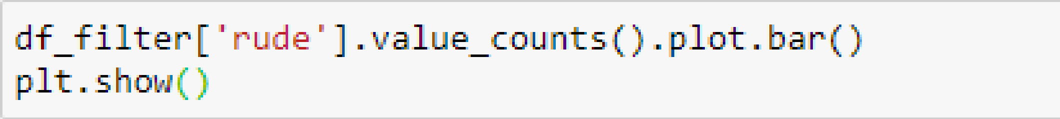
We can see that there are less no of loathe comments



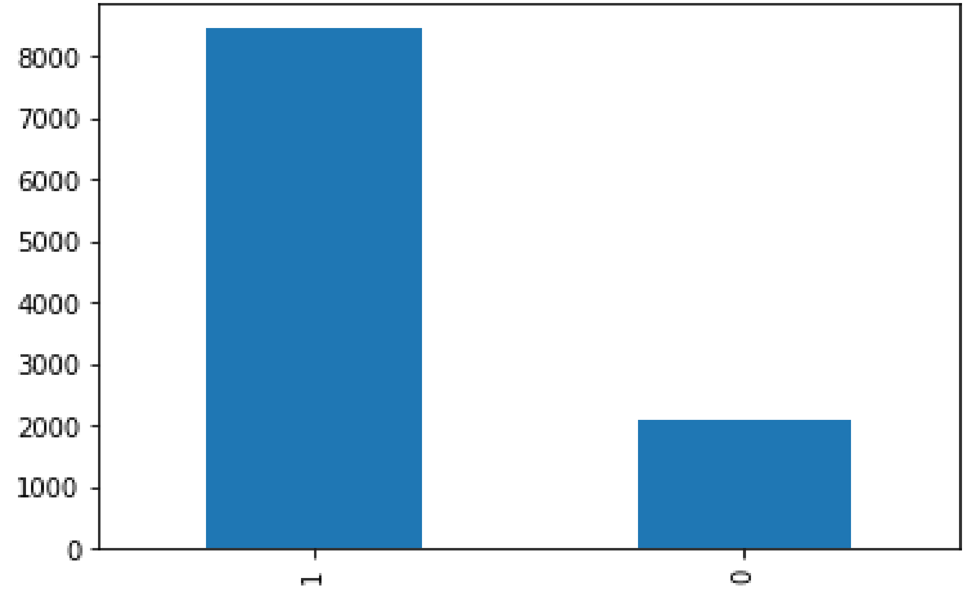
```
#Getting sense of words which are loathe
from wordcloud import WordCloud
mal = df_filter['comment_text'][df_filter['loathe']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



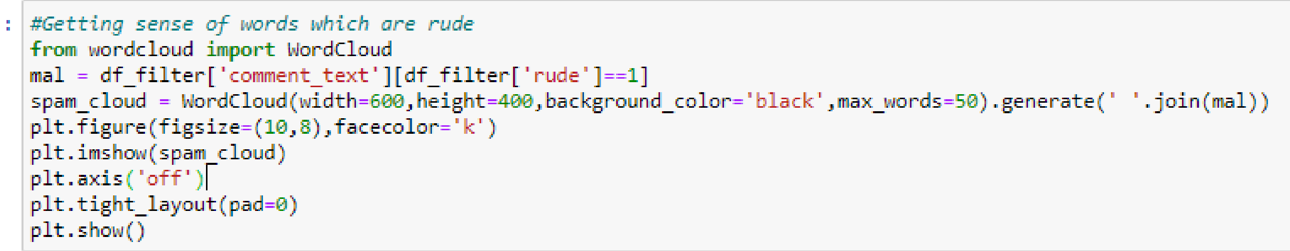
Rude



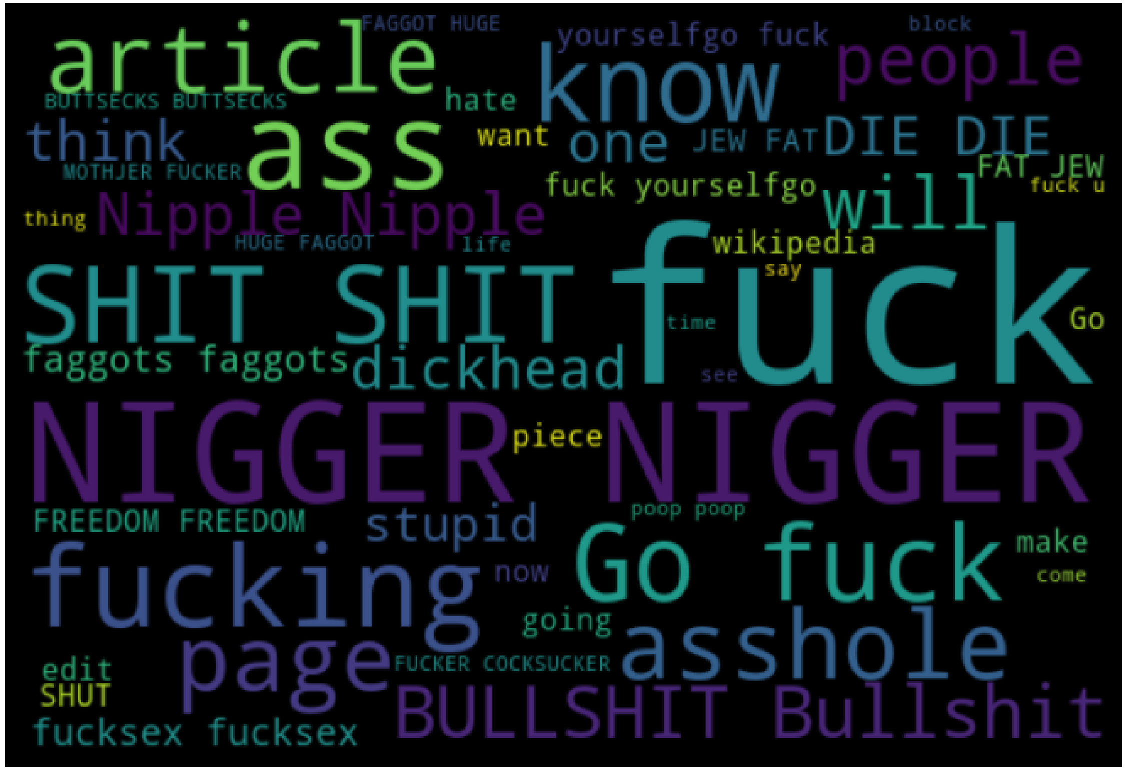
```
df_filter['rude'].value_counts().plot.bar()
plt.show()
```



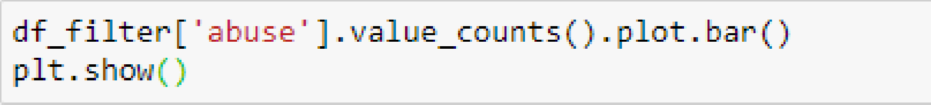
We can see that there are more no of rude comments



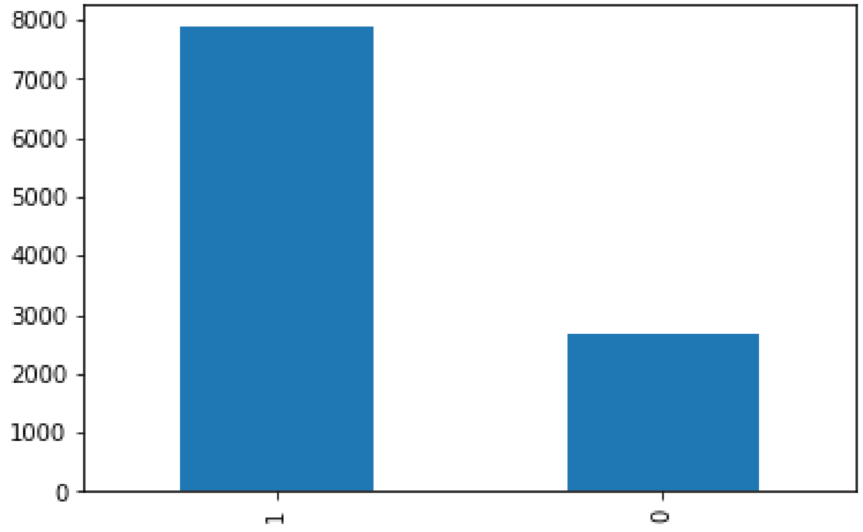
```
#Getting sense of words which are rude
from wordcloud import WordCloud
mal = df_filter['comment_text'][df_filter['rude']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



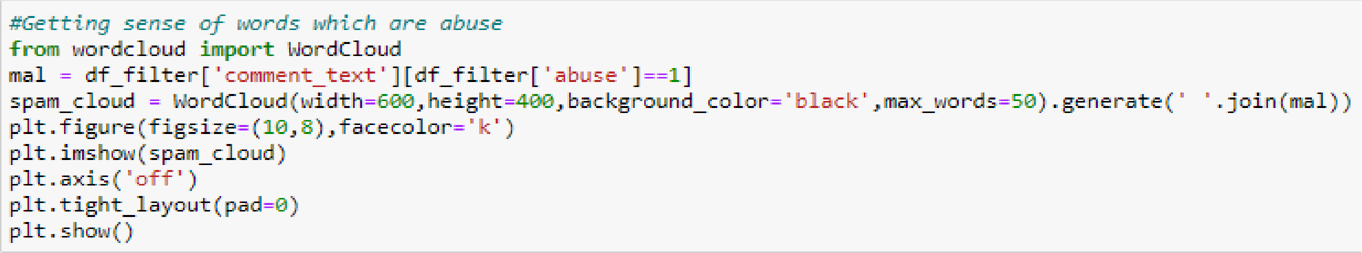
Abuse



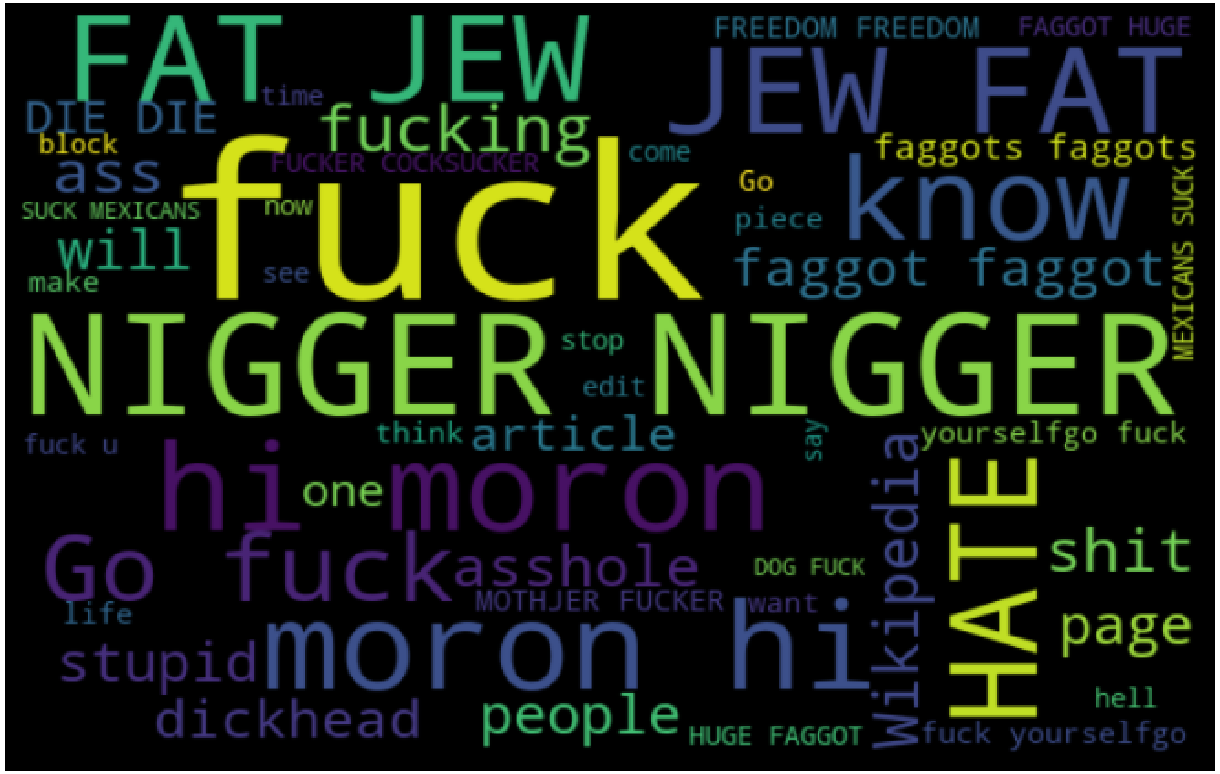
```
df_filter['abuse'].value_counts().plot.bar()
plt.show()
```



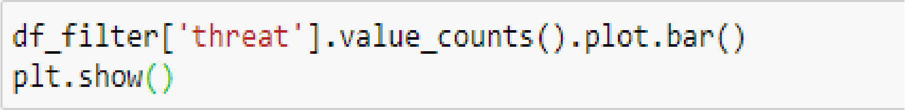
We can see that there are more no of abusive comments



