In [ ]:
```
import pandas as pd
df = pd.read_csv('./complaints5k.csv')
df.head()
```

Out[ ]:

	Date received	Product	Sub-product	Issue	Sub-issue	Consumer complaint narrative	Company public response	Company	Stat
0	2023-01-24	Credit reporting, credit repair services, or o...	Credit reporting	Improper use of your report	Reporting company used your report improperly	NaN	NaN	EQUIFAX, INC.	LA
1	2023-03-03	Credit reporting, credit repair services, or o...	Credit reporting	Incorrect information on your report	Information belongs to someone else	NaN	NaN	Experian Information Solutions Inc.	CA
2	2023-03-02	Credit reporting, credit repair services, or o...	Credit reporting	Incorrect information on your report	Account information incorrect	NaN	NaN	Experian Information Solutions Inc.	FL
3	2023-03-03	Credit reporting, credit repair services, or o...	Credit reporting	Problem with a credit reporting company's inve...	Investigation took more than 30 days	NaN	NaN	Experian Information Solutions Inc.	GA
4	2023-03-03	Credit reporting, credit repair services, or o...	Credit reporting	Problem with a credit reporting company's inve...	Investigation took more than 30 days	NaN	NaN	Experian Information Solutions Inc.	CA

In [ ]:
```
df = df[pd.notnull(df['Consumer complaint narrative'])]
```

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 635 entries, 7 to 2983
Data columns (total 18 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Date received                  635 non-null    object 
 1   Product                        635 non-null    object 
 2   Sub-product                    635 non-null    object 
 3   Issue                          635 non-null    object 
 4   Sub-issue                      596 non-null    object 
 5   Consumer complaint narrative   635 non-null    object 
 6   Company public response        481 non-null    object 
 7   Company                        635 non-null    object 
 8   State                          634 non-null    object 
 9   ZIP code                       634 non-null    float64
 10  Tags                           56 non-null     object 
 11  Consumer consent provided?     635 non-null    object 
 12  Submitted via                  635 non-null    object 
 13  Date sent to company           635 non-null    object 
 14  Company response to consumer   635 non-null    object 
 15  Timely response?               635 non-null    object 
 16  Consumer disputed?             0 non-null      object 
 17  Complaint ID                   635 non-null    int64  
dtypes: float64(1), int64(1), object(16)
memory usage: 94.3+ KB
```

In [ ]:
```
col = ['Product', 'Consumer complaint narrative']
df = df[col]
```

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['Product', 'Consumer complaint narrative'], dtype='object')
```

In [ ]:
```
df.columns = ['Product', 'Consumer_complaint_narrative']
```

In [ ]:
```
df['category_id'] = df['Product'].factorize()[0]
from io import StringIO
category_id_df = df[['Product', 'category_id']].drop_duplicates().sort_value
category_to_id = dict(category_id_df.values)
id_to_category = dict(category_id_df[['category_id', 'Product']].values)
```

