## Steps to follow

- 1. Data Cleaning
- 2.EDA(Exploratory Data Analysis)
- 3. Text Preprocessing
- 4. Model Building
- 5. Evaluation & Improvement
- ▼ 1.Data Cleaning

- ▼ We will take product,issue Columns for the analysis
- ▼ For Catergory 0 Credit reporting,repair or other

```
import pandas as pd

data = TC['Product']
df = pd.DataFrame(data)

condition1 = df['Product'] == 'Credit reporting, credit repair services, or other personal consumer reports'
condition2 = df['Product'] == 'Credit card or prepaid card'
condition3 = df['Product'] == 'Credit reporting or other personal consumer reports'
condition4 = df['Product'] == 'Credit card'
condition5 = df['Product'] == 'Credit card'
condition6 = df['Product'] == 'Prepaid card'
condition7 = df['Product'] == 'Bank account or service'
condition8 = df['Product'] == 'Credit reporting'
condition9 = df['Product'] == 'Other financial service'

sentence_to_set = "Credit Reporting ,repair or other"
df.loc[condition1 | condition2 | condition3|condition4|condition5|condition6|condition7|condition8|condition9 , 'Product'] = sentence_to_
print(df)
```

Product

- O Credit Reporting ,repair or other
- 1 Credit Reporting , repair or other
- 2 Credit Reporting ,repair or other

```
Credit Reporting ,repair or other
Credit Reporting ,repair or other

Credit Reporting ,repair or other

Credit Reporting ,repair or other

Credit Reporting ,repair or other

Credit Reporting ,repair or other

Mortgage

4086375 Debt collection

Credit Reporting ,repair or other

Credit Reporting ,repair or other

[4086377 rows x 1 columns]
```

### ▼ for Category 1- Debt collection

```
import pandas as pd

data = df['Product']
df1 = pd.DataFrame(data)

condition1 = df['Product'] == 'Debt collection'
condition2 = df['Product'] == 'Debt or credit management'

sentence_to_set = "Debt Collection"
df1.loc[condition1 | condition2, 'Product'] = sentence_to_set

print(df1)

Product
```

```
O Credit Reporting ,repair or other
Mortgage
4086375
Debt Collection
Credit Reporting ,repair or other
[4086377 rows x 1 columns]
```

#### ▼ for Category 2- Consumer Loan

```
import pandas as pd

data = df1['Product']
df2 = pd.DataFrame(data)

condition1 = df1['Product'] == 'Payday loan, title loan, personal loan, or advance loan'
condition2 = df1['Product'] == 'Student loan'
condition3 = df1['Product'] == 'Noney transfer, virtual currency, or money service'
condition4 = df1['Product'] == 'Payday loan, title loan, or personal loan'
condition5 = df1['Product'] == 'Vehicle loan or lease'
condition6 = df1['Product'] == 'Consumer Loan'
condition7 = df1['Product'] == 'Payday loan'
condition8 = df1['Product'] == 'Payday loan'
condition8 = df1['Product'] == 'Virtual currency'
condition9 = df1['Product'] == 'Money transfers'

sentence_to_set = "Consumer Loan"
df2.loc[condition1 | condition2 |condition3|condition4|condition5|condition6|condition7|condition8|condition9, 'Product'] = sentence_to_
print(df2)
```

```
O Credit Reporting ,repair or other
...

4086372 Credit Reporting ,repair or other
Credit Reporting ,repair or other
```

```
4086374
                                          Mortgage
       4086375
                                   Debt Collection
       4086376 Credit Reporting , repair or other
       [4086377 rows x 1 columns]
  TC['Product']=df2
  TC['Product'].nunique()
       4
  TC['Product'].unique()
       array(['Credit Reporting ,repair or other', 'Debt Collection', 'Mortgage',
               'Consumer Loan'], dtype=object)
▼ Label Mapping
  0- credit reporting, repair & other
  1-Debt collection
  2-consumer loan
  3-Mortgage
  data = TC['Product']
  df3 = pd.DataFrame(data)
  label_mapping = {
      'Credit Reporting ,repair or other': '0',
'Debt Collection': '1',
       'Consumer Loan': '2',
       'Mortgage': '3'
  }
  df3['Label'] = TC['Product'].map(label_mapping)
  print(df3)
                                           Product Label
                Credit Reporting , repair or other
                Credit Reporting ,repair or other
       2
                Credit Reporting ,repair or other
                                                       0
                Credit Reporting ,repair or other
       3
                                                       0
       4
                Credit Reporting ,repair or other
                                                       0
       4086372\, Credit Reporting ,repair or other
                                                       0
       4086373\, Credit Reporting ,repair or other
                                                       0
       4086374
                                          Mortgage
                                                       3
       4086375
                                   Debt Collection
                                                       1
       4086376 Credit Reporting , repair or other
       [4086377 rows x 2 columns]
  TC['Product'] = df3['Label']
  TC=TC[['Product','Issue']]
  TC.isnull().sum()
       Product
       Issue
       dtype: int64
  TC['Issue'].duplicated().sum()
       4086201
  data =TC
```