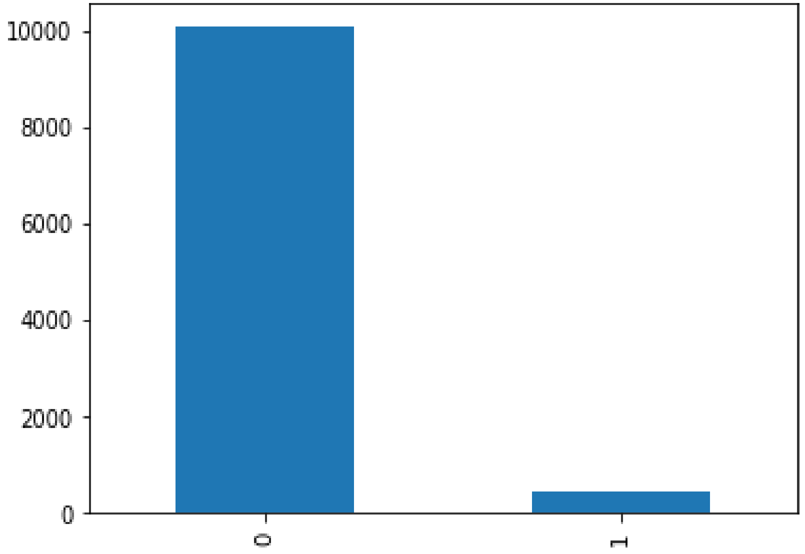
```
#Getting sense of words which are abuse
from wordcloud import WordCloud
mal = df_filter['comment_text'][df_filter['abuse']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



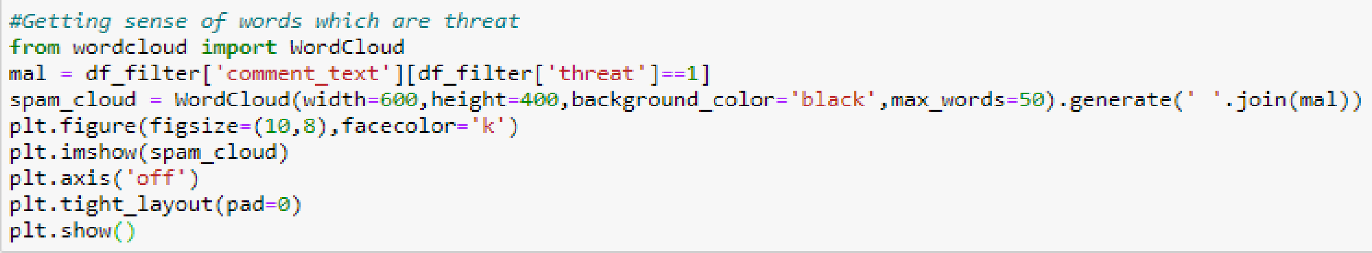
Threat



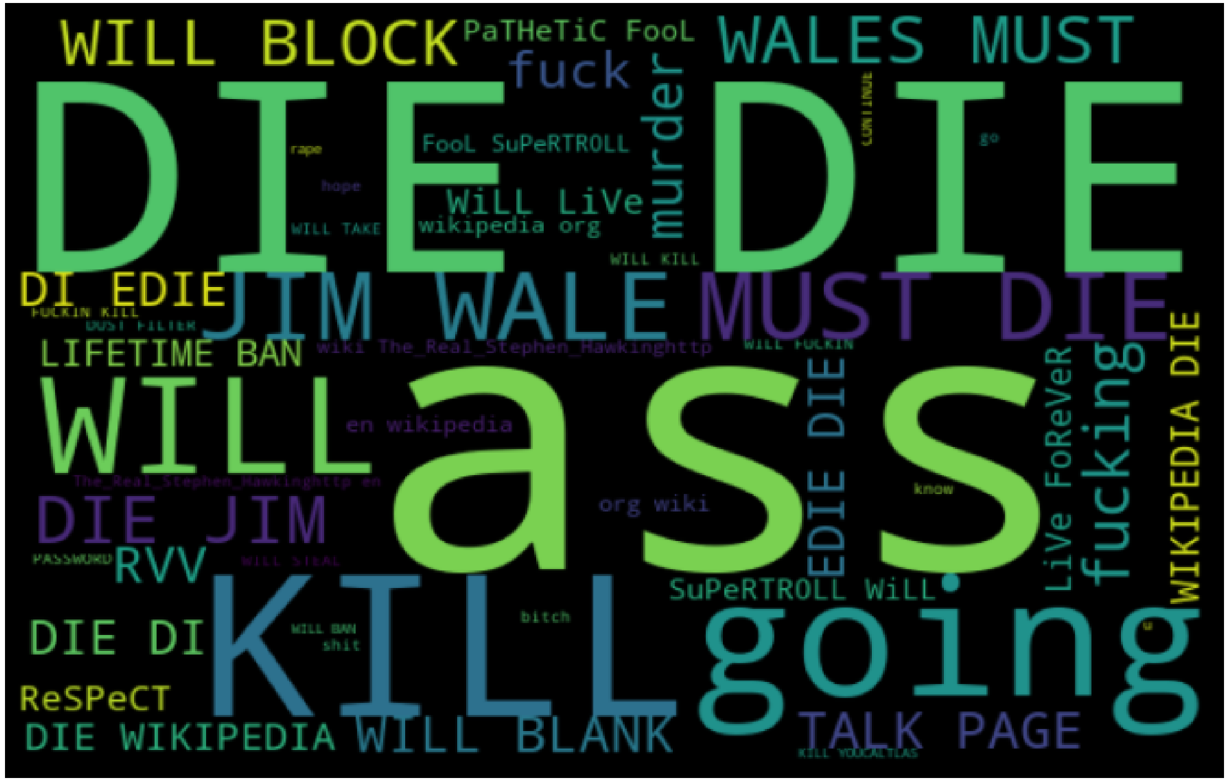
```
df_filter['threat'].value_counts().plot.bar()
plt.show()
```



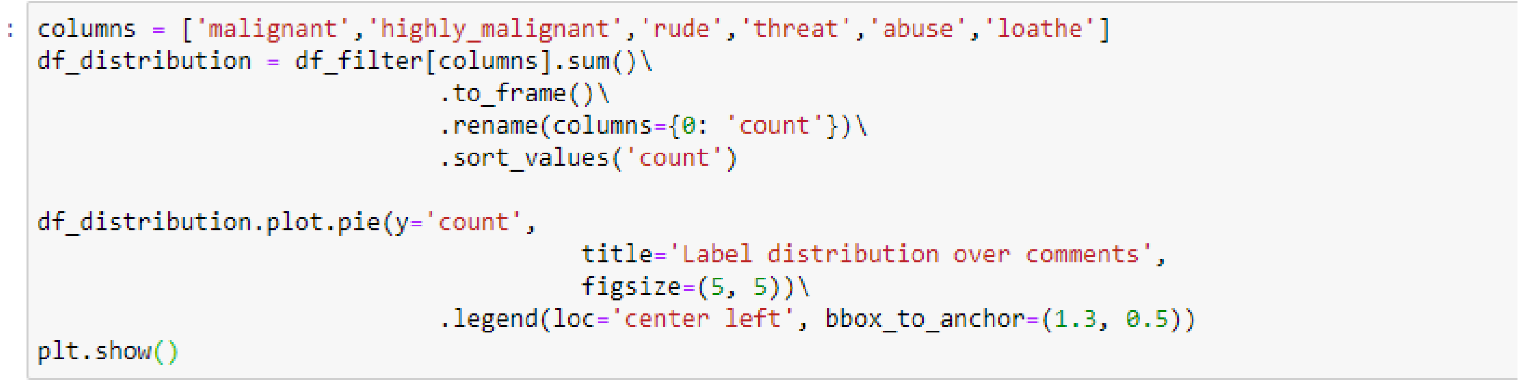
We can see that there are very few threat comments



```
#Getting sense of words which are threat
from wordcloud import WordCloud
mal = df_filter['comment_text'][df_filter['threat']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

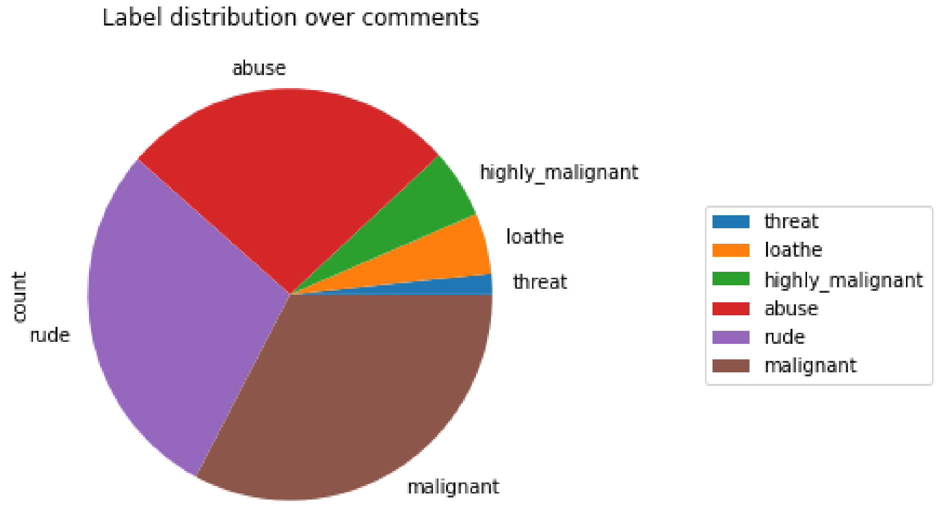


Distribution



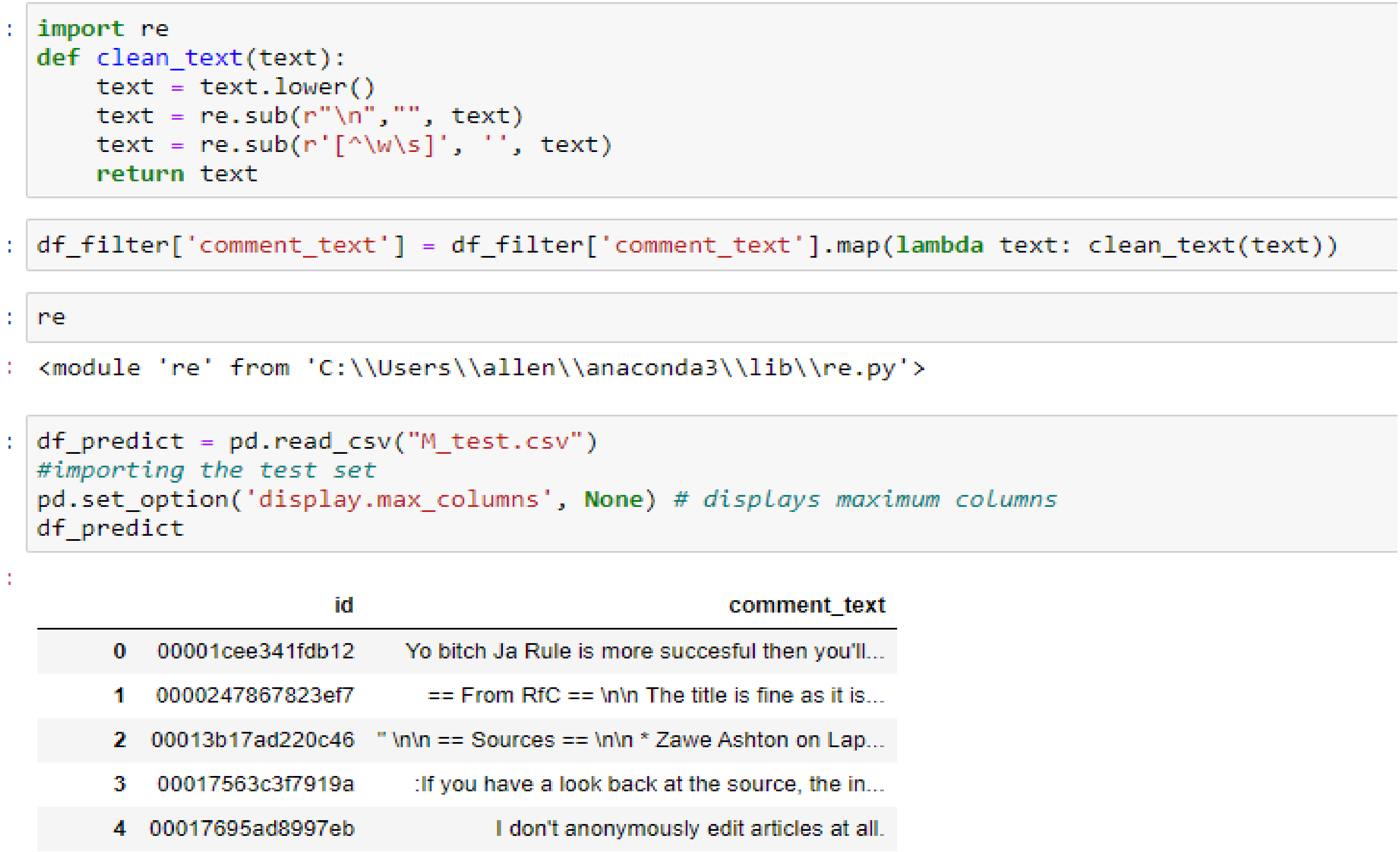
```
columns = ['malignant','highly_malignant','rude','threat','abuse','loathe']
df_distribution = df_filter[columns].sum()\
                            .to_frame()\
                            .rename(columns={0: 'count'})\
                            .sort_values('count')

df_distribution.plot.pie(y='count',
                                      title='Label distribution over comments',
                                      figsize=(5, 5))\
                            .legend(loc='center left', bbox_to_anchor=(1.3, 0.5))
plt.show()
```



We an see here that maximum of the comments are malignant, rude and abusive. The threat kind of comments are the least

Natural Language Processing



```
import re
def clean_text(text):
    text = text.lower()
    text = re.sub(r"\n","", text)
    text = re.sub(r'[^\w\s]', '', text)
    return text
```

```
df_filter['comment_text'] = df_filter['comment_text'].map(lambda text: clean_text(text))
```

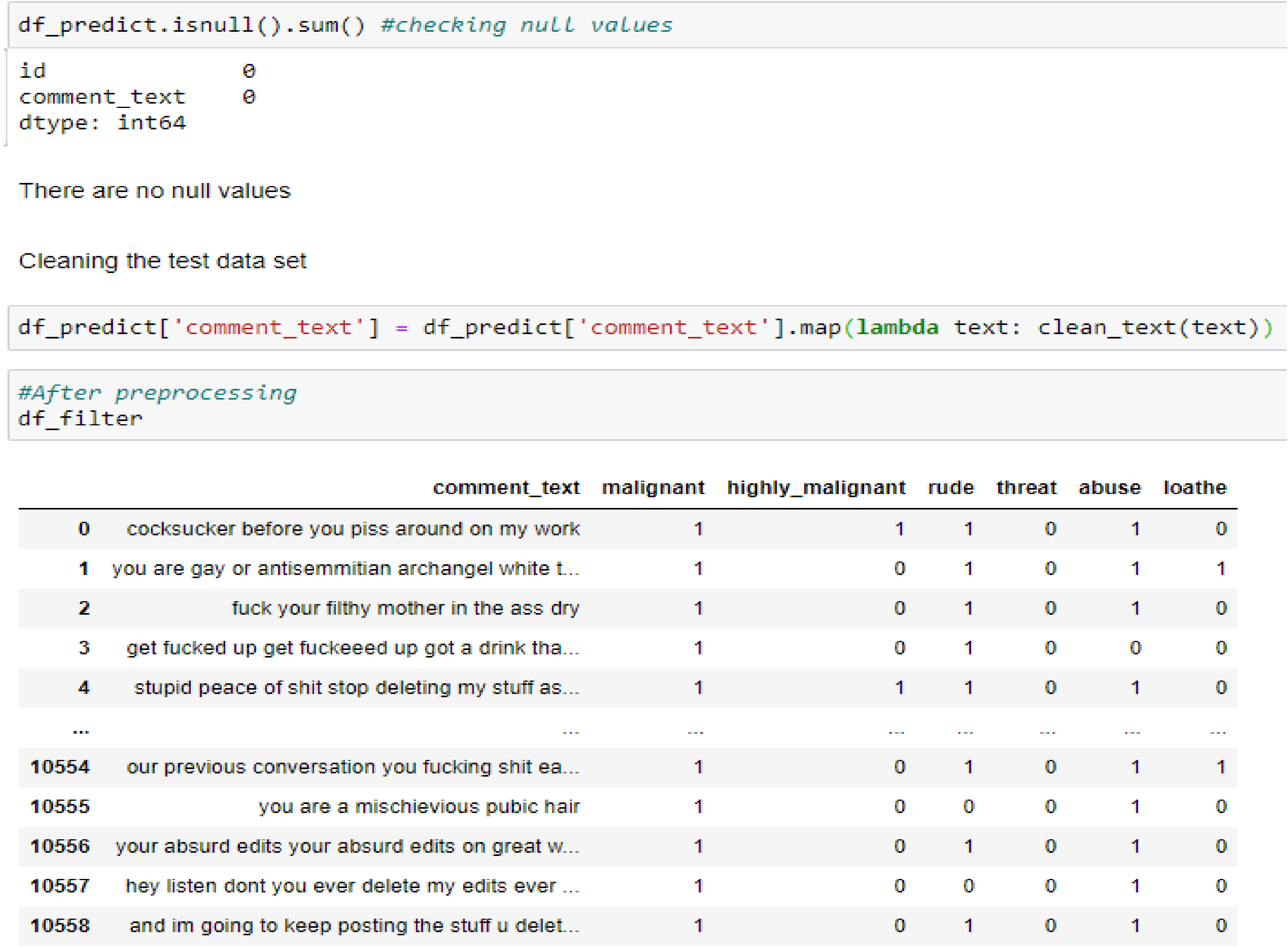
```
re
```

```
<module 're' from 'C:\\Users\\allen\\anaconda3\\lib\\re.py'>
```

```
df_predict = pd.read_csv("M_test.csv")
#importing the test set
pd.set_option('display.max_columns', None) # displays maximum columns
df_predict
```

	id	comment_text
0	00001cee341fdb12	Yo bitch Ja Rule is more succesful then you'll...
1	0000247867823ef7	== From RfC == \n\n The title is fine as it is...
2	00013b17ad220c46	" \n\n == Sources == \n\n * Zawe Ashton on Lap...
3	00017563c3f7919a	:If you have a look back at the source, the in...
4	00017695ad8997eb	I don't anonymously edit articles at all.

