Text Classification (Assignment 1)

Group 7

8795048 Yuting Cao
300254157 Manjie Hou
300250954 Haiwei Nan
300151213 Yunzhou Wang

University of Ottawa
GNG5125 Data Science Applications
Feb 9, 2023

Table of Contents

1 Prepare the data

1.1 Sample Book Selection

Five children's literature works with the same genre and the same semantics selected from Gutenberg digital books, are

Children literature

"Peter Pan" by J. M. Barrie https://www.gutenberg.org/files/16/16-0.txt

"The Adventures of Tom Sawyer" by Mark Twain https://www.gutenberg.org/files/74/74-0.txt

"The Wind in the Willows" by Kenneth Grahame https://www.gutenberg.org/files/289/289-0.txt

"The Secret Garden" by Frances Hodgson Burnett https://www.gutenberg.org/cache/epub/17396/pg17396.txt

"Treasure Island" by Robert Louis Stevenson https://www.gutenberg.org/cache/epub/120/pg120.txt

Add two novels with different themes as a control group.

Romance fiction

"Pride and Prejudice" by Jane Austen https://www.gutenberg.org/cache/epub/1342/pg1342.txt

Mystery fiction

"The Adventures of Sherlock Holmes" by Sir Arthur Conan Doyle https://www.gutenberg.org/files/1661/1661-0.txt

1.2 Download and save each book

```
# Define the URL and filenames for each book
books = [
    {"url": "https://www.gutenberg.org/files/16/16-0.txt", "filename": "Peter_Pan.txt"},
    {"url": "https://www.gutenberg.org/files/74/74-0.txt", "filename": "The_Adventures_of_Tom_Sawyer.txt"},
    {"url": "https://www.gutenberg.org/cache/epub/120/pg120.txt", "filename": "Treasure_Island.txt"},
    {"url": "https://www.gutenberg.org/files/289/289-0.txt", "filename": "The_Wind_in_the_Willows.txt"},
    {"url": "https://www.gutenberg.org/cache/epub/17396/pg17396.txt", "filename": "The_Secret_Garden.txt"},
    {"url": "https://www.gutenberg.org/cache/epub/1342/pg1342.txt", "filename": "Pride_and_Prejudice.txt"},
    {"url": "https://www.gutenberg.org/files/1661/1661-0.txt", "filename": "The_Adventures_of_Sherlock_Holmes.txt"},
]

# Download and save each book
for book in books:
    url = book["url"]
    filename = book["filename"]
    urllib.request.urlretrieve(url, filename)
    print(f"{filename} has been saved.")
```

```
Peter_Pan.txt has been saved.
The_Adventures_of_Tom_Sawyer.txt has been saved.
Treasure_Island.txt has been saved.
The_Wind_in_the_Willows.txt has been saved.
The_Secret_Garden.txt has been saved.
Pride_and_Prejudice.txt has been saved.
The_Adventures_of_Sherlock_Holmes.txt has been saved.
```

1.3 Define the sample_digital_book function

Implement changing the book name as well as the number and size of partitions.
Create a csv file containing corpus data.
A function to label each section according to which book it belongs to, as well as a function to create a csv file containing sections from multiple books.

```
def sample_digital_book(book_name, num_partitions, size_partition):

    # Download the digital book from the local directory
    book_file = open(book_name, "r", encoding='utf-8')
    book = book_file.read()
    book_file.close()

    # use 'word_tokenize' function to tokenize the book into words.
    # Then, divide digital book into each partitions of the specified size (100 words)
    partitions = nltk.word_tokenize(book)
    partitions = [partitions[i : i+size_partition] for i in range(0, len(partitions), size_partition)]

    # Check num_partitions is valid
    if num_partitions > len(partitions) or num_partitions < 0:
        num_partitions = len(partitions)
    partitions = partitions[:num_partitions]

    # Create labels
    labels = [book_name[:1]]
    # Repeat the labels for the number of times that can fit in the partitions
    label_list = labels*(num_partitions//len(labels))
    # Get the remainder labels that are needed.
    label_list += labels[:num_partitions%len(labels)]


    # Use regular expression to manipulate the text
    # and the regular expression r'[^\w\s]' is used to remove non-alphanumeric characters from the text.
    partitions = [[re.sub(r'[^\w\s]', '', word) for word in partition] for partition in partitions]

    # Remove empty strings from the list
    partitions = [[word for word in partition if word] for partition in partitions]
```

2 Preprocess the data

2.1 Remove stop-words

Removing them from the text helps reduce noise and speed up the retrieval process.

```
#added by Nan
    # Remove stop words
    stop_words = set(stopwords.words('english'))
    partitions = [[word for word in partition if word.lower() not in stop_words] for partition in partitions]
```

2.2 Stemming and Lemmatization

Use stemmer.stem(word) to stem each word in each partition.
Stemming can help further reduce text redundancy and speeds up analysis.
Use lemmatizer.lemmatize(word) on each word in each partition to perform lemmatization.
Lemmatization can help identify the grammatical role of words to better understand the meaning of the text.

```
    # Stemming
    stemmer = PorterStemmer()
    partitions = [[stemmer.stem(word) for word in partition] for partition in partitions]

    # Lemmatization
    lemmatizer = WordNetLemmatizer()
    partitions = [[lemmatizer.lemmatize(word) for word in partition] for partition in partitions]

#added stoped
    # Create pandas dataframe to store the text data
    data = {'partition': partitions, 'label': label_list}
    df = pd.DataFrame(data)

    # Serialize dataframe to csv
    df.to_csv(book_name + '.csv', index=False)

    return partitions
```

2.3 Get dataset

Input all books, and label each book, then get the Children_Literatture_Book_data.csv file.

```
# Testing for multiple books:
book_name1 = "Peter_Pan.txt"
book_name2 = "The_Adventures_of_Tom_Sawyer.txt"
book_name3 = "Treasure_Island.txt"
book_name4 = "The_Wind_in_the_Willows.txt"
book_name5 = "The_Secret_Garden.txt"
book_name6 = "Pride_and_Prejudice.txt"
book_name7 = "The_Adventures_of_Sherlock_Holmes.txt"
book_list = [book_name1, book_name2, book_name3, book_name4, book_name5, book_name6, book_name7]
# If book_list > label_list, add labels.
label_list = ["a","b","c","d","e","f","g"]
df_list = []
for i, book_name in enumerate(book_list):
    partitions = sample_digital_book(book_name, 200, 100)
    temp = pd.DataFrame({'partition': partitions, 'label': label_list[i]})
    df_list.append(temp)

df = pd.concat(df_list)
df.to_csv("Children_Literature_books_data.csv", index=False)
```

3 Feature Engineering

3.1 Transform

3.1.1 BOW (Bag of Words)

It fits the CountVectorizer to a list created from the “partition” column of a pandas dataframe and transforms it into a count matrix. CountVectorizer will exclude stop words from text and only consider meaningful words in English.

```
# Load the data from the csv file
df = pd.read_csv("Children_Literature_books_data.csv")

sw_nltk = stopwords.words('english')
print(sw_nltk)
print(df['partition'].tolist())
# Convert the data into a Bag-of-Words representation using CountVectorizer
count_vectorizer = CountVectorizer(stop_words=sw_nltk)
count_matrix = count_vectorizer.fit_transform(df['partition'].to_list())
```

3.1.2 TF-IDF (Term Frequency-Inverse Document Frequency)

TfidfVectorizer computes a term frequency-inverse document frequency (TF-IDF) value for each token in each document. TF-IDF values give higher weight to words that occur frequently in documents but infrequently in the entire corpus. The resulting TF-IDF matrix is a sparse matrix of text data representing the TF-IDF value for each token in each document.

```
# Convert the data into a TF-IDF representation using TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer(stop_words=sw_nltk)
tfidf_matrix = tfidf_vectorizer.fit_transform(df['partition'].to_list())
```

3.1.3 N-gram

The initialize n-gram range is (2, 2), which is bigrams as tokens. Then, fit and transform the data into n-grams.

```
#n-gram
# Initialize the CountVectorizer object
vectorizer = CountVectorizer(ngram_range=(2, 2))
# Fit and transform the data into n-grams
ngram_matrix = vectorizer.fit_transform(df['partition'].to_list())
```