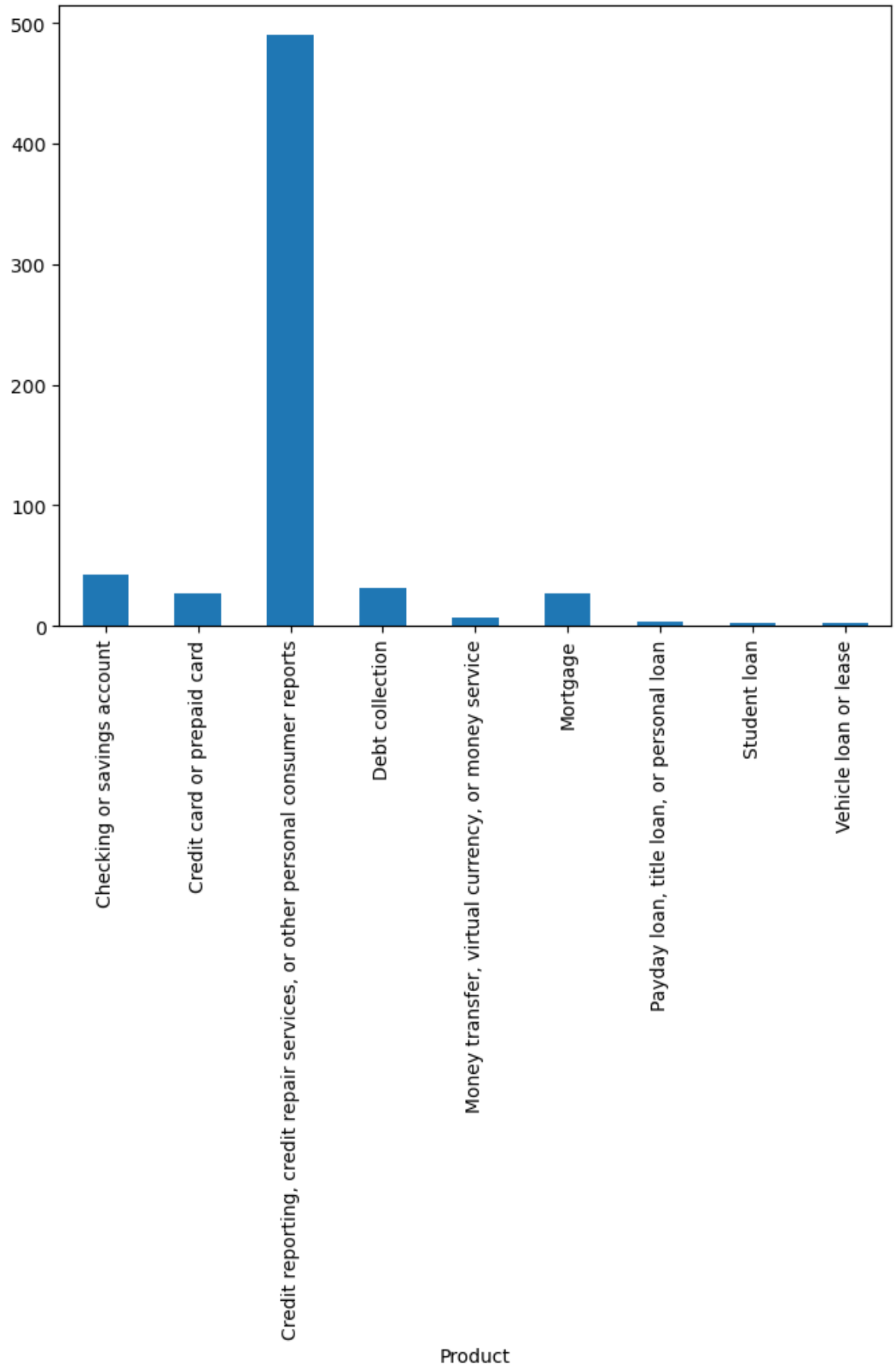
In [ ]:
```
df.head()
```

Out[ ]:

	Product	Consumer_complaint_narrative	category_id
7	Credit reporting, credit repair services, or o...	In accordance with the Fair Credit Reporting a...	0
9	Credit reporting, credit repair services, or o...	This company is still reporting on an account ...	0
28	Credit reporting, credit repair services, or o...	ON XX/XX/2022, MY XX/XX/2022 RECORDED CALL FRO...	0
37	Credit reporting, credit repair services, or o...	XXXX/ XXXX credit card balance was incorrectl...	0
38	Credit reporting, credit repair services, or o...	My credit report contains a significant number...	0

In [ ]:

```
import matplotlib.pyplot as plt
fig = plt.figure(figsize=(8,6))
df.groupby('Product').Consumer_complaint_narrative.count().plot.bar(ylim=0)
plt.show()
```



In [ ]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
tfidf = TfidfVectorizer(sublinear_tf=True, min_df=5, norm='l2', encoding='la

features = tfidf.fit_transform(df.Consumer_complaint_narrative).toarray()
labels = df.category_id
features.shape
```

Out[ ]: (635, 2476)

In [ ]:
```
from sklearn.feature_selection import chi2
import numpy as np

N = 2
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("# '{}':".format(Product))
  print("  . Most correlated unigrams:\n       . {}".format('\n       . '.jo
  print("  . Most correlated bigrams:\n       . {}".format('\n       . '.joi
```