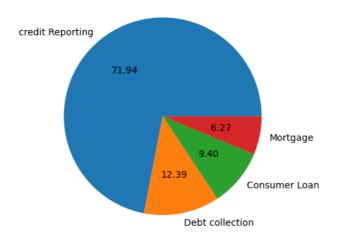
```
df4 = pd.DataFrame(data)
df4.rename(columns={'Product': 'Categories'}, inplace=True)
print(df4)
             Categories
                      0 Problem with a credit reporting company's inve...
                         Problem with a purchase shown on your statement
                                              Improper use of your report
                                    Problem caused by your funds being low
                     0 Problem with a credit reporting company's inve...
                                                          Sale of account
     4086372
     4086373
                                   Incorrect information on credit report
     4086374
                      3 Applying for a mortgage or refinancing an exis...
     4086375
                                        Attempts to collect debt not owed
     4086376
                                                      Managing an account
     [4086377 rows x 2 columns]
TC['Labels'] = df3['Product']
```

## ▼ 2.Exploratory Data Analysis(EDA) & Feature Engineering

```
TC['Categories'].value_counts()

0     2939555
1     506405
3     384089
2     256328
Name: Categories, dtype: int64

import matplotlib.pyplot as plt
plt.pie(TC['Categories'].value_counts(),labels=['credit Reporting','Debt collection','Consumer Loan','Mortgage'],autopct="%0.2f")
plt.show()
```



```
import nltk

nltk.download('punkt')

    [nltk_data] Downloading package punkt to /root/nltk_data...
    [nltk_data] Package punkt is already up-to-date!
    True

TC['Issue_Characters']= TC['Issue'].apply(len)

TC.head()
```

Categories Labels Issue\_Characters  $\blacksquare$ Issue Problem with a credit reporting company's Credit Reporting ,repair or 0 other inve... Problem with a purchase shown on your Credit Reporting ,repair or 0 47 statement other Credit Reporting ,repair or 2 0 Improper use of your report 27 TC['Issue\_words']=TC['Issue'].apply(lambda x:len(nltk.word\_tokenize(x)))

TC['Issue\_sentence']=TC['Issue'].apply(lambda x:len(nltk.sent\_tokenize(x)))

#taking 1 Lakh sentences instead of 40 lakh sentences for better representation
TC[['Issue\_Characters','Issue\_words','Issue\_sentence']].iloc[:100000].describe()

	Issue_Characters	Issue_words	Issue_sentence	$\blacksquare$
count	100000.000000	100000.000000	100000.000000	ıl.
mean	40.704620	6.302660	1.000090	
std	17.639514	2.661621	0.009486	
min	4.000000	1.000000	1.000000	
25%	27.000000	5.000000	1.000000	
50%	36.000000	5.000000	1.000000	
75%	40.000000	7.000000	1.000000	
max	80.000000	16.000000	2.000000	