3.1.4 Store each method representations as separate dataframe

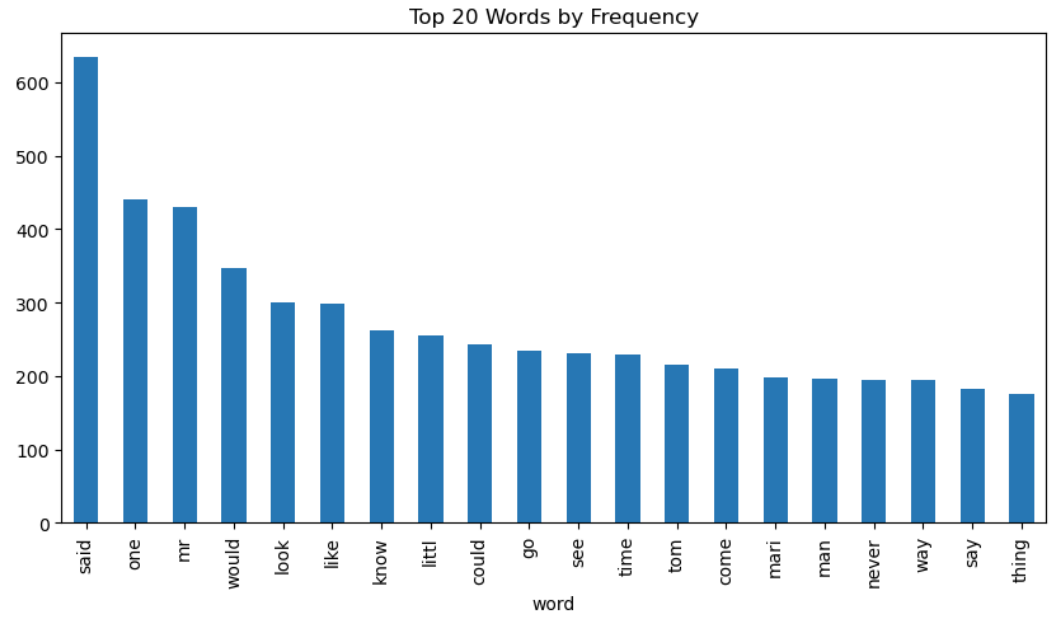
Create a pandas dataframe by converting the matrix to an array using the “toarray” method. The resulting dense array is then passed as the data argument to the pandas dataframe constructor to create the dataframes df_bow, df_tfidf, and df_ngram. The dataframes represent the features and their values (counts) for each document.

```
# Get the feature names
feature_names_bow = count_vectorizer.get_feature_names_out()
feature_names_tfidf = tfidf_vectorizer.get_feature_names_out()
feature_names_ngram = vectorizer.get_feature_names_out()

# Store the BOW and TF-IDF representations as separate dataframes
df_bow = pd.DataFrame(count_matrix.toarray(), columns=feature_names_bow)
print("Here is the BOW result:",df_bow)
df_tfidf = pd.DataFrame(tfidf_matrix.toarray(), columns=feature_names_tfidf)
print("Here is the TF-IDF result:",df_tfidf)
df_ngram=pd.DataFrame(ngram_matrix.toarray(),columns=feature_names_ngram)
print("Here is the n-gram result:", df_ngram)
```

3.2 Visualization

The first we get word frequency counts from the CountVectorizer object. Then, create the dataframe of words and their frequency. Next, we can plot the top 20 words by frequency.

```
# Get word frequency counts from the CountVectorizer object
word_freq = count_matrix.toarray().sum(axis=0)

# Create a dataframe of words and their frequency
word_df = pd.DataFrame({'word': feature_names_bow, 'freq': word_freq})
word_df.sort_values('freq', ascending=False, inplace=True)

# Plot the top n words
n = 20
word_df[:n].plot.bar(x='word', y='freq', legend=False, figsize=(10,5))
plt.title('Top {} Words by Frequency'.format(n))
plt.show()
```



3.3 Train and Test

We set train set size about 80% and test set size is 20%, then we split it.

```
from sklearn.model_selection import train_test_split
x = df['partition']
y = df['label']
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)
```

4 Evaluation

4.1 Ten-fold Cross-validation -- Confusion Matrix and Accuracy

The function “analysis” performs several evaluations of the machine learning pipeline. Use “StratifiedKFold” to perform 10-fold cross-validation. The "cross_val_predict" method is used to predict the target label for each fold.

Accuracy is calculated as the average accuracy across all folds. Confusion matrix uses the "confusion_matrix" function to calculate the confusion matrix for cross-validation predictions. The unique_labels variable assigns unique labels in the target data.

The draw_confusion_matrix function to visualize the confusion matrix.

Finally, the function prints out a classification report that provides a summary of precision, recall, f1-score, and support for each label in the target data.

```
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
from sklearn.model_selection import cross_val_score,  cross_val_predict, StratifiedKFold

def analysis(pipeline, data, label, x_train, x_test, y_train, y_test):

    #confusion matrix
    pipeline.fit(x_train, y_train)
    pred = pipeline.predict(x_test)
    unique_labels = np.unique(df['label'])
    cf_matrix = confusion_matrix(y_test, pred)
    draw_confusion_matrix(cf_matrix, unique_labels)

    #cross validation
    cv = StratifiedKFold(n_splits=10)

    y_pred = cross_val_predict(pipeline, data, label, cv=cv)
    accuracy = np.mean(label == y_pred)
    print('Accuracy:' + str(accuracy))

    print (classification_report(label, y_pred))
```

```
import matplotlib.pyplot as plt
def draw_confusion_matrix(cf_matrix, labels):
    cm_df = pd.DataFrame(cf_matrix, labels, labels)
    plt.figure(figsize=(len(labels),len(labels)))
    sns.heatmap(cf_matrix, annot=True)
    plt.title('Confusion Matrix')
    plt.ylabel('Actal Values')
    plt.xlabel('Predicted Values')
    plt.show()
```

4.2 Vectorizer

Create bow, tfidf and n_gram vectorizer

```
bow = CountVectorizer(stop_words=sw_nltk)
tfidf = TfidfVectorizer(stop_words=sw_nltk)
n_gram =  CountVectorizer(ngram_range=(2, 2))

vectorizer_dict = {'BOW':bow, 'TF-IDF':tfidf, 'N-gram':n_gram}
```

4.3 KNN -- find best k with BOW, TFIDF and N-gram

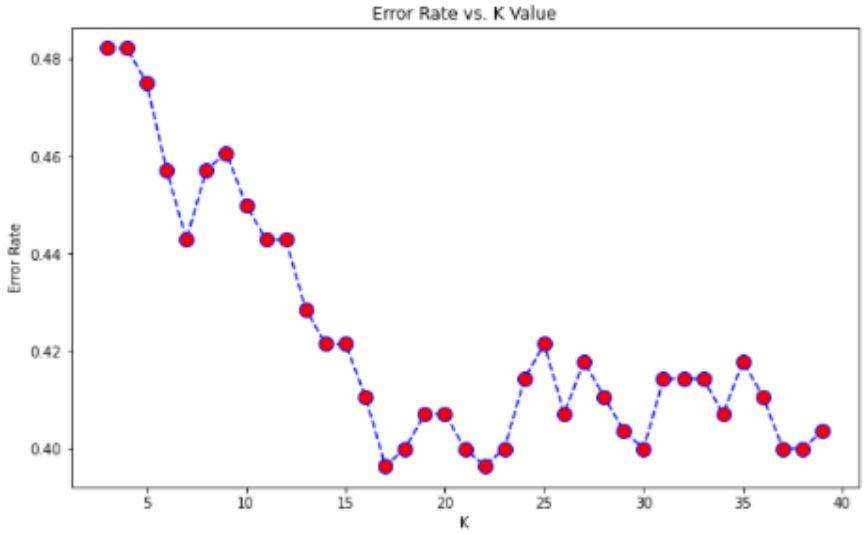
We use a loop to train and evaluate different KNN models using three different feature representation methods.
We set up an empty list called “error_rate” to store the error rate of each KNN method.
For each k value from the range of 3 to 40, we will train an KNN model using the feature representation method and k value. Then, we predict the target labels of the test data using the trained model. Next, we compute the error rate by taking the average of the mean, and then append the error rate to the list.
Find the best k value by finding the index of the minimum error rate in the “error_rate” list.
Call the “analysis” function to evaluate the final KNN model by getting its accuracy, confusion matrix, and classification report.

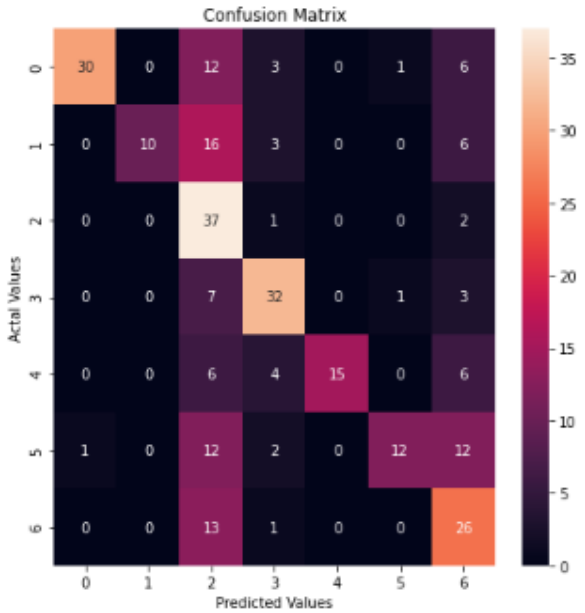
```
from sklearn.pipeline import Pipeline
from sklearn.neighbors import KNeighborsClassifier


for key in vectorizer_dict:
    error_rate = []
    for i in range(3,40):
        knn_clf = Pipeline([
            ('trans', vectorizer_dict[key]),
            ('clf', KNeighborsClassifier(n_neighbors=i))
        ])

        knn_clf.fit(x_train, y_train)
        pred = knn_clf.predict(x_test)
        error_rate.append(np.mean(pred != y_test))
    # find the optimal K
    import matplotlib.pyplot as plt
    plt.figure(figsize=(10,6))
    plt.plot(range(3,40),error_rate,color='blue', linestyle='dashed', marker='o',markerfacecolor='red', markersize=10)
    plt.title('Error Rate vs. K Value')
    plt.xlabel('K')
    plt.ylabel('Error Rate')

    best_k = error_rate.index(min(error_rate))

    best_knn = Pipeline([
            ('trans', vectorizer_dict[key]),
            ('clf', KNeighborsClassifier(n_neighbors=best_k))
        ])
    print('The report for KNN with ' + key)
    print('The best value k is ' + str(best_k))
    analysis(best_knn, x, y, x_train, x_test, y_train, y_test)
    print('')
    print('')
```

4.3.1 The report for KNN with BOW

We got the best value k is 14 and accuracy is 0.54.

```
The report for KNN with BOW
The best value k is 14
```



