MSDS 422-57 | Module 6 Assignment 1 | Group 5
Jul 31, 2022 | Digit Recognizer | Scott Jue
Dr. Anil Chaturvedi | | Zach Watson

We built our models using the MNIST ("Modified National Institute of Standards and Technology") data. The data set contains gray-scale images of hand-drawn digits ranging from zero to nine. Each image is represented by 784 pixels (24 pixels high and 24 pixels wide); pixels have values ranging from 0 to 255 that correspond to their darkness (higher numbers are darker pixels). Our EDA found that the training dataset included 42,000 rows and 785 columns. The testing data has a shape of 28,000 rows and 784 columns. Each row represents a hand-drawn digit. The first column corresponds to the image label (not included in the testing data), and all subsequent columns correspond to pixel values. Consequently, we prepared the training data by removing the ‘label’ column to use as our output variable.

We believe that the major design flaw in the proposed experiment was the lack of a train-test split between the training data (from training.csv). Not splitting the data prevents us from having separate training and testing sets for validating the model performance on new unseen data. Consequently, we tuned each model twice, resulting in six sets of predictions. The first three models only have Kaggle scores to determine their accuracy. These models use the full set of variables in the train.csv as the training set, which makes them slower to tune. The next three models were tuned using data split into training and testing groups of 80% and 20%, respectively. It takes longer to test models (we used a cv=5), but we’re able to simulate the models’ performance with new data and compare them using additional metrics, like accuracy.

We began by fitting a random forest classifier using the complete set of explanatory variables in the model training set. Training the initial random forest model (RF1) takes 18.5 seconds to run. The original random forest model receives a Kaggle score of 0.966. The updated random forest model takes 16 seconds to run and receives F1, precision, recall, and accuracy scores of 0.96 and a Kaggle score of 0.966.

Next, we executed principal components analysis (PCA) on the entire training data. We set the n_components parameter to 0.95 so that the components represent 95% of the variability in explanatory variables (scaled pixel values). The number of components reduces from 784 components to 154 components, and the PCA takes 2.1 seconds to complete. Next, we fit a new random forest model using the PCA components. This random forest using the original PCA model takes 52.2 seconds to train. The original random forest model using PCA receives a Kaggle score of 0.944. The number of components for the model trained using a train-test split decreases by one to 153. The updated PCA model takes 1.9 seconds and the updated random forest model using the components from PCA took 36.1 seconds to run and receives F1, precision, recall, and accuracy scores of 0.94 and a Kaggle score of 0.938.

Following this, we used k-means clustering to group MNIST observations into categories and assign labels. Initially, we tried using 10 clusters, but we ultimately decided to set n_clusters to 256 as that yielded a higher accuracy. We then used a function to extract the number label from the cluster number. Using the number labels, we created a dictionary to help get the appropriate number label from the cluster number when generating our predictions for Kaggle. The original k-means model received a Kaggle score of 0.898. The updated k-means model receives F1, precision, recall, and accuracy scores of 0.89 and a Kaggle score of .896.

Ultimately, we were relatively happy with the accuracy of our models, and the final versions (using train-test split) had Kaggle scores and accuracies ranging from 0.89 to 0.96. You can see all of our final Kaggle scores in the index. We had the most difficulty building the k-means model, which was also our lowest scoring, so that would be an area for further exploration. Additionally, this code has lots of similar and repeating blocks, so a more refined version would probably implement additional loops to improve clarity and conciseness.

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Index:

Models without train-test split:

YOUR RECENT SUBMISSION

rf_1_pred-group_5_msds_422.csv — **Score: 0.96575**
Submitted by ZachWat · Submitted just now

Jump to your leaderboard position

YOUR RECENT SUBMISSION

pca_1_pred-group_5_msds_422.csv — **Score: 0.94403**
Submitted by ZachWat · Submitted just now

Jump to your leaderboard position

YOUR RECENT SUBMISSION

kmeans_pred-group_5_msds_422.csv — **Score: 0.89778**
Submitted by ZachWat · Submitted just now

Jump to your leaderboard position

Models with train-test split:

YOUR RECENT SUBMISSION

rf_a_pred-group_5_msds_422.csv — **Score: 0.96257**
Submitted by ZachWat · Submitted just now