```
# 'Checking or savings account':
  . Most correlated unigrams:
       . funds
       . bank
  . Most correlated bigrams:
       . wells fargo
       . checking account
# 'Credit card or prepaid card':
  . Most correlated unigrams:
       . charged
       . card
  . Most correlated bigrams:
       . credit card
       . 15 days
# 'Credit reporting, credit repair services, or other personal consumer rep
orts':
  . Most correlated unigrams:
       . wells
       . fargo
  . Most correlated bigrams:
       . bank america
       . wells fargo
# 'Debt collection':
  . Most correlated unigrams:
       . validation
       . collection
  . Most correlated bigrams:
       . debt collection
       . collection company
# 'Money transfer, virtual currency, or money service':
  . Most correlated unigrams:
       . tax
       . compromised
  . Most correlated bigrams:
       . received email
       . case xxxx
# 'Mortgage':
  . Most correlated unigrams:
       . property
       . mortgage
  . Most correlated bigrams:
       . wells fargo
       . mortgage xxxx
# 'Payday loan, title loan, or personal loan':
  . Most correlated unigrams:
       . saw
       . finance
  . Most correlated bigrams:
       . loan xxxx
       . told xxxx
# 'Student loan':
  . Most correlated unigrams:
       . limited
       . servicer
  . Most correlated bigrams:
       . told xxxx
```

```
        . 90 days
# 'Vehicle loan or lease':
  . Most correlated unigrams:
        . explaining
        . purchased
  . Most correlated bigrams:
        . xxxx initially
        . soon possible
```

In [ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.naive_bayes import MultinomialNB

X_train, X_test, y_train, y_test = train_test_split(df['Consumer_complaint_r
count_vect = CountVectorizer()
X_train_counts = count_vect.fit_transform(X_train)
tfidf_transformer = TfidfTransformer()
X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)

clf = MultinomialNB().fit(X_train_tfidf, y_train)
```

In [ ]:
```
print(clf.predict(count_vect.transform(["This company refuses to provide me
```

```
['Credit reporting, credit repair services, or other personal consumer repo
rts']
```

In [ ]:
```
print(clf.predict(count_vect.transform(["I am disputing the inaccurate infor
```

```
['Credit reporting, credit repair services, or other personal consumer repo
rts']
```

In [ ]:
```
df[df['Consumer_complaint_narrative'].str.contains("I discovered that some c
```

Out[ ]:

	Product	Consumer_complaint_narrative	category_id
99	Credit reporting, credit repair services, or o...	I discovered that some of the information on m...	0
1199	Credit reporting, credit repair services, or o...	I discovered that some of the information on m...	0
2360	Credit reporting, credit repair services, or o...	I discovered that some of the information on m...	0
2385	Credit reporting, credit repair services, or o...	I discovered that some of the information on m...	0
2412	Credit reporting, credit repair services, or o...	I discovered that some of the information on m...	0
2514	Credit reporting, credit repair services, or o...	I discovered that some of the information on m...	0
2684	Credit reporting, credit repair services, or o...	I discovered that some of the information on m...	0
2743	Credit reporting, credit repair services, or o...	I discovered that some of the information on m...	0

In [ ]:
```
df[df['Consumer_complaint_narrative'].str.contains("We refinanced our Wells
```

Out[ ]:

	Product	Consumer_complaint_narrative	category_id
1125	Mortgage	We refinanced our Wells Fargo mortgage with XX...	4

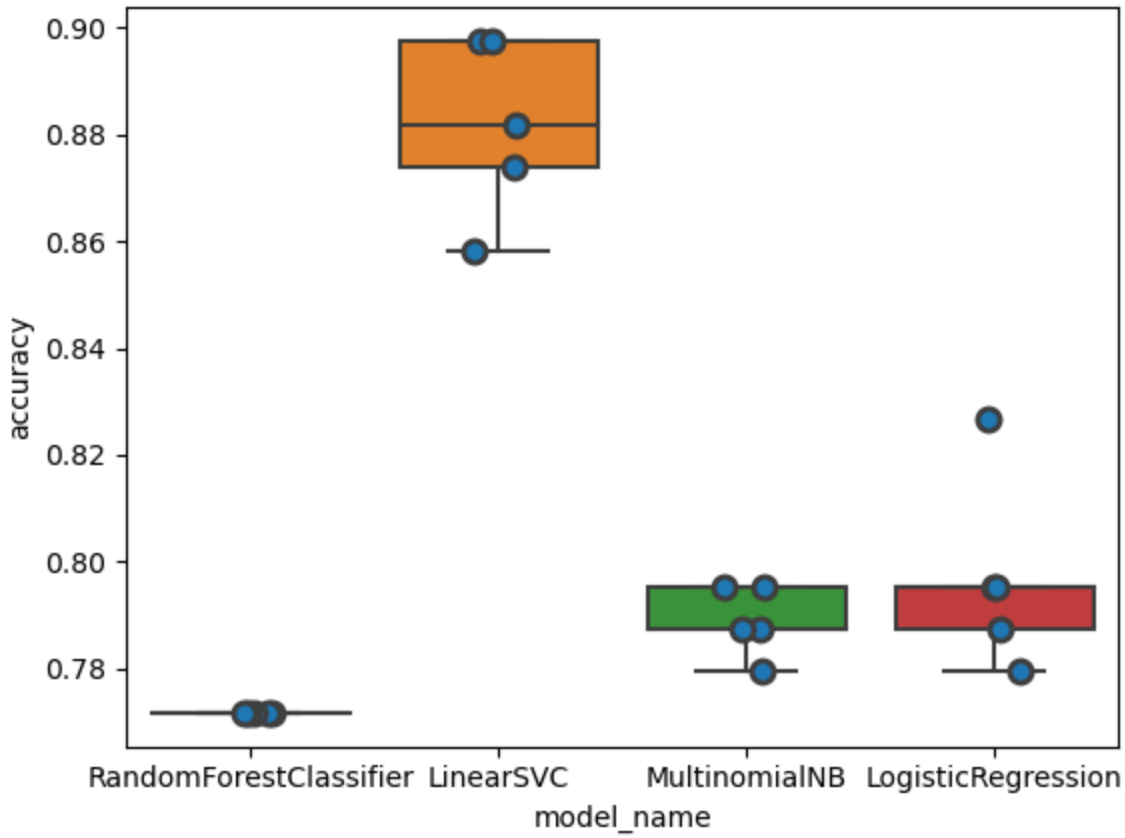
In [ ]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import LinearSVC