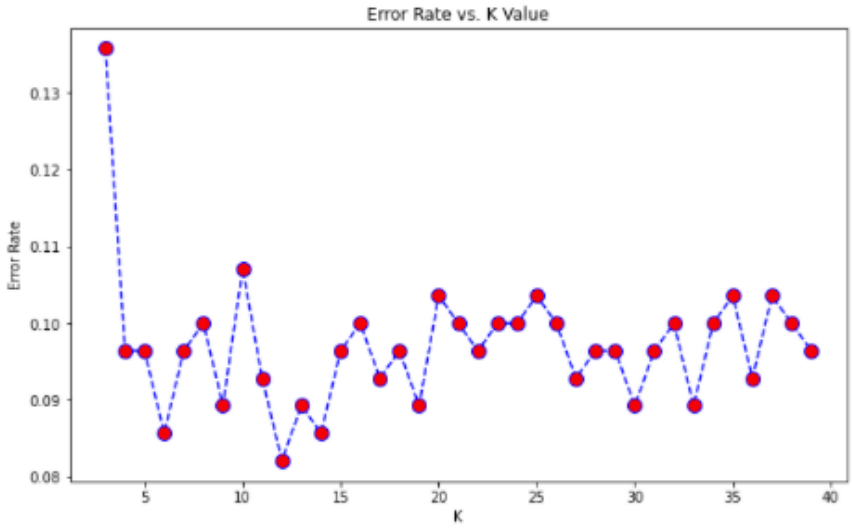


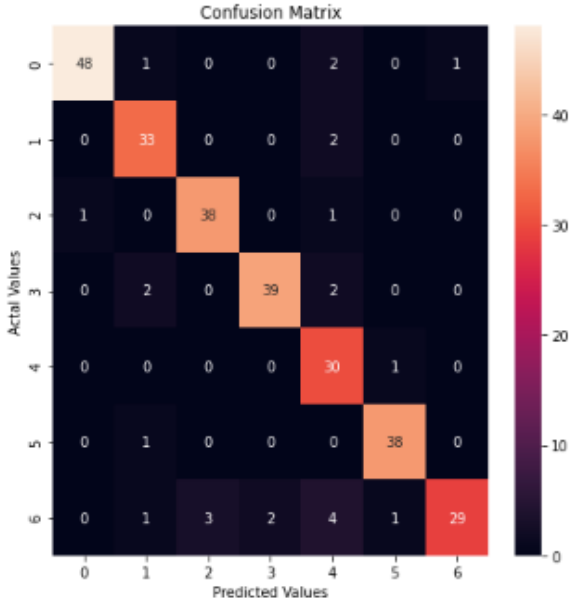

```
Accuracy:0.5421428571428571
              precision    recall  f1-score   support

           a       0.91      0.54      0.68       200
           b       0.91      0.37      0.53       200
           c       0.31      0.91      0.46       200
           d       0.77      0.69      0.73       200
           e       0.99      0.35      0.52       200
           f       0.88      0.34      0.50       200
           g       0.41      0.59      0.48       200

    accuracy                           0.54      1400
   macro avg       0.74      0.54      0.56      1400
weighted avg       0.74      0.54      0.56      1400
```

4.3.2 The report for KNN with TF-IDF

We got the best value k is 9 and accuracy is 0.85.

```
The report for KNN with TF-IDF
The best value k is 9
```



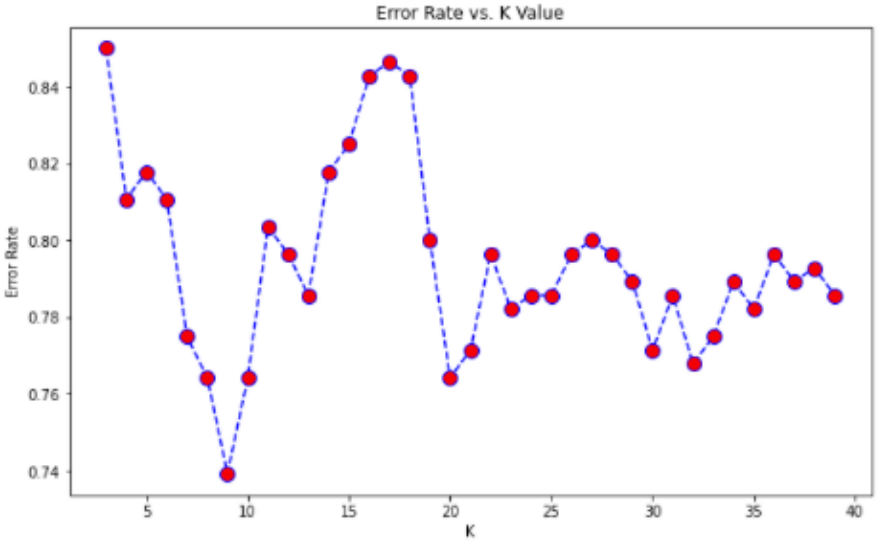


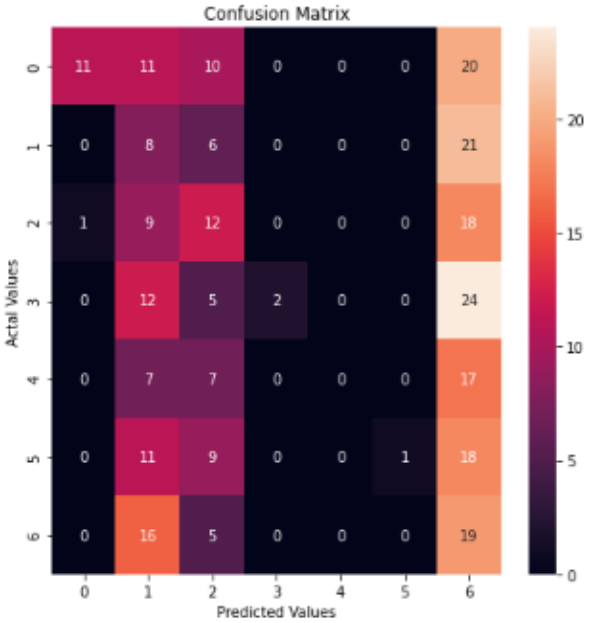

```
Accuracy:0.8471428571428572
              precision    recall  f1-score   support

           a       0.78      0.92      0.84       200
           b       0.88      0.77      0.82       200
           c       0.83      0.84      0.84       200
           d       0.91      0.85      0.88       200
           e       0.78      0.96      0.86       200
           f       0.86      0.88      0.87       200
           g       0.95      0.71      0.82       200

    accuracy                           0.85      1400
   macro avg       0.86      0.85      0.85      1400
weighted avg       0.86      0.85      0.85      1400
```

4.3.3 The report for KNN with N-gram

We got the best value k is 6 and accuracy is 0.15.

```
The report for KNN with N-gram
The best value k is 6
```






```
Accuracy:0.1492857142857143
              precision    recall  f1-score   support

           a       1.00      0.04      0.07       200
           b       0.14      0.80      0.24       200
           c       0.15      0.21      0.18       200
           d       0.00      0.00      0.00       200
           e       0.00      0.00      0.00       200
           f       0.00      0.00      0.00       200
           g       0.00      0.00      0.00       200

    accuracy                           0.15      1400
   macro avg       0.19      0.15      0.07      1400
weighted avg       0.19      0.15      0.07      1400
```

4.4 XGboots

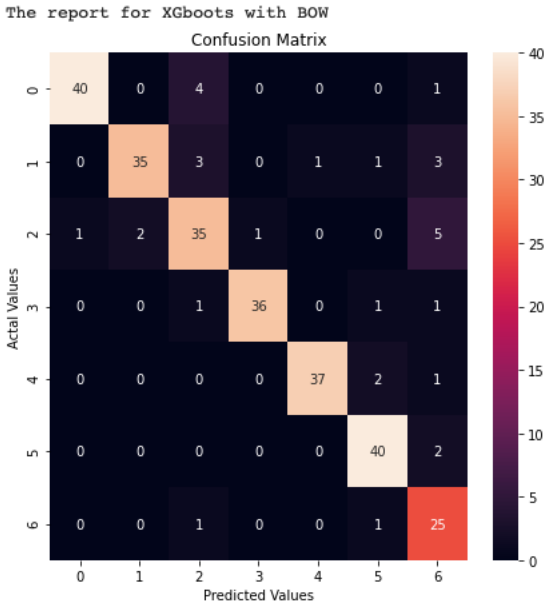
The pipeline consists of two steps, transforming the text data using the “vectorizer” and training an XGboots classifier on the transformed data.

The same step above, call the “analysis” function for each pipeline to print out the accuracy, confusion matrix, and classification report for the XGboots classifier.

```
from sklearn import preprocessing
from xgboost import XGBClassifier

le = preprocessing.LabelEncoder()
y_xg = le.fit_transform(y)
y_train_xg = le.fit_transform(y_train)
y_test_xg = le.fit_transform(y_test)

for key in vectorizer_dict:
    xgboots_cfl = Pipeline([
    ('trans', vectorizer_dict[key]),
    ('clf', XGBClassifier())
    ])

    print('The report for XGboots with ' + key)
    analysis(xgboots_cfl, x, y_xg, x_train, x_test, y_train_xg, y_test_xg)

    print('')
    print('')
```

4.4.1 The report for XGboots with BOW

We got the accuracy is 0.83.