#### TC.isnull().sum()

Categories 0
Issue 0
Labels 0
Issue\_Characters 0
Issue\_words 0
Issue\_sentence 0
dtype: int64

#category 0- credit reporting ,repair and others

TC[TC['Labels']=='Credit Reporting ,repair or other'][['Issue\_Characters','Issue\_words','Issue\_sentence']].iloc[:100000].describe()

	Issue_Characters	Issue_words	Issue_sentence	$\blacksquare$
count	100000.000000	100000.000000	100000.000000	ıl.
mean	41.948320	6.447500	1.000220	
std	18.846072	2.811662	0.014831	
min	4.000000	1.000000	1.000000	
25%	27.000000	5.000000	1.000000	
50%	36.000000	5.000000	1.000000	
75%	48.000000	8.000000	1.000000	
max	80.000000	12.000000	2.000000	

#category 1- Debt Collection

TC[TC['Labels']=='Debt Collection'][['Issue\_Characters','Issue\_words','Issue\_sentence']].describe()

	Issue_Characters	Issue_words	Issue_sentence	$\blacksquare$
count	506405.000000	506405.000000	506405.0	ılı
mean	33.469504	5.275635	1.0	
std	7.071830	1.789356	0.0	
min	21.000000	2.000000	1.0	
25%	31.000000	4.000000	1.0	
50%	33.000000	6.000000	1.0	
75%	34.000000	6.000000	1.0	
max	61.000000	9.000000	1.0	

#category 2- Consumer Loan'
TC[TC['Labels']=='Consumer Loan'][['Issue\_Characters','Issue\_words','Issue\_sentence']].describe()

	Issue_Characters	Issue_words	Issue_sentence	
count	256328.000000	256328.000000	256328.0	th
mean	31.316887	5.600543	1.0	
std	11.792060	1.976741	0.0	
min	12.000000	1.000000	1.0	
25%	25.000000	5.000000	1.0	
50%	29.000000	5.000000	1.0	
75%	36.000000	6.000000	1.0	
max	80.000000	16.000000	1.0	

#### #category 3-Mortgage

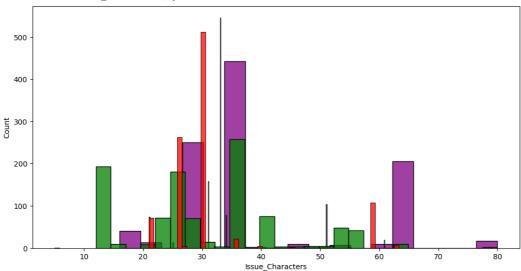
TC[TC['Labels']=='Mortgage'][['Issue\_Characters','Issue\_words','Issue\_sentence']].describe()

	Issue_Characters	Issue_words	Issue_sentence	
count	384089.000000	384089.000000	384089.0	1
mean	36.019160	5.546373	1.0	
std	9.226585	1.572494	0.0	
min	5.000000	1.000000	1.0	
25%	30.000000	4.000000	1.0	
50%	40.000000	6.000000	1.0	
75%	40.000000	7.000000	1.0	
max	80.000000	12.000000	1.0	

import seaborn as sns

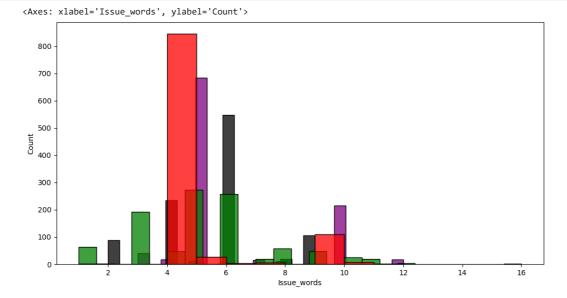
```
plt.figure(figsize=(12,6))
sns.histplot(TC['Categories']=='0']['Issue_Characters'].iloc[:1000],color='purple')
sns.histplot(TC['Categories']=='1']['Issue_Characters'].iloc[:1000],color='black')
sns.histplot(TC['Categories']=='2']['Issue_Characters'].iloc[:1000],color='green')
sns.histplot(TC['Categories']=='3']['Issue_Characters'].iloc[:1000],color='red')
```