from sklearn.model_selection import cross_val_score


models = [
    RandomForestClassifier(n_estimators=200, max_depth=3, random_state=0),
    LinearSVC(),
    MultinomialNB(),
    LogisticRegression(random_state=0),
]
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',
  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']
```

```
/home/deepcode/.local/lib/python3.9/site-packages/sklearn/model_selection/_
split.py:700: UserWarning: The least populated class in y has only 3 member
s, which is less than n_splits=5.
  warnings.warn(
/home/deepcode/.local/lib/python3.9/site-packages/sklearn/model_selection/_
split.py:700: UserWarning: The least populated class in y has only 3 member
s, which is less than n_splits=5.
  warnings.warn(
/home/deepcode/.local/lib/python3.9/site-packages/sklearn/model_selection/_
split.py:700: UserWarning: The least populated class in y has only 3 member
s, which is less than n_splits=5.
  warnings.warn(
/home/deepcode/.local/lib/python3.9/site-packages/sklearn/model_selection/_
split.py:700: UserWarning: The least populated class in y has only 3 member
s, which is less than n_splits=5.
  warnings.warn(
```

In [ ]:

```
import seaborn as sns

sns.boxplot(x='model_name', y='accuracy', data=cv_df)
sns.stripplot(x='model_name', y='accuracy', data=cv_df,
              size=8, jitter=True, edgecolor="gray", linewidth=2)
plt.show()
```

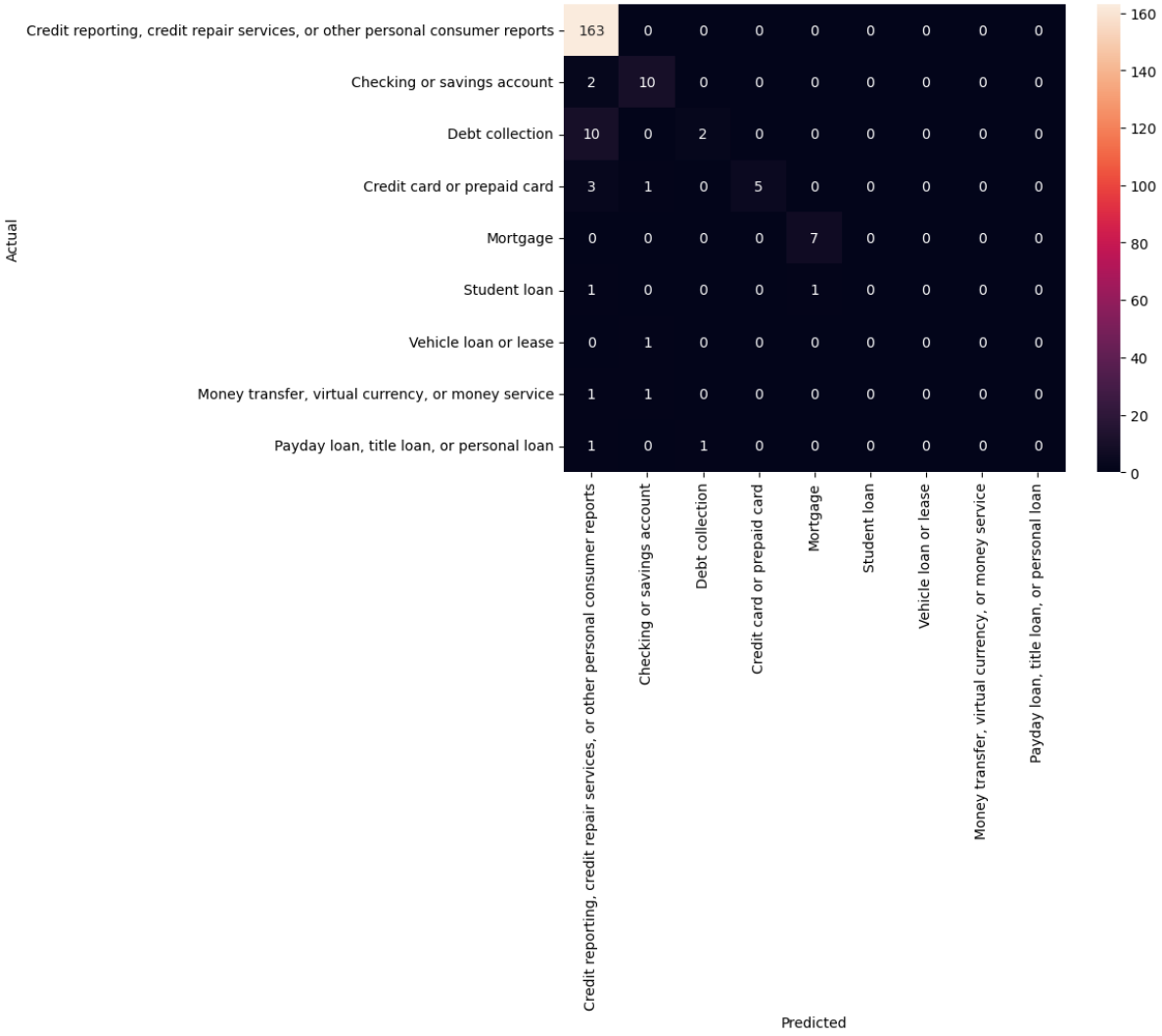


In [ ]:
```
cv_df.groupby('model_name').accuracy.mean()
```

Out[ ]:
```
model_name
LinearSVC                 0.881890
LogisticRegression        0.796850
MultinomialNB             0.788976
RandomForestClassifier    0.771654
Name: accuracy, dtype: float64
```

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

model = LinearSVC()

X_train, X_test, y_train, y_test, indices_train, indices_test = train_test_s