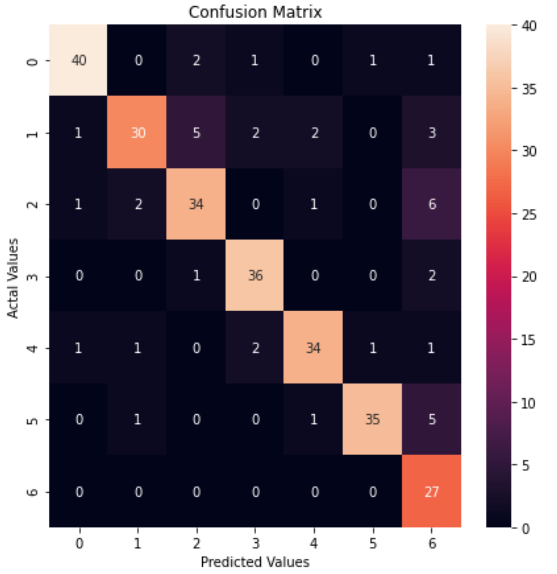
Accuracy:0.8292857142857143

	precision	recall	f1-score	support
0	0.93	0.85	0.89	200
1	0.75	0.76	0.75	200
2	0.74	0.78	0.76	200
3	0.91	0.84	0.87	200
4	0.88	0.92	0.90	200
5	0.92	0.87	0.89	200
6	0.71	0.80	0.75	200
accuracy			0.83	1400
macro avg	0.83	0.83	0.83	1400
weighted avg	0.83	0.83	0.83	1400

4.4.2 The report for XGboots with TF-IDF

We got the accuracy is 0.81.

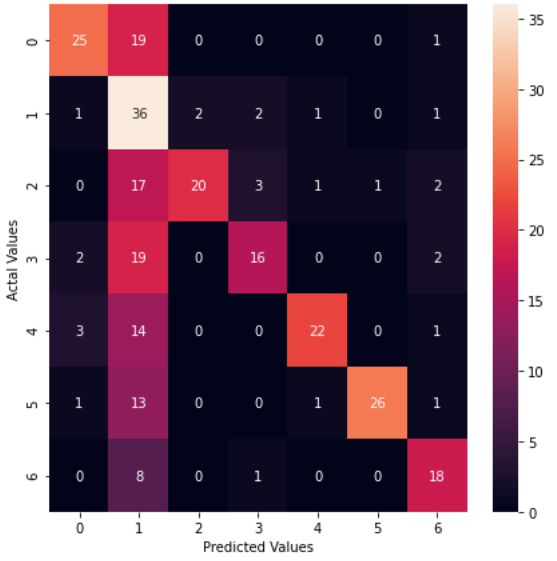
The report for XGboots with TF-IDF



Accuracy:0.8142857142857143

	precision	recall	f1-score	support
0	0.93	0.83	0.88	200
1	0.79	0.72	0.75	200
2	0.71	0.77	0.73	200
3	0.89	0.84	0.87	200
4	0.87	0.91	0.89	200
5	0.92	0.84	0.88	200
6	0.66	0.79	0.72	200
accuracy			0.81	1400
macro avg	0.82	0.81	0.82	1400
weighted avg	0.82	0.81	0.82	1400

The report for XGboots with N-gram



Accuracy:0.5764285714285714

	precision	recall	f1-score	support
0	0.81	0.51	0.62	200
1	0.27	0.88	0.42	200
2	0.83	0.46	0.59	200
3	0.76	0.47	0.58	200
4	0.88	0.63	0.73	200
5	0.90	0.65	0.75	200
6	0.80	0.45	0.57	200
accuracy			0.58	1400
macro avg	0.75	0.58	0.61	1400
weighted avg	0.75	0.58	0.61	1400

4.4.3 The report for XGboots with N-gram

We got the accuracy is 0.58.

The graph is to the right of the figure above.

4.5 Decision Tree -- find best value of max_depth

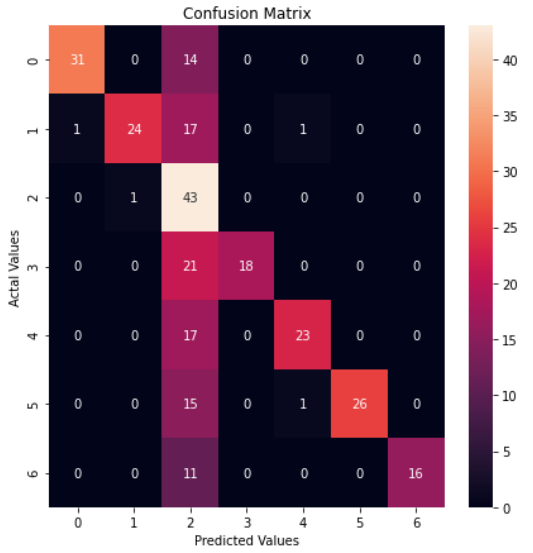
The pipeline is to use a specific vectorizer method whose type is stored keyed by this key in the dictionary “vectorizer_dict”. Next, use “GridSearchCV” to perform a grid search on the hyperparameters of the classifier, where the defined hyperparameter space is the range of “dt__max_depth”, from 1 to 11. Finally, the optimal hyperparameters for each classifier pipeline and the accuracy with which it was used to classify the data are reported.

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV

for key in vectorizer_dict:

    dt_clf = Pipeline([('vect', vectorizer_dict[key]),
             ('dt', DecisionTreeClassifier())])


    # Define the hyperparameter search space
    param_grid = {'dt__max_depth': range(1, 11)}

    # Create the grid search object
    grid_search = GridSearchCV(dt_clf, param_grid, cv=5)

    # Fit the grid search to the data
    grid_search.fit(x, y)

    # Get the best hyperparameters
    best_depth = grid_search.best_params_['dt__max_depth']

    print('The report for DT with ' + key)
    print('The best value of max depth is ' + str(best_depth))

    best_dt = Pipeline([
        ('trans', vectorizer_dict[key]),
        ('clf',  DecisionTreeClassifier(max_depth = best_depth))
        ])

    analysis(best_dt, x, y)

    print('')
    print('')
```

4.5.1 The report for DT with BOW

The best value of max depth is 10, and accuracy: 0.6.

```
The report for DT with BOW
The best value of max depth is 10
```

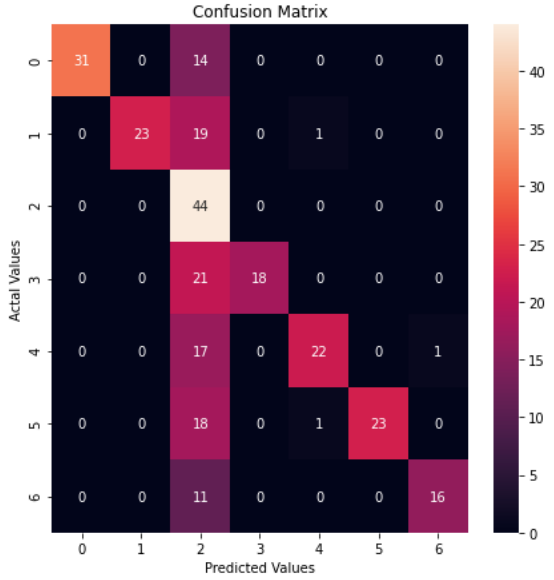



```
Accuracy:0.5964285714285714
              precision    recall  f1-score   support

           a       0.98      0.64      0.77       200
           b       0.91      0.55      0.68       200
           c       0.27      0.97      0.42       200
           d       0.98      0.60      0.75       200
           e       0.88      0.61      0.72       200
           f       0.95      0.41      0.57       200
           g       1.00      0.41      0.58       200

    accuracy                           0.60      1400
   macro avg       0.85      0.60      0.64      1400
weighted avg       0.85      0.60      0.64      1400
```

4.5.2 The report for DT with TF-IDF

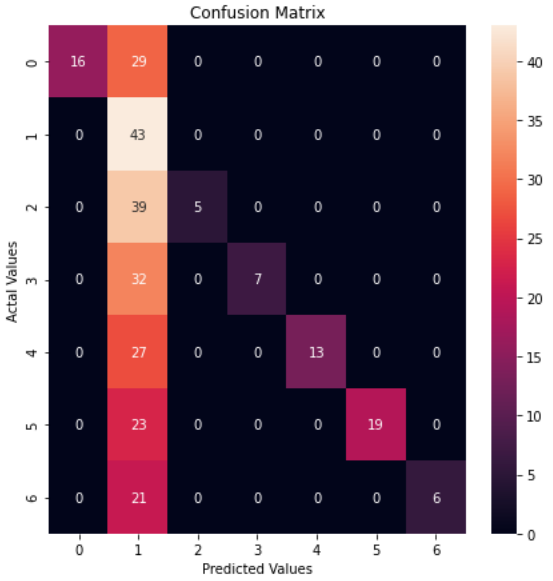
The best value of max depth is 10, and accuracy: 0.59.

