→ 1.Import Libraies

```
#Import Libraries
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn import metrics
import matplotlib.pyplot as plt
from sklearn.svm import LinearSVC
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification report
from sklearn.naive_bayes import MultinomialNB
from sklearn.model selection import cross val score
from sklearn.model_selection import train_test_split
from sklearn.feature extraction.text import CountVectorizer
from sklearn.feature extraction.text import TfidfTransformer
import warnings
warnings.filterwarnings('ignore')
```

2 import Datasets

```
#import datasets
data=pd.read_csv("/content/drive/MyDrive/complaints.csv")
```

3.Data Undestanding

```
#Pick up nessasary columns
data=data[['Product', 'Consumer complaint narrative']]
#check whether any null value avilible
data.isnull().sum()
```

```
Product
     Consumer complaint narrative
                                     1653441
     dtype: int64
#Drop null values
data=data.dropna()
#Number of rows and columns
data.shape
     (888973, 2)
#Data Type
data.dtypes
                                     object
     Product
     Consumer complaint narrative
                                     object
     dtype: object
#Rename column name to easy interpritation
data.columns=['product','complaint']
#Encode the object as an enumerated type or categorical variable
data['category id'] = data['product'].factorize()[0]
#drop duplicates() method helps in removing duplicates from the data frame
#Returns a sorted Data Frame with Same dimensions as of the function caller Data Frame.
complain_df=data[['product','category_id']].drop_duplicates().sort_values('category_id').reset_index(drop=True)
category_id_df=dict(complain_df.values)
category_id_df
     {'Bank account or service': 11,
      'Checking or savings account': 0,
      'Consumer Loan': 9,
      'Credit card': 14,
      'Credit card or prepaid card': 2,
      'Credit reporting': 12,
      'Credit reporting, credit repair services, or other personal consumer reports': 1,
      'Debt collection': 4,
```

```
'Money transfer, virtual currency, or money service': 8,
   'Money transfers': 16,
   'Mortgage': 3,
   'Other financial service': 15,
   'Payday loan': 10,
   'Payday loan, title loan, or personal loan': 7,
   'Prepaid card': 13,
   'Student loan': 6,
   'Vehicle loan or lease': 5,
   'Virtual currency': 17}

#Top 5 rows of datasets.
data=data.reset_index(drop=True)
data.head()
```

category_id	complaint	product	
0	This Bank FNBO is terrible! Stay away from the	Checking or savings account	0
1	First Progress Card was notified throughout th	Credit reporting, credit repair services, or o	1
1	As by Law, under 15 U.S Code 1601- Congression	Credit reporting, credit repair services, or o	2
1	This is a copy of my most recent email to XXXX	Credit reporting, credit repair services, or o	3
2	This is in reference to case number XXXX. This	Credit card or prepaid card	4

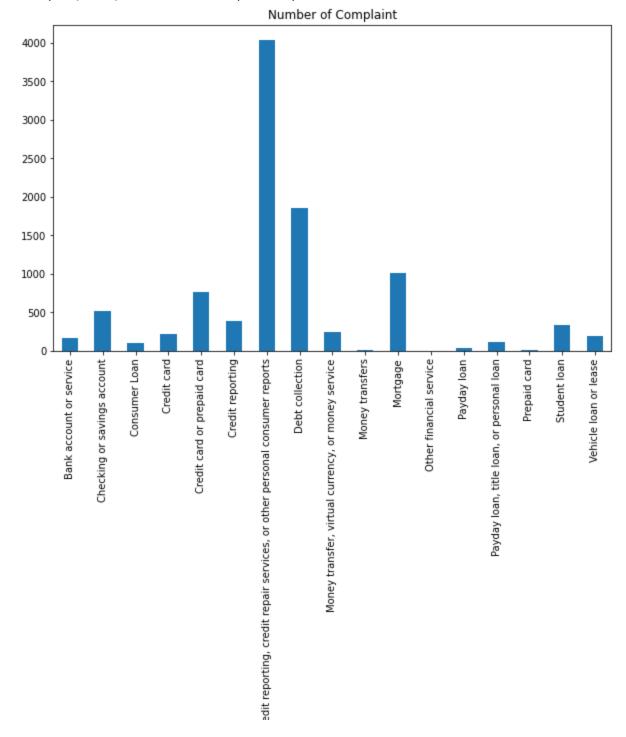
```
# Input: Consumer_complaint_narrative
```