Cleaned Training Data



```
df_predict.isnull().sum() #checking null values
```

```
id              0
comment_text    0
dtype: int64
```

There are no null values

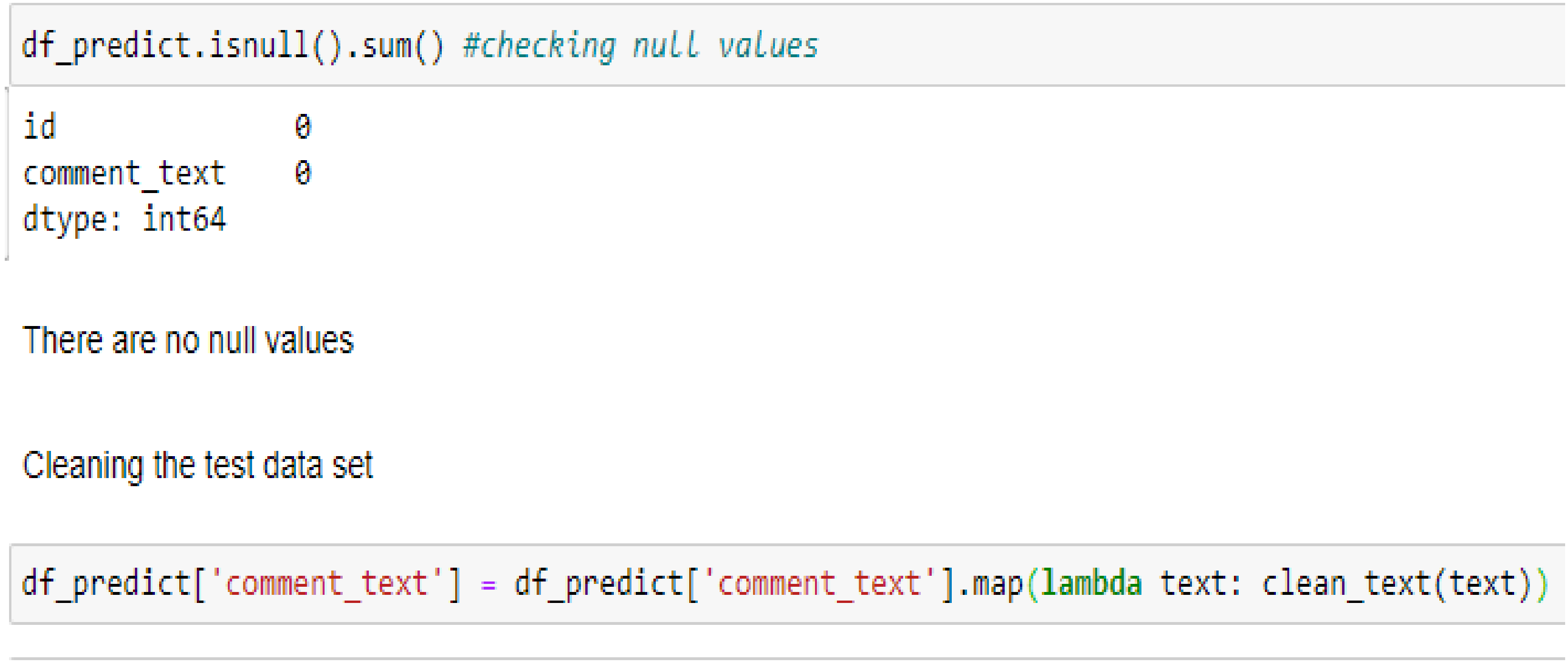
Cleaning the test data set

```
df_predict['comment_text'] = df_predict['comment_text'].map(lambda text: clean_text(text))
```

```
#After preprocessing
df_filter
```

	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
0	cocksucker before you piss around on my work	1	1	1	0	1	0
1	you are gay or antisemmitian archangel white t...	1	0	1	0	1	1
2	fuck your filthy mother in the ass dry	1	0	1	0	1	0
3	get fucked up get fuckeeed up got a drink tha...	1	0	1	0	0	0
4	stupid peace of shit stop deleting my stuff as...	1	1	1	0	1	0
...	...	...	...	...	...	...	...
10554	our previous conversation you fucking shit ea...	1	0	1	0	1	1
10555	you are a mischievious pubic hair	1	0	0	0	1	0
10556	your absurd edits your absurd edits on great w...	1	0	1	0	1	0
10557	hey listen dont you ever delete my edits ever ...	1	0	0	0	1	0
10558	and im going to keep posting the stuff u delet...	1	0	1	0	1	0

Test Data preprocessing



```
df_predict.isnull().sum() #checking null values
```

```
id              0
comment_text    0
dtype: int64
```

There are no null values

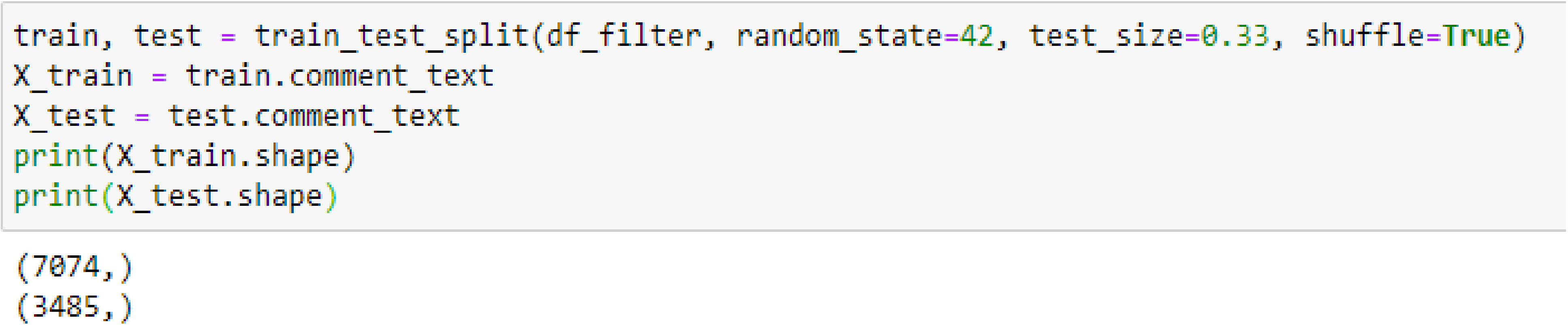
Cleaning the test data set

```
df_predict['comment_text'] = df_predict['comment_text'].map(lambda text: clean_text(text))
```

Data Inputs- Logic- Output Relationships

In the data we can see that there are 8 columns namely, 'id', 'comment_text', 'malignant', 'highly_malignant', 'rude', 'threat', 'abuse' and 'loathe'. Here the 'comment_text' column is input variable and the rest of the columns except ‘id’ are output variables. We need to train the model using training set and predict the test data set using the trained model.

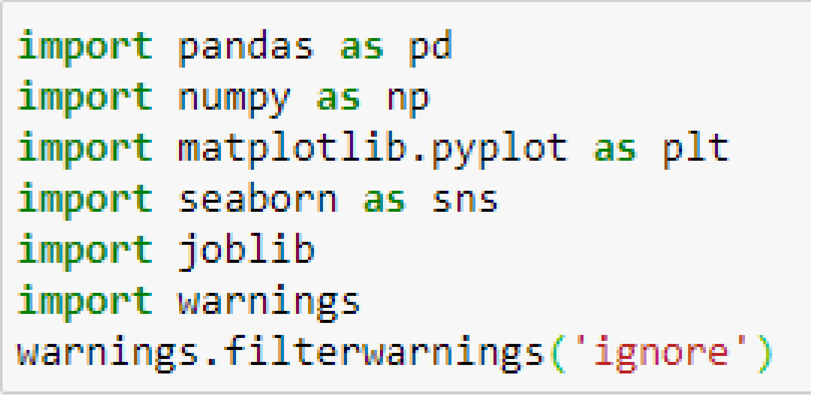
Splitting data



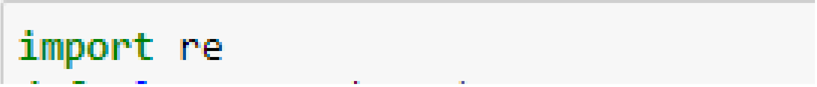
```
train, test = train_test_split(df_filter, random_state=42, test_size=0.33, shuffle=True)
X_train = train.comment_text
X_test = test.comment_text
print(X_train.shape)
print(X_test.shape)
```

```
(7074,)
(3485,)
```

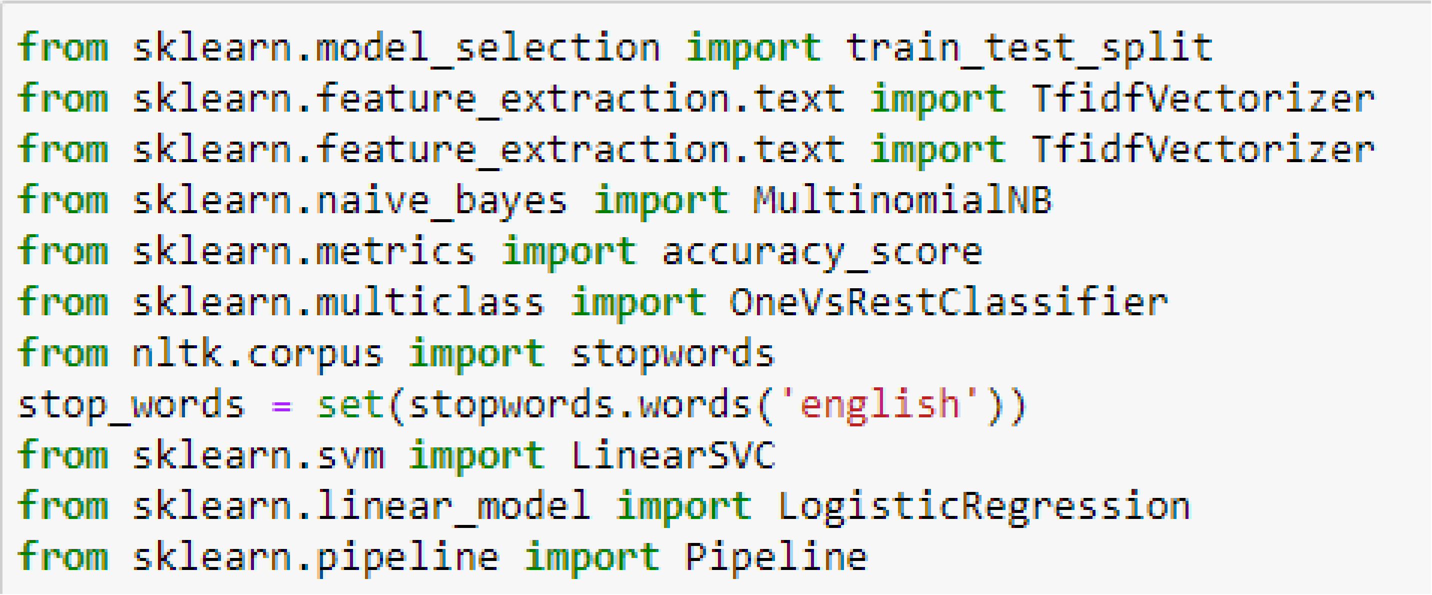
Hardware and Software Requirements and Tools Used



```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import joblib
import warnings
warnings.filterwarnings('ignore')
```



```
import re
```

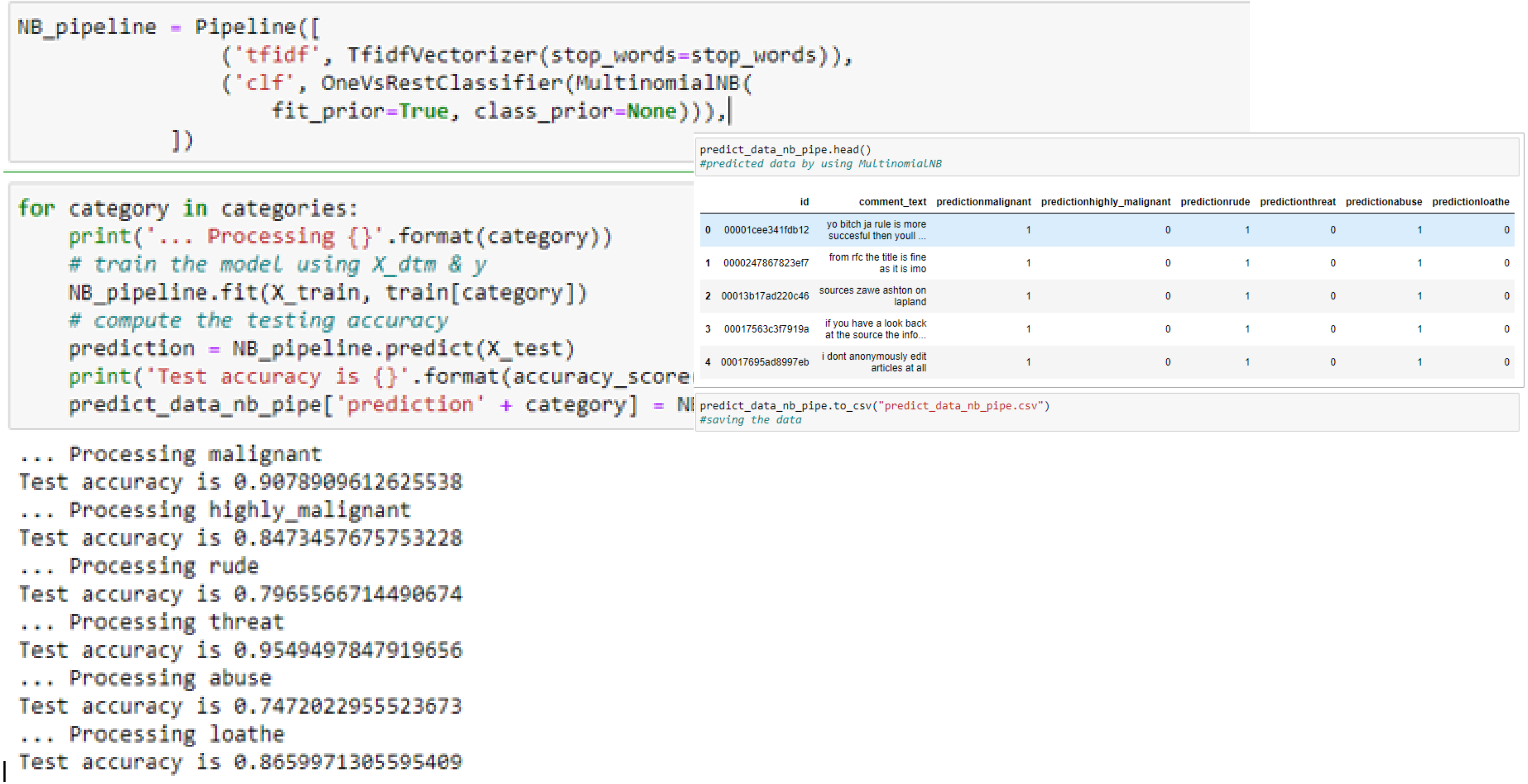


```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score
from sklearn.multiclass import OneVsRestClassifier
from nltk.corpus import stopwords
stop_words = set(stopwords.words('english'))
from sklearn.svm import LinearSVC
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
```

