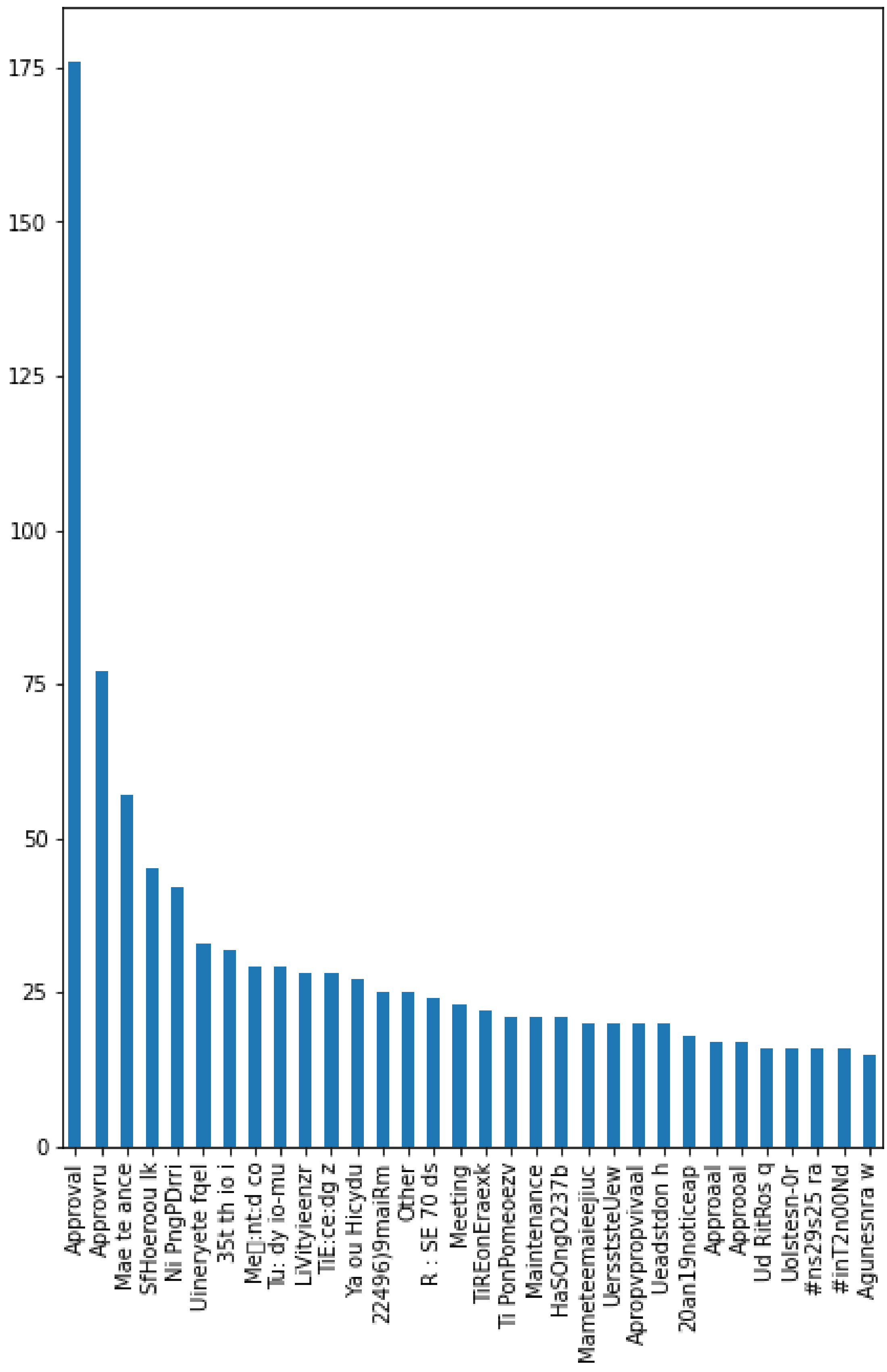
```
import warnings

warnings.filterwarnings("ignore")

import pandas as pd
df = pd.read_excel('Project_Data.xls', sheet_name='EmailReport')

## Importing libs and dependencies.
import os
import pandas as pd
import numpy as np

## Rows and column count for our data
print(df.shape)
```

(9486, 7)

```
# df.head(3).T

## Based on my initial analysis. I think we will not require
(ConversationId,UnitNumber)
## Category sees to be the lable and that's what we want to predict
based on the Subject and Category of the data.

