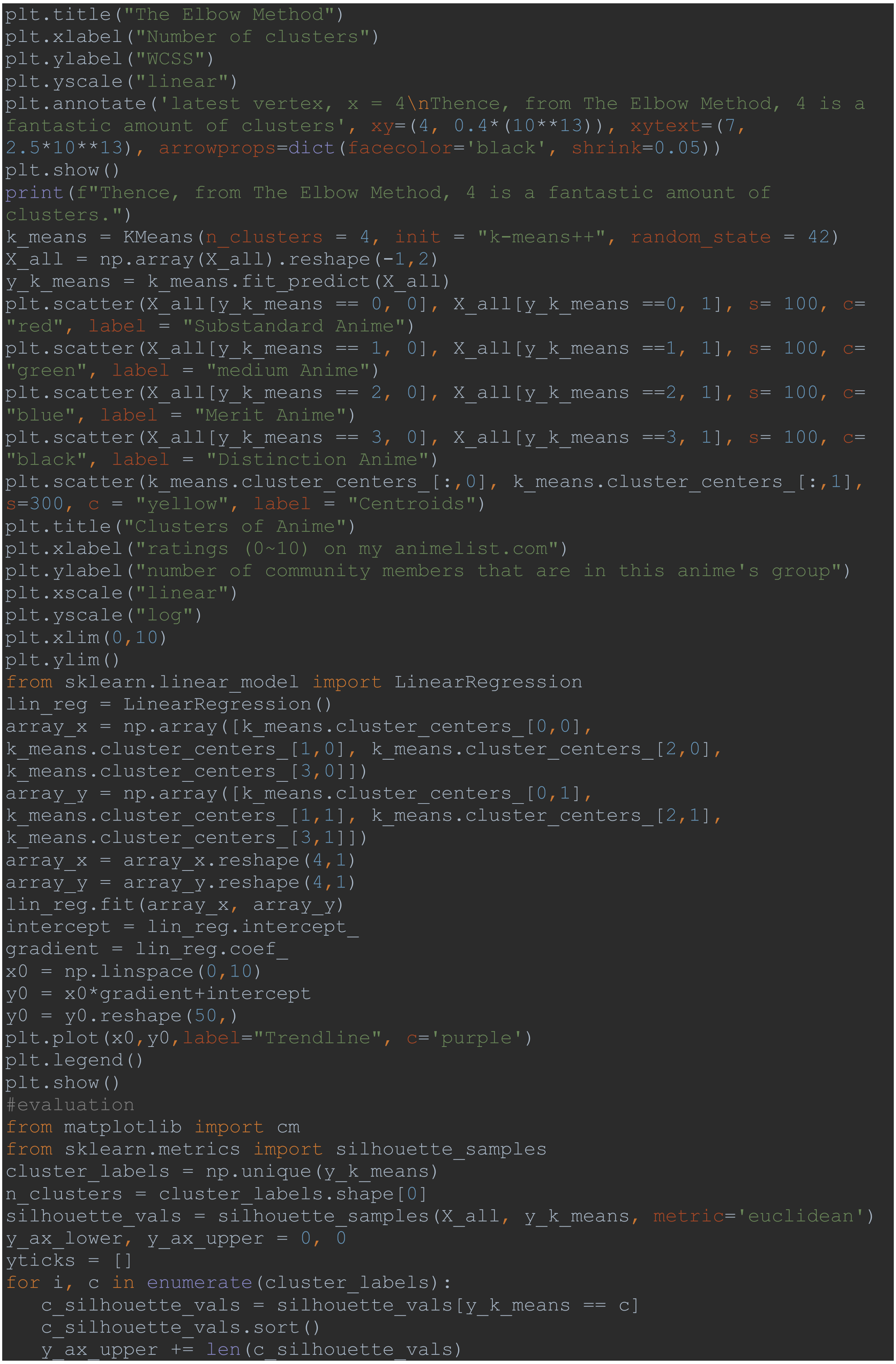
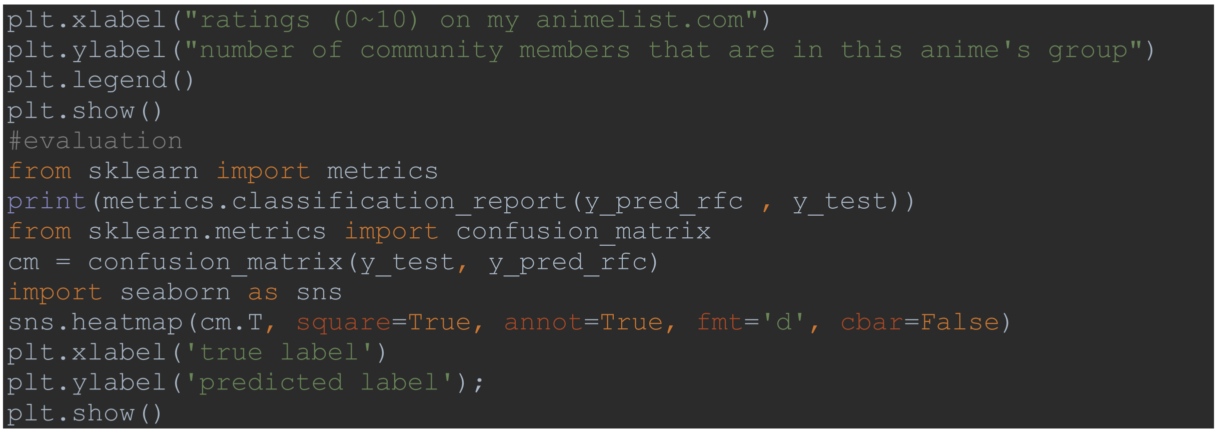
```
# -*- coding: utf-8 -*-
"""assignment 3.ipynb

Automatically generated by Colaboratory.

Original file is located at

https://colab.research.google.com/drive/1cBzcS027YXnz8_g2DhLWsE9nse2hIRNS

Assignment III

Due: June 5, 2022.
Pick a dataset of your choice. From UCI classification datasets
(https://archive.ics.uci.edu/ml/datasets.php?format=&task=cla&att=&area=&nu
mAtt=&numIns=&type=&sort=nameUp&view=table)
Use the RandomForest method for classification.
Take from UCI dataset from the clustering section and run k-means algorithm
on it.
Submit:
 1) code in Python
2)  a word file summarizing the result include some measure of performance
such as confusion matrix, and accuracy.

Enjoy!!
"""

# Commented out IPython magic to ensure Python compatibility.
#constructing dataframe
from google.colab import drive
drive.mount('/content/drive')
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
# %matplotlib inline
#classification
#clustering
df = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/anime.csv",