4.Imbalance Data

```
plt.figure(figsize=(10,6))
data.groupby("product").complaint.count().plot.bar()
plt.title("Number of Complaint")
# We see that the number of complaints per product is imbalanced.
# Consumers' complaints are more biased towards Debt collection, Credit reporting and Mortgage.
```

[#] Output: product

Text(0.5, 1.0, 'Number of Complaint')



calculate a tf-idf vector for each of consumer complaint narratives: from sklearn.feature_extraction.text import TfidfVectorizer

```
tfid=TfidfVectorizer(stop_words='english', #stop_words is set to "english" to remove all common pronouns ("a", "the", ...)

norm='l2', #ensure all our feature vectors have a euclidian norm of 1

sublinear_tf=True, #set to True to use a logarithmic form for frequency.

encoding='latin-1', #maps possible byte values to first Unicode code points,ensures decoding errors will never occur regardless of the configured entin_df=5, # minimum numbers of documents a word must be present in to be kept.

ngram_range=(1,2)) #set to (1, 2) to indicate that we want to consider both unigrams and bigrams
```

#We Randomly pick up 10000 data for easy interpretation
data=data.sample(10000,random_state=12).reset_index(drop=True,)
data.head()

Transform a count matrix to a normalized tf or tf-idf representation.

x_train_tfid=tfid_transformer.fit_transform(x_train count)

tfid_transformer=TfidfTransformer()

2	category_id	complaint	product	
	6	I was charged {\$42.00} per month for the past	Student loan	0
	3	My mortgage servicer, Nationstar Mortgage, is	Mortgage	1
	4	I have been receiving numerous phone calls fro	Debt collection	2
	1	I faxed over a copy of my drivers license, soc	Credit reporting, credit repair services, or o	3
	14	I SAW PROMOTION FOR CREDIT CARD ON XXXX FOR WE	Credit card	4

```
#Define Fetures and labels
fetures=tfid.fit_transform(data.complaint).toarray()
labels=data.category_id

#devide train and test dataset
x_train,y_test,y_train,y_test=train_test_split(data['complaint'],data['product'],random_state=0)

# tokenize a collection of text documents and build a vocabulary of known words, but also to encode new documents using that vocabulary.
cv=CountVectorizer()
x_train_count=cv.fit_transform(x_train)
```

Naive Bayes Classifier .the one most suitable for word counts is the multinomial variant.
clf=MultinomialNB().fit(x_train_tfid,y_train)

5.prediction

data[data['complaint']== "I have been monitoring my credit report with Transunion only for about 3 months. I had an identity theft a few years ago and it was never resolved

	product complaint category_id	***
•	9998 Credit reporting, credit repair services, or o I have been monitoring my credit report with T 1	
print(clf.predict(cv.transform(['After receiving this paper bill through the mail, I called my dental	office to verify. My dental office said I was all paid up and had a XX
]	'Credit reporting, credit repair services, or other personal consumer reports']	
print(clf.predict(cv.transform(["In XXXX I got an American Express card, In XXXX I was not receiving m	y bills, I contacted American Express, They told me that my account wa
]	'Credit reporting, credit repair services, or other personal consumer reports']	
#Predio	ction clf.predict(cv.transform(['On XX/XX/2021 my unemployment weekly amount was put on my Way2go card	. Immediately after I transferred the entire amount to my XXXX XXXX
['Credit reporting, credit repair services, or other personal consumer reports']	

product	complaint	category_id	1

1 Mortgage My mortgage servicer, Nationstar Mortgage, is ...

print(clf.predict(cv.transform(['I recently applied for a home loan and was denied do to fraudulent activities. I have never applied for AMEX or have I used this credit care ['Credit reporting, credit repair services, or other personal consumer reports']

data[data['complaint']=='My mortgage servicer, Nationstar Mortgage, is attempting to perform a foreclosure sale on my property, by using falsified documents. There are many