print(df["Category"].value_counts())

df['Category'].value_counts().head(32).plot(kind='bar',
figsize=(7,10))
```

<AxesSubplot:>


175
150
125
100
75
50
25
0
Approval
Approvru
Mae te ance
SfHoeroou lk
Ni PngPDrri
Uineryete fqel
35t th io i
Me▯:nt:d co
Tu: dy io-mu
LiVityieenzr
TiE:ce:dg z
Ya ou Hicydu
22496)9maiRm
Other
R : SE 70 ds
Meeting
TiREonEraexk
Ti PonPomeoezv
Maintenance
HaSOngO237b
Mameteemaieejiuc
UersststeUew
Apropvpropvivaal
Ueadstdon h
20an19noticeap
Approaal
Approoal
Ud RitRos q
UoIstesn-0r
#ns29s25 ra
#inT2n00Nd
Agunesnra w

```
total_count = df["Category"].value_counts().sum()
print(f"Total category occurance count: {total_count}")
```

```
Total category occurance count: 3210
```

```
num_categories = len(df["Category"].unique())
print(f"Number of unique categories: {num_categories}")
print(f"Average category occurrence: {total_count / num_categories}")
```

```
Number of unique categories: 996
Average category occurrence: 3.2228915662650603
```

```
df['Category'].unique()
```

```
## Applying domain knowledge of email category to analyse the
categorys.

### 1) A lot of category label do not make any sense.
### 2) Some of the lable are in different language.
```

```
df.isnull().sum()
```

```
ConversationId         0
Subject                0
Body                  70
Category            6276
HasAttachment          0
DateTimeReceived       0
UnitNumber          6523
dtype: int64
```

```
## So our data set is missing a lot of lables to train on (6276 out of
9486) rows do not contain a lable.
```

```
# Removing ConversationId and UnitNumber
df = df.drop(['ConversationId','UnitNumber'], axis=1)
```

```
#Check if we have duplicates values
df.duplicated().sum()
## will come back to it later
```

```
7
```

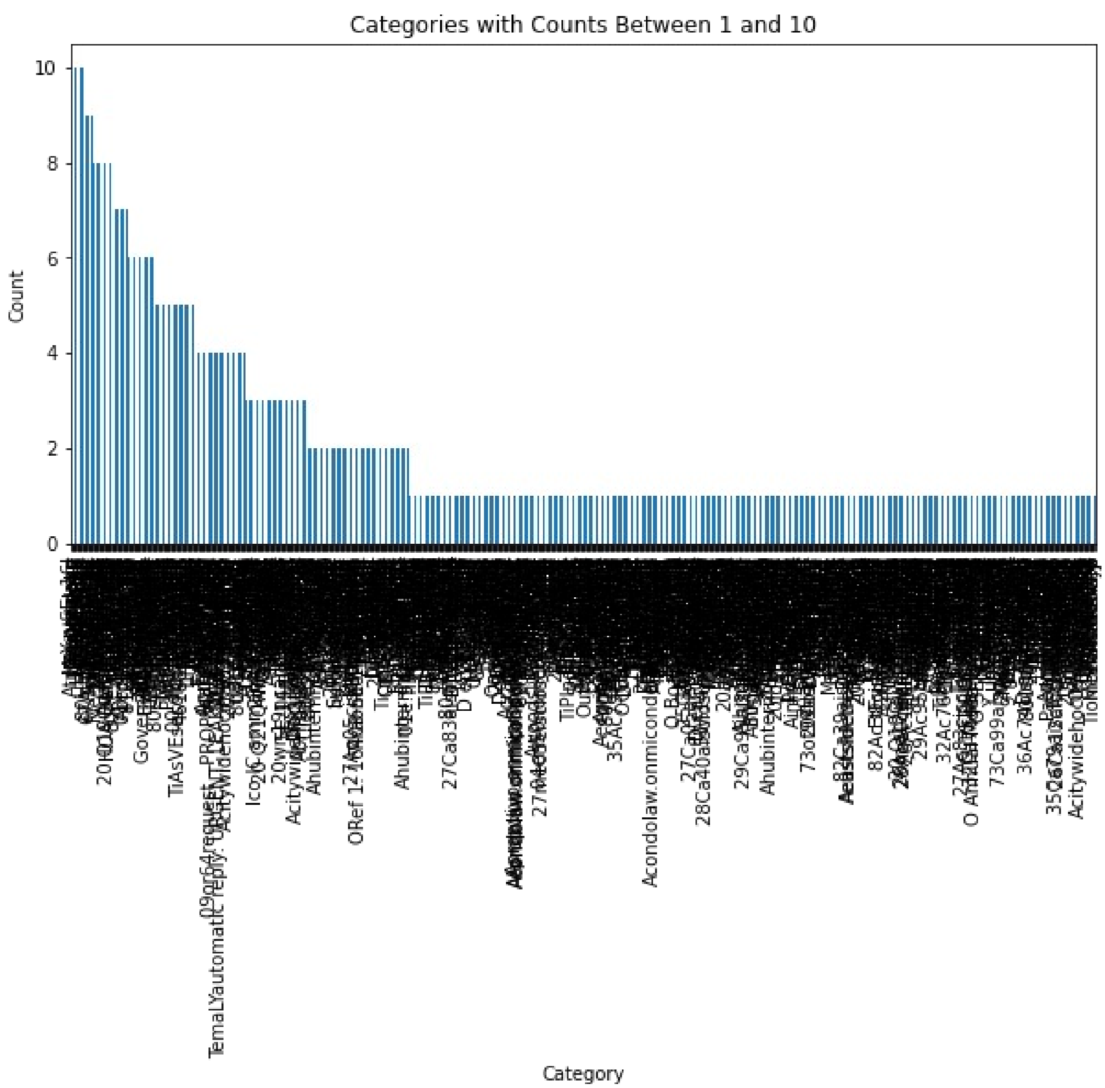
```
## Visualizing how the category values are distributed!
```

```
max_count=10
counts = df["Category"].value_counts()
filtered_counts = counts[(counts >= 1) & (counts <= max_count)]
print(f"Number of categories with occurance count between 1 and