sep=",")
df['episodes'] = pd.to_numeric(df["episodes"],
errors='coerce').fillna(1000).astype(int)
df.episodes[df.episodes <= 25]  = 0
df.episodes[df.episodes > 25]  = 1
df = df.dropna(how="any")
print("\n")
print(f"The whole dataframe looks like:\n {df}.")
print("\n")
print("The dataframe information is: ")
print(f"{df.info()}.")
print("\n")
print(f"The dataframe shape is: {df.shape}.")
X_all = df.iloc[:, 5:7]
y = df["episodes"]

#K-Means
from sklearn.cluster import KMeans
wcss = []
for i in range(1,11):
  k_means = KMeans(n_clusters= i, init = "k-means++", random_state = 42)
  k_means.fit(X_all)
  wcss.append(k_means.inertia_)
plt.plot(range(1,11), wcss)
```



```
plt.title("The Elbow Method")
plt.xlabel("Number of clusters")
plt.ylabel("WCSS")
plt.yscale("linear")
plt.annotate('latest vertex, x = 4\nThence, from The Elbow Method, 4 is a
fantastic amount of clusters', xy=(4, 0.4*(10**13)), xytext=(7,
2.5*10**13), arrowprops=dict(facecolor='black', shrink=0.05))
plt.show()
print(f"Thence, from The Elbow Method, 4 is a fantastic amount of
clusters.")