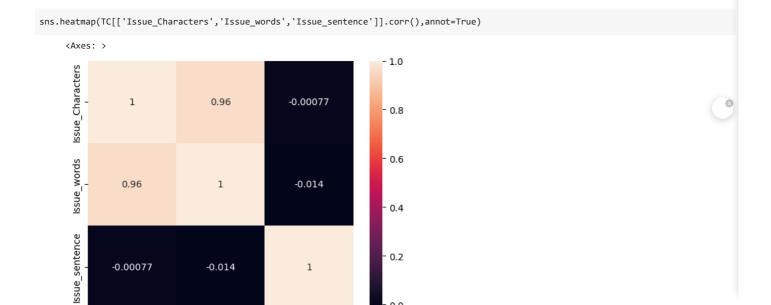




```
plt.figure(figsize=(12,6))
sns.histplot(TC[TC['Categories']=='0']['Issue_words'].iloc[:1000],color='purple')
sns.histplot(TC[TC['Categories']=='1']['Issue_words'].iloc[:1000],color='black')
```

sns.histplot(TC[TC['Categories']=='2']['Issue\_words'].iloc[:1000],color='green') sns.histplot(TC[TC['Categories']=='3']['Issue\_words'].iloc[:1000],color='red')





# → 3.Text Preprocessing

-0.00077

Issue\_Characters

-0.014

Issue\_words

Issue\_sentence

## ▼ Techniques

Lowercase

Tokenization

Removing Special character

Removing stop words and punctuation

Stemming

import nltk  $from \ nltk.corpus \ import \ stopwords$ 

```
nltk.download('stopwords')
print(stopwords.words('english'))
     ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours', 'yours'
     [nltk_data] Downloading package stopwords to /root/nltk_data...
     [nltk_data] Package stopwords is already up-to-date!
    4
import string
string.punctuation
     '!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~'
from nltk.stem.porter import PorterStemmer
ps=PorterStemmer()
TC[TC['Categories']=='2'].value_counts().sum()
     256328
category_0=TC[TC['Categories']=='0'].iloc[:25000]
category_1=TC[TC['Categories']=='1'].iloc[:25000]
category_2=TC[TC['Categories']=='2'].iloc[:25000]
category_3=TC[TC['Categories']=='3'].iloc[:25000]
import pandas as pd
my_list = category_0
df = pd.DataFrame(my_list, columns=['Issue'])
print(df)
            Problem with a credit reporting company's inve...
     1
              Problem with a purchase shown on your statement
     2
                                  Improper use of your report
                       Problem caused by your funds being low
     3
            Problem with a credit reporting company's inve...
     4
     27496
                         Incorrect information on your report
     27497
                                  Improper use of your report
     27498
                                  Improper use of your report
     27499
                                  Improper use of your report
     27500
                                             Fees or interest
     [25000 rows x 1 columns]
import pandas as pd
my_list = category_1
df = pd.DataFrame(my_list, columns=['Issue'])
print(df)
     11
                             Attempts to collect debt not owed
     13
                             Attempts to collect debt not owed
     24
                               Written notification about debt
     25
                             Attempts to collect debt not owed
     29
                               Written notification about debt
     244903
                             Attempts to collect debt not owed
     244906
                             Attempts to collect debt not owed
     244913 Threatened to contact someone or share informa...
     244920
                             Attempts to collect debt not owed
     244921
                               Written notification about debt
     [25000 rows x 1 columns]
import pandas as pd
```

```
my_list = category_2
df = pd.DataFrame(my list, columns=['Issue'])
print(df)
     28
                     Problem when making payments
           Dealing with your lender or servicer
              Issue where my lender is my school
                    Struggling to pay your loan
                                    Fraud or scam
     111
     399323 Incorrect information on your report
     399349
                      Managing the loan or lease
                    Struggling to repay your loan % \left\{ 1,2,\ldots ,n\right\}
     399356
     399362
                            Other service problem
     399403
                                    Fraud or scam
     [25000 rows x 1 columns]
import pandas as pd
my_list = category_3
df = pd.DataFrame(my_list, columns=['Issue'])
print(df)
             Trouble during payment process
     34
            Trouble during payment process
     52
            Trouble during payment process
     114
                 Struggling to pay mortgage
     251
                 Struggling to pay mortgage
     386817 Trouble during payment process
     386821
                 Struggling to pay mortgage
