KAIBURR ASSESSMENT

6.DATA SCIENCE

Perform a Text Classification on consumer complaint dataset

NAME: JEYANTHIS

REG NO:19MJD0131

Importing packages and loading data

```
import pandas as pd
import numpy as np
from scipy.stats import randint
import seaborn as sns # used for plot interactive graph.
import matplotlib.pyplot as plt
import seaborn as sns
from io import StringIO
from \ sklearn.feature\_extraction.text \ import \ TfidfVectorizer
from sklearn.feature_selection import chi2
from IPython.display import display
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear model import LogisticRegression
from \ sklearn. ensemble \ import \ Random Forest Classifier
from sklearn.svm import LinearSVC
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn import metrics
df = pd.read_csv('https://files.consumerfinance.gov/ccdb/complaints.csv')
df.shape
     (4065103, 18)
```

Exploratory Data Analysis (EDA) and Feature Engineering

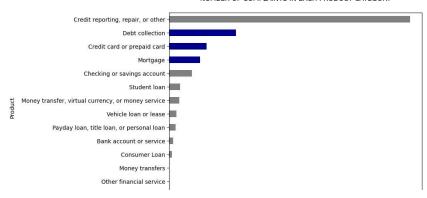
df.head(2).T # Columns are shown in rows for easy reading

```
Date received
                                              2023-09-04
                                                                            2023-09-06
                              Money transfer, virtual currency,
             Product
                                                                         Debt collection
# Create a new dataframe with two columns
df1 = df[['Product', 'Consumer complaint narrative']].copy()
# Remove missing values (NaN)
df1 = df1[pd.notnull(df1['Consumer complaint narrative'])]
# Renaming second column for a simpler name
df1.columns = ['Product', 'Consumer complaint']
df1.shape
     (1472203, 2)
                                       # Percentage of complaints with text
total = df1['Consumer_complaint'].notnull().sum()
round((total/len(df)*100),1)
     36.2
        CONSUME COMSEM
                                                    NaN
                                                                                 NaN
pd.DataFrame(df.Product.unique()).values
     array([['Money transfer, virtual currency, or money service'],
             'Debt collection'],
            ['Checking or savings account'],
            ['Credit reporting or other personal consumer reports'],
            ['Mortgage'],
            ['Credit card'],
            ['Vehicle loan or lease'],
            ['Credit reporting, credit repair services, or other personal consumer reports'],
            ['Student loan'],
            ['Payday loan, title loan, personal loan, or advance loan'],
            ['Credit card or prepaid card'],
            ['Consumer Loan'],
            ['Prepaid card'],
            ['Bank account or service'],
            ['Payday loan, title loan, or personal loan'],
            ['Debt or credit management'],
            ['Credit reporting'],
            ['Payday loan'],
            ['Money transfers'],
            ['Other financial service'],
            ['Virtual currency']], dtype=object)
# Because the computation is time consuming (in terms of CPU), the data was sampled
df2 = df1.sample(10000, random_state=1).copy()
# Renaming categories
df2.replace({'Product':
             {'Credit reporting, credit repair services, or other personal consumer reports':
              'Credit reporting, repair, or other',
              'Credit reporting': 'Credit reporting, repair, or other',
             'Credit card': 'Credit card or prepaid card',
             'Prepaid card': 'Credit card or prepaid card',
             'Payday loan': 'Payday loan, title loan, or personal loan',
             'Money transfer': 'Money transfer, virtual currency, or money service',
             'Virtual currency': 'Money transfer, virtual currency, or money service'}},
            inplace= True)
pd.DataFrame(df2.Product.unique())
```

```
0
                                                Credit reporting, repair, or other
             1
                                                                                    Mortgage
             2