{max_count}: {filtered_counts.sum()}. This makes
```

```python
{round(((filtered_counts.sum()/total_count)*100),2)}% of total categories")
```

```
Number of categories with occurance count between 1 and 10: 1945. This makes 60.59% of total categories
```

```python
##Warning: Don't run this if your device is slow

import matplotlib.pyplot as plt
try:
    plt.figure(figsize=(10, 5))
    filtered_counts.plot(kind='bar')
    plt.xlabel('Category')
    plt.ylabel('Count')
    plt.title(f'Categories with Counts Between 1 and {max_count}')
    plt.show()
except:
    pass
```



```python
#The trend graph clearly shows that most of the category only got one occurance in over 3500 entry.
#And we know that statics does not work on this low count. The data is heavily skewed, we will have to make do some data preprocessing.
```

```python
pd.DataFrame(df.Category.unique()).values
```

```python
# Just for testing if we can't seperate categories which are in english

## Not going to use this in production
import numpy as np
from langdetect import detect

def detect_language(label):
    return detect(label)

categories = np.array(df['Category'].unique())

english_categories = []
for word in categories:
    try:
        if isinstance(word, str) and detect_language(word) == "en":
            english_categories.append(word)
    except Exception as e:
        continue
```

```python
# print(english_categories)
```

```python
len(english_categories)
```

```
175
```

```python
## Dropping all the rows where category is not defined as we can't use it for training. (~ 6500 rows will be removed)

df= df.dropna(subset=['Category'],axis = 0)
```

```python
df.isnull().sum()
```

```
Subject              0
Body                11
Category             0
HasAttachment        0
DateTimeReceived     0
dtype: int64
```

```python
df.shape
```

```
(3210, 5)

## Removing any unnecessary characters, such as punctuation and
special symbols, converting all words to lowercase, and removing any
stop words or irrelevant words from the categories.