k_means = KMeans(n_clusters = 4, init = "k-means++", random_state = 42)
X_all = np.array(X_all).reshape(-1,2)
y_k_means = k_means.fit_predict(X_all)
plt.scatter(X_all[y_k_means == 0, 0], X_all[y_k_means ==0, 1], s= 100, c=
"red", label = "Substandard Anime")
plt.scatter(X_all[y_k_means == 1, 0], X_all[y_k_means ==1, 1], s= 100, c=
"green", label = "medium Anime")
plt.scatter(X_all[y_k_means == 2, 0], X_all[y_k_means ==2, 1], s= 100, c=
"blue", label = "Merit Anime")
plt.scatter(X_all[y_k_means == 3, 0], X_all[y_k_means ==3, 1], s= 100, c=
"black", label = "Distinction Anime")
plt.scatter(k_means.cluster_centers_[:,0], k_means.cluster_centers_[:,1],
s=300, c = "yellow", label = "Centroids")
plt.title("Clusters of Anime")
plt.xlabel("ratings (0~10) on my animelist.com")
plt.ylabel("number of community members that are in this anime's group")
plt.xscale("linear")
plt.yscale("log")
plt.xlim(0,10)
plt.ylim()
from sklearn.linear_model import LinearRegression
lin_reg = LinearRegression()
array_x = np.array([k_means.cluster_centers_[0,0],
k_means.cluster_centers_[1,0], k_means.cluster_centers_[2,0],
k_means.cluster_centers_[3,0]])
array_y = np.array([k_means.cluster_centers_[0,1],
k_means.cluster_centers_[1,1], k_means.cluster_centers_[2,1],
k_means.cluster_centers_[3,1]])