Jump to your leaderboard position

YOUR RECENT SUBMISSION

pca_b_pred-group_5_msds_422.csv — **Score: 0.93825**
Submitted by ZachWat · Submitted just now

Jump to your leaderboard position

YOUR RECENT SUBMISSION

kmeans_pred2-group_5_msds_422.csv — **Score: 0.89596**
Submitted by ScottJ · Submitted just now

Jump to your leaderboard position

Intro

Links

Canvas: https://canvas.northwestern.edu/courses/167719/assignments/1078606?module_item_id=2319265

Kaggle: https://www.kaggle.com/c/digit-recognizer

Modules

In [2]:
```
#For data manipulation and visualization
#from google.colab import files

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
from matplotlib.pyplot import subplots_adjust


from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score, f1_score, classification_report, confusion_
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import MiniBatchKMeans
from sklearn import cluster

from datetime import datetime
```

Import Data

In [3]:
```
#Import data.csv from the Kaggle page linked above
# from google.colab import files
# files.upload()
```

In [4]:
```
df = pd.read_csv("train.csv")
```

EDA

Intro Stats

In [5]:
```
df.shape
```

Out[5]:
```
(42000, 785)
```

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42000 entries, 0 to 41999
Columns: 785 entries, label to pixel783
dtypes: int64(785)
memory usage: 251.5 MB
```

In [7]:

```
# check for missing values
print(df.isna().sum().sum())
print(np.isnan(df).sum().sum())
print(df.isnull().sum().sum())
```

```
0
0
0
```

In [8]:

```
df.head(10)
```

Out[8]:

	label	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	...	pixel774	pixel775	p
0	1	0	0	0	0	0	0	0	0	0	...	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	
2	1	0	0	0	0	0	0	0	0	0	...	0	0	
3	4	0	0	0	0	0	0	0	0	0	...	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	
5	0	0	0	0	0	0	0	0	0	0	...	0	0	
6	7	0	0	0	0	0	0	0	0	0	...	0	0	
7	3	0	0	0	0	0	0	0	0	0	...	0	0	
8	5	0	0	0	0	0	0	0	0	0	...	0	0	
9	3	0	0	0	0	0	0	0	0	0	...	0	0	

10 rows × 785 columns

Data Prep

In [9]:

```
y = df['label']
X = df.drop(columns = ['label'])
```

Scale Data

In [10]:

```
# Conversion to float
X = X.astype('float32')
```

```
# Normalization
X = X/255.0
```

Models w/o Train/Test split

Random Forest

In [11]:

```
start=datetime.now()
rf_clf = RandomForestClassifier(random_state=42)
rf_clf.fit(X, y)
end=datetime.now()
print(end-start)
```

```
0:00:18.502054
```

PCA

In [12]:

```
# PCA on the combined training and test set data together
start=datetime.now()
pca = PCA(n_components=0.95)
X_reduced = pca.fit_transform(X)
end=datetime.now()
print(end-start)
```

```
0:00:02.116401
```

In [13]:

```
pca.n_components_
```

Out[13]:

```
154
```

In [14]:

```
pca.explained_variance_ratio_
```

Out[14]:

```
array([0.09748938, 0.07160266, 0.06145903, 0.05379302, 0.04894262,
       0.04303214, 0.03277051, 0.02892103, 0.02766902, 0.02348871,
       0.02099325, 0.02059001, 0.01702553, 0.01692787, 0.01581126,
       0.0148324 , 0.01319688, 0.01282727, 0.01187976, 0.01152755,
       0.01072191, 0.01015199, 0.00964902, 0.00912846, 0.00887641,
       0.00838766, 0.00811856, 0.00777406, 0.00740635, 0.00686661,
       0.00657982, 0.00638799, 0.00599367, 0.00588913, 0.00564335,
       0.00540967, 0.00509222, 0.00487505, 0.00475569, 0.00466545,
       0.00452952, 0.00444989, 0.00418255, 0.00397506, 0.00384542,
       0.00374919, 0.00361013, 0.00348522, 0.00336488, 0.00320738,
       0.00315467, 0.00309146, 0.00293709, 0.00286541, 0.00280759,
       0.00269618, 0.00265831, 0.00256299, 0.00253821, 0.00246178,
       0.00239716, 0.0023874 , 0.00227591, 0.00221518, 0.00213934,
       0.00206133, 0.00202851, 0.00195977, 0.00193639, 0.00188485,
       0.00186751, 0.0018167 , 0.00176891, 0.00172592, 0.00166121,
       0.0016331 , 0.00160601, 0.00154472, 0.0014685 , 0.00142376,
       0.00141098, 0.00140228, 0.00138835, 0.00135417, 0.00132307,
       0.0013078 , 0.00129674, 0.0012424 , 0.00122249, 0.00119624,
       0.0011584 , 0.00113859, 0.00112263, 0.00110475, 0.00108133,
       0.00107413, 0.00103866, 0.00103322, 0.00101495, 0.00099997,
       0.00097482, 0.00094506, 0.00093864, 0.00091222, 0.00090731,
       0.00088887, 0.0008637 , 0.00084423, 0.00083554, 0.00081665,
```