Algorithms used:

- Naïve bayes
- LinearSVC
- LogisticRegression

Naïve bayes



```
NB_pipeline = Pipeline([
                ('tfidf', TfidfVectorizer(stop_words=stop_words)),
                ('clf', OneVsRestClassifier(MultinomialNB(
                    fit_prior=True, class_prior=None))),
            ])
```

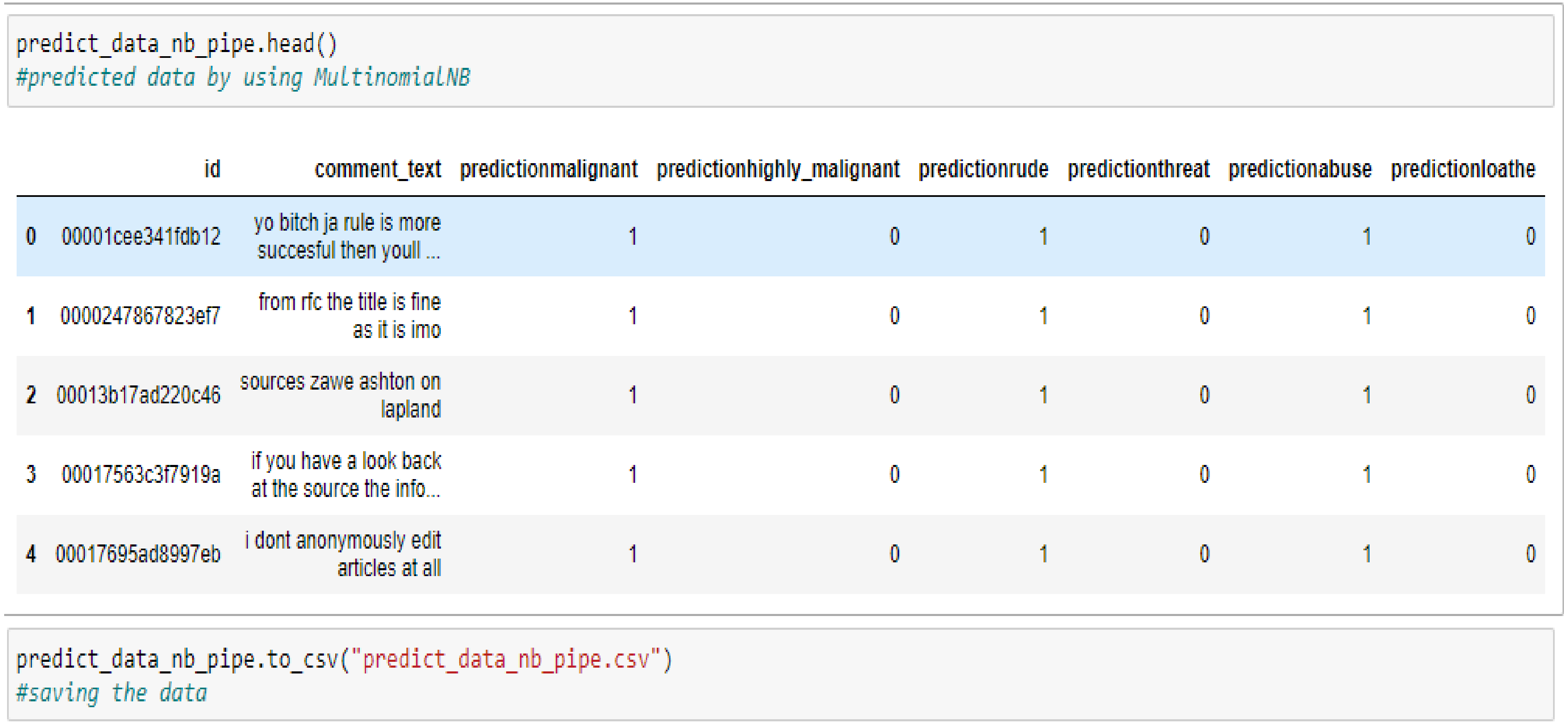
```
for category in categories:
    print('... Processing {}'.format(category))
    # train the model using X_dtm & y
    NB_pipeline.fit(X_train, train[category])
    # compute the testing accuracy
    prediction = NB_pipeline.predict(X_test)
    print('Test accuracy is {}'.format(accuracy_score
    predict_data_nb_pipe['prediction' + category] = N
```

```
... Processing malignant
Test accuracy is 0.9078909612625538
... Processing highly_malignant
Test accuracy is 0.8473457675753228
... Processing rude
Test accuracy is 0.7965566714490674
... Processing threat
Test accuracy is 0.9549497847919656
... Processing abuse
Test accuracy is 0.7472022955523673
... Processing loathe
Test accuracy is 0.8659971305595409
```

```
predict_data_nb_pipe.head()
#predicted data by using MultinomialNB
```

	id	comment_text	predictionmalignant	predictionhighly_malignant	predictionrude	predictionthreat	predictionabuse	predictionloathe
0	00001cee341fdb12	yo bitch ja rule is more succesful then youll ...	1	0	1	0	1	0
1	0000247867823ef7	from rfc the title is fine as it is imo	1	0	1	0	1	0
2	00013b17ad220c46	sources zawe ashton on lapland	1	0	1	0	1	0
3	00017563c3f7919a	if you have a look back at the source the info...	1	0	1	0	1	0
4	00017695ad8997eb	i dont anonymously edit articles at all	1	0	1	0	1	0

```
predict_data_nb_pipe.to_csv("predict_data_nb_pipe.csv")
#saving the data
```

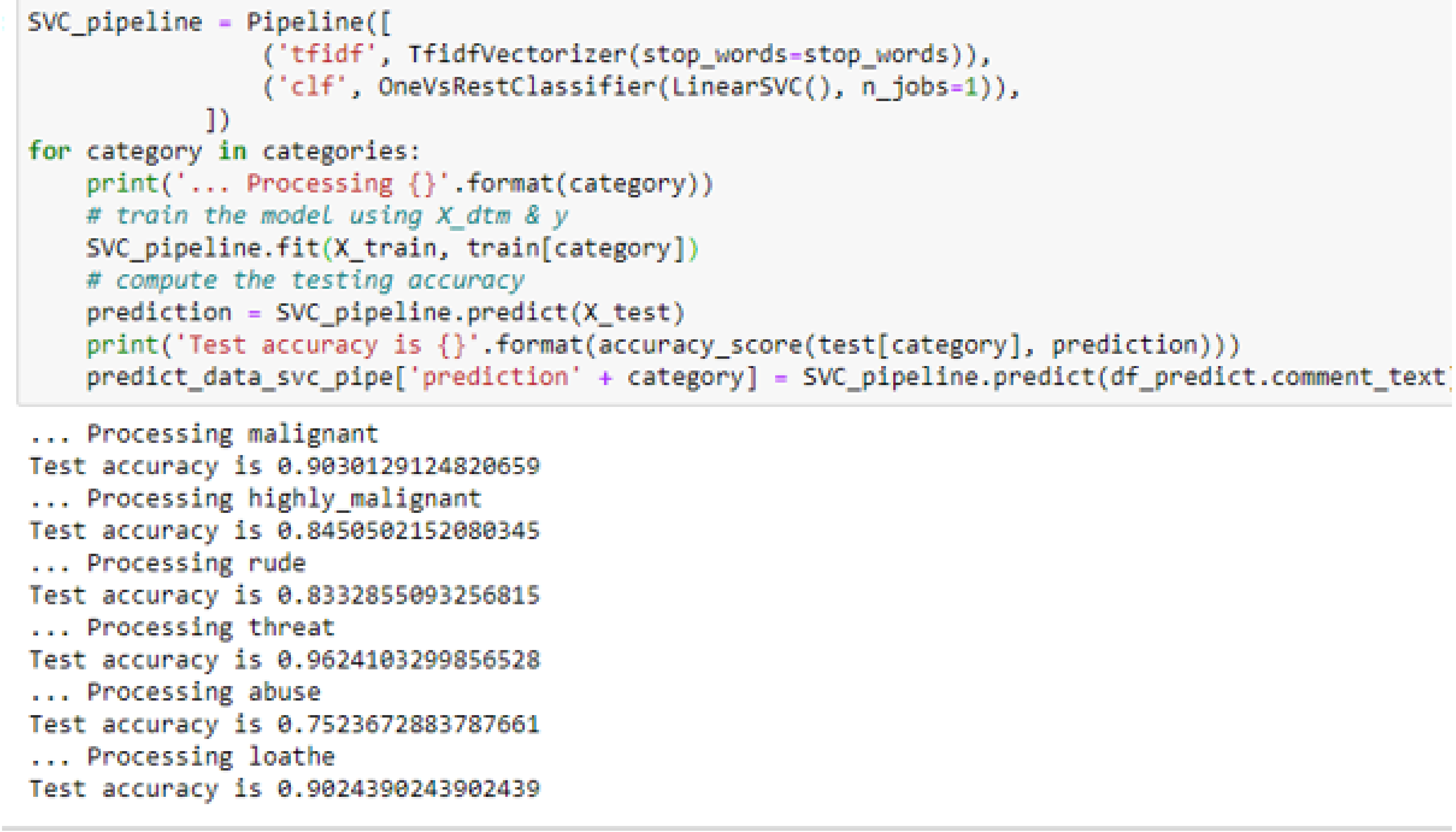


```
predict_data_nb_pipe.head()
#predicted data by using MultinomialNB
```

	id	comment_text	predictionmalignant	predictionhighly_malignant	predictionrude	predictionthreat	predictionabuse	predictionloathe
0	00001cee341fdb12	yo bitch ja rule is more succesful then youll ...	1	0	1	0	1	0
1	0000247867823ef7	from rfc the title is fine as it is imo	1	0	1	0	1	0
2	00013b17ad220c46	sources zawe ashton on lapland	1	0	1	0	1	0
3	00017563c3f7919a	if you have a look back at the source the info...	1	0	1	0	1	0
4	00017695ad8997eb	i dont anonymously edit articles at all	1	0	1	0	1	0

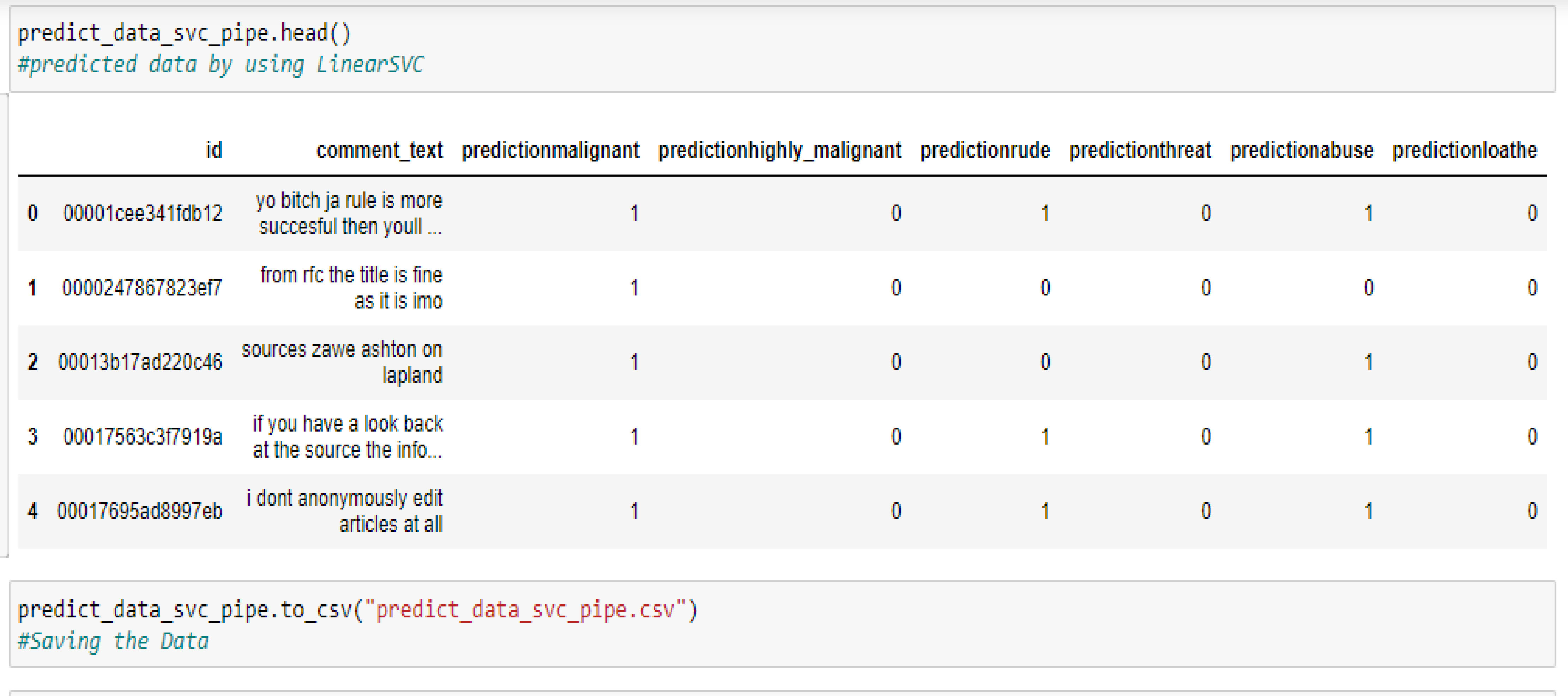
```
predict_data_nb_pipe.to_csv("predict_data_nb_pipe.csv")
#saving the data
```