```
The report for DT with TF-IDF
The best value of max depth is 10
```




```
Accuracy:0.59
              precision    recall  f1-score   support

           a       0.98      0.64      0.78       200
           b       0.90      0.55      0.68       200
           c       0.27      0.97      0.42       200
           d       0.99      0.61      0.76       200
           e       0.88      0.60      0.71       200
           f       0.95      0.35      0.51       200
           g       1.00      0.41      0.58       200

    accuracy                           0.59      1400
   macro avg       0.85      0.59      0.63      1400
weighted avg       0.85      0.59      0.63      1400
```

```
The report for DT with N-gram
The best value of max depth is 10
```




```
Accuracy:0.3092857142857143
              precision    recall  f1-score   support

           a       1.00      0.24      0.39       200
           b       0.17      1.00      0.29       200
           c       1.00      0.01      0.03       200
           d       1.00      0.14      0.25       200
           e       1.00      0.28      0.43       200
           f       1.00      0.32      0.48       200
           g       1.00      0.17      0.29       200

    accuracy                           0.31      1400
   macro avg       0.88      0.31      0.31      1400
weighted avg       0.88      0.31      0.31      1400
```

4.5.3 The report for DT with N-gram

The best value of max depth is 10, and accuracy: 0.31.

The graph is to the right of the figure above.

4.6 SVM.SVC

Use a different vectorizer as defined in the "vectorizer_dict" dictionary.

For each vectorizer, it creates a pipeline with the vectorizer and SVM classifier.

Call the analysis function to fit the model, make predictions, evaluate accuracy, print confusion matrix and classification report.

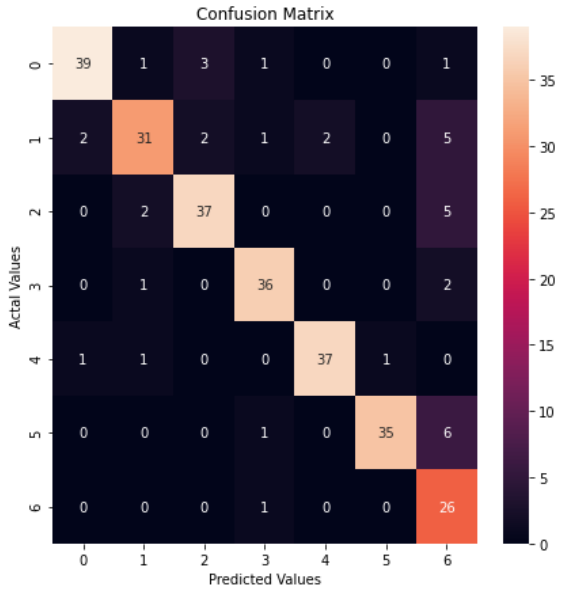
It will repeat this process for each vectorizer, printing the result of each vectorizer.

```
from sklearn import svm

for key in vectorizer_dict:
    svc_cfl = Pipeline([
    ('trans', vectorizer_dict[key]),
    ('clf', svm.SVC())
    ])

    print('The report for SVM.SVC with ' + key)
    analysis(svc_cfl, x, y, x_train, x_test, y_train, y_test)

    print('')
    print('')
```

4.6.1 The report for SVM.SVC with BOW

We got the accuracy is 0.85.

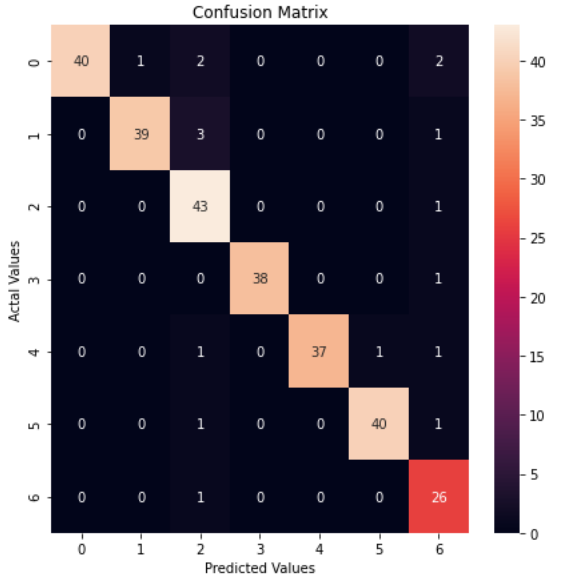
The report for SVM.SVC with BOW



Accuracy:0.8471428571428572

	precision	recall	f1-score	support
a	0.95	0.81	0.87	200
b	0.85	0.75	0.80	200
c	0.74	0.88	0.80	200
d	0.96	0.83	0.89	200
e	0.97	0.90	0.93	200
f	0.95	0.83	0.89	200
g	0.66	0.93	0.77	200
accuracy			0.85	1400
macro avg	0.87	0.85	0.85	1400
weighted avg	0.87	0.85	0.85	1400

The report for SVM.SVC with TF-IDF



Accuracy:0.9021428571428571

	precision	recall	f1-score	support
a	0.99	0.82	0.90	200
b	0.87	0.85	0.86	200
c	0.80	0.94	0.87	200
d	0.97	0.89	0.93	200
e	0.98	0.95	0.97	200
f	0.95	0.93	0.94	200
g	0.80	0.93	0.86	200
accuracy			0.90	1400
macro avg	0.91	0.90	0.90	1400
weighted avg	0.91	0.90	0.90	1400

4.6.2 The report for SVM.SVC with TF-IDF

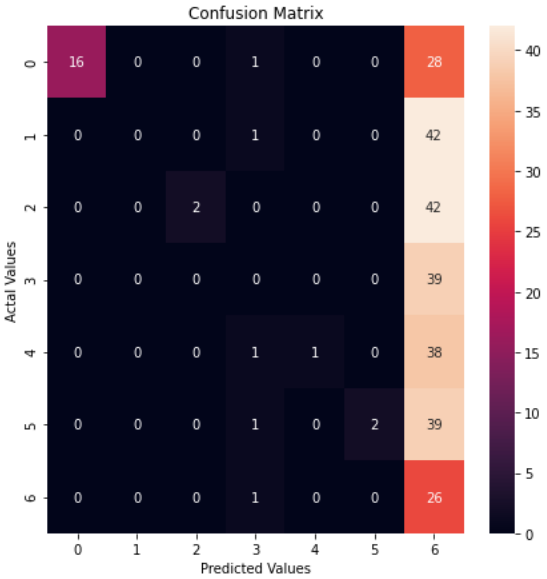
We got the accuracy is 0.90.

The graph is to the right of the figure above.

4.6.3 The report for SVM.SVC with N-gram

We got the accuracy is 0.20.

```
The report for SVM.SVC with N-gram
```




```
Accuracy:0.2007142857142857
              precision    recall  f1-score   support

           a       1.00      0.23      0.37       200
           b       0.00      0.00      0.00       200
           c       1.00      0.15      0.27       200
           d       1.00      0.01      0.01       200
           e       1.00      0.01      0.02       200
           f       1.00      0.01      0.02       200
           g       0.15      1.00      0.26       200

    accuracy                           0.20      1400
   macro avg       0.74      0.20      0.14      1400
weighted avg       0.74      0.20      0.14      1400
```

4.7 LinearSVC

Comparing the performance of the LinearSVC algorithm on a text classification task using different vectorization methods.

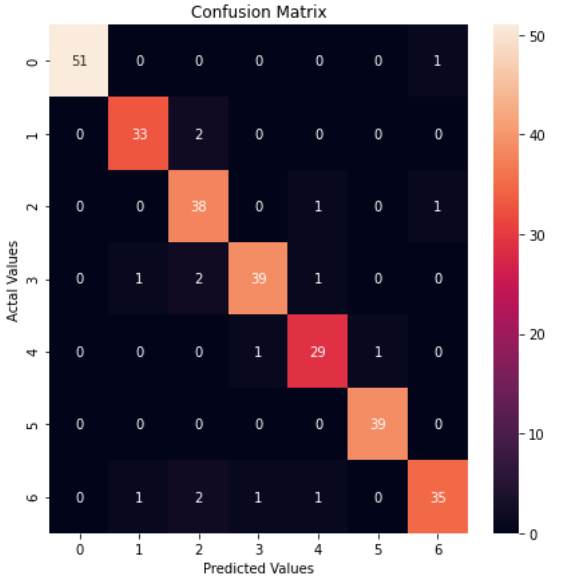
For each vectorization method, a pipeline is created, as in the previous steps.

```
from sklearn.svm import LinearSVC

for key in vectorizer_dict:
    linearsvc_cfl = Pipeline([
    ('trans', vectorizer_dict[key]),
    ('clf', LinearSVC())
    ])

    print('The report for LinearSVC with ' + key)
    analysis(linearsvc_cfl, x, y, x_train, x_test, y_train, y_test)

    print('')
    print('')
```

4.7.1 The report for LinearSVC with BOW

We got the accuracy is 0.89.

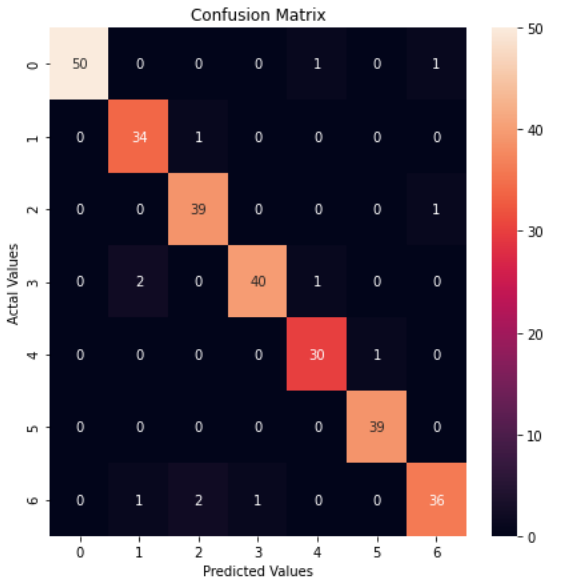
The report for LinearSVC with BOW



Accuracy:0.8885714285714286

	precision	recall	f1-score	support
a	0.93	0.90	0.91	200
b	0.88	0.81	0.84	200
c	0.81	0.85	0.83	200
d	0.93	0.90	0.91	200
e	0.90	0.94	0.92	200
f	0.94	0.94	0.94	200
g	0.84	0.88	0.86	200
accuracy			0.89	1400
macro avg	0.89	0.89	0.89	1400
weighted avg	0.89	0.89	0.89	1400

The report for LinearSVC with TF-IDF



Accuracy:0.915

	precision	recall	f1-score	support
a	0.95	0.91	0.93	200
b	0.88	0.84	0.86	200
c	0.86	0.92	0.89	200
d	0.94	0.92	0.93	200
e	0.92	0.98	0.95	200
f	0.94	0.96	0.95	200
g	0.91	0.89	0.90	200
accuracy			0.92	1400
macro avg	0.92	0.92	0.91	1400
weighted avg	0.92	0.92	0.91	1400

4.7.2 The report for LinearSVC with TF-IDF

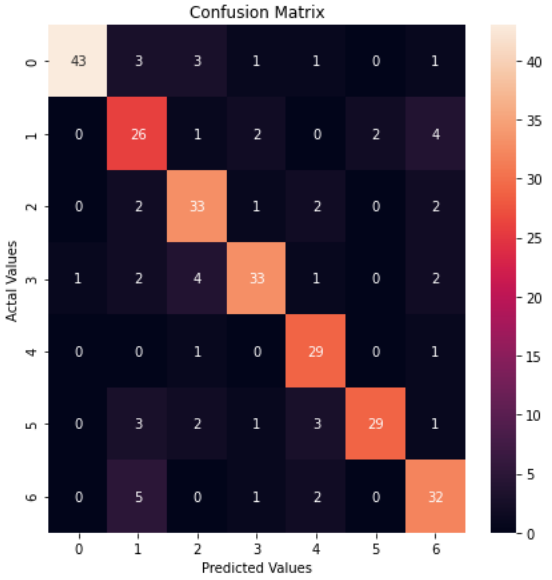
We got the accuracy is 0.915.

The graph is to the right of the figure above.

4.7.4 The report for LinearSVC with N-gram

We got the accuracy is 0.75.