array_x = array_x.reshape(4,1)
array_y = array_y.reshape(4,1)
lin_reg.fit(array_x, array_y)
intercept = lin_reg.intercept_
gradient = lin_reg.coef_
x0 = np.linspace(0,10)
y0 = x0*gradient+intercept
y0 = y0.reshape(50,)
plt.plot(x0,y0,label="Trendline", c='purple')
plt.legend()
plt.show()
#evaluation
from matplotlib import cm
from sklearn.metrics import silhouette_samples
cluster_labels = np.unique(y_k_means)
n_clusters = cluster_labels.shape[0]
silhouette_vals = silhouette_samples(X_all, y_k_means, metric='euclidean')
y_ax_lower, y_ax_upper = 0, 0
yticks = []
for i, c in enumerate(cluster_labels):
    c_silhouette_vals = silhouette_vals[y_k_means == c]
    c_silhouette_vals.sort()
    y_ax_upper += len(c_silhouette_vals)
```

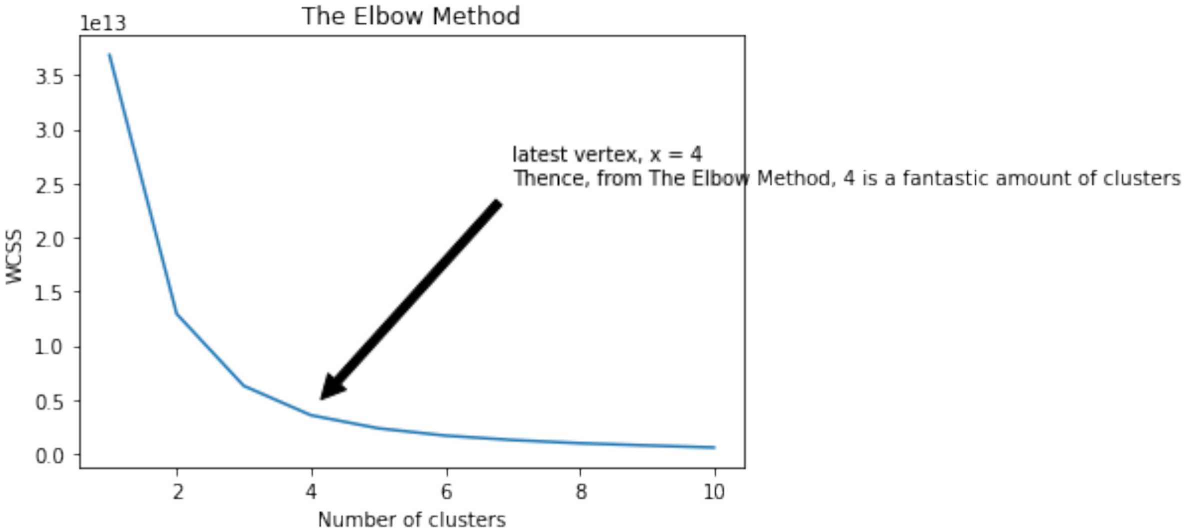
```
   color = cm.jet(i / n_clusters)
   plt.barh(range(y_ax_lower, y_ax_upper), c_silhouette_vals, height=1.0,
edgecolor='none', color=color)
   yticks.append((y_ax_lower + y_ax_upper) / 2)
   y_ax_lower += len(c_silhouette_vals)
silhouette_avg = np.mean(silhouette_vals)
plt.axvline(silhouette_avg, color="red", linestyle="--")
plt.yticks(yticks, cluster_labels + 1)
plt.ylabel('Cluster')
plt.xlabel('Silhouette coefficient')
plt.show()

#Random Forest
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_all, y, test_size =