LinearSVC



```
SVC_pipeline = Pipeline([
                ('tfidf', TfidfVectorizer(stop_words=stop_words)),
                ('clf', OneVsRestClassifier(LinearSVC(), n_jobs=1)),
            ])
for category in categories:
    print('... Processing {}'.format(category))
    # train the model using X_dtm & y
    SVC_pipeline.fit(X_train, train[category])
    # compute the testing accuracy
    prediction = SVC_pipeline.predict(X_test)
    print('Test accuracy is {}'.format(accuracy_score(test[category], prediction)))
    predict_data_svc_pipe['prediction' + category] = SVC_pipeline.predict(df_predict.comment_text
```

```
... Processing malignant
Test accuracy is 0.9030129124820659
... Processing highly_malignant
Test accuracy is 0.8450502152080345
... Processing rude
Test accuracy is 0.8332855093256815
... Processing threat
Test accuracy is 0.9624103299856528
... Processing abuse
Test accuracy is 0.7523672883787661
... Processing loathe
Test accuracy is 0.9024390243902439
```

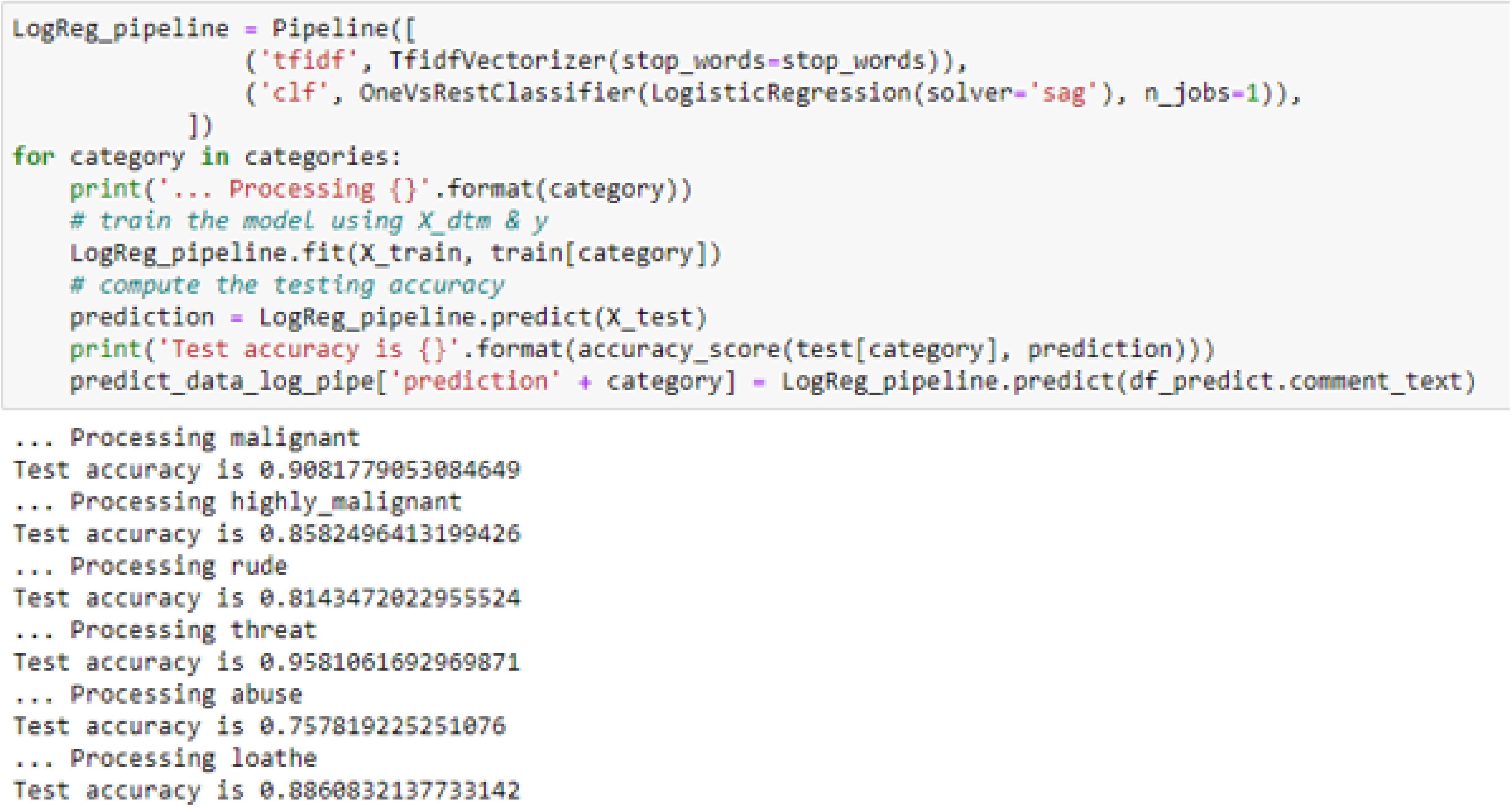


```
predict_data_svc_pipe.head()
#predicted data by using LinearSVC
```

	id	comment_text	predictionmalignant	predictionhighly_malignant	predictionrude	predictionthreat	predictionabuse	predictionloathe
0	00001cee341fdb12	yo bitch ja rule is more succesful then youll ...	1	0	1	0	1	0
1	0000247867823ef7	from rfc the title is fine as it is imo	1	0	0	0	0	0
2	00013b17ad220c46	sources zawe ashton on lapland	1	0	0	0	1	0
3	00017563c3f7919a	if you have a look back at the source the info...	1	0	1	0	1	0
4	00017695ad8997eb	i dont anonymously edit articles at all	1	0	1	0	1	0

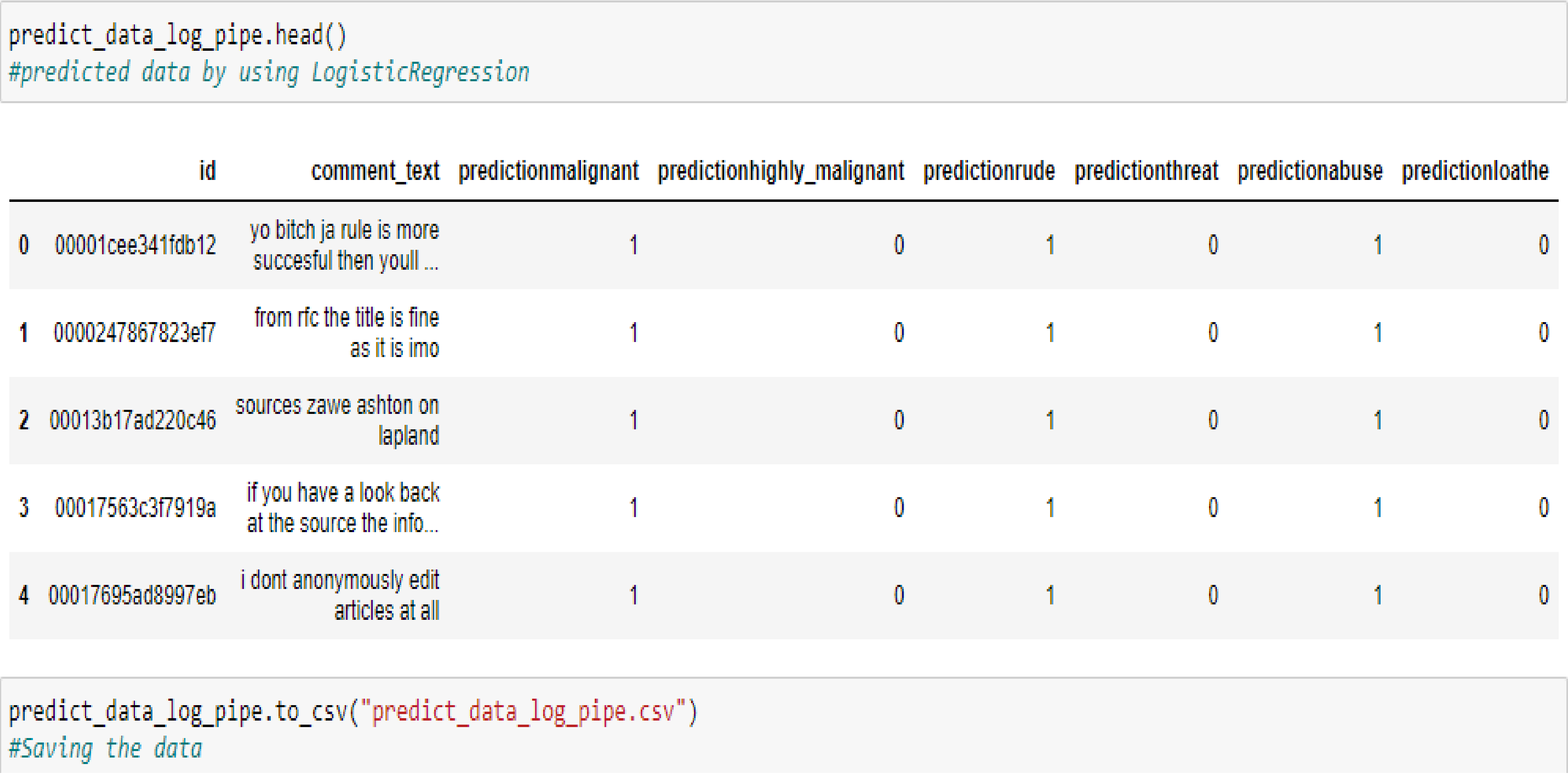
```
predict_data_svc_pipe.to_csv("predict_data_svc_pipe.csv")
#Saving the Data
```

LogisticRegression



```
LogReg_pipeline = Pipeline([
                ('tfidf', TfidfVectorizer(stop_words=stop_words)),
                ('clf', OneVsRestClassifier(LogisticRegression(solver='sag'), n_jobs=1)),
            ])
for category in categories:
    print('... Processing {}'.format(category))
    # train the model using X_dtm & y
    LogReg_pipeline.fit(X_train, train[category])
    # compute the testing accuracy
    prediction = LogReg_pipeline.predict(X_test)
    print('Test accuracy is {}'.format(accuracy_score(test[category], prediction)))
    predict_data_log_pipe['prediction' + category] = LogReg_pipeline.predict(df_predict.comment_text)
```

```
... Processing malignant
Test accuracy is 0.9081779053084649
... Processing highly_malignant
Test accuracy is 0.8582496413199426
... Processing rude
Test accuracy is 0.8143472022955524
... Processing threat
Test accuracy is 0.9581061692969871
... Processing abuse
Test accuracy is 0.757819225251076
... Processing loathe
Test accuracy is 0.8860832137733142
```

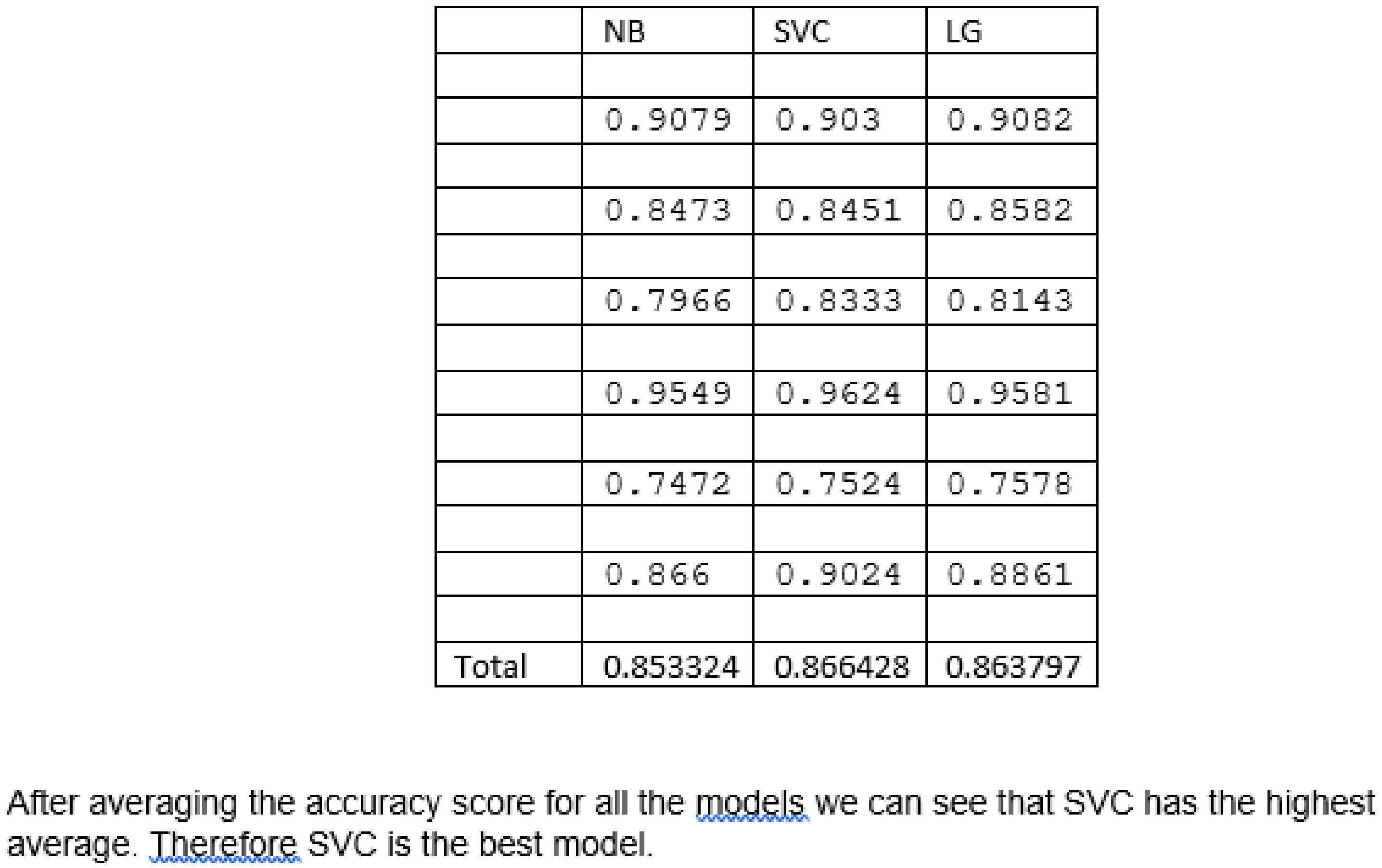


```
predict_data_log_pipe.head()
#predicted data by using LogisticRegression
```

	id	comment_text	predictionmalignant	predictionhighly_malignant	predictionrude	predictionthreat	predictionabuse	predictionloathe
0	00001cee341fdb12	yo bitch ja rule is more succesful then youll ...	1	0	1	0	1	0
1	0000247867823ef7	from rfc the title is fine as it is imo	1	0	1	0	1	0
2	00013b17ad220c46	sources zawe ashton on lapland	1	0	1	0	1	0
3	00017563c3f7919a	if you have a look back at the source the info...	1	0	1	0	1	0
4	00017695ad8997eb	i dont anonymously edit articles at all	1	0	1	0	1	0

```
predict_data_log_pipe.to_csv("predict_data_log_pipe.csv")
#Saving the data
```