```
       0.00078768, 0.00078156, 0.00077746, 0.00077193, 0.00075784,
       0.00075022, 0.00073448, 0.00072577, 0.00071532, 0.00070032,
       0.00069305, 0.00068574, 0.00067993, 0.00066572, 0.00065614,
       0.0006448 , 0.00063539, 0.00062612, 0.00061851, 0.00060574,
       0.00060385, 0.00059145, 0.0005859 , 0.00058463, 0.00057548,
       0.00056972, 0.0005645 , 0.00055317, 0.00053434, 0.00052578,
       0.00052197, 0.00051119, 0.00050514, 0.00049992, 0.00049532,
       0.00049235, 0.0004844 , 0.00047669, 0.00047467, 0.00046789,
       0.0004653 , 0.00046136, 0.00045634, 0.00045176])
```

Random Forest

In [15]:

```
# random forest using PCA components
start=datetime.now()
rf_pca = RandomForestClassifier(random_state=42)
rf_pca.fit(X_reduced, y)
end=datetime.now()
print(end-start)
```

```
0:00:52.246855
```

k-Means Clustering

In [16]:

```
# reshape data for k-means
X_k = X.values.reshape(len(X),-1)
```

In [17]:

```
# train k-means clustering model
kmeans = MiniBatchKMeans(n_clusters = 256, random_state=42)
kmeans.fit(X_k)
```

```
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1836: UserWarning:
MiniBatchKMeans is known to have a memory leak on Windows with MKL, when there are less
chunks than available threads. You can prevent it by setting batch_size >= 2048 or by se
tting the environment variable OMP_NUM_THREADS=4
  warnings.warn(
```

Out[17]:

```
▾                MiniBatchKMeans

MiniBatchKMeans(n_clusters=256, random_state=42)
```

In [18]:

```
kmeans.labels_
```

Out[18]:

```
array([ 50, 112,  33, ..., 111, 232, 167])
```

In [19]:

```
# kmeans cluster numbers do no represent the label numbers, so we need to create a func
# Associates most probable label with each cluster in KMeans model returns: dictionary
def retrieve_info(cluster_labels, y):

  # Initializing
  reference_labels = {}

# For loop to run through each label of cluster label
  for i in range(len(np.unique(kmeans.labels_))):
    index = np.where(cluster_labels == i,1,0)
```

```
    num = np.bincount(y[index==1]).argmax()
    reference_labels[i] = num
  return reference_labels
```

In [20]:
```
# Calculating reference_labels
reference_labels = retrieve_info(kmeans.labels_, y)

# create a list which denotes the number displayed in image
number_labels = np.random.rand(len(kmeans.labels_))

for i in range(len(kmeans.labels_)):
  number_labels[i] = reference_labels[kmeans.labels_[i]]
```

In [21]:
```
d = dict(zip(kmeans.labels_, number_labels))
```

Models w/ Train-Test Split

In [22]:
```
y = df['label']
X = df.drop(columns = ['label'])
```

Split Data for Training

In [23]:
```
# split data in to training and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4
```

Scale Data

In [24]:
```
# Conversion to float
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')

# Normalization
X_train = X_train/255.0
X_test = X_test/255.0
```

Random Forest

In [25]:
```
start=datetime.now()
rf_clf2 = RandomForestClassifier(random_state=42)
rf_clf2.fit(X_train, y_train)
end=datetime.now()
print(end-start)
```