     386823 Trouble during payment process
     386825
                 Struggling to pay mortgage
     386826
                 Struggling to pay mortgage
     [25000 rows x 1 columns]
category_1['Issue'].head(5)
          Attempts to collect debt not owed
     13
          Attempts to collect debt not owed
     24
            Written notification about debt
     25
           Attempts to collect debt not owed
            Written notification about debt
     Name: Issue, dtype: object
import pandas as pd
TC1 = pd.concat([category_0,category_1,category_2,category_3], axis=0)
# TC1 now contains the concatenated DataFrame
TC1.iloc[::10000]
```

```
Labels Issue_Characters Issue_words Issue_sentence
                                                                                                        \blacksquare
             Categories
                                   Issue
                                                 Credit
                                                                                                        th
                            Problem with a
def transform_text(text):
   text = text.lower()
    text = nltk.word_tokenize(text)
   y=[]
    for i in text:
       if i.isalnum():
           y.append(i)
    text =y[:]
    y.clear()
    for i in text:
       if i not in stopwords.words('english') and i not in string.punctuation:
           y.append(i)
    text=y[:]
   y.clear()
    for i in text:
       y.append(ps.stem(i))
    return " ".join(y)
TC1["Issue"]=TC1["Issue"].apply(transform_text)
```

TC1.sample(25)
----------------

(	Categories	Issue	Labels	Issue_Characters	Issue_words	Issue_sentence
115973	2	struggl pay loan	Consumer Loan	27	5	1
73999	1	attempt collect debt owe	Debt Collection	33	6	1
13969	0	improp use report	Credit Reporting ,repair or other	27	5	1
105132	1	attempt collect debt owe	Debt Collection	33	6	1
4461	0	problem compani investig exist problem	Credit Reporting ,repair or other	63	10	1
221039	1	attempt collect debt owe	Debt Collection	33	6	1
20471	0	incorrect inform report	Credit Reporting ,repair or other	36	5	1
391299	2	struggl pay loan	Consumer Loan	27	5	1
31857	2	servic problem	Consumer Loan	21	3	1
90009	1	written notif debt	Debt Collection	31	4	1
36430	1	fals statement represent	Debt Collection	34	4	1
74002	1	fals statement represent	Debt Collection	34	4	1
13295	0	incorrect inform report	Credit Reporting ,repair or other	36	5	1
93768	1	disclosur verif debt	Debt Collection	31	4	1
165595	3	struggl pay mortgag	Mortgage	26	4	1

```
pip install wordcloud
    Requirement already satisfied: wordcloud in /usr/local/lib/python3.10/dist-packages (1.9.2)
    Requirement already satisfied: numpy>=1.6.1 in /usr/local/lib/python3.10/dist-packages (from wordcloud) (1.23.5)
    Requirement already satisfied: pillow in /usr/local/lib/python3.10/dist-packages (from wordcloud) (9.4.0)
    Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from wordcloud) (3.7.1)
    Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (1.1.0)
    Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (0.11.0)
    Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (4.42.1)
    Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (1.4.5)
    Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (23.1)
    Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (3.1.1)
    Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (2.8.2)
    Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib->wordclou
from wordcloud import WordCloud
wc= WordCloud(width=500,height=500,min font size=10,background color='white')
c_0 =wc.generate(TC1[TC1['Categories']=='0']["Issue"].str.cat(sep =" "))
plt.figure(figsize=(15,6))
plt.imshow(c_0)
    <matplotlib.image.AxesImage at 0x7b0e699c4b20>
           problem improp report improp
                      investig exist
               inform repor
     100
           compani investig
               credit report improp use
     200
             report problem

account incorrect USE report

problem incorrect
     300
          incorrect inform
     *report incorrect
                            exist problem
                   problem compani
                   100
```