```
The report for LinearSVC with N-gram
```




```
Accuracy:0.75
              precision    recall  f1-score   support

           a       0.83      0.76      0.79       200
           b       0.58      0.69      0.63       200
           c       0.72      0.76      0.74       200
           d       0.73      0.70      0.72       200
           e       0.86      0.85      0.86       200
           f       0.95      0.73      0.82       200
           g       0.67      0.76      0.71       200

    accuracy                           0.75      1400
   macro avg       0.76      0.75      0.75      1400
weighted avg       0.76      0.75      0.75      1400
```

4.8 SGD

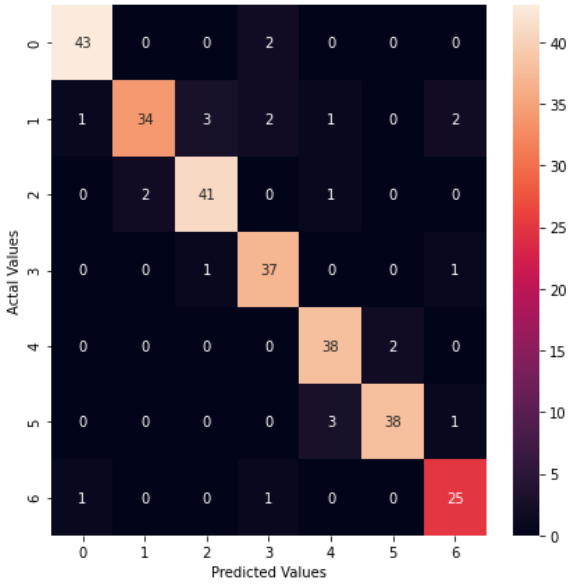
Evaluate stochastic gradient descent(SGD) classifier performance with different text vectorizers. A pipeline of vectorizers and classifiers is fitted to the data, and multiple cross-validations are performed on the pipeline for reporting.

```
from sklearn.linear_model import SGDClassifier

for key in vectorizer_dict:
    linearsvc_cfl = Pipeline([
    ('trans', vectorizer_dict[key]),
    ('clf', SGDClassifier())
    ])

    print('The report for SGD with ' + key)
    analysis(linearsvc_cfl, x, y, x_train, x_test, y_train, y_test)

    print('')
    print('')
```

4.8.2 The report for SGD with BOW

We got the accuracy is 0.84.

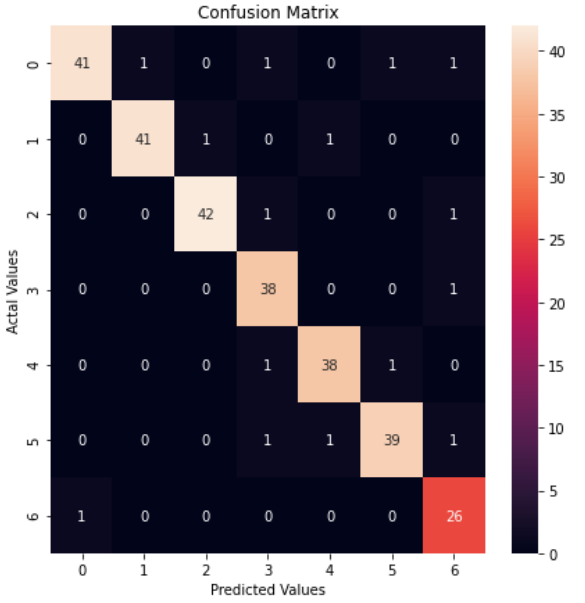
The report for SGD with BOW



Accuracy:0.8371428571428572

	precision	recall	f1-score	support
a	0.89	0.86	0.88	200
b	0.79	0.74	0.76	200
c	0.76	0.76	0.76	200
d	0.88	0.87	0.88	200
e	0.88	0.92	0.90	200
f	0.84	0.91	0.87	200
g	0.81	0.80	0.80	200
accuracy			0.84	1400
macro avg	0.84	0.84	0.84	1400
weighted avg	0.84	0.84	0.84	1400

The report for SGD with TF-IDF



Accuracy:0.9114285714285715

	precision	recall	f1-score	support
a	0.95	0.91	0.93	200
b	0.87	0.83	0.85	200
c	0.86	0.92	0.89	200
d	0.95	0.91	0.93	200
e	0.92	0.97	0.95	200
f	0.94	0.96	0.95	200
g	0.90	0.87	0.89	200
accuracy			0.91	1400
macro avg	0.91	0.91	0.91	1400
weighted avg	0.91	0.91	0.91	1400

4.8.3 The report for SGD with TF-IDF

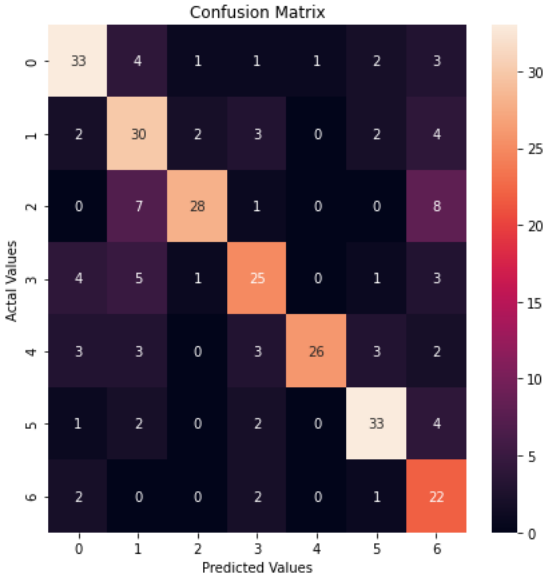
We got the accuracy is 0.91.

The graph is to the right of the figure above.

4.8.4 The report for SGD with N-gram

We got the accuracy is 0.70.

The report for SGD with N-gram



Accuracy:0.7035714285714286

	precision	recall	f1-score	support
a	0.82	0.69	0.75	200
b	0.54	0.69	0.61	200
c	0.79	0.63	0.70	200
d	0.63	0.69	0.66	200
e	0.91	0.76	0.83	200
f	0.69	0.78	0.73	200
g	0.67	0.69	0.68	200
accuracy			0.70	1400
macro avg	0.72	0.70	0.71	1400
weighted avg	0.72	0.70	0.71	1400

4.9 Perform the champion model

We sorted out and summarized the accuracy between six different algorithms, and we selected the highest models.

	KNN	XGboots	DT	SVM.SVC	LinearSVC	SGD
BOW	0.54	0.83	0.60	0.85	0.89	0.84
TF-IDF	0.85	0.81	0.59	0.90	**0.92**	0.91
N-gram	0.15	0.58	0.31	0.20	0.75	0.70

The best model is TF-IDF*LinearSVC.

The resulting pipeline is stored in the variable "best_model".

```
best_model = Pipeline([
    ('trans', TfidfVectorizer(stop_words=sw_nltk)),
    ('clf', LinearSVC())
    ])
```

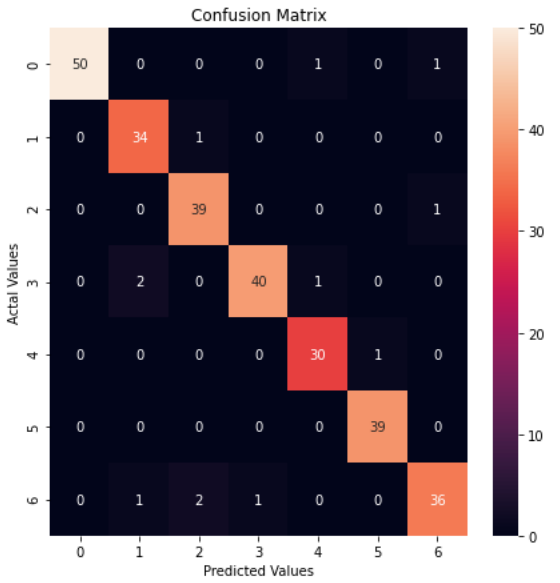
We define a test function that will test a model on a given test data and output the accuracy of the model.

```
def test(model, x_train, y_train, x_test, y_test):
    model.fit(x_train, y_train)
    pred = model.predict(x_test)
    accuracy = np.mean(pred == y_test)

    print("accuracy: " + str(accuracy))

    unique_labels = np.unique(df['label'])
    cf_matrix = confusion_matrix(y_test, pred)
    draw_confusion_matrix(cf_matrix, unique_labels)
    print (classification_report(y_test, pred))
```

```
print('The performance of the best model on test set:')
test(best_model,  x_train, y_train, x_test, y_test)
```

Then, we got the performance of the best model on the test set is accuracy of 0.96.