```
0:00:16.026886
```

In [26]:
```
# y predictions
y_pred = rf_clf2.predict(X_test)
```

In [27]:
```
# cross-validation
rf_scores = cross_val_score(rf_clf2, X_train, y_train, cv=5)
rf_scores.mean()
```

Out[27]: 0.9615476190476191

In [28]:
```
# random forest model performance
print('f1-score:',f1_score(y_test, y_pred, average='macro'))
print('precision:',precision_score(y_test, y_pred, average="macro"))
print('recall:', recall_score(y_test, y_pred, average="macro"))
print('accuracy:', accuracy_score(y_test, y_pred))
```

```
f1-score: 0.9629039101845235
precision: 0.9628494321468949
recall: 0.9630201177608895
accuracy: 0.9629761904761904
```

PCA

In [29]:
```
# PCA on the the train set (applied to the test set)
start=datetime.now()
pca2 = PCA(n_components=0.95)
X_train_pca2 = pca2.fit_transform(X_train)
X_test_pca2 = pca2.transform(X_test)
end=datetime.now()
print(end-start)
```

```
0:00:01.999114
```

In [30]:
```
pca2.n_components_
```

Out[30]: 153

In [31]:
```
pca2.explained_variance_ratio_
```

Out[31]:
```
array([0.09770722, 0.07129345, 0.06175413, 0.05389551, 0.04892553,
       0.04336844, 0.03276574, 0.02892703, 0.02770703, 0.02329171,
       0.02093107, 0.02047164, 0.01707795, 0.01683206, 0.01584721,
       0.01487983, 0.01323098, 0.01283937, 0.01183384, 0.01151186,
       0.01075969, 0.01024215, 0.00966626, 0.00917296, 0.00884714,
       0.00833528, 0.00815071, 0.00775332, 0.00741987, 0.00693325,
       0.00660848, 0.00633209, 0.00603213, 0.0058873 , 0.0056183 ,
       0.00539861, 0.0050791 , 0.00487127, 0.00471253, 0.00464556,
       0.0045249 , 0.00444059, 0.00416518, 0.00395636, 0.00383604,
       0.00373128, 0.00360705, 0.00348865, 0.003342  , 0.00318011,
       0.00314205, 0.00307234, 0.00292367, 0.00286554, 0.00279118,
       0.00269329, 0.00264929, 0.00256639, 0.00252853, 0.00245253,
       0.0024055 , 0.00239097, 0.00226894, 0.00221636, 0.00214605,
       0.00205814, 0.0020172 , 0.00196308, 0.0019362 , 0.00188242,
       0.00185615, 0.00181757, 0.00175209, 0.0017258 , 0.00165174,
       0.00163086, 0.00159816, 0.00153838, 0.00146718, 0.00141971,
       0.00140977, 0.00139752, 0.00138852, 0.00135292, 0.00131958,
       0.00130494, 0.00129886, 0.00123586, 0.00121821, 0.00120113,
       0.00115699, 0.00113996, 0.00112739, 0.00110193, 0.00108005,
       0.00107146, 0.00103751, 0.00103329, 0.00100968, 0.00100022,
       0.00097082, 0.00095057, 0.00093759, 0.0009155 , 0.00090927,
```

```
       0.00088799, 0.00086964, 0.00084898, 0.00083351, 0.00081177,
       0.00078614, 0.00077889, 0.0007729 , 0.00076339, 0.00075888,
       0.00074785, 0.00073248, 0.00072807, 0.00071441, 0.00070241,
       0.000694  , 0.00068458, 0.00067703, 0.00066386, 0.0006504 ,
       0.00064964, 0.0006357 , 0.00063028, 0.00061677, 0.00060516,
       0.00059988, 0.00059068, 0.00058703, 0.0005826 , 0.00057527,
       0.00056912, 0.00056495, 0.00055527, 0.00053446, 0.00052773,
       0.00052118, 0.00051244, 0.00051041, 0.00049978, 0.00049226,
       0.00048958, 0.0004829 , 0.00047799, 0.00047268, 0.00046723,
       0.00046266, 0.00046129, 0.00045363])
```

Random Forest

In [32]:

```
start=datetime.now()
rf_pca2 = RandomForestClassifier(random_state=42)
rf_pca2.fit(X_train_pca2, y_train)
end=datetime.now()
print(end-start)
```

```
0:00:36.097300
```

In [33]:

```
# y predictions
y_pred = rf_pca2.predict(X_test_pca2)
```

In [34]:

```
# cross-validation
rf_scores = cross_val_score(rf_pca2, X_train_pca2, y_train, cv=5)
rf_scores.mean()
```

Out[34]:

```
0.9372023809523811
```

In [35]:

```
# random forest model performance with PCA
print('f1-score:',f1_score(y_test, y_pred, average='macro'))
print('precision:',precision_score(y_test, y_pred, average="macro"))
print('recall:', recall_score(y_test, y_pred, average="macro"))
print('accuracy:', accuracy_score(y_test, y_pred))
```

```
f1-score: 0.9392950955646109
precision: 0.9393349587176504
recall: 0.9393751480200129
accuracy: 0.9394047619047619
```

k-Means Clustering

In [36]:

```
# reshape data for k-means
X_train_k = X_train.values.reshape(len(X_train),-1)
X_test_k = X_test.values.reshape(len(X_test),-1)
```

In [37]:

```
# train k-means clustering model
kmeans2 = MiniBatchKMeans(n_clusters = 256, random_state=42)
kmeans2.fit(X_train_k)
```

```
C:\Users\sjue\Anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1836: UserWarning:
MiniBatchKMeans is known to have a memory leak on Windows with MKL, when there are less
```

```
chunks than available threads. You can prevent it by setting batch_size >= 2048 or by se
tting the environment variable OMP_NUM_THREADS=4
  warnings.warn(
```

Out[37]:
```
MiniBatchKMeans

MiniBatchKMeans(n_clusters=256, random_state=42)
```

In [38]:
```
kmeans2.labels_
```

Out[38]:
```
array([208, 121,  34, ..., 171, 131,  90])
```

In [39]:
```
# kmeans cluster numbers do no represent the label numbers, so we need to create a func
# Associates most probable label with each cluster in KMeans model returns: dictionary
def retrieve_info(cluster_labels, y_train):

  # Initializing
  reference_labels = {}

# For loop to run through each label of cluster label
  for i in range(len(np.unique(kmeans.labels_))):
    index = np.where(cluster_labels == i,1,0)
    num = np.bincount(y_train[index==1]).argmax()
    reference_labels[i] = num
  return reference_labels
```

In [40]:
```
# Calculating reference_labels
reference_labels = retrieve_info(kmeans2.labels_, y_train)

# create a list which denotes the number displayed in image
number_labels = np.random.rand(len(kmeans2.labels_))

for i in range(len(kmeans2.labels_)):
  number_labels[i] = reference_labels[kmeans2.labels_[i]]
```

In [41]:
```
# check number labels from fitted k_means model
number_labels
```

Out[41]:
```
array([6., 5., 3., ..., 4., 6., 0.])
```

In [42]:
```
print('Accuracy score:{}'.format(accuracy_score(number_labels, y_train)))
```