import re
def normalize_category(text):
    if(not text):
        return
    text=str(text)

   #1. Normalize: Convert to lower case and remove punctuation
    text = re.sub(r"[^a-zA-Z0-9]", " ", text.strip())

    # not performing tokenization and other operation on the labels

    return text

df['Category'] = df['Category'].apply(lambda x: normalize_category(x))




## Iteration 1

## First itertation with only Subject and Body and run basic npl
classification algorithm


# import libraries

#Load-data Libraries
import pandas as pd

#Text Processing libraries
import nltk
# nltk.download('stopwords')
# nltk.download(['punkt', 'wordnet', 'averaged_perceptron_tagger'])
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.tokenize import word_tokenize
import re


#Model libraries
from sklearn.pipeline import Pipeline, FeatureUnion
from sklearn.multioutput import MultiOutputClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer,
```

```
TfidfTransformer
from sklearn.naive_bayes import MultinomialNB

#Save the model
import joblib
from joblib import dump, load

#Evaluate the model
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix

# removing all other columns which are not required.
data = df.drop(['HasAttachment','DateTimeReceived'], axis=1)

stop_words = stopwords.words("english")
lemmatizer = WordNetLemmatizer()

def tokenize(text):
    text=str(text)

   #1. Normalize: Convert to lower case and remove punctuation
    text = re.sub(r"[^a-zA-Z0-9]", " ", text.lower().strip())

   #2. Tokenizing: split text into words
    tokens = word_tokenize(text)

   #3. Remove stop words: if a token is a stop word, then remove it
    words = [w for w in tokens if w not in stopwords.words("english")]

    #4. Lemmatize and Stemming
    lemmed_words = [WordNetLemmatizer().lemmatize(w) for w in words]

    clean_tokens = []

    for i in lemmed_words:
        clean_tokens.append(i)

        ## back to string from list
    text = " ".join(clean_tokens)
    return text

    #return clean_tokens

data['Subject'] = data['Subject'].apply(lambda x: tokenize(x))
data['Body'] = data['Body'].apply(lambda x: tokenize(x))

## Will removing numbers will change the result? -> will come back to
it

X = data['Subject']+" "+data["Body"]
y = data['Category']
```

```
#split data into training 80% and test 20%
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.20, random_state=42)

pipeline = Pipeline([
        ('vect', CountVectorizer(tokenizer=tokenize)),
        ('tfidf', TfidfTransformer()),
        ('clf', MultinomialNB())
    ])

#train pipeline
pipeline.fit(X_train, y_train)
```

```
Pipeline(steps=[('vect',
                 CountVectorizer(tokenizer=<function tokenize at
0x7f9d63bb20d0>)),
                ('tfidf', TfidfTransformer()), ('clf',
MultinomialNB())])
```

```
# Predit using the trained model
predicted = pipeline.predict(X_test)
```

```
from sklearn.metrics import accuracy_score
## Accuracy, Precision, Recall
accuracy = accuracy_score(y_test, predicted)

print("Accuracy:",  round(accuracy,2))

# print("Other Metrics:")
# print(classification_report(y_test, predicted))
```

```
Accuracy: 0.05
```

```
## So as we see the basic test fails and we can find lot of insght
from it.
### 1) Number of categorys are too huge and training varity is not
available for it
### 2) We will have to reduce the number of categories and train the
model on different algorithms.
