# PCA on MNIST dataset and Logistic Regression

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# PCA

In [1]:

```
#Import all libraries needed for data analysis
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
data = pd.read_csv('train.csv')
print(data.head(5)) # print first five rows of data.
```

```
   label  pixel0  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  \
0      1       0       0       0       0       0       0       0       0   
1      0       0       0       0       0       0       0       0       0   
2      1       0       0       0       0       0       0       0       0   
3      4       0       0       0       0       0       0       0       0   
4      0       0       0       0       0       0       0       0       0   

   pixel8  ...  pixel774  pixel775  pixel776  pixel777  pixel778  pixel779  \
0       0  ...         0         0         0         0         0         0   
1       0  ...         0         0         0         0         0         0   
2       0  ...         0         0         0         0         0         0   
3       0  ...         0         0         0         0         0         0   
4       0  ...         0         0         0         0         0         0   

   pixel780  pixel781  pixel782  pixel783  
0         0         0         0         0  
1         0         0         0         0  
2         0         0         0         0  
3         0         0         0         0  
4         0         0         0         0  

[5 rows x 785 columns]
```

# Simplifying Given Dataset

In [2]:

```
l = data['label']# save the labels into a variable l.
d = data.drop("label",axis=1)# Drop the label feature and store the pixel data in d.
```

# Data preprocessing

In [3]:

```
from sklearn.preprocessing import StandardScaler
standardized_data = StandardScaler().fit_transform(data)
print(standardized_data.shape)
```

```
(42000, 785)
```

# Compute Covariance Matrix

In [4]:
```
#find the co-variance matrix which is : A^T * A
sample_data = standardized_data
# matrix multiplication using numpy
covar_matrix = np.matmul(sample_data.T , sample_data)
print ("The shape of variance matrix = ", covar_matrix.shape)
```

```
The shape of variance matrix =  (785, 785)
```

# Compute eigenvalue and eigenvector

In [5]:
```
from scipy.linalg import eigh
# the parameter 'eigvals' is defined (low value to heigh value)
# eigh function will return the eigen values in asending order
# this code generates only the top 2 (782 and 783)(index) eigenvalues.
values, vectors = eigh(covar_matrix, eigvals=(782,783))
print("Shape of eigen vectors = ",vectors.shape)
# converting the eigen vectors into (2,d) shape for easyness of further computations
vectors = vectors.T
print("Updated shape of eigen vectors = ",vectors.shape)
# here the vectors[1] represent the eigen vector corresponding 1st principal eigen v
# here the vectors[0] represent the eigen vector corresponding 2nd principal eigen v
```

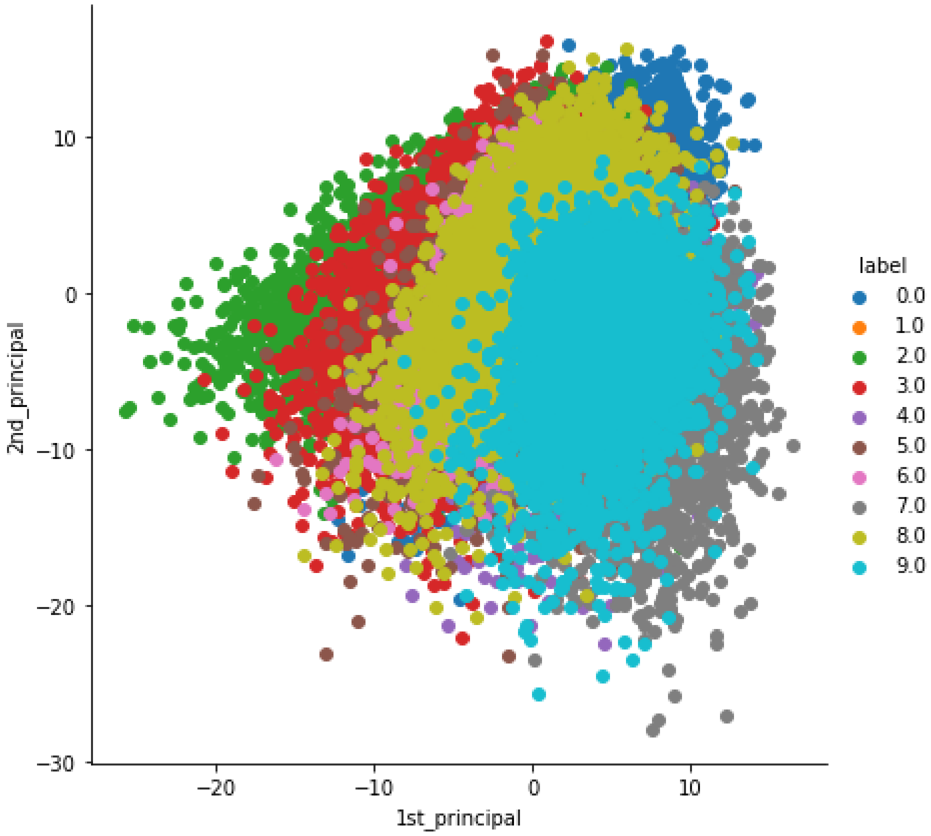
```
Shape of eigen vectors =  (785, 2)
Updated shape of eigen vectors =  (2, 785)
```