```
Accuracy score:0.8978571428571429
```

In [43]:
```
# get cluster centrioids
centroids = kmeans.cluster_centers_
centroids.shape
```

Out[43]:
```
(256, 784)
```

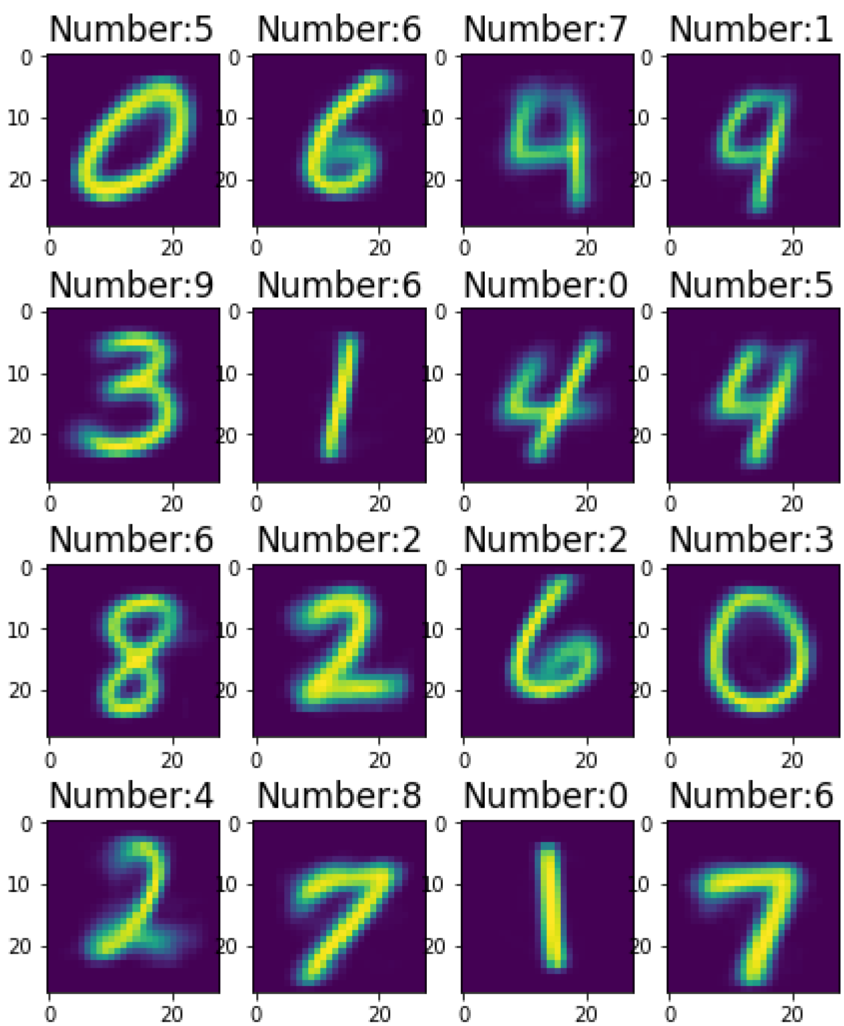
In [44]:
```
# reshape centroids
centroids = centroids.reshape(256,28,28)
```

In [45]:
```
# de-normalize centroids
centroids = centroids * 255
```

In [46]:
```
# plot fitted model results
plt.figure(figsize = (10,9))

bottom = 0.35

for i in range(16):
 plt.subplots_adjust(bottom)
 plt.subplot(4,4,i+1)
 plt.title('Number:{}'.format(reference_labels[i]),fontsize = 17)
 plt.imshow(centroids[i])
```



In [47]:
```
# use fitted model to predict using test split data
y_pred = kmeans2.predict(X_test_k)
```

In [48]:
```
# revise retrieve_info function to work with y_pred and y_test variables
def retrieve_info_2(cluster_labels, y_test):

  # Initializing
```

```
  reference_labels = {}

# For loop to run through each label of cluster label
  for i in range(len(np.unique(y_pred))):
    index = np.where(cluster_labels == i,1,0)
    num = np.bincount(y_test[index==1]).argmax()
    reference_labels[i] = num
  return reference_labels
```

In [49]:
```
# Calculating reference_labels
reference_labels = retrieve_info_2(y_pred, y_test)

# create a list which denotes the number displayed in image
y_pred_labels = np.random.rand(len(y_pred))

for i in range(len(y_pred)):
  y_pred_labels[i] = reference_labels[y_pred[i]]
```

In [50]:
```
# orginal y_pred results (not 0-10)
y_pred
```

Out[50]:
```
array([218,   3, 112, ..., 193,  99,  45])
```

In [51]:
```
# y_pred results with correct number labels (0-10)
y_pred_labels
```

Out[51]:
```
array([8., 1., 9., ..., 3., 0., 9.])
```

In [52]:
```
print('Accuracy score:{}'.format(accuracy_score(y_pred_labels, y_test)))
```

```
Accuracy score:0.8938095238095238
```

In [53]:
```
print('f1-score:{}'.format(f1_score(y_pred_labels, y_test, average='macro')))
print('precision:{}'.format(precision_score(y_pred_labels, y_test, average='macro')))
print('recall:{}'.format(recall_score(y_pred_labels, y_test, average='macro')))
```

```
f1-score:0.8933410732445408
precision:0.893399547141453
recall:0.8938762506974571
```

In [54]:
```
d2 = dict(zip(kmeans2.labels_, number_labels))
```

Testing

In [55]:
```
#create dataframe using test data from kaggle
df_test = pd.read_csv("test.csv")
```

In [56]:
```
len(df_test)
```

Out[56]: 28000

Scale Data

In [57]:
```
# Conversion to float
df_float = df_test.astype('float32')