                                                    Checking or savings account
                                                        Credit card or prepaid card
             3
             4
                                                                            Debt collection
                     Money transfer, virtual currency, or money ser...
             6
                                   Payday loan, title loan, or personal loan
             7
                                                                               Student loan
# Create a new column 'category_id' with encoded categories
df2['category_id'] = df2['Product'].factorize()[0]
category_id_df = df2[['Product', 'category_id']].drop_duplicates()
# Dictionaries for future use
category_to_id = dict(category_id_df.values)
id_to_category = dict(category_id_df[['category_id', 'Product']].values)
# New dataframe
print(df2)
                                                                                    Product \
          337270 Credit reporting, repair, or other
                            Credit reporting, repair, or other
          814826
          1157572 Credit reporting, repair, or other
                                                                                  Mortgage
          589205
          2863449
                                           Checking or savings account
          3409083 Credit reporting, repair, or other
          2756499
                            Credit reporting, repair, or other
          3392408 Credit reporting, repair, or other
          326256
                            Credit reporting, repair, or other
          1258628
                                                                   Debt collection
                                                                                            Consumer complaint category id
                            The date of my first letter was XXXX. I sent a...
          337270
          814826
                            I was XXXX and my ID and social security card \dots
                                                                                                                                                           0
          1157572 I'm really not sure what happened. I have mail...
                                                                                                                                                           0
          589205 I was impacted by hurricane Irma and then Mich...
                                                                                                                                                           1
          2863449 I am a XXXX XXXX XXXX by trade. \n\nAt the en...
                                                                                                                                                           2
          3409083 XXXX XXXX XXXX XXXX and National Credit Adjust...
          2756499 Hi I am submitting this XXXX XXXX XXXX without...
                                                                                                                                                           0
          3392408
                            Equifax has been non-compliant with removing t...
                                                                                                                                                           0
                            XXXX XXXX XXXX XXXX XXXX XXXX, OH XXXX DO...
                                                                                                                                                           0
          1258628 Bank of America is reporting a charged off acc...
          [10000 rows x 3 columns]
fig = plt.figure(figsize=(8,6))
colors = ['grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','grey','
        'grey','darkblue','darkblue','darkblue']
df2.groupby('Product').Consumer_complaint.count().sort_values().plot.barh(
       ylim=0, color=colors, title= 'NUMBER OF COMPLAINTS IN EACH PRODUCT CATEGORY\n')
```