```
The performance of the best model on test set:
accuracy: 0.9571428571428572
```



	precision	recall	f1-score	support
a	1.00	0.96	0.98	52
b	0.92	0.97	0.94	35
c	0.93	0.97	0.95	40
d	0.98	0.93	0.95	43
e	0.94	0.97	0.95	31
f	0.97	1.00	0.99	39
g	0.95	0.90	0.92	40
accuracy			0.96	280
macro avg	0.95	0.96	0.96	280
weighted avg	0.96	0.96	0.96	280

5 Perform Error Analysis

5.1 Data

For our best model. If we used unbalanced data, we would get different results. These results are mainly divided into three aspects.

5.1.1 Change the train test split ratio

We changed training-test ratio and compared the performance of linear SVC with TF-IDF model under different sample scale. Then, we got the figure that scale of training data and accuracy shows below.

```
def set_diff_scale(df, ratio):

  x_train_diff_scale, x_test_diff_scale, y_train_diff_scale, y_test_diff_scale = train_test_split(x, y, train_size=ratio, random_state=0)
  return x_train_diff_scale, x_test_diff_scale, y_train_diff_scale, y_test_diff_scale
```

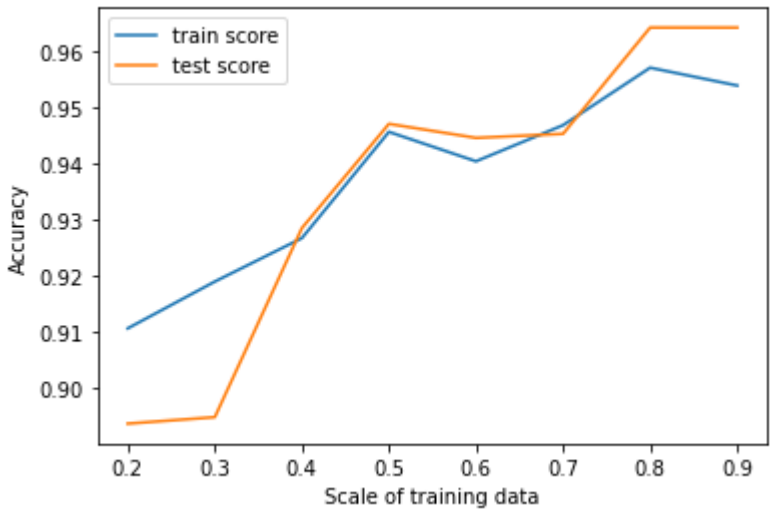
```
def run_diff_scale(ratio_list):
  scores_train = []
  scores_test = []
  for ratio in ratio_list:
    x_train_diff_scale, x_test_diff_scale, y_train_diff_scale, y_test_diff_scale = set_diff_scale(df, ratio)

    best_model.fit(x_train_diff_scale, y_train_diff_scale)
    cross_val = cross_val_score(best_model, x_train_diff_scale, y_train_diff_scale, cv=10, scoring='accuracy')
    accuracy_train = np.mean(cross_val)
    scores_train.append(accuracy_train)

    pred_test = best_model.predict(x_test_diff_scale)
    accuracy_test = np.mean(pred_test == y_test_diff_scale)
    scores_test.append(accuracy_test)

  return scores_train, scores_test
```

```
# Compare the performance of linear SVC with tfidf model under diffrent sample scale
ratio_list = [0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9]
scores_train_diff_scale, scores_test_diff_scale = run_diff_scale(ratio_list)
```

```
print(scores_train_diff_scale)
print(scores_test_diff_scale)
plt.plot(ratio_list,scores_train_diff_scale, label = "train score")
plt.plot(ratio_list,scores_test_diff_scale, label = "test score")
plt.xlabel('Scale of training data')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
[0.9107142857142858, 0.9190476190476191, 0.9267857142857142, 0.9457142857142857, 0.9404761904761904, 0.9469072164948453, 0.9571428571428571, 0.9539682539682539]
[0.89375, 0.8948979591836734, 0.9285714285714286, 0.9471428571428572, 0.9446428571428571, 0.9453681710213777, 0.9642857142857143, 0.9642857142857143]
```

-



In this situation, we can clearly see that, when the training data set is getting smaller, the accuracy scores of the model get lower both on training data and testing data.

However, the overall performance of the data is still very good -- the accuracy is more than 0.9. The influence of data scale on the model is not so big as the influence of unbalancing and shorter segment.

5.1.2 Make the train set and test set unbalanced

We changed the distribution of each label segment on training and test set to make the data unbalanced.

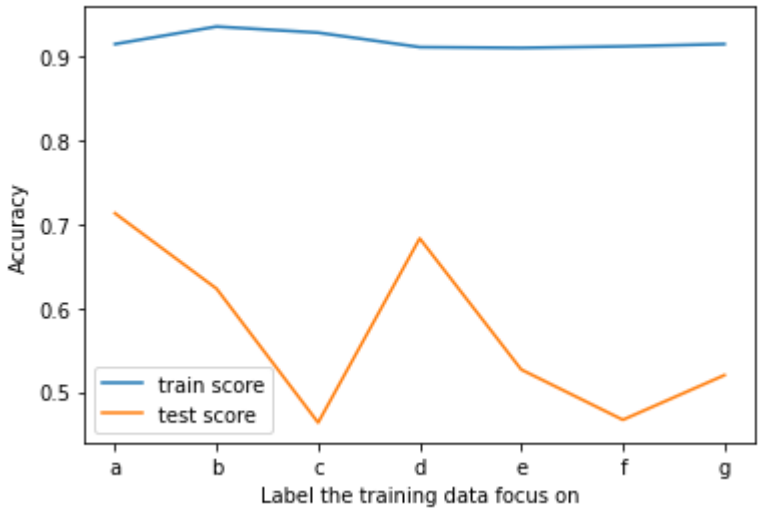
```
# create an imbalanced training and testing data set
def set_imb(df_all, char):
  df_train = pd.DataFrame()
  df_test = pd.DataFrame()
  label_list = ['a', 'b', 'c', 'd', 'e', 'f', 'g']
  for label in label_list:
    if label != char:
      df_train = df_train.append(df[df['label']==label][:180], ignore_index=True)
      df_test = df_test.append(df[df['label']==label][180:], ignore_index=True)
    else:
      df_train = df_train.append(df[df['label']==label][:20], ignore_index=True)
      df_test = df_test.append(df[df['label']==label][20:], ignore_index=True)

  x_train_imb, y_train_imb, x_test_imb, y_test_imb = df_train['partition'], df_train['label'], df_test['partition'], df_test['label']

  return x_train_imb, y_train_imb, x_test_imb, y_test_imb
```

```
def run_imb(char_list):
  scores_train = []
  scores_test = []
  for char in char_list:
    x_train_imb, y_train_imb, x_test_imb, y_test_imb = set_imb(df, char)
    best_model.fit(x_train_imb, y_train_imb)

    cross_val = cross_val_score(best_model, x_train_imb, y_train_imb, cv=10, scoring='accuracy')
    accuracy_train = np.mean(cross_val)
    scores_train.append(accuracy_train)

    pred_test_imb = best_model.predict(x_test_imb)
    accuracy_test = np.mean(pred_test_imb == y_test_imb)
    scores_test.append(accuracy_test)

  return scores_train, scores_test
```

```
char_list = ['a', 'b', 'c', 'd', 'e', 'f', 'g']
scores_train_imb, scores_test_imb = run_imb(char_list)
print(scores_train_imb)
print(scores_test_imb)
plt.plot(char_list,scores_train_imb, label = "train score")
plt.plot(char_list,scores_test_imb,  label = "test score")
plt.xlabel('Label the training data focus on')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
[0.9154545454545454, 0.9363636363636363, 0.9290909090909091, 0.9118181818181817, 0.9109090909090908, 0.9127272727272728, 0.9154545454545454]
[0.7133333333333334, 0.6233333333333333, 0.4633333333333333, 0.6833333333333333, 0.5266666666666666, 0.4666666666666667, 0.52]
```

Then, we got the performance of the best model on unbalanced data set as the figure shows below.



In this situation, the model is overfitting!
Since the train data set includes such a big amount of segment with a certain label, the model pays a lot of attention to training data and get more feature of some certain samples but not with the other labels.
As a results, this model does not generalize on the data which it hasn't seen before. So, the model performs very well on training data but has high error rates on test data

5.1.3 Reduce the word number of each segment

We changed the number of words of each segment from 200 to 25. Then, we got the performance of the best model on shorter segment data set as the figure shows below.

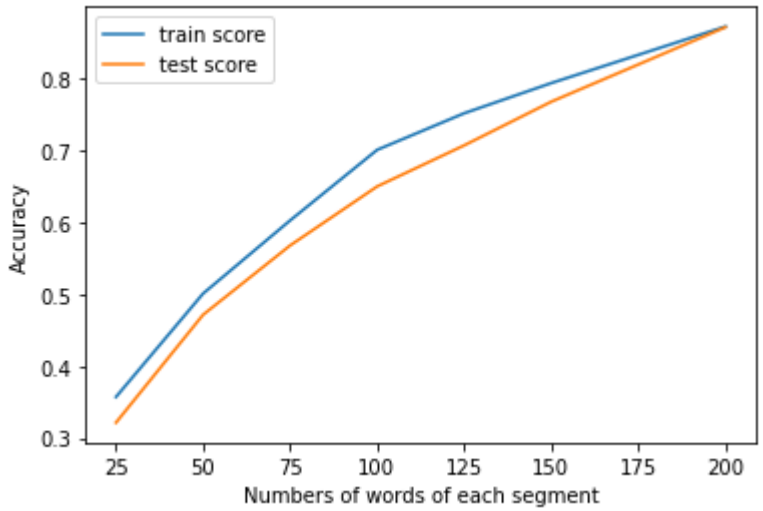
```python
# Create new training and testing data set with different length of segment
def set_diff_len(x_train, x_test, y_train, y_test, length):
  x_train_list = []
  for segment in x_train:
    x_train_list.append(segment[:length])
  x_test_list = []
  for segment in x_test:
    x_test_list.append(segment[:length])