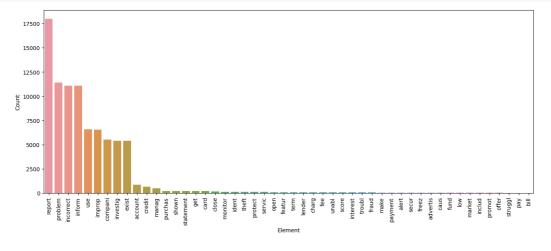
```
c_1 =wc.generate(TC1[TC1['Categories']=='1']["Issue"].str.cat(sep =" "))
plt.figure(figsize=(15,6))
plt.imshow(c_1)
```

```
<matplotlib.image.AxesImage at 0x7b0e68d0d810>
               owe commun
                             notif debt
         owe took represent attempt
              fals statementneg legal
     100
                      written notif
c_2 =wc.generate(TC1[TC1['Categories']=='2']["Issue"].str.cat(sep =" "))
              сассіс ассетрі
plt.figure(figsize=(15,6))
plt.imshow(c_2)
    <matplotlib.image.AxesImage at 0x7b0e69bc24a0>
                                   vail promis
                          dealar pay loan
                                close mobil
     200
             struggl
     300
                             pay
                             epay
             open close
         leas managtransact
            interest expect manag
                100
                         200
                                            400
c_3 =wc.generate(TC1[TC1['Categories']=='3']["Issue"].str.cat(sep =" "))
plt.figure(figsize=(15,6))
print(plt.imshow(c_3))
    AxesImage(size=(500, 500))
     100 -
                 ser
                                      mortgag
              count
Egag
     200
        ymen
                      modif
                                          roubl
                       process
         ā
                          exist mortgag
     400
                100
                         200
                                  300
                                            400
```

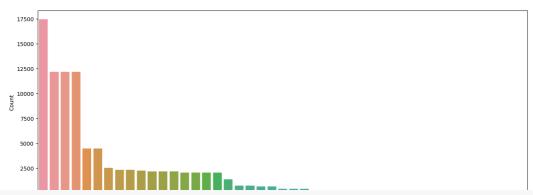
```
c0_corpus=[]
for msg in TC1[TC1['Categories']=='0']["Issue"].tolist():
 for msg in msg.split():
    c0_corpus.append(msg)
c1_corpus=[]
for msg in TC1[TC1['Categories']=='1']["Issue"].tolist():
 for msg in msg.split():
   c1_corpus.append(msg)
c2_corpus=[]
for msg in TC1[TC1['Categories']=='2']["Issue"].tolist():
 for msg in msg.split():
   c2_corpus.append(msg)
c3_corpus=[]
for msg in TC1[TC1['Categories']=='3']["Issue"].tolist():
 for msg in msg.split():
   c3_corpus.append(msg)
print(len(c0_corpus))
```