0.5, random_state = 0)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = np.array(X_train).reshape(-1,2)
X_train = sc.fit_transform(X_train)
X_test = np.array(X_test).reshape(-1,2)
X_test = sc.transform(X_test)
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(n_estimators = 500, criterion="entropy",
random_state = 0)
rfc.fit(X_train, y_train)
y_pred_rfc = rfc.predict(X_test)
#train set
from matplotlib.colors import ListedColormap
X_set, y_set = X_train, y_train
X1, X2 = np.meshgrid(np.arange(start = X_set[:,0].min()-1, stop =
X_set[:,0].max()+1, step = 0.01), np.arange(start=X_set[:,1].min() -1, stop
= X_set[:,1].max() +1, step= 0.01))
plt.contourf(X1, X2, rfc.predict(np.array([X1.ravel(),
X2.ravel()]).T).reshape(X1.shape), alpha=0.75, cmap=
ListedColormap(("red","blue")))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i,j in enumerate(np.unique(y_set)):
  plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c =
ListedColormap(("red", "blue"))(i), label = j)
plt.title("Random Forest Classification (Trainning Set)")
plt.xlabel("ratings (0~10) on my animelist.com")
plt.ylabel("number of community members that are in this anime's group")
plt.legend()
plt.show()
#test set
from matplotlib.colors import ListedColormap