# Projecting the original data sample on the plane formed by two principal eigenvectors by vector-vector multiplication.

In [6]:
```
new_coordinates = np.matmul(vectors, sample_data.T)
new_coordinates = np.vstack((new_coordinates,l)).T
dataframe = pd.DataFrame(data=new_coordinates, columns=("1st_principal", "2nd_princi
print(dataframe.head())
```

```
   1st_principal  2nd_principal  label
0      -3.834079       5.498016    1.0
1      -1.533175      -6.018994    0.0
2      -2.425707       1.959875    1.0
3      -2.284497      -5.716447    4.0
4      -1.153826      -6.049490    0.0
```

In [7]:
```
# ploting the 2d data points with seaborn
import seaborn as sn
sn.FacetGrid(dataframe, hue="label", height=6).map(plt.scatter, '1st_principal', '2n
plt.show()
```




# PCA using SciKit Learn

In [8]:

```
# initializing the pca
from sklearn import decomposition
pca = decomposition.PCA()
```

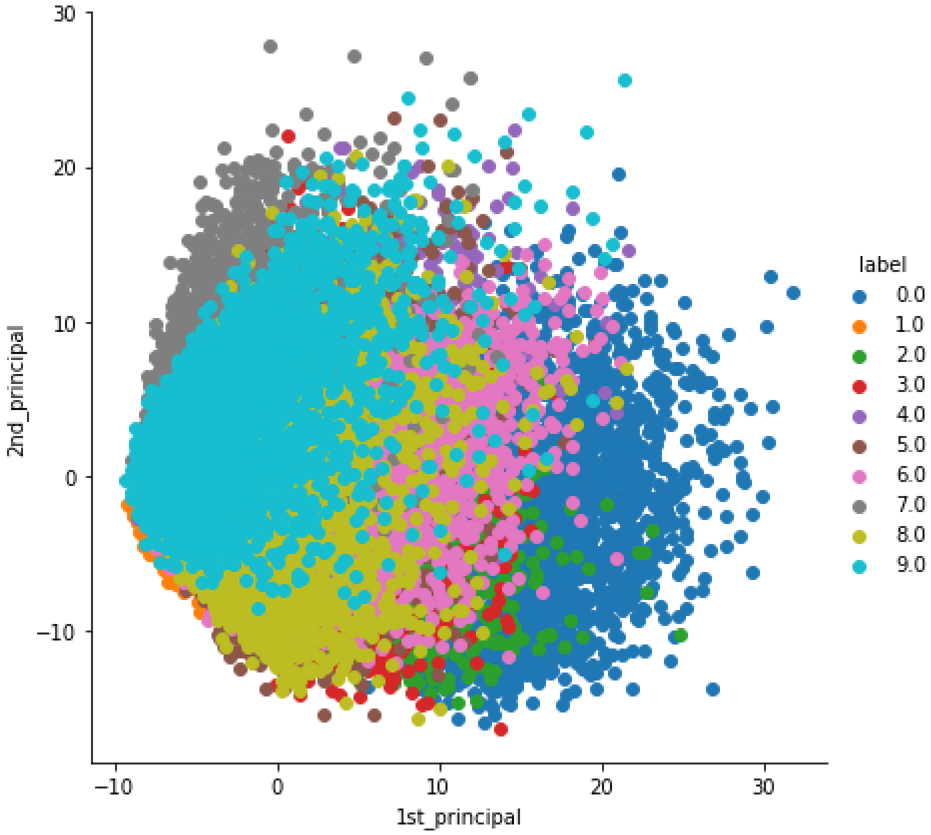
In [9]:

```
# configuring the parameteres
# the number of components = 2
pca.n_components = 2
pca_data = pca.fit_transform(sample_data)
# pca_reduced will contain the 2-d projects of simple data
print("Shape of pca_reduced.shape = ", pca_data.shape)
```

```
Shape of pca_reduced.shape =  (42000, 2)
```

In [10]:

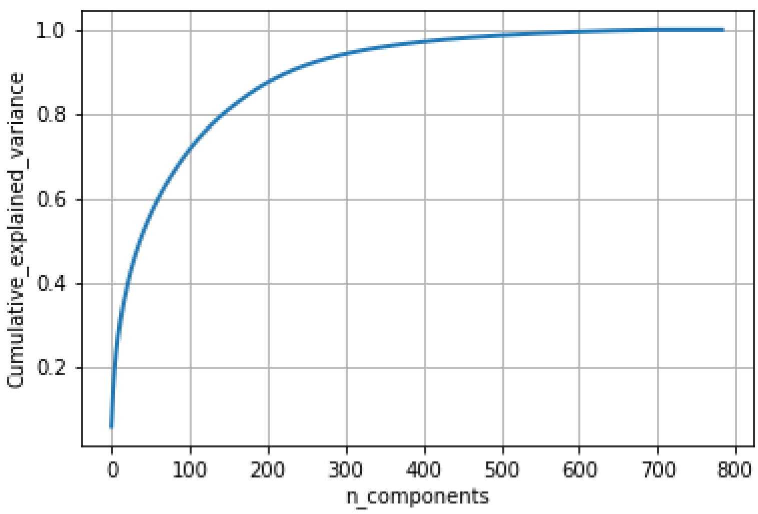
```
# attaching the label for each 2-d data point
pca_data = np.vstack((pca_data.T, l)).T
# creating a new data fram which help us in ploting the result data
pca_df = pd.DataFrame(data=pca_data, columns=("1st_principal", "2nd_principal", "lab
sn.FacetGrid(pca_df, hue="label",height=6).map(plt.scatter, '1st_principal', '2nd_pr
plt.show()
```




# PCA for dimensionality reduction

In [11]:

```
# PCA for dimensionality redcution (non-visualization)
pca.n_components = 784
pca_data = pca.fit_transform(sample_data)
percentage_var_explained = pca.explained_variance_ / np.sum(pca.explained_variance_)
cum_var_explained = np.cumsum(percentage_var_explained)
# Plot the PCA spectrum
plt.figure(1, figsize=(6, 4))
plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()
# If we take approximately 300-dimensions, approx. 90% of variance is explained.
```



**By applying Scikit-Learn PCA and preserving 95% of the variance, the number of features reduces from 784 to approximately 331.**

# Logistic Regression on MNIST dataset

Loading data (Digits dataset)

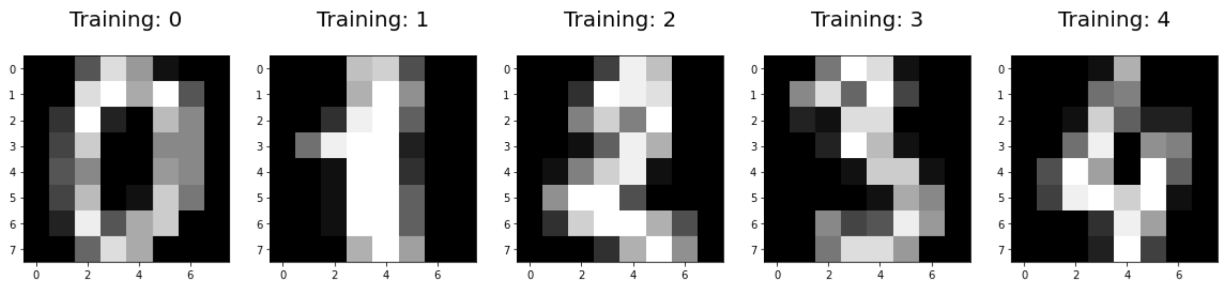
In [12]:
```
from sklearn.datasets import load_digits
digits = load_digits()
```

In [13]:
```
# Print to show there are 1797 images (8 by 8 images for a dimensionality of 64)
print("Image Data Shape" , digits.data.shape)
# Print to show there are 1797 labels (integers from 0-9)
print("Label Data Shape", digits.target.shape)
```

```
Image Data Shape (1797, 64)
Label Data Shape (1797,)
```

Showing the Images and the Labels (Digits Dataset)

In [14]:
```
plt.figure(figsize=(20,4))
for index, (image, label) in enumerate(zip(digits.data[0:5], digits.target[0:5])):
 plt.subplot(1, 5, index + 1)
 plt.imshow(np.reshape(image, (8,8)), cmap=plt.cm.gray)
 plt.title('Training: %i\n' % label, fontsize = 20)
```




Split data into testing and training datasets (Digit dataset)

In [15]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(digits.data, digits.target, test
```

Import the model to be used, Make an instance of the Model and Train the model on the data, storing the information learned from the data

In [16]:
```
from sklearn.linear_model import LogisticRegression
# all parameters not specified are set to their defaults
logisticRegr = LogisticRegression()
logisticRegr.fit(x_train, y_train)
```

```
c:\users\shiva\appdata\local\programs\python\python39\lib\site-packages\sklearn\line
ar_model\_logistic.py:763: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
```