86830

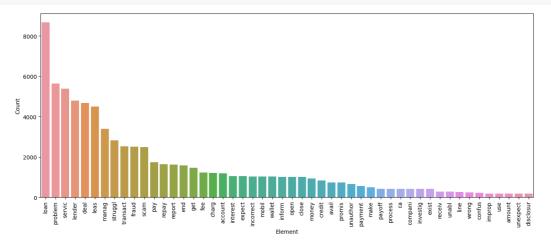
```
from collections import Counter
pd.DataFrame(Counter(c0_corpus).most_common(30))
data = pd.DataFrame(Counter(c0_corpus).most_common(50), columns=['Element', 'Count'])
plt.figure(figsize=((16,6)))
sns.barplot(x='Element', y='Count', data=data)
plt.xticks(rotation='vertical')
plt.show()
```



```
pd.DataFrame(Counter(c1_corpus).most_common(30))
data = pd.DataFrame(Counter(c1_corpus).most_common(50), columns=['Element', 'Count'])
plt.figure(figsize=((16,6)))
sns.barplot(x='Element', y='Count', data=data)
plt.xticks(rotation='vertical')
plt.show()
```



```
pd.DataFrame(Counter(c2_corpus).most_common(30))
data = pd.DataFrame(Counter(c2_corpus).most_common(50), columns=['Element', 'Count'])
plt.figure(figsize=((16,6)))
sns.barplot(x='Element', y='Count', data=data)
plt.xticks(rotation='vertical')
plt.show()
```



```
pd.DataFrame(Counter(c3_corpus).most_common(30))
data = pd.DataFrame(Counter(c3_corpus).most_common(50), columns=['Element', 'Count'])
plt.figure(figsize=((16,6)))
sns.barplot(x='Element', y='Count', data=data)
plt.xticks(rotation='vertical')
plt.show()
```

```
▼ 4.Model Building & Evaluation

                               Vectorization
▼ Keeping TF-idf vectorizer and GaussianNB for classification
                               from sklearn.feature_extraction.text import CountVectorizer,TfidfVectorizer
      cv=CountVectorizer()
      tfidf=TfidfVectorizer(max_features=10000)
                                                                infinite and a second control 
                                or Fig. 1
                                                                                                                                                                  d de d
      X=tfidf.fit_transform(TC1['Issue']).toarray()
      X.shape
                 (100000, 153)
     y=TC1['Categories'].values
      print(y)
                 ['0' '0' '0' ... '3' '3' '3']
     y.shape
                 (100000,)
      from sklearn.model_selection import train_test_split
      X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=2)
      from sklearn.naive_bayes import GaussianNB,MultinomialNB,BernoulliNB
      from sklearn.metrics import accuracy_score,precision_score
      from sklearn.metrics import confusion_matrix
      gnb=GaussianNB()
      mnb=MultinomialNB()
     bnb=BernoulliNB()
      gnb.fit(X_train,y_train)
     y_pred1=gnb.predict(X_test)
     print("Accuracy score =",accuracy_score(y_test,y_pred1)*100)
print("Precision Score=",precision_score(y_test,y_pred1,average='macro')*100)
      \verb|print("Confusion Matrix\n",confusion_matrix(y_test, y_pred1))|\\
                 Accuracy score = 95.48
                 Precision Score= 95.8400124859264
                 Confusion Matrix
                   [[7548 0 3
[ 0 7493 3
                   [ 601 2 6229 515]
                                   0 0 7374]]
                   [ 180
     mnb.fit(X_train,y_train)
     y_pred2=mnb.predict(X_test)
      print("Accuracy score =",accuracy_score(y_test,y_pred2)*100)
      print("Precision Score=",precision_score(y_test,y_pred2,average='macro')*100)
      print("Confusion Matrix\n",confusion_matrix(y_test, y_pred2))
                 Accuracy score = 95.0066666666666
                 Precision Score= 95.05917249350024
                 Confusion Matrix
                   [[7252 0 291 60]
                   [ 0 7489 7 0]
[ 464 2 6440 441]