plt.xlabel('Number of ocurrences', fontsize = 10);

NUMBER OF COMPLAINTS IN EACH PRODUCT CATEGORY

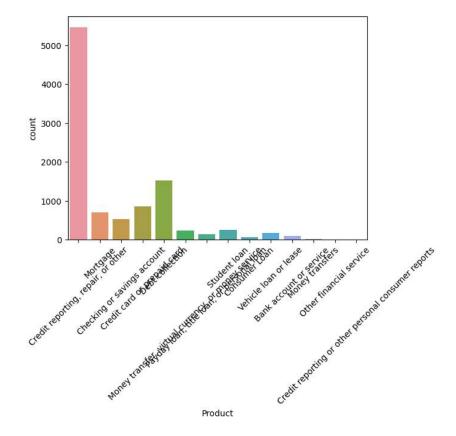


Text Preprocessing

```
tfidf = TfidfVectorizer(sublinear_tf=True, min_df=5,
                        ngram_range=(1, 2),
                        stop_words='english')
# We transform each complaint into a vector
features = tfidf.fit transform(df2.Consumer complaint).toarray()
labels = df2.category_id
print("Each of the %d complaints is represented by %d features (TF-IDF score of unigrams and bigrams)" %(features.shape))
     Each of the 10000 complaints is represented by 26339 features (TF-IDF score of unigrams and bigrams)
def function(train):
    comment_words = ""
    for i in train['Product']:
        val = str(i)
        tokens = val.split()
        for k in range(len(tokens)):
            tokens[k] = tokens[k].lower()
        comment words += " ".join(tokens)+" "
    return comment_words
def plot_wordcloud(train):
    from wordcloud import WordCloud, STOPWORDS
    stopwords = set(STOPWORDS)
   comment words = function(train)
   wordcloud = WordCloud(width=400,
                      height=330,
                      max_words=150,
                      colormap='tab20c',
                      stopwords=stopwords,
                      collocations=True).generate_from_text(comment_words)
    # plot the WordCloud image
   plt.figure(figsize = (8, 8), facecolor = None)
   plt.imshow(wordcloud)
    plt.axis("off")
   plt.tight_layout(pad = 0)
    plt.show()
temp = df2
plot_wordcloud(temp)
```



```
sns.countplot(data=df2,x="Product")
plt.xticks(rotation=45)
plt.show()
```



```
N = 3
for Product, category_id in sorted(category_to_id.items()):
    features_chi2 = chi2(features, labels == category_id)
    indices = np.argsort(features_chi2[0])
    feature_names = np.array(tfidf.get_feature_names_out())[indices]
    unigrams = [v for v in feature_names if len(v.split(' ')) == 1]
    bigrams = [v for v in feature_names if len(v.split(' ')) == 2]
    print("\n==> %<" %(Product))</pre>
```

```
print(" * Most Correlated Unigrams are: %s" %(', '.join(unigrams[-N:])))
print(" * Most Correlated Bigrams are: %s" %(', '.join(bigrams[-N:])))
     ==> Bank account or service:
       * Most Correlated Unigrams are: cd, stocks, promotion
       ^{st} Most Correlated Bigrams are: checking account, xxxx 2015, posting xxxx
     ==> Checking or savings account:
       * Most Correlated Unigrams are: deposited, overdraft, bank
       * Most Correlated Bigrams are: overdraft fees, savings account, checking account
     ==> Consumer Loan:
       * Most Correlated Unigrams are: vehicle, car, motor
       ^{st} Most Correlated Bigrams are: title loan, chrysler capital, car car
     ==> Credit card or prepaid card:
       * Most Correlated Unigrams are: express, amex, card
       * Most Correlated Bigrams are: use card, american express, credit card
     ==> Credit reporting or other personal consumer reports:
        * Most Correlated Unigrams are: usc, treat, 166b
       * Most Correlated Bigrams are: end consumer, late purpose, 166b creditor
     ==> Credit reporting, repair, or other:
       * Most Correlated Unigrams are: 1681, section, reporting
       * Most Correlated Bigrams are: consumer reporting, 15 1681, 1681 section
     ==> Debt collection:
        * Most Correlated Unigrams are: collect, collection, debt
       ^{st} Most Correlated Bigrams are: collection agency, debt collection, collect debt
     ==> Money transfer, virtual currency, or money service:
        * Most Correlated Unigrams are: zelle, coinbase, paypal
       * Most Correlated Bigrams are: send money, coinbase account, paypal account
     ==> Money transfers:
       * Most Correlated Unigrams are: misunderstanding, traded, game
       * Most Correlated Bigrams are: way contact, complaint said, took money
     ==> Mortgage:
       * Most Correlated Unigrams are: escrow, modification, mortgage
       * Most Correlated Bigrams are: mortgage payment, mortgage company, loan modification
     ==> Other financial service:
       * Most Correlated Unigrams are: resend, apology, proposal
       * Most Correlated Bigrams are: pay sent, limited income, money order
     ==> Payday loan, title loan, or personal loan:
        Most Correlated Unigrams are: loan, tribal, payday
       * Most Correlated Bigrams are: lending club, main financial, payday loan
     ==> Student loan:
       * Most Correlated Unigrams are: loans, student, navient
       ^{st} Most Correlated Bigrams are: loan forgiveness, student loans, student loan
     ==> Vehicle loan or lease:
       * Most Correlated Unigrams are: santander, car, vehicle
       * Most Correlated Bigrams are: ally financial, consumer usa, santander consumer
Spliting the data into train and test sets
X = df2['Consumer complaint'] # Collection of documents
y = df2['Product'] # Target or the labels we want to predict (i.e., the 13 different complaints of products)
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                      test_size=0.25,
                                                      random_state = 0)
Multi-Classification models
models = [
   RandomForestClassifier(n_estimators=100, max_depth=5, random_state=0),
   LinearSVC(),
   MultinomialNB(),
    Logistic Regression (random\_state=0),\\
1
```