Results

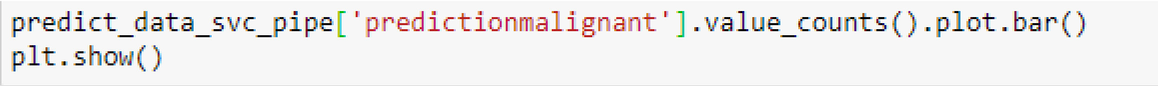


	NB	SVC	LG
	0.9079	0.903	0.9082
	0.8473	0.8451	0.8582
	0.7966	0.8333	0.8143
	0.9549	0.9624	0.9581
	0.7472	0.7524	0.7578
	0.866	0.9024	0.8861
Total	0.853324	0.866428	0.863797

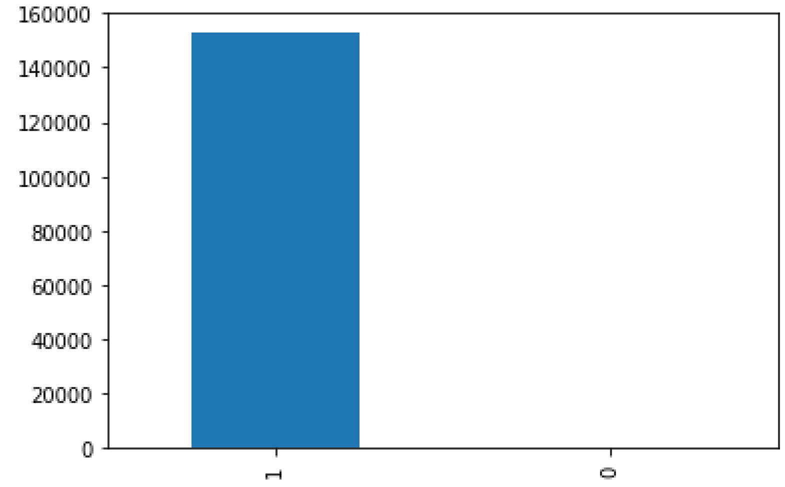
After averaging the accuracy score for all the models we can see that SVC has the highest average. Therefore SVC is the best model.

Exploratory Data Analysis for the Test data Predicted using Linear SVC Model:

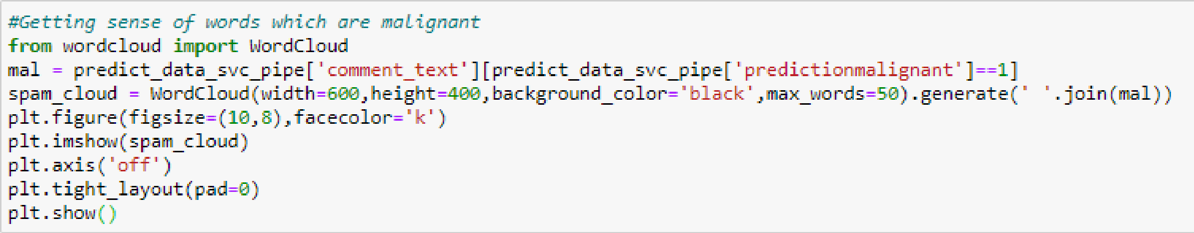
Malignant



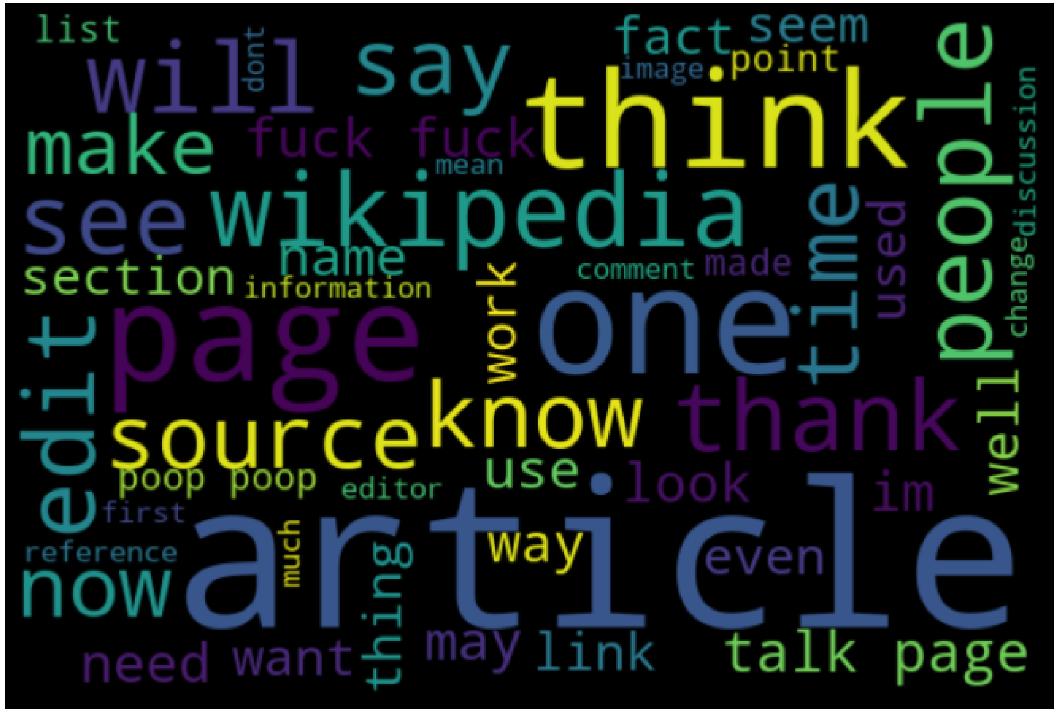
```
predict_data_svc_pipe['predictionmalignant'].value_counts().plot.bar()
plt.show()
```



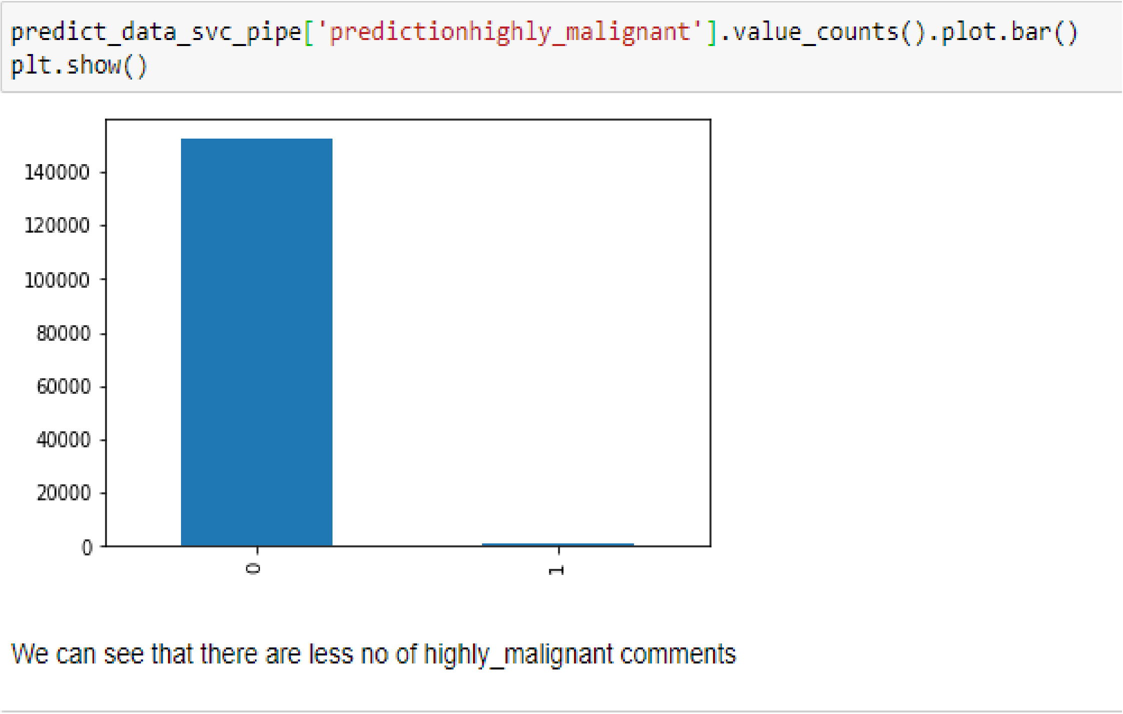
We can see that maximum of the comments are malignant



```
#Getting sense of words which are malignant
from wordcloud import WordCloud
mal = predict_data_svc_pipe['comment_text'][predict_data_svc_pipe['predictionmalignant']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

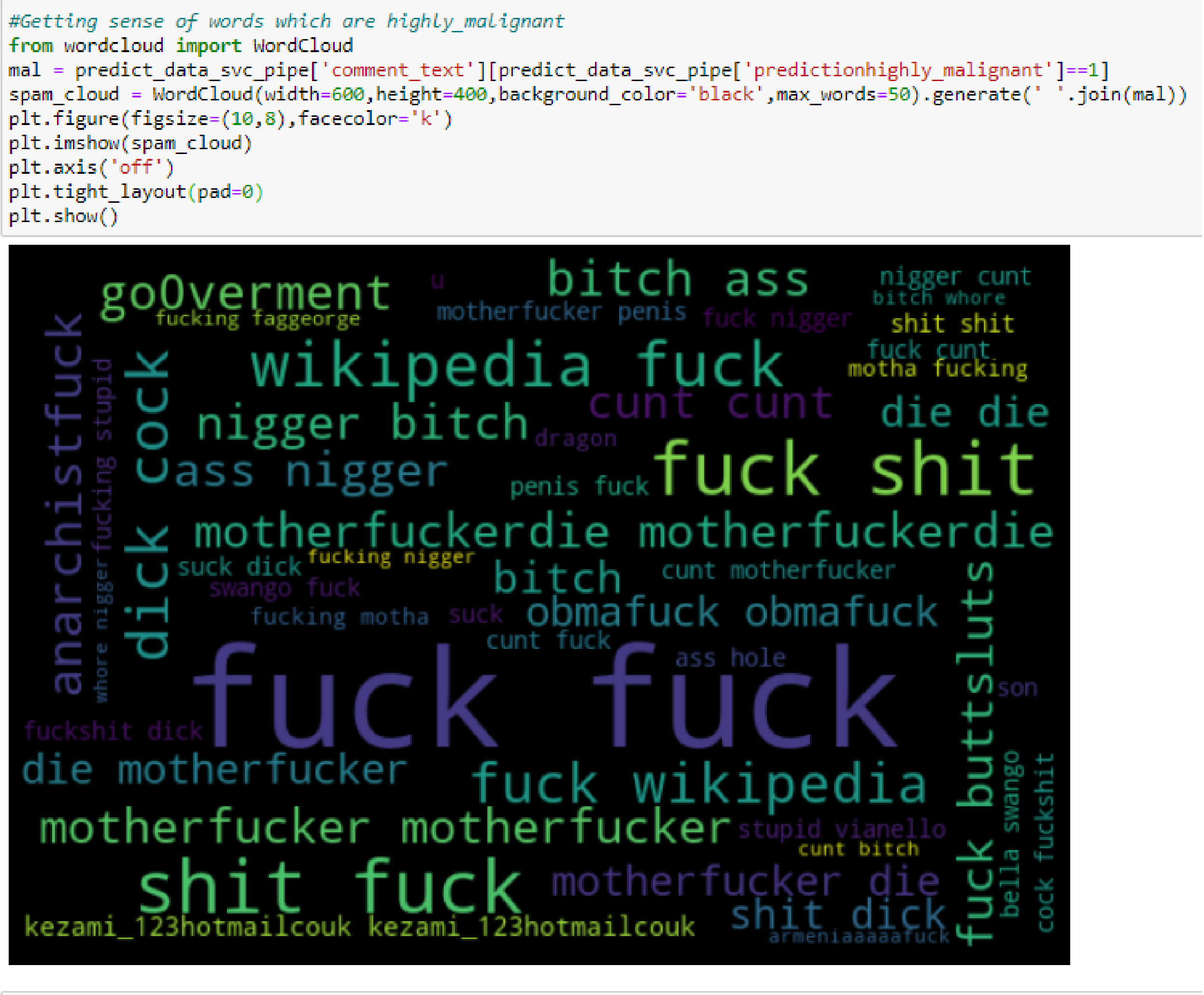


Highly Malignant



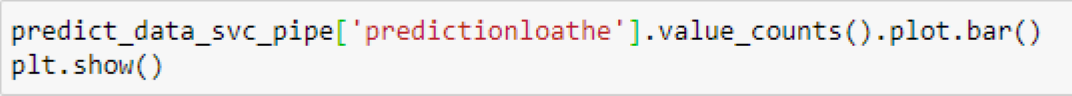
```
predict_data_svc_pipe['predictionhighly_malignant'].value_counts().plot.bar()
plt.show()
```

We can see that there are less no of highly_malignant comments

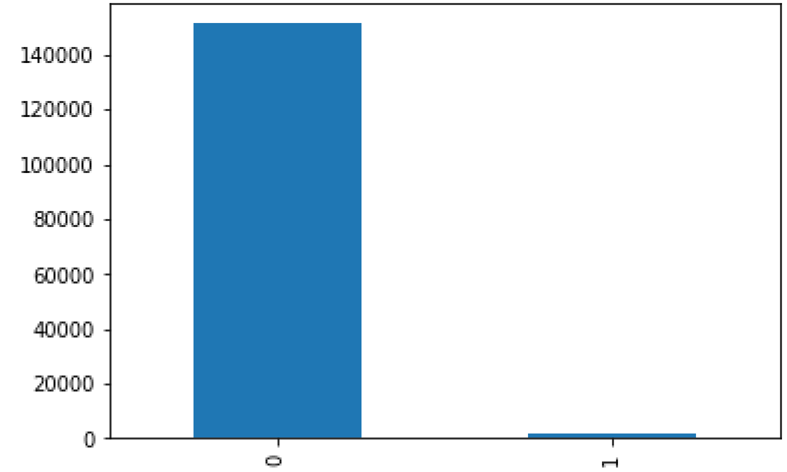


```
#Getting sense of words which are highly_malignant
from wordcloud import WordCloud
mal = predict_data_svc_pipe['comment_text'][predict_data_svc_pipe['predictionhighly_malignant']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

