

```
# MNIST dataset downloaded from Kaggle :
# Source: https://www.kaggle.com/c/digit-recognizer/data

id = "1CzTCrwCNA3ozCfdR4lJmlurVlmMRt62m"
print("https://drive.google.com/uc?export=download&id=" + id)

https://drive.google.com/uc?export=download&id=1CzTCrwCNA3ozCfdR4lJmlurVlmMRt62m

!wget "https://drive.google.com/uc?export=download&id=1CzTCrwCNA3ozCfdR4lJmlurVlmMRt62m"

--2022-04-04 17:50:33-- https://drive.google.com/uc?export=download&id=1CzTCrwCNA3ozCfdR4lJmlurVlmMRt62m
Resolving drive.google.com (drive.google.com)... 173.194.217.138, 173.194.217.138
Connecting to drive.google.com (drive.google.com)|173.194.217.138|:443... conn
HTTP request sent, awaiting response... 303 See Other
Location: https://doc-0s-ag-docs.googleusercontent.com/docs/securesc/ha0ro937c
Warning: wildcards not supported in HTTP.
--2022-04-04 17:50:36-- https://doc-0s-ag-docs.googleusercontent.com/docs/securesc/ha0ro937c
Resolving doc-0s-ag-docs.googleusercontent.com (doc-0s-ag-docs.googleusercontent.com)... 173.194.217.138
Connecting to doc-0s-ag-docs.googleusercontent.com (doc-0s-ag-docs.googleusercontent.com)|173.194.217.138|:443... conn
HTTP request sent, awaiting response... 200 OK
Length: 76775041 (73M) [text/csv]
Saving to: 'mnist.csv'

mnist.csv          100%[=====>]  73.22M   121MB/s   in 0.6s

2022-04-04 17:50:38 (121 MB/s) - 'mnist.csv' saved [76775041/76775041]
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
d0 = pd.read_csv('./mnist.csv')

print(d0.head(5)) # print first five rows of d0.

# save the labels into a variable l.
l = d0['label']

# Drop the label feature and store the pixel data in d.
d = d0.drop("label",axis=1)
```

	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]

```
print(d.shape)
print(l.shape)
```

```
(42000, 784)
(42000,)
```

```
# display or plot a number.
plt.figure(figsize=(7,7))
idx = 100
```

```
grid_data = d.iloc[idx].to_numpy().reshape(28,28) # reshape from 1d to 2d pixel ar
plt.imshow(grid_data, cmap = "gray")
plt.show()
```

```
print(l[idx])
```

▼ 2D-Visualization

```
# Pick first 15K data-points to work on for time-effeciency.
#Excercise: Perform the same analysis on all of all data-points.

labels = l.head(15000)
data = d.head(15000)

print("the shape of sample data = ", data.shape)

    the shape of sample data =  (15000, 784)

# Data-preprocessing: Standardizing the data

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

    (15000, 784)

#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 =  (784, 784)

# finding the top two eigen-values and corresponding eigen-vectors
# for projecting onto a 2-Dim space.

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) eigenvalues.
values, vectors = eigh(covar_matrix, eigvals=(782,783))

print("Shape of eigen vectors = ",vectors.shape)
print(values)

    Shape of eigen vectors =  (784, 2)
    [435532.55785282  605719.29173629]

#vectors[:,0] represents the eigen vector corresponding to the 2nd eigen value.(Fir
#vectors[:,1] represents the eigen vector correspondign to the 1st eigen value.(Sec

#Note : Eigen values are arranged in ascending order so the Eigen vectors too.
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```
# converting the eigen vectors into (2,d) shape for ease of computation which we do
vector = vectors.T
```

```
print("Updated shape of eigen vectors = ",vector.shape)
# Here, vectors[0] represent the eigen vector corresponding to the 2nd eigen value.
# Here, vectors[1] represent the eigen vector corresponding to the 1st eigen value.
```

```
Updated shape of eigen vectors = (2, 784)
```

```
#Now, we need to swap the rows of the vector matrix such that the first row corresp
vector[[0,1]]=vector[[1,0]]
```

```
# projecting the original data onto the eigen basis.
# Basically, we form a matrix with the eigen vectors in row order. Then, we do a ma
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```
import matplotlib.pyplot as plt
new_coordinates = np.matmul(vector, sample_data.T)
```

```
print (" resultant new data points' shape ", vector.shape, "X", sample_data.T.shape
resultant new data points' shape (2, 784) X (784, 15000) = (2, 15000)
```

```
# appending label to the 2d projected data
new_coordinates = np.vstack((new_coordinates, labels)).T
```

```
# creating a new data frame for plotting the labeled points.
dataframe = pd.DataFrame(data=new_coordinates, columns=("1st_principal", "2nd_princ
print(dataframe.head())
```

	1st_principal	2nd_principal	label
0	-5.043558	-5.558661	1.0
1	19.305278	6.193635	0.0
2	-7.678775	-1.909878	1.0
3	-0.464845	5.525748	4.0
4	26.644289	6.366527	0.0

```
# plotting the 2d data points with seaborn
import seaborn as sn
sn.FacetGrid(dataframe, hue="label", size=7).map(plt.scatter, '1st_principal', '2nd
plt.show()
```

▼ PCA using Scikit-Learn

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

# 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 = (15000, 2)

# attaching the label for each 2-d data point
pca_data = np.vstack((pca_data.T, labels)).T

# creating a new data fram which help us in plotting the result data
pca_df = pd.DataFrame(data=pca_data, columns=("1st_principal", "2nd_principal", "label"))
sns.FacetGrid(pca_df, hue="label", size=6).map(plt.scatter, '1st_principal', '2nd_principal')
plt.show()
```

▼ PCA for dimensionality reduction (not for visualization)

```
# PCA for dimensionality reduction (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(ppercentage_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 200-dimensions, approx. 90% of variance is explained.
```

▼ t-SNE (covered in the future)

We will learn the mathematics underlying t-SNE in depth later in the program.

```
# TSNE

from sklearn.manifold import TSNE

# Picking the top 1000 points as TSNE takes a lot of time for 15K points
data_1000 = standardized_data[0:1000,:]
labels_1000 = labels[0:1000]

model = TSNE(n_components=2, random_state=0)
# configuring the parameteres
# the number of components = 2

tsne_data = model.fit_transform(data_1000)

# creating a new data frame which help us in plotting the result data
tsne_data = np.vstack((tsne_data.T, labels_1000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_subplot(1, 1, 1)
plt.show()
```

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