5 Cross-validation

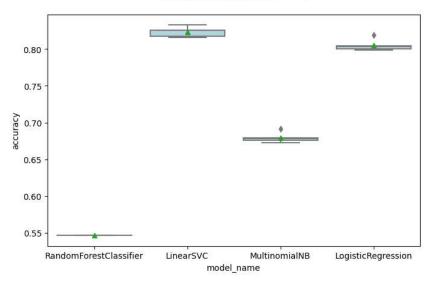
```
CV = 5
cv_df = pd.DataFrame(index=range(CV * len(models)))
entries = []
for model in models:
  model_name = model._
                                  _class__._name_
   accuracies = cross_val_score(model, features, labels, scoring='accuracy', cv=CV)
   for fold idx, accuracy in enumerate(accuracies):
      entries.append((model_name, fold_idx, accuracy))
cv_df = pd.DataFrame(entries, columns=['model_name', 'fold_idx', 'accuracy'])
        /usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700: UserWarning: The least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y has only 1 magnetic formula of the least populated class in y h
           warnings.warn(
        /usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700: UserWarning: The least populated class in y has only 1 me
           warnings.warn(
        /usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700: UserWarning: The least populated class in y has only 1 me
          warnings.warn(
        /usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700: UserWarning: The least populated class in y has only 1 mc
           warnings.warn(
        /usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
       STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
       Increase the number of iterations (max iter) or scale the data as shown in:
              https://scikit-learn.org/stable/modules/preprocessing.html
       Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
           n iter i = check optimize result(
        /usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
       STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
       Increase the number of iterations (\max\_iter) or scale the data as shown in:
              https://scikit-learn.org/stable/modules/preprocessing.html
        Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
           n_iter_i = _check_optimize_result(
        /usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
       STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
       Increase the number of iterations (max_iter) or scale the data as shown in:
              https://scikit-learn.org/stable/modules/preprocessing.html
       Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
           n iter i = check optimize result(
        /usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
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       Increase the number of iterations (max iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html
       Please also refer to the documentation for alternative solver options:
              https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
           n_iter_i = _check_optimize_result(
        /usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
       STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
       Increase the number of iterations (\max\_iter) or scale the data as shown in:
              https://scikit-learn.org/stable/modules/preprocessing.html
       Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
           n_iter_i = _check_optimize_result(
```

Comparison of model performance

Mean Accuracy Standard deviation

```
model_name
                  ---
                                                         . . . . . . . .
plt.figure(figsize=(8,5))
sns.boxplot(x='model_name', y='accuracy',data=cv_df,color='lightblue', showmeans=True)
plt.title("MEAN ACCURACY (cv = 5)\n", size=14);
```

MEAN ACCURACY (cv = 5)



Model Evaluation

```
#Model Evaluation
from sklearn.metrics import classification report
X_train, X_test, y_train, y_test,indices_train,indices_test = train_test_split(features, labels,df2.index, test_size=0.25, random_state=0)
model = LinearSVC()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
y_pred.shape
     (2500,)
```

Precision, Recall, F1-score

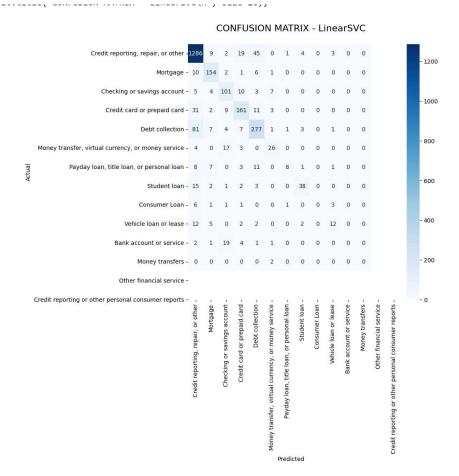
```
from sklearn import metrics
print('\t\t\tCLASSIFICATIION METRICS\n')
classification\_report(y\_test, y\_pred, labels=np. arange(0, len(df2['Product']), 1), target\_names=df2['Product'], digits=4, zero\_division=0)
```