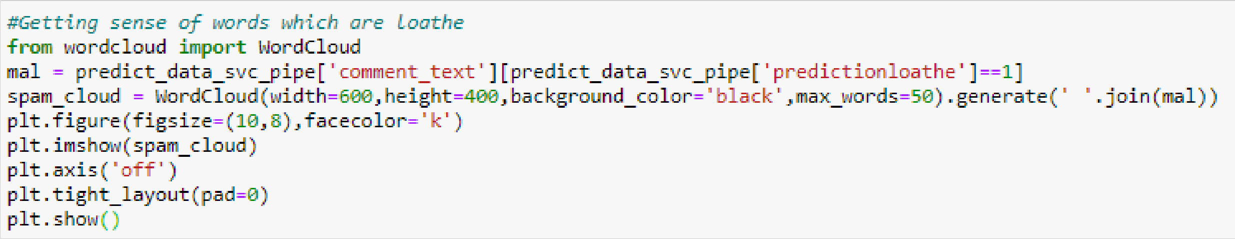
Loathe



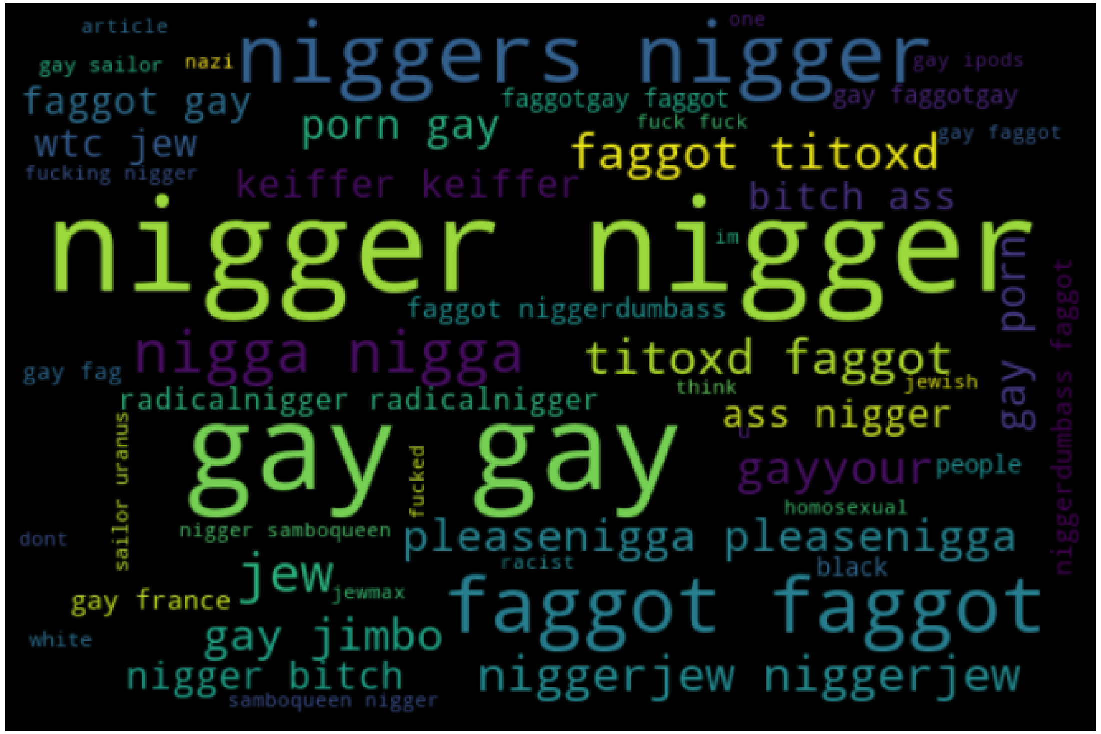
```
predict_data_svc_pipe['predictionloathe'].value_counts().plot.bar()
plt.show()
```



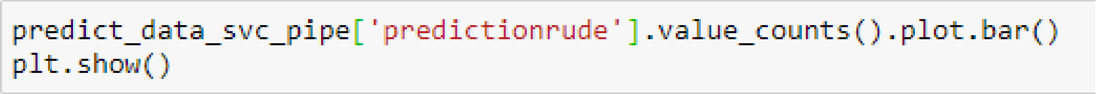
We can see that there are less no of loathe comments



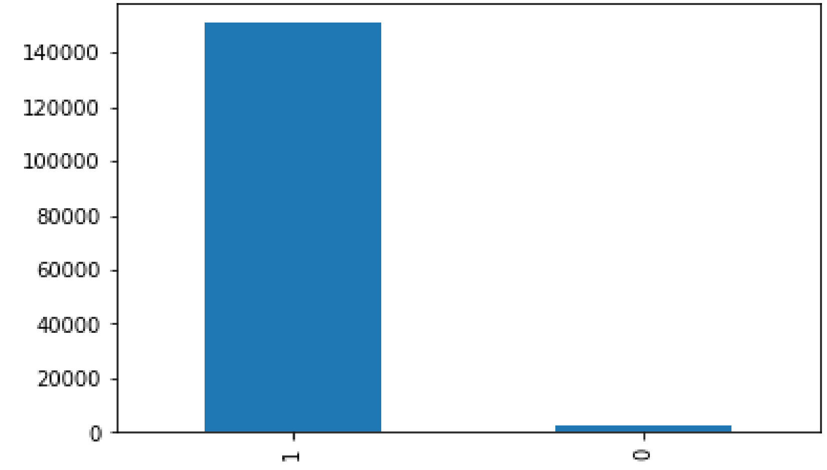
```
#Getting sense of words which are loathe
from wordcloud import WordCloud
mal = predict_data_svc_pipe['comment_text'][predict_data_svc_pipe['predictionloathe']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



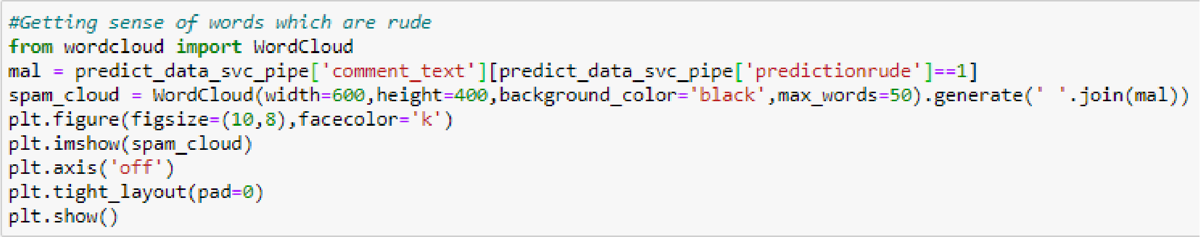
Rude



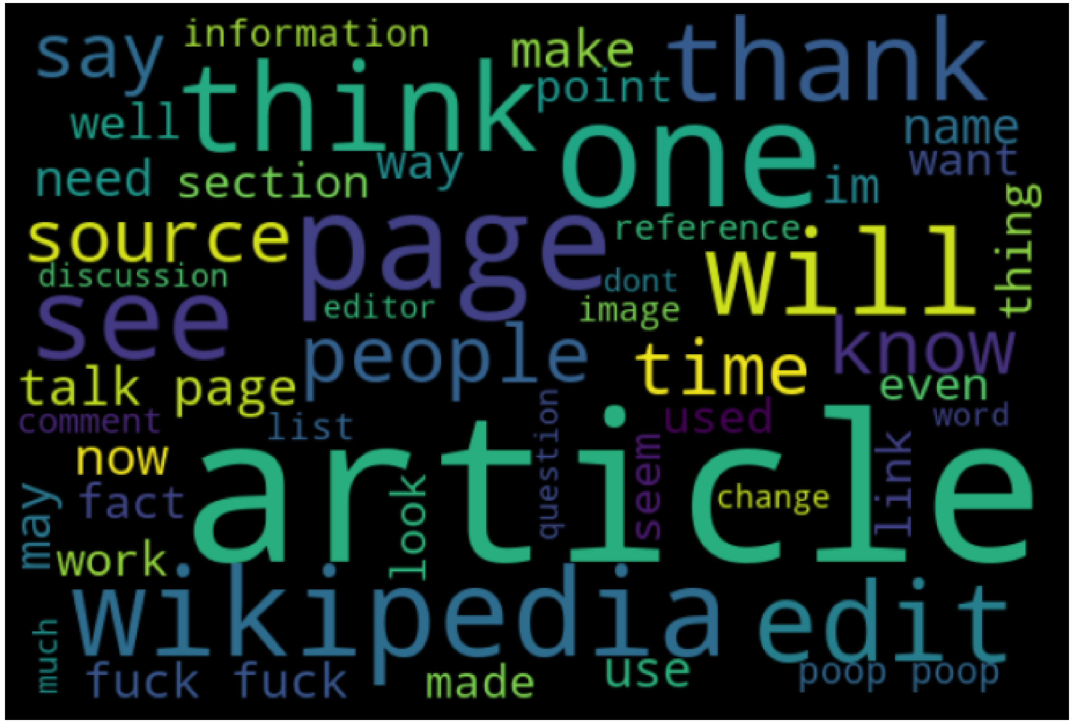
```
predict_data_svc_pipe['predictionrude'].value_counts().plot.bar()
plt.show()
```



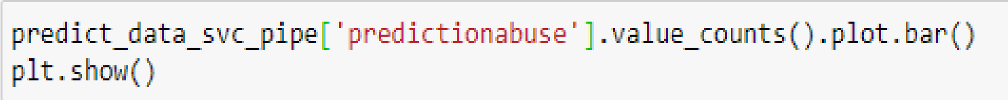
We can see that there are more no of rude comments



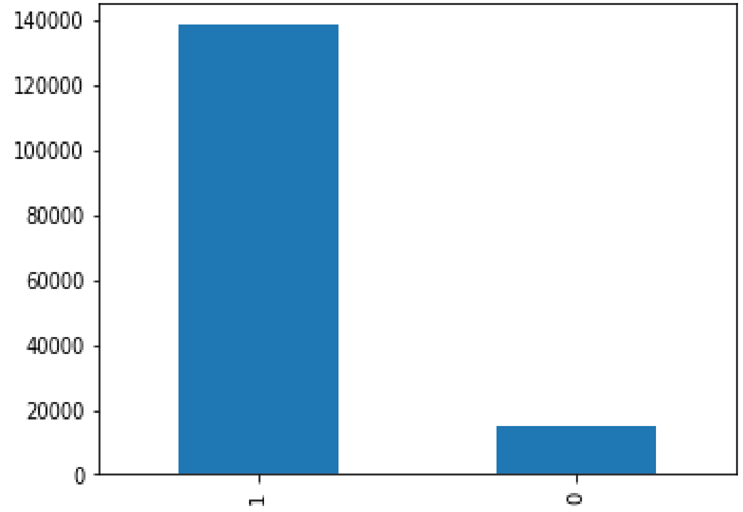
```
#Getting sense of words which are rude
from wordcloud import WordCloud
mal = predict_data_svc_pipe['comment_text'][predict_data_svc_pipe['predictionrude']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



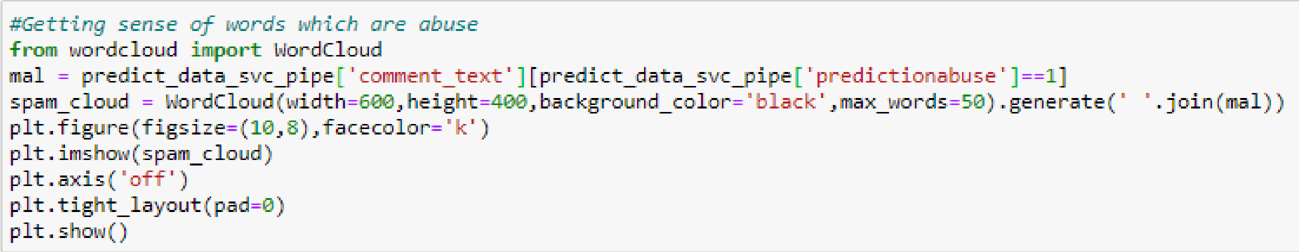
Abuse



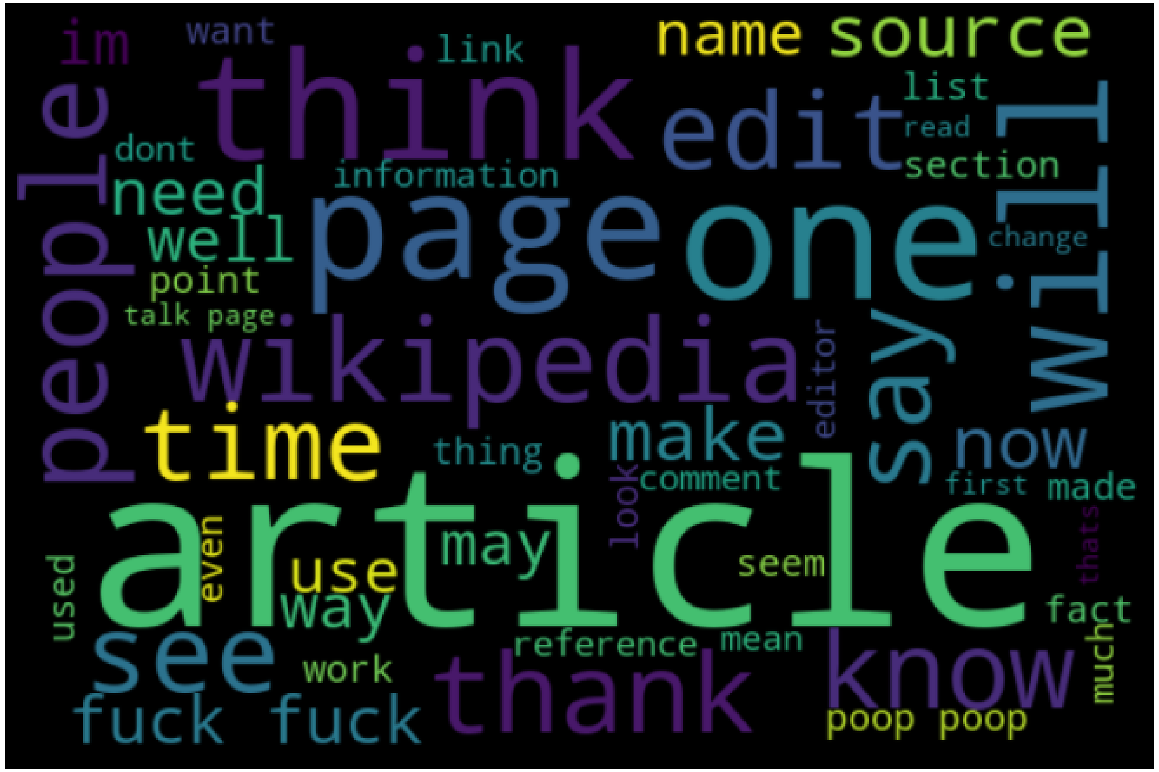
```
predict_data_svc_pipe['predictionabuse'].value_counts().plot.bar()
plt.show()
```