→ 6.Model Building

```
#Split data in training and testing
x_train, x_test, y_train, y_test, indices_train, indices_test = train_test_split(fetures, labels, data.index, test_size=0.33, random_state=0)

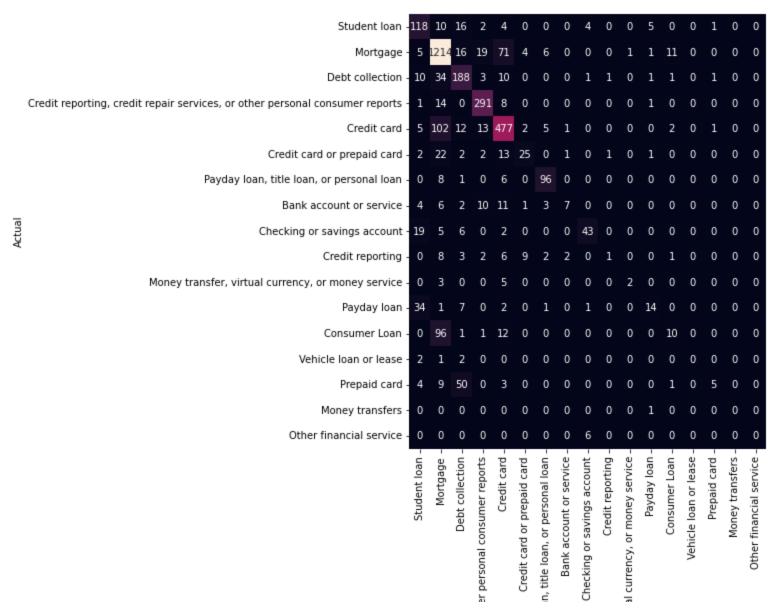
# The objective of a Linear SVC (Support Vector Classifier) is to fit to the data you provide,
# returning a "best fit" hyperplane that divides, or categorizes, your data.
#Build the model
model=LinearSVC()
model.fit(x_train,y_train)

LinearSVC()
```

→ 7.Model Testing

7.1 Heat Map

```
#Plot Heat map
#Heatmap contains values representing various shades of the same colour for each value to be plotted
fig,ax=plt.subplots(figsize=(8,8))
sns.heatmap(con_matrix,annot=True,fmt='d',xticklabels=data['product'].unique(),yticklabels=data['product'].unique())
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()
```



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JS

- 1200

- 1000

- 800

- 600

- 400

- 200

7.2 classification report

print(classification_report(y_pred,y_test))

	precision	recall	f1-score	support
0	0.74	0.58	0.65	204
1	0.90	0.79	0.84	1533
2	0.75	0.61	0.68	306
3	0.92	0.85	0.88	343

4	0.77	0.76	0.76	630
5	0.36	0.61	0.45	41
6	0.86	0.85	0.86	113
7	0.16	0.64	0.25	11
8	0.57	0.78	0.66	55
9	0.03	0.33	0.05	3
10	0.20	0.67	0.31	3
11	0.23	0.58	0.33	24
12	0.08	0.38	0.14	26
13	0.00	0.00	0.00	0
14	0.07	0.62	0.12	8
15	0.00	0.00	0.00	0
16	0.00	0.00	0.00	0
accuracy			0.75	3300
macro avg	0.39	0.53	0.41	3300
weighted avg	0.82	0.75	0.78	3300

#From we get 75% accuracy