CLASSIFICATIION METRICS

```
recall f1-sco
                                                    precision
    support\n\n
                                Credit reporting, repair, or other
                                                                   0.8808
re
0.9394
                                           Credit reporting, repair, or other
         0.9092
                     1369\n
0.8021
         0.8851
                   0.8415
                                174\n
                                                     Credit reporting, repair,
            0.6474
                      0.7769
                                0.7063
                                            130\n
                                            217\n
Mortgage
            0.7559
                      0.7419
                               0.7488
                                                                        Checki
ng or savings account
                      0.7716 0.7251
                                            0.7476
                                                         382\n
Credit card or prepaid card
                               0.6341
                                       0.5200
                                                 0.5714
```

Confusion Matrix

```
conf_mat = confusion_matrix(y_test, y_pred)
fig, ax = plt.subplots(figsize=(8,8))
sns.heatmap(conf_mat, annot=True, cmap="Blues", fmt='d',
            xticklabels=category_id_df.Product.values,
            yticklabels=category_id_df.Product.values)
plt.ylabel('Actual')
plt.xlabel('Predicted')
nlt.title("CONFUSTON MATRIX - LinearSVC\n". size=16):
```



Most correlated terms with each category

```
#Most correlated terms with each category
model.fit(features, labels)

N = 4
for Product, category_id in sorted(category_to_id.items()):
    indices = np.argsort(model.coef_[category_id])
    feature_names = np.array(tfidf.get_feature_names_out())[indices]
    unigrams = [v for v in reversed(feature_names) if len(v.split(' ')) == 1][:N]
    bigrams = [v for v in reversed(feature_names) if len(v.split(' ')) == 2][:N]
    print("\n=> '{}':".format(Product))
    print(" * Top unigrams: %s" %(', '.join(unigrams)))
    print(" * Top bigrams: %s" %(', '.join(bigrams)))

==> 'Bank account or service':
```

```
* Top unigrams: bank, promotion, branch, 2016
       * Top bigrams: xxxx 2015, xx 2016, bank did, checking account
    ==> 'Checking or savings account':
       * Top unigrams: bank, savings, chime, checking
       * Top bigrams: debit card, savings account, 36 00, overdraft fees
     ==> 'Consumer Loan':
       * Top unigrams: car, motor, vehicle, acceptance
       * Top bigrams: xxxx 16, report owe, going pay, auto xxxx
    ==> 'Credit card or prepaid card':
       * Top unigrams: card, amex, purchase, capital
       * Top bigrams: american express, pay balance, missed payment, care credit
    ==> 'Credit reporting or other personal consumer reports':
       * Top unigrams: 166b, usc, 604, purpose
       * Top bigrams: 166b creditor, 15 usc, xxxx violated, late purpose
     ==> 'Credit reporting, repair, or other':
       * Top unigrams: equifax, experian, transunion, inquiries
       * Top bigrams: victim identity, xxxx xxxx, experian xxxx, late payments
    ==> 'Debt collection':
       * Top unigrams: debt, recovery, collection, owed
       * Top bigrams: credit loan, account belongs, owed money, negative report
    ==> 'Money transfer, virtual currency, or money service':
       * Top unigrams: paypal, coinbase, zelle, transfer
       * Top bigrams: send money, cash app, xxxx told, check xxxx
    ==> 'Money transfers':
       * Top unigrams: traded, game, essentially, money
       * Top bigrams: took money, business days, complaint said, company party
     ==> 'Mortgage':
       * Top unigrams: mortgage, escrow, modification, home
       * Top bigrams: loan care, payment xx, mortgage company, loan modification
    ==> 'Other financial service':
       * Top unigrams: proposal, apology, resend, compensate
       * Top bigrams: money order, pay sent, limited income, contact creditors
    ==> 'Payday loan, title loan, or personal loan':
       * Top unigrams: loan, payday, affirm, finance
       * Top bigrams: aware charge, reporting negative, personal loan, loan said
     ==> 'Student loan':
       * Top unigrams: navient, loans, school, repayment
       * Top bigrams: student loan, fedloan servicing, great lakes, pick phone
    ==> 'Vehicle loan or lease':
       * Top unigrams: vehicle, bridgecrest, payments, santander
       * Top bigrams: delete credit, right xxxx, santander consumer, ally financial
Predictions
X train, X test, y train, y test = train test split(X, y,test size=0.25,random state = 0)
tfidf = TfidfVectorizer(sublinear_tf=True, min_df=5,ngram_range=(1, 2), stop_words='english')
fitted_vectorizer = tfidf.fit(X_train)