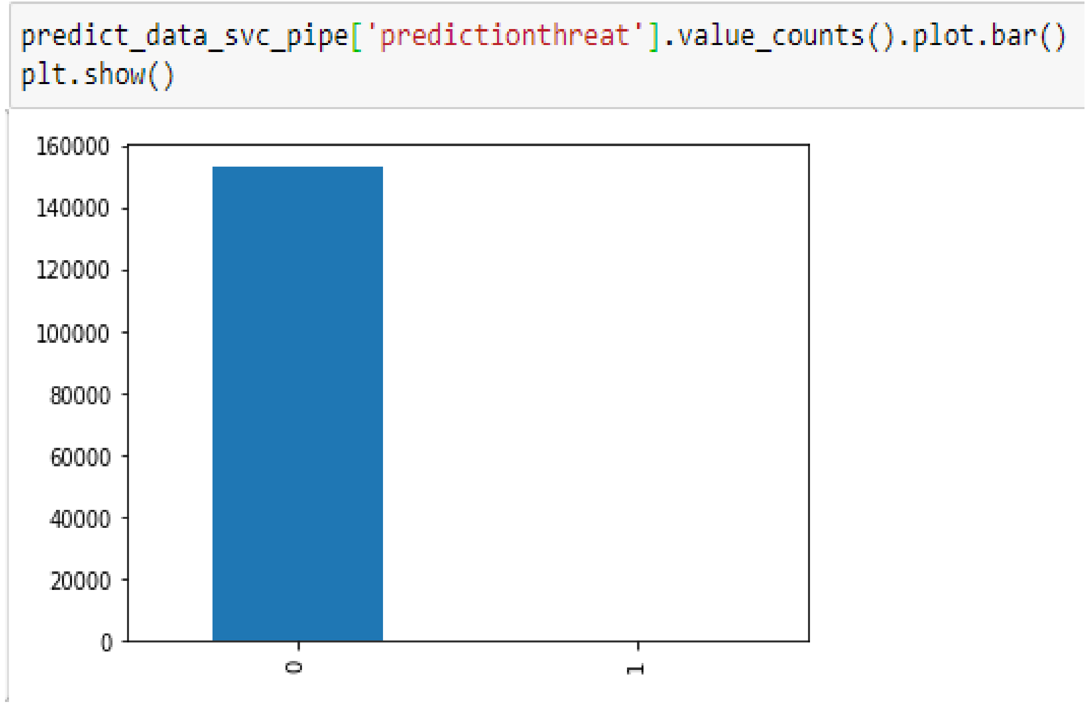
We can see that there are more no of abusive comments



```
#Getting sense of words which are abuse
from wordcloud import WordCloud
mal = predict_data_svc_pipe['comment_text'][predict_data_svc_pipe['predictionabuse']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

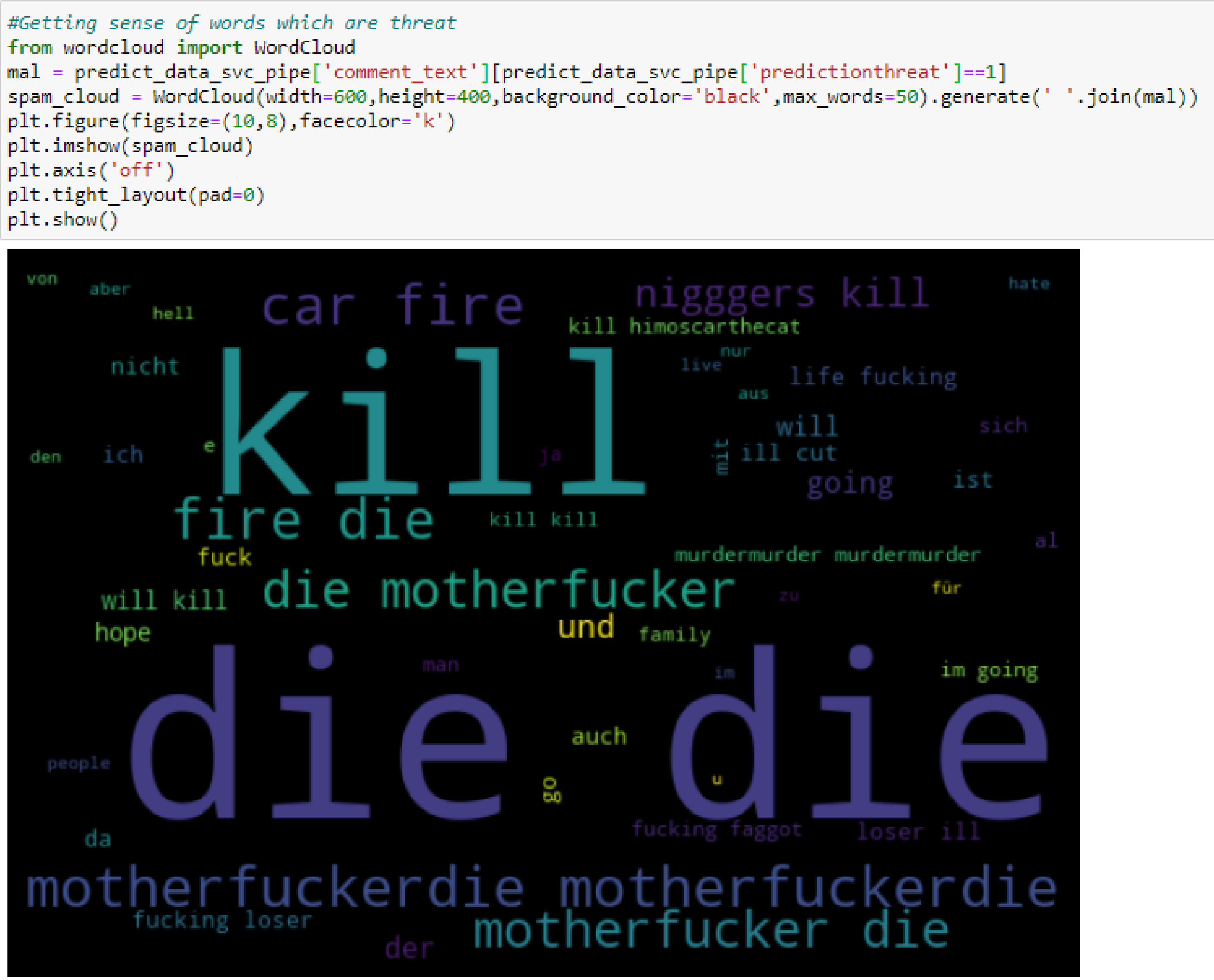


Threat



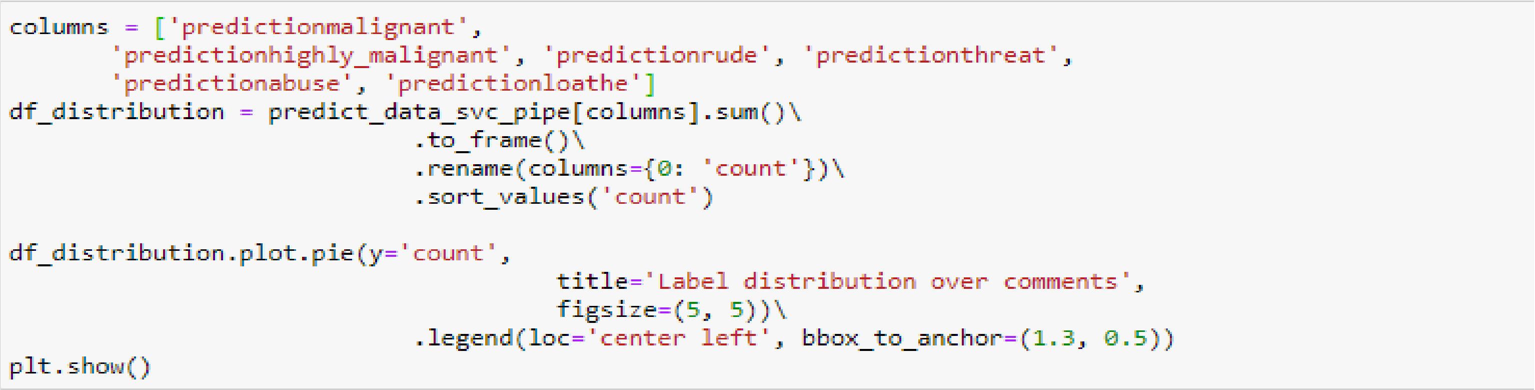
```
predict_data_svc_pipe['predictionthreat'].value_counts().plot.bar()
plt.show()
```

We can see that there are very few threat comments



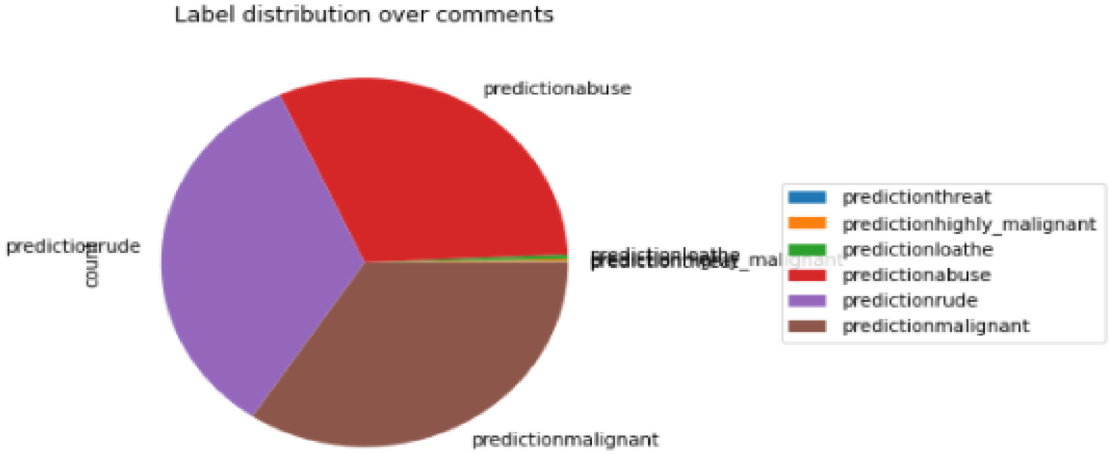
```
#Getting sense of words which are threat
from wordcloud import WordCloud
mal = predict_data_svc_pipe['comment_text'][predict_data_svc_pipe['predictionthreat']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(mal))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

Distribution



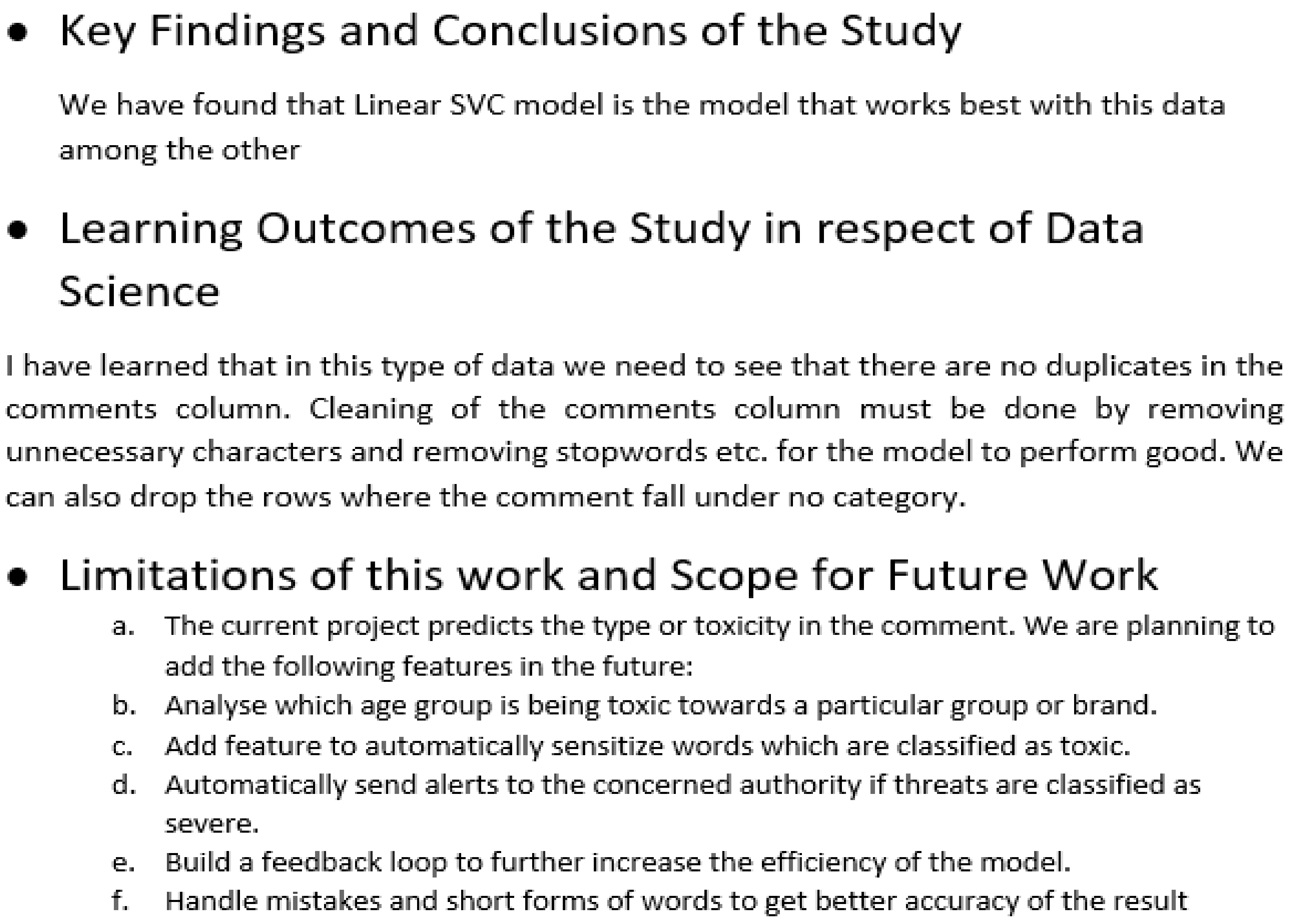
```
columns = ['predictionmalignant',
       'predictionhighly_malignant', 'predictionrude', 'predictionthreat',
       'predictionabuse', 'predictionloathe']
df_distribution = predict_data_svc_pipe[columns].sum()\
                            .to_frame()\
                            .rename(columns={0: 'count'})\
                            .sort_values('count')

df_distribution.plot.pie(y='count',
                                      title='Label distribution over comments',
                                      figsize=(5, 5))\
                            .legend(loc='center left', bbox_to_anchor=(1.3, 0.5))
plt.show()
```



We an see here that maximum of the comments are malignant, rude and abusive. The threat kind of comments are the least

Conclusion



- Key Findings and Conclusions of the Study

  We have found that Linear SVC model is the model that works best with this data among the other

- Learning Outcomes of the Study in respect of Data Science

I have learned that in this type of data we need to see that there are no duplicates in the comments column. Cleaning of the comments column must be done by removing unnecessary characters and removing stopwords etc. for the model to perform good. We can also drop the rows where the comment fall under no category.

- Limitations of this work and Scope for Future Work

  a. The current project predicts the type or toxicity in the comment. We are planning to add the following features in the future:
  b. Analyse which age group is being toxic towards a particular group or brand.
  c. Add feature to automatically sensitize words which are classified as toxic.
  d. Automatically send alerts to the concerned authority if threats are classified as severe.
  e. Build a feedback loop to further increase the efficiency of the model.
  f. Handle mistakes and short forms of words to get better accuracy of the result

Thank You