  x_train_diff_len = pd.Series(x_train_list)
  x_test_diff_len = pd.Series(x_test_list)

  return x_train_diff_len, x_test_diff_len
```

```python
def run_diff_len(length_list):
  scores_train = []
  scores_test = []
  for length in length_list:
    # Genarate the new data set
    x_train_diff_len, x_test_diff_len = set_diff_len(x_train, x_test, y_train, y_test, length)
    # Train the model with the new data set
    best_model.fit(x_train_diff_len, y_train)
    # We use the mean accuracy of cross validation on training data to measure the performance of model on training data
    cross_val = cross_val_score(best_model, x_train_diff_len, y_train, cv=10, scoring='accuracy')
    accuracy_train = np.mean(cross_val)
    scores_train.append(accuracy_train)
    # Compare with the accuracy on test data
    pred_test = best_model.predict(x_test_diff_len)
    accuracy_test = np.mean(pred_test == y_test)
    scores_test.append(accuracy_test)

  return scores_train, scores_test
```

```python
# We choose 25, 50, ... words of each segment anc compare the performance of the model under diffrent length of segment.
length_list = [25, 50, 75, 100, 125, 150, 200]
scores_train_diff_len, scores_test_diff_len = run_diff_len(length_list)
```

```python
import matplotlib.pyplot as plt

print(scores_train_diff_len)
print(scores_test_diff_len)
plt.plot(length_list,scores_train_diff_len, label = "train score")
plt.plot(length_list,scores_test_diff_len,  label = "test score")
plt.xlabel('Numbers of words of each segment')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
[0.35714285714285715, 0.5008928571428571, 0.6026785714285714, 0.7008928571428572, 0.7517857142857143, 0.79375, 0.8723214285714287]
[0.32142857142857145, 0.4714285714285714, 0.5678571428571428, 0.65, 0.7071428571428572, 0.7678571428571429, 0.8714285714285714]
```



The model is under fitting with short segment!
Clearly, we can see that, with a shorter segment, the performance of the model would get worse. Since less feature the model can learn with shorter segment, the bias is increasing.

Model with high bias pays very little attention to the training data and oversimplifies the model. It always leads to high error on training and test data.

5.2 Feature Engineering

Different transformer also can influence the result.

In this project, we can see that, for each model, the performance of transformer TF-IDF is always better than the transformer BOW. That's because the TF-IDF transformer takes into account the frequency of words in a document as well as the rarity of each word in the corpus. BOW only considers the frequency of words in a document, ignoring the fact that some words may be very frequent but carry little meaning (such as "stop words"). TF-IDF weights the words in a document by their rarity in the corpus, resulting in a representation that better captures the semantic content of the document.

On the other side, the N-gram transformer didn't perform well, and it caused the underfitting. The performance on training set and test set is both bad. That's because we only tried the N-gram model with hyper parameters n=2, which is not a good transformer model. This story told us no matter how hi-tech a model is, a less trained transformer model can always ruin the final result!

In future, we need to find some better hyper parameters to train a better N-gram transformer.

5.3 Wrong word prediction

In order to specify the error analysis, detailing the wrong words prediction problem is a good method.

```
def display_error(model, return_error=False):

    y_pred = model.predict(x_test)
    compare_dict = pd.DataFrame({'Predicted': y_pred, 'Actual': y_test})
    errors = compare_dict.loc[(compare_dict['Predicted'] != compare_dict['Actual'])]
    idx = errors.index.values.tolist()
    error_words = []
    for i in idx:
        error_words.append(x_test[i])

    trans = CountVectorizer(stop_words=sw_nltk)
    count = trans.fit_transform(error_words)
    feature =  trans.get_feature_names_out()
    freq = count.toarray().sum(axis=0)
    error_df = pd.DataFrame({'word': feature, 'freq': freq})
    error_df.sort_values('freq', ascending=False, inplace=True)

    # Plot the top n words
    n = 20
    error_df[:n].plot.bar(x='word', y='freq', legend=False, figsize=(10,5))
    plt.title('Top {} Error Words by Frequency'.format(n))
    plt.show()

    if return_error == True:
        return error_df
```

```
pip install wordcloud
```

Predicts the class of the test data using the input model, and stores the predictions in y_pred.
Creates a comparison data frame (compare_dict) between the actual and predicted classes.
Selects all instances where the prediction is incorrect (i.e., not equal to the actual class) and stores their indices in idx.
For each index in idx, the corresponding test instance is added to the error_words list.

A CountVectorizer object (trans) is created with the stop_words argument set to a list of stop words, and it is fit and transformed on the error_words list.

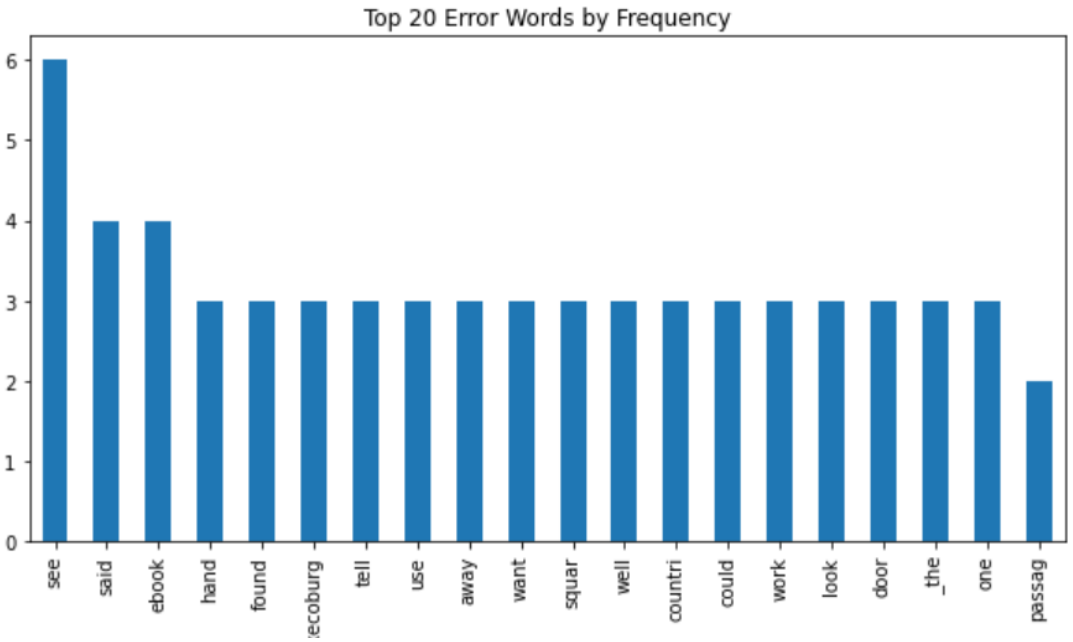
```
from wordcloud import WordCloud

def show_wordcloud(word_freq):
    wordcloud = WordCloud(width=800, height=400, random_state=0, max_font_size=110).generate_from_frequencies(dict(zip(word_freq.word, wo

    # Plot the wordcloud
    plt.figure(figsize=(10, 5))
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis('off')
    plt.show()
```

```
error_df = display_error(best_model, return_error=True)
error_df
```

The function “show_wordcloud” is used to create a wordcloud visualization of the words and their frequency.
The “error_df” dataframe would show the words and their frequencies for the words that caused the most errors in the predictions made by the model.
Then, we got three different types of error word frequency maps.

5.3.1 The top 20 words

The top 20 words in error_df are plotted as a bar chart using Matplotlib. The chart shows the word frequency for the top 20 error words.



The feature names and their frequencies are extracted from the transformed object (count) and stored in error_df. The words in error_df are sorted by frequency in descending order.

	word	freq
293	see	6
286	said	4
91	ebook	4
147	hand	3
125	found	3
...	...	...
131	front	1
130	french	1
129	freemasonri	1
128	frederick	1
375	york	1

376 rows × 2 columns

By using WordCloud with a dictionary that combined the word column and the frequency from word_freq table, we can use matplotlib to create a figure as below

5.4 Classifier

Different classifier also can influence the result. In this project, we found that the LinerSVC is a better classifier for this case.

However, in this project, we found that the influence from classifier is much less than the influence from transformer and data itself, which is very interesting. Sometimes, the data preparation and feature engineering may be more important than classify algorithms.

5.5 Conclusion

All in all, there are so many factors that can affect the performance of the model.
The famous machine learning scientist Andrew Ng said: “Good data is always more important than big data”.

In this project we noticed that how important the data would influence the final result. The most important thing is how to change big data to good data.

First, we should choose enough data we want analyze, and do data preparation, which contains the cleaning words, stemming and lemmatization to make sure all the data can keep the features we want and drop the garbage features.

Then, we should train a good transformer model, such as TF-IDF, which can help us to highlight the important features.

Also, we need make sure the training data redundant and balanced.

If we complete all of these, no matter what task we are going to do, such as classification, clustering etc., the final success will be only one step away from us.

All in all, the golden data is the most important thing!