```

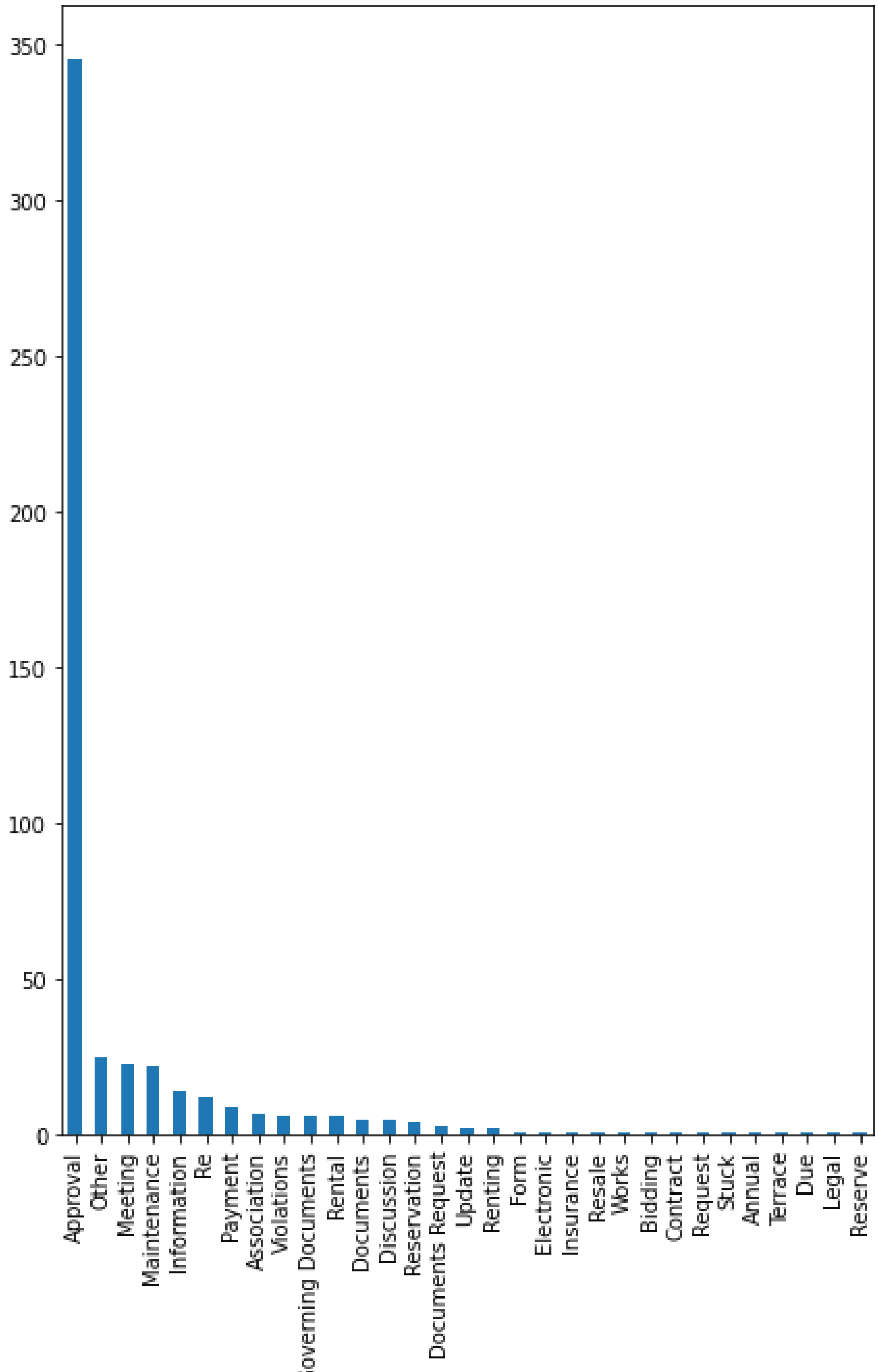
```
## Iteration 2 (Reducing the number of categories by using domain
knowledge.) =>> Target is to reduce the number of categories to 20-25

import pandas as pd
```

```
old_names = ['Approval', 'Approvru', 'Approoal', 'Approuru',
'Approtal', 'Approoru', 'Approcal', 'Approaal', 'Approcru',
'Approrru', 'Approsal', 'Approual', 'Approwal', 'Approaru',
'Approiru', 'Appronru', 'Appronal', 'Approial', 'Approlal',
'ApproTal', 'Approral', 'Approtru', 'Approeal']
new_name = "Approval"
category_array = ['Maintenance', 'Other', 'Payment', 'Hoa Demand
Request', 'Information', 'Update', 'Violations', 'Insurance',
'Documents', 'Meeting', 'Approval', 'Governing Documents',
'Discussion', 'Reserve', 'Contract', 'Bidding', 'Documents Request',
'Reservation', 'Legal', 'Rental', 'Form', 'Electronic', 'Re',
'Resale', 'Works', 'Renting', 'Association', 'Request', 'Stuck',
'Annual', 'Terrace', 'Due']

category_array.extend(old_names)
df2 = data[data["Category"].isin(category_array)]
df2["Category"].replace(to_replace=old_names, value=new_name,
inplace=True)
```

```
df2['Subject'] = df2['Subject'].apply(lambda x: tokenize(x))
df2['Body'] = df2['Body'].apply(lambda x: tokenize(x))
# df2.head()
```

```
df2['Category'].value_counts().head(32).plot(kind='bar',
figsize=(7,10))
```

```
<AxesSubplot:>
```



350
300
250
200
150
100
50
0
Approval
Other
Meeting
Maintenance
Information
Re
Payment
Association
Violations
ioverning Documents
Rental
Documents
Discussion
Reservation
Documents Request
Update
Renting
Form
Electronic
Insurance
Resale
Works
Bidding
Contract
Request
Stuck
Annual
Terrace
Due
Legal
Reserve

```
X = df2['Subject']+" "+df2["Body"]
y = df2['Category']

#split data into training 80% and test 20%
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.20, random_state=42)

pipeline = Pipeline([
        ('vect', CountVectorizer(tokenizer=tokenize)),
        ('tfidf', TfidfTransformer()),
        ('clf', MultinomialNB())
    ])

#train pipeline
pipeline.fit(X_train, y_train)
```

```
Pipeline(steps=[('vect',
                 CountVectorizer(tokenizer=<function tokenize at