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

In [ ]:
```
from sklearn.metrics import confusion_matrix

conf_mat = confusion_matrix(y_test, y_pred)
fig, ax = plt.subplots(figsize=(8,6))
sns.heatmap(conf_mat, annot=True, fmt='d',
            xticklabels=category_id_df.Product.values, yticklabels=category_
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()
```



In [ ]:
```
from IPython.display import display

for predicted in category_id_df.category_id:
  for actual in category_id_df.category_id:
    if predicted != actual and conf_mat[actual, predicted] >= 6:
      print("'{}' predicted as '{}' : {} examples.".format(id_to_category[ac
      display(df.loc[indices_test[(y_test == actual) & (y_pred == predicted)
      print('')
```

```
'Debt collection' predicted as 'Credit reporting, credit repair services, o
r other personal consumer reports' : 10 examples.
```

	Product	Consumer_complaint_narrative
2738	Debt collection	please reference attachments for complaint, ex...
2786	Debt collection	I was informed by my mortage company XXXX Newr...
1569	Debt collection	On XX/XX/22 I was contacted by (XXXX) XXXX a...
2967	Debt collection	Two weeks ago I received a notification/alert ...
1155	Debt collection	I need to dispute the account. This is not a b...
2771	Debt collection	To whom it may concern. \nPlease be advised th...
1754	Debt collection	A letter dated XX/XX/XXXX from XXXX of Ohio, ...
593	Debt collection	collection company added a closed account to m...
1995	Debt collection	I received an alert from XXXX XXXX XXXX XXXX X...
2440	Debt collection	After reviewing my credit profile on XX/XX/XXX...

In [ ]:
```
model.fit(features, labels)
```

Out[ ]:
```
▼ LinearSVC
LinearSVC()
```

In [ ]:
```
from sklearn.feature_selection import chi2