tfidf_vectorizer_vectors = fitted_vectorizer.transform(X_train)
model = LinearSVC().fit(tfidf vectorizer vectors, y train)
new_complaint = """I have been enrolled back at XXXX XXXX University in the XX/XX/XXXX. Recently, i have been harassed by \
Navient for the last month. I have faxed in paperwork providing them with everything they needed. And yet I am still getting \
phone calls for payments. Furthermore, Navient is now reporting to the credit bureaus that I am late. At this point, \
Navient needs to get their act together to avoid me taking further action. I have been enrolled the entire time and my \
deferment should be valid with my planned graduation date being the XX/XX/XXXX."""
print(model.predict(fitted_vectorizer.transform([new_complaint])))
     ['Student loan']
df2[df2['Consumer_complaint'] == new_complaint]
print(df2)
```

```
337270 Credit reporting, repair, or other
    814826
             Credit reporting, repair, or other
    1157572 Credit reporting, repair, or other
    589205
                                       Mortgage
                    Checking or savings account
    2863449
     3409083 Credit reporting, repair, or other
     2756499 Credit reporting, repair, or other
    3392408 Credit reporting, repair, or other
    326256
             Credit reporting, repair, or other
    1258628
                                Debt collection
                                            Consumer_complaint category_id
             The date of my first letter was XXXX. I sent a...
             I was XXXX and my ID and social security card ...
                                                                         0
    1157572 I'm really not sure what happened. I have mail...
                                                                         0
    589205
             I was impacted by hurricane Irma and then Mich...
                                                                         1
    2863449 I am a XXXX XXXX XXXX by trade. \n\nAt the en...
                                                                         2
    3409083 XXXX XXXX XXXX XXXX and National Credit Adjust...
    2756499 Hi I am submitting this XXXX XXXX without...
    3392408
             Equifax has been non-compliant with removing t...
                                                                         0
             XXXX XXXX XXXX XXXX XXXX XXXX, OH XXXX DO...
    326256
                                                                         0
    1258628 Bank of America is reporting a charged off acc...
    [10000 rows x 3 columns]
new complaint 2 = """Equifax exposed my personal information without my consent, as part of their recent data breach. \
In addition, they dragged their feet in the announcement of the report, and even allowed their upper management to sell \
off stock before the announcement."""
print(model.predict(fitted_vectorizer.transform([new_complaint_2])))
     ['Credit reporting, repair, or other']
df2[df2['Consumer_complaint'] == new_complaint_2]
print(df2)
                                        Product \
    337270 Credit reporting, repair, or other
    814826 Credit reporting, repair, or other
    1157572 Credit reporting, repair, or other
    589205
                                       Mortgage
    2863449
                    Checking or savings account
    3409083 Credit reporting, repair, or other
    2756499 Credit reporting, repair, or other
    3392408 Credit reporting, repair, or other
    326256
             Credit reporting, repair, or other
    1258628
                                Debt collection
                                            Consumer_complaint category_id
    337270 The date of my first letter was XXXX. I sent a...
             I was XXXX and my ID and social security card ...
    1157572 I'm really not sure what happened. I have mail...
                                                                         a
             I was impacted by hurricane Irma and then Mich...
                                                                         1
    2863449 I am a XXXX XXXX XXXX by trade. \n\nAt the en...
                                                                         2
    3409083 XXXX XXXX XXXX XXXX and National Credit Adjust...
                                                                         0
    2756499
             Hi I am submitting this XXXX XXXX XXXX without...
                                                                         0
    3392408 Equifax has been non-compliant with removing t...
             XXXX XXXX XXXX XXXX XXXX XXXX, OH XXXX DO...
                                                                         0
    326256
    1258628 Bank of America is reporting a charged off acc...
                                                                         4
     [10000 rows x 3 columns]
```

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