# Normalization
X = df_float/255.0

X.head()
```

Out[57]:

	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel774	pixel775
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0

5 rows × 784 columns

Test Models

Models w/o Train-Test Split

In [58]:
```
#Random Forest One
rf_1_pred = pd.DataFrame(rf_clf.predict(X),columns = ['Label'])

rf_1_pred.insert(0, 'ImageId', range(1, 1 + len(X)))

rf_1_pred.head()
```

Out[58]:

	ImageId	Label
0	1	2
1	2	0
2	3	9
3	4	9
4	5	3

In [59]:
```
#Random Forest Two

#Transform the Data to Fit
X_pca1 = pca.transform(X)
```

```
# y predictions
pca_1_pred = pd.DataFrame(rf_pca.predict(X_pca1),columns = ['Label'])

pca_1_pred.insert(0, 'ImageId', range(1, 1 + len(X)))

pca_1_pred.head()
```

Out[59]:

	ImageId	Label
0	1	2
1	2	0
2	3	9
3	4	4
4	5	2

In [60]:

```
#k-Means Clustering
X_k = X.values.reshape(len(X),-1)
# y predictions
k_means_pred = kmeans.predict(X_k)

keys = k_means_pred

k_means_pred = np.array([d[key] for key in keys])

kmeans_pred = pd.DataFrame(k_means_pred, columns = ['Label']).astype('int')

kmeans_pred.insert(0, 'ImageId', range(1, 1 + len(X)))

kmeans_pred.head()
```

Out[60]:

	ImageId	Label
0	1	2
1	2	0
2	3	7
3	4	8
4	5	3

Models w/ Train-Test Split

In [61]:

```
#Random Forest One v2
rf_a_pred = pd.DataFrame(rf_clf2.predict(X),columns = ['Label'])

rf_a_pred.insert(0, 'ImageId', range(1, 1 + len(X)))

rf_a_pred.head()
```

Out[61]:

	ImageId	Label

	ImageId	Label
0	1	2
1	2	0
2	3	9
3	4	9
4	5	3

In [62]:

```
#Random Forest Two v2

#Transform the Data to Fit
X_pca2 = pca2.transform(X)

# y predictions
pca_b_pred = rf_pca2.predict(X_pca2)

# y predictions
pca_b_pred = pd.DataFrame(rf_pca2.predict(X_pca2),columns = ['Label'])

pca_b_pred.insert(0, 'ImageId', range(1, 1 + len(X)))

pca_b_pred.head()
```

Out[62]:

	ImageId	Label
0	1	2
1	2	0
2	3	9
3	4	4
4	5	3

In [63]:

```
#k-Means Clustering v2
X_k = X.values.reshape(len(X),-1)

# y predictions
k_means_pred2 = kmeans2.predict(X_k)

# Loop through predictions and get key values(number labels) from dictionary
keys = k_means_pred2

k_means_pred2 = np.array([d2[key] for key in keys])

# create df with new labels
kmeans_pred2 = pd.DataFrame(k_means_pred2, columns = ['Label']).astype('int')

kmeans_pred2.insert(0, 'ImageId', range(1, 1 + len(X)))

kmeans_pred2.head()
```

Out[63]:

	ImageId	Label
0	1	2
1	2	0
2	3	9
3	4	7
4	5	3

Download the Files

Leave these commented out unless downloading a final version.

In [64]:

```
# rf_1_pred.to_csv('rf_1_pred-group_5_msds_422.csv', index=False)
# files.download('rf_1_pred-group_5_msds_422.csv')
```

In [65]:

```
# pca_1_pred.to_csv('pca_1_pred-group_5_msds_422.csv', index=False)
# files.download('pca_1_pred-group_5_msds_422.csv')
```

In [66]:

```
# kmeans_pred.to_csv('kmeans_pred-group_5_msds_422.csv', index=False)
# files.download('kmeans_pred-group_5_msds_422.csv')
```

In [67]:

```
# rf_a_pred.to_csv('rf_a_pred-group_5_msds_422.csv', index=False)
# files.download('rf_a_pred-group_5_msds_422.csv')
```

In [68]:

```
# pca_b_pred.to_csv('pca_b_pred-group_5_msds_422.csv', index=False)
# files.download('pca_b_pred-group_5_msds_422.csv')
```

In [69]:

```
# kmeans_pred2.to_csv('kmeans_pred2-group_5_msds_422.csv', index=False)
# files.download('kmeans_pred2-group_5_msds_422.csv')
```