```
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[16]:
```
LogisticRegression()
```

Predict labels for new data (new images)- Uses the information the model learned during the model training process

In [17]:
```
# Returns a NumPy Array
# Predict for One Observation (image)
logisticRegr.predict(x_test[0].reshape(1,-1))
```

Out[17]:
```
array([2])
```

Predict for Multiple Observations (images) at Once

In [18]:
```
logisticRegr.predict(x_test[0:10])
```

Out[18]:
```
array([2, 8, 2, 6, 6, 7, 1, 9, 8, 5])
```

Make predictions on entire test data

In [19]:
```
predictions = logisticRegr.predict(x_test)
```

Measuring Model Performance (Digits Dataset)

In [20]:
```
# Use score method to get accuracy of model
score = logisticRegr.score(x_test, y_test)
print(score)
```

```
0.9511111111111111
```

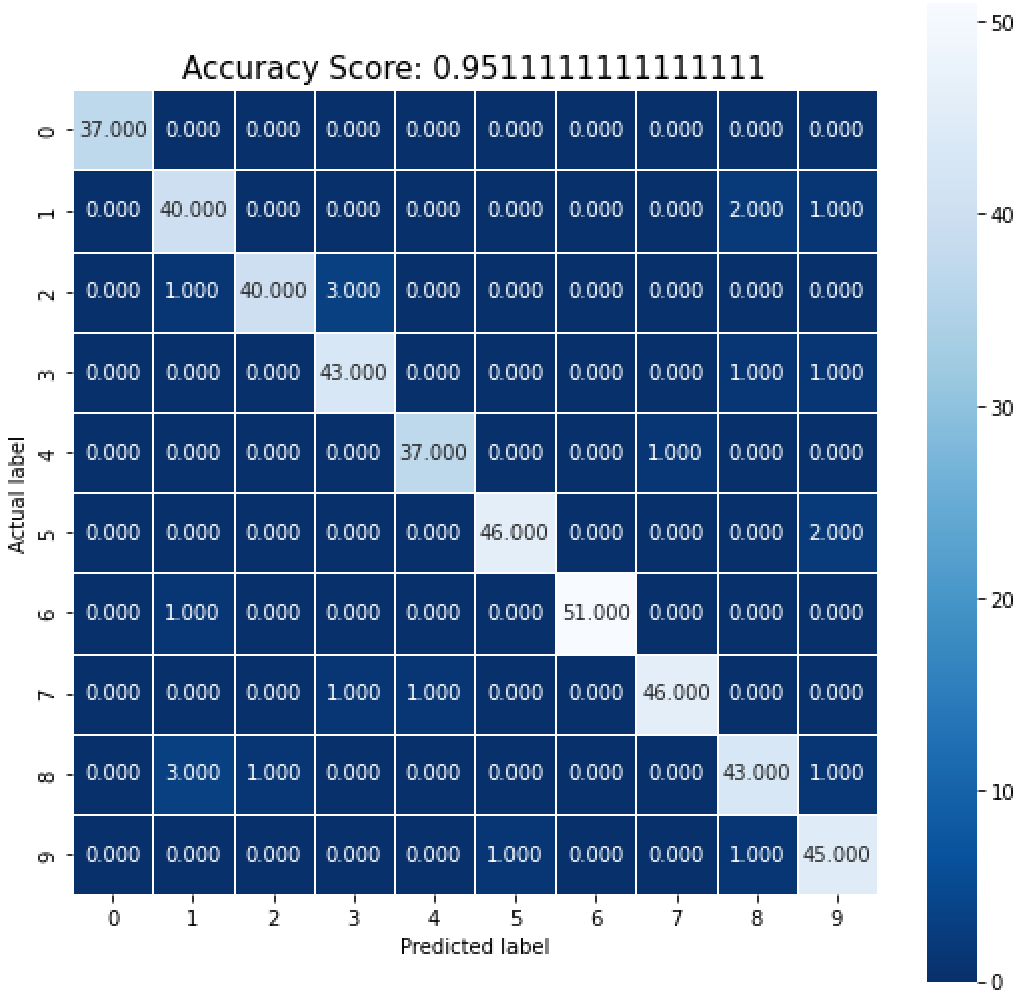
# Confusion Matrix (Digits Dataset)

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known.

In [21]:
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
```

Confusion matrix using seaborn

In [22]:
```
plt.figure(figsize=(9,9))
cm = metrics.confusion_matrix(y_test, predictions)
sns.heatmap(cm, annot=True, fmt=".3f", linewidths=.5, square = True, cmap = 'Blues_r
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Accuracy Score: {0}'.format(score)
plt.title(all_sample_title, size = 15);
```




**Accuracy of the model is 95.11%**