0x7f9d63bb20d0>)),
                ('tfidf', TfidfTransformer()), ('clf',
MultinomialNB())])
```

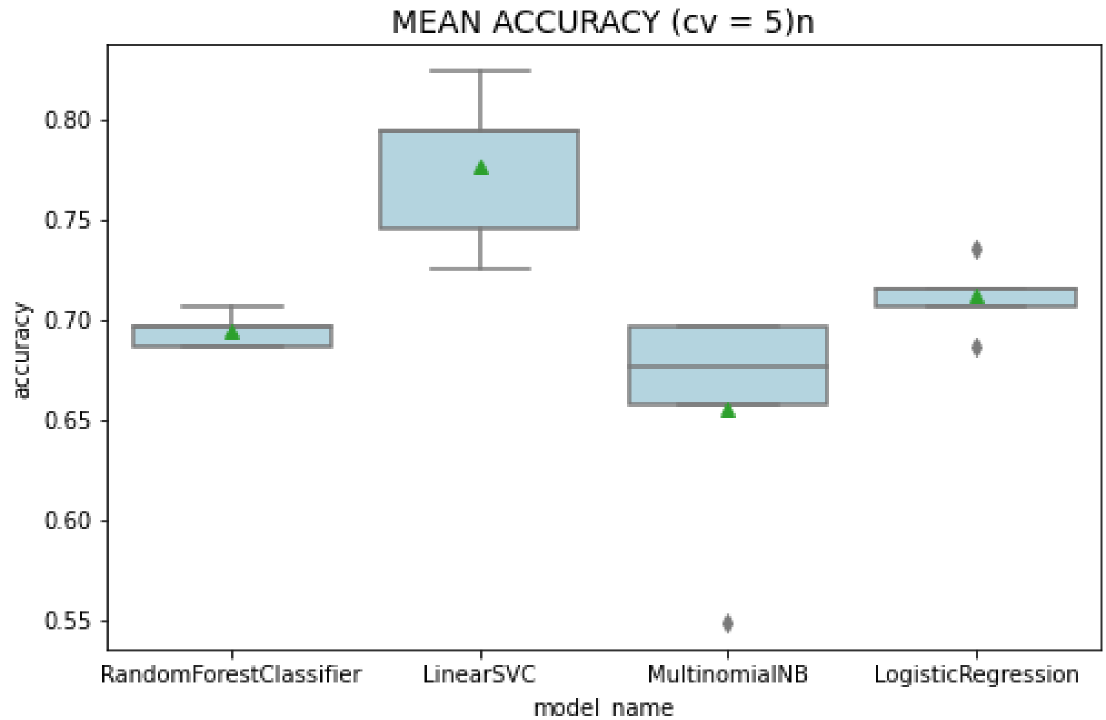
```
# Predit using the trained model
predicted = pipeline.predict(X_test)


from sklearn.metrics import accuracy_score
## Accuracy, Precision, Recall
accuracy = accuracy_score(y_test, predicted)

print("Accuracy:",  round(accuracy,2))

print("Other Metrics:")
print(classification_report(y_test, predicted))
```

```
Accuracy: 0.66
```

```
## Iteration 3

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 RandomForestClassifier
from sklearn.svm import LinearSVC
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn import metrics

# Create a new column 'category_id' with encoded categories
df2['category_id'] = df2['Category'].factorize()[0]
category_id_df = df2[['Category', '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',
'Category']].values)
# New dataframe
df2.head()

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.Subject +' '+df2.Body).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 510 complaints is represented by 3096 features (TF-IDF
score of unigrams and bigrams)

# Now, we will find the most correlated terms with each of the defined
product categories. Here we are finding only three most correlated
terms.

# Finding the three most correlated terms with each of the product
categories
N = 3
for Category, 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())[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==> %s:" %(Category))
    print("  * Most Correlated Unigrams are: %s" %(',
'.join(unigrams[-N:])))
    print("  * Most Correlated Bigrams are: %s" %(', '.join(bigrams[-
N:])))

# The classification models which we are using:

# Random Forest
```

```
# Linear Support Vector Machine
# Multinomial Naive Bayes
# Logistic Regression.

X = df2['Subject']+" "+df2["Body"] # Collection of documents
y = df2['Category']
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.25,
                                                    random_state = 0)

models = [
    RandomForestClassifier(n_estimators=100, max_depth=5,
random_state=0),
    LinearSVC(),