X_set, y_set = X_test, y_test
X1, X2 = np.meshgrid(np.arange(start = X_set[:,0].min()-1, stop =
X_set[:,0].max()+1, step = 0.01), np.arange(start=X_set[:,1].min() -1, stop
= X_set[:,1].max() +1, step= 0.01))
plt.contourf(X1, X2, rfc.predict(np.array([X1.ravel(),
X2.ravel()]).T).reshape(X1.shape), alpha=0.75, cmap=
ListedColormap(("red","blue")))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i,j in enumerate(np.unique(y_set)):
  plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c =
ListedColormap(("red", "blue"))(i), label = j)
plt.title("Random Forest Classification (Test Set)")
```



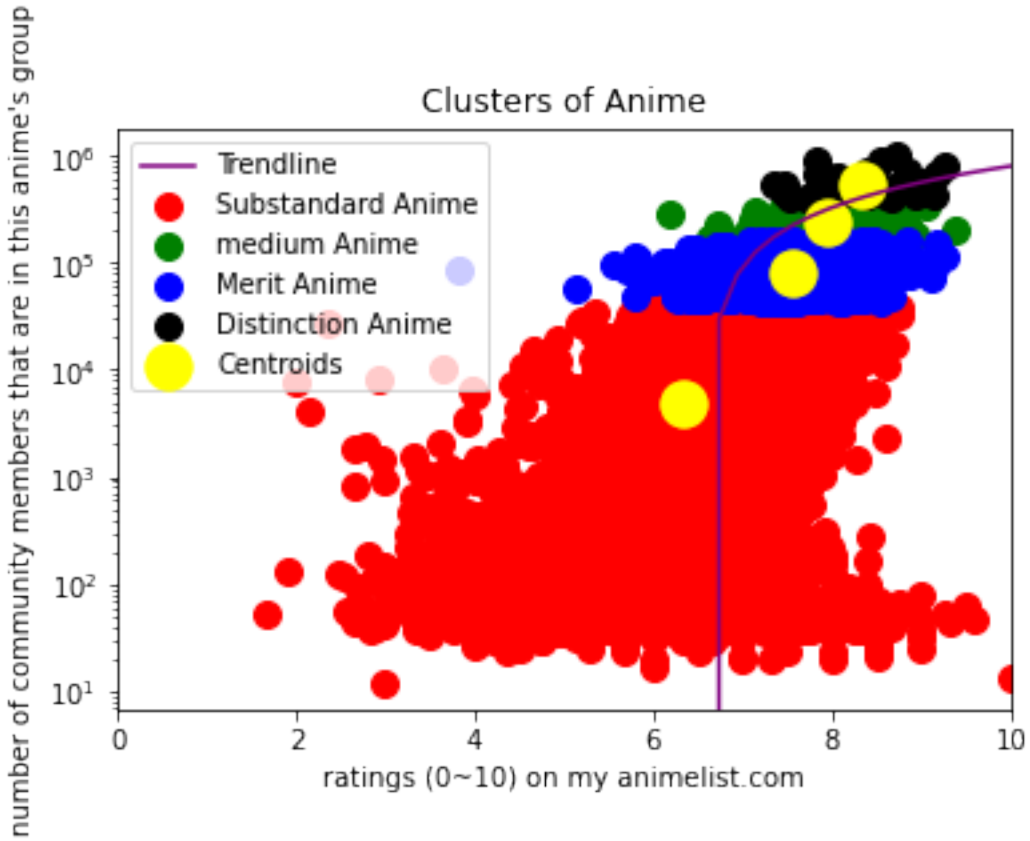
```
plt.xlabel("ratings (0~10) on my animelist.com")
plt.ylabel("number of community members that are in this anime's group")
plt.legend()
plt.show()
#evaluation
from sklearn import metrics
print(metrics.classification_report(y_pred_rfc , y_test))
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_rfc)
import seaborn as sns
sns.heatmap(cm.T, square=True, annot=True, fmt='d', cbar=False)
plt.xlabel('true label')
plt.ylabel('predicted label');
plt.show()
```

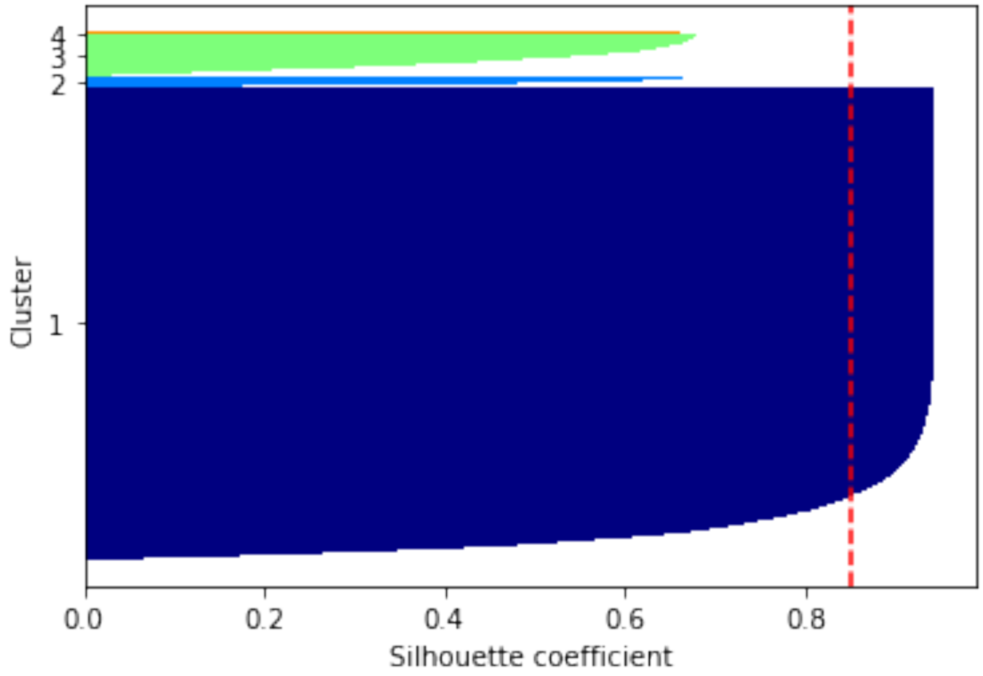
Results:

For k-means:



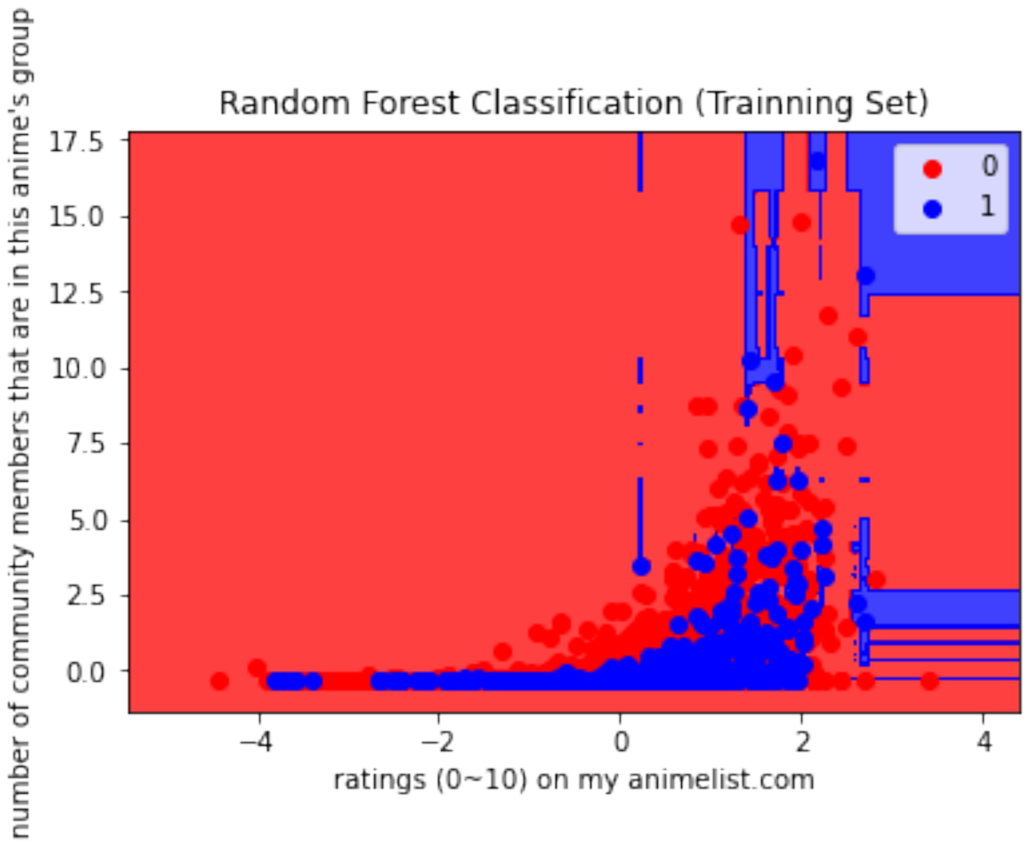
```
Thence, from The Elbow Method, 4 is a fantastic amount of clusters.