                   [ 177
                                   0 56 7321]]
      bnb.fit(X_train,y_train)
     y pred3=bnb.predict(X test)
```

```
print("Accuracy score =",accuracy_score(y_test,y_pred3)*100)
  \verb|print("Precision Score=",precision_score(y_test,y_pred3,average='macro')*100)| \\
  print("Confusion Matrix\n",confusion_matrix(y_test, y_pred3))
       Accuracy score = 94.98333333333333
       Precision Score= 95.02457367438568
       Confusion Matrix
        [[7233 0 310
[ 0 7489 7
                         601
                         0]
        [ 452
               2 6452 441]
        [ 175
                0 58 7321]]

▼ 5.Multi-classification Models

    Selection

    Comparision

  from sklearn.linear_model import LogisticRegression
  from sklearn.svm import SVC
  from sklearn.naive_bayes import MultinomialNB
  from sklearn.tree import DecisionTreeClassifier
  from sklearn.neighbors import KNeighborsClassifier
  from sklearn.ensemble import RandomForestClassifier
  from sklearn.ensemble import AdaBoostClassifier
  from sklearn.ensemble import BaggingClassifier
  #from sklearn.ensemble import ExtraTreeClassifier
  from \ sklearn. ensemble \ import \ Gradient Boosting Classifier
  #from xgboost import XGBClassifier
  svc=SVC(kernel='sigmoid',gamma=1.0)
  knc=KNeighborsClassifier()
  mnb=MultinomialNB()
  dtc=DecisionTreeClassifier(max_depth=5)
  lrc=LogisticRegression(solver='liblinear',penalty='l1')
  \verb|rfc=RandomForestClassifier(n_estimators=50, \verb|random_state=2|)||
  abc=AdaBoostClassifier(n_estimators=50,random_state=2)
  bc=BaggingClassifier(n_estimators=50,random_state=2)
  gbdt=GradientBoostingClassifier(n_estimators=50,random_state=2)
  #xgb=XGBClassifier(n_estimators=50,random_state=2)
  clfs={
      'SVC':svc,
      'KN':knc,
      'NB':mnb,
      'DT':dtc,
      'LR':lrc,
      'RF':rfc,
      'AdaBoost':abc,
      'Bgc':bc,
      'GBDT':gbdt
  }
  from sklearn.metrics import accuracy_score, precision_score
  def train_classifier(clf, X_train, y_train, X_test, y_test):
      clf.fit(X_train, y_train)
      y_pred = clf.predict(X_test)
      accuracy = accuracy_score(y_test, y_pred) # Use different variable names here
      return accuracy, precision
  # Define lists to store accuracy and precision scores
  accuracy_scores = []
  precision_scores = []
  for name, clf in clfs.items():
      print("for", name)
      print("accuracy =", current_accuracy)
      print("precision =", current_precision)
      \# Append scores to the respective lists
      accuracy_scores.append(current_accuracy)
      precision_scores.append(current_precision)
```

```
for SVC
precision = 0.9765143234042329
for KN
accuracy = 0.978766666666667
precision = 0.9795765107827843
for NB
precision = 0.9505917249350024
for DT
accuracy = 0.8427666666666667
precision = 0.8898951217212933
for LR
accuracy = 0.9788
precision = 0.9796128650588629
for RF
accuracy = 0.9788333333333333
precision = 0.9796428201582466
for AdaBoost
accuracy = 0.8829666666666667
precision = 0.8854765158941607
for Bgc
accuracy = 0.97883333333333333
precision = 0.9796428201582466
for GBDT
accuracy = 0.9747333333333333
precision = 0.9752747932078918
```

### → 6.Prediction

	Algorithms	Accuracy	Precision	
5	RF	0.978833	0.979643	ıl.
7	Bgc	0.978833	0.979643	
4	LR	0.978800	0.979613	
1	KN	0.978767	0.979577	
0	SVC	0.975033	0.976514	
8	GBDT	0.974733	0.975275	
2	NB	0.950067	0.950592	
6	AdaBoost	0.882967	0.885477	
3	DT	0.842767	0.889895	