    MultinomialNB(),
    LogisticRegression(random_state=0),
]
# 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'])
print(cv_df)

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);
```




```
## We can see the SVM is giving the best results so we will be using
it for the final model.


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=1)
model = LinearSVC()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

# Classification report
print('CLASSIFICATIION METRICS')
print(metrics.classification_report(y_test, y_pred,
                                    target_names=
df2['Category'].unique()[:16]))

ttttCLASSIFICATIION METRICSn
                     precision    recall  f1-score   support

        Maintenance       0.50      1.00      0.67         1
              Other       0.25      0.20      0.22         5
            Payment       0.00      0.00      0.00         5
        Information       0.20      1.00      0.33         1
             Update       1.00      1.00      1.00         2
         Violations       1.00      0.50      0.67         2
          Insurance       0.86      1.00      0.92         6
```

```
          Documents       0.87      0.97      0.91        89
            Meeting       1.00      1.00      1.00         2
           Approval       1.00      1.00      1.00         1
Governing Documents       0.00      0.00      0.00         1
         Discussion       0.00      0.00      0.00         0
           Contract       0.00      0.00      0.00         1
            Bidding       0.00      0.00      0.00         7
  Documents Request       0.00      0.00      0.00         1
        Reservation       1.00      1.00      1.00         4

           accuracy                           0.82       128
          macro avg       0.48      0.54      0.48       128
       weighted avg       0.75      0.82      0.78       128
```

```
## Final model and testing the model.

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)

print(model.predict(fitted_vectorizer.transform([df.Subject[2]+"
"+df.Body[2]])))
```

```
['Maintenance']
```

```
df.Category[2]
```

```
'Maintenance'
```