N = 2
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][
  bigrams = [v for v in reversed(feature_names) if len(v.split(' ')) == 2][:
  print("# '{}':".format(Product))
  print("  . Top unigrams:\n       . {}".format('\n       . '.join(unigrams)
  print("  . Top bigrams:\n       . {}".format('\n       . '.join(bigrams)))
```

```
# 'Checking or savings account':
  . Top unigrams:
       . funds
       . deposit
  . Top bigrams:
       . check xxxx
       . checking account
# 'Credit card or prepaid card':
  . Top unigrams:
       . card
       . charged
  . Top bigrams:
       . credit card
       . 15 days
# 'Credit reporting, credit repair services, or other personal consumer rep
orts':
  . Top unigrams:
       . report
       . transunion
  . Top bigrams:
       . credit report
       . xx 2021
# 'Debt collection':
  . Top unigrams:
       . collection
       . stating
  . Top bigrams:
       . collection company
       . xxxx stating
# 'Money transfer, virtual currency, or money service':
  . Top unigrams:
       . money
       . compromised
  . Top bigrams:
       . received email
       . case xxxx
# 'Mortgage':
  . Top unigrams:
       . mortgage
       . property
  . Top bigrams:
       . mortgage xxxx
       . payment xxxx
# 'Payday loan, title loan, or personal loan':
  . Top unigrams:
       . loan
       . payments
  . Top bigrams:
       . told xxxx
       . loan xxxx
# 'Student loan':
  . Top unigrams:
       . servicer
       . loans
  . Top bigrams:
       . 90 days
```

```
        . told xxxx
# 'Vehicle loan or lease':
  . Top unigrams:
        . purchased
        . starting
  . Top bigrams:
        . soon possible
        . xxxx initially
```

In [ ]:
```
texts = ["I requested a home loan modification through Bank of America. Bank
         "It has been difficult for me to find my past due balance. I misse
         "I can't get the money out of the country.",
         "I have no money to pay my tuition",
         "Coinbase closed my account for no reason and furthermore refused t
text_features = tfidf.transform(texts)
predictions = model.predict(text_features)
for text, predicted in zip(texts, predictions):
  print('"{}"'.format(text))
  print("  - Predicted as: '{}'".format(id_to_category[predicted]))
  print("")
```

```
"I requested a home loan modification through Bank of America. Bank of Amer
ica never got back to me."
  - Predicted as: 'Checking or savings account'

"It has been difficult for me to find my past due balance. I missed a regul
ar monthly payment"
  - Predicted as: 'Credit reporting, credit repair services, or other perso
nal consumer reports'

"I can't get the money out of the country."
  - Predicted as: 'Checking or savings account'

"I have no money to pay my tuition"
  - Predicted as: 'Checking or savings account'

"Coinbase closed my account for no reason and furthermore refused to give m
e a reason despite dozens of request"
  - Predicted as: 'Credit reporting, credit repair services, or other perso
nal consumer reports'
```

In [ ]:
```
from sklearn import metrics
print(metrics.classification_report(y_test, y_pred,
                                    target_names=df['Product'].unique()))
```

```
precision    recall  f1-score   support

Credit reporting, credit repair services, or other personal consumer report
s       0.90      1.00      0.95       163
                                                   Checking or savings accoun
t       0.77      0.83      0.80        12
                                                               Debt collectio
n       0.67      0.17      0.27        12
                                                   Credit card or prepaid car
d       1.00      0.56      0.71         9
                                                                      Mortgag
e       0.88      1.00      0.93         7
                                                                  Student loa
n       0.00      0.00      0.00         2
                                                         Vehicle loan or leas
e       0.00      0.00      0.00         1
                          Money transfer, virtual currency, or money servic
e       0.00      0.00      0.00         2
                                   Payday loan, title loan, or personal loa
n       0.00      0.00      0.00         2

                                                                      accurac
y                           0.89       210
                                                                     macro av
g       0.47      0.40      0.41       210
                                                                  weighted av
g       0.85      0.89      0.86       210
```

```
/home/deepcode/.local/lib/python3.9/site-packages/sklearn/metrics/_classifi
cation.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/deepcode/.local/lib/python3.9/site-packages/sklearn/metrics/_classifi
cation.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/deepcode/.local/lib/python3.9/site-packages/sklearn/metrics/_classifi
cation.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```