```

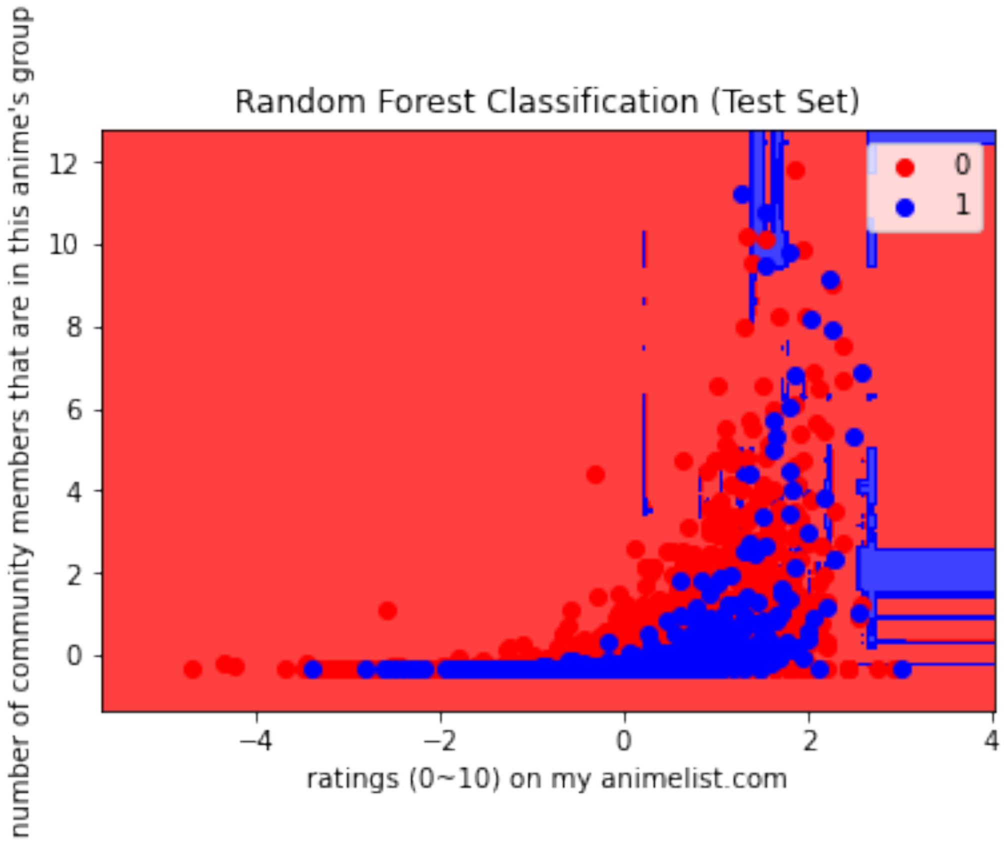




Using the Elbow method, I could automatically what number of clusters best suits my data, so by looking at the vertex, I find 4 clusters to set, and when I deploy them, there is a nice trend created. The performance, however, is not satisfying because the clustering of 4 areas are not evenly distributed, as we can see from the Silhouette model.

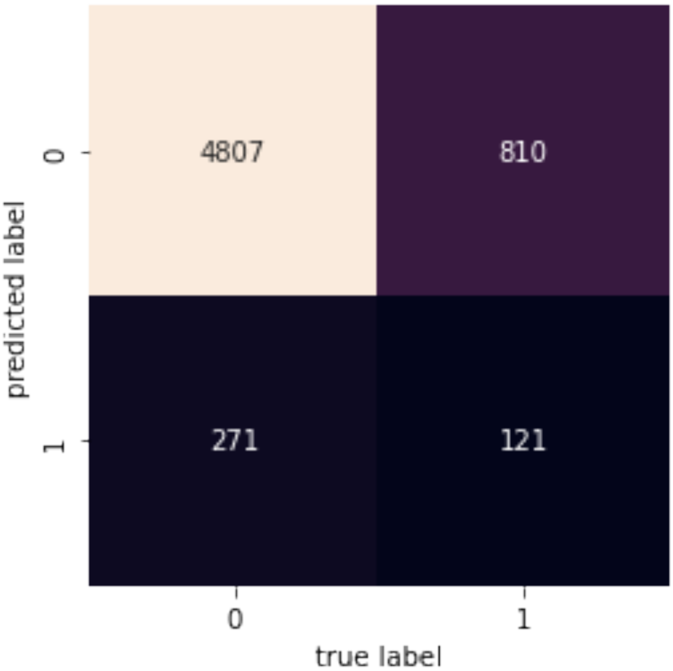
For Random Forest:





```
precision    recall  f1-score   support
```

```
           0       0.95      0.86      0.90      5617
           1       0.13      0.31      0.18       392

    accuracy                           0.82      6009
   macro avg       0.54      0.58      0.54      6009
weighted avg       0.89      0.82      0.85      6009
```



The weighted accuracy of 89% seems decently high, but it is not perfect. Although, on the first glance, the ListedColormaps look identical, but details are quite different, even the scale is different. Nonetheless, this method is the very accurate one available to people.