

## Week - 1

Write a python program to import and export data using Pandas library function

(i) Reading data from CSV file

(ii) import pandas as pd

```
airbnb_data = pd.read_csv ("./content/Airbnb-open-data.csv")
```

```
airbnb_data.head()
```

• Output:

	id	Name	neighbourhood	country	Service fee
0	1001294	Skyline Mystery	Manhattan	United States	\$ 28

(ii) #Reading data from URL

```
import pandas as pd
```

```
url = "https://archive.ics.uci.edu/ml/iris/iris.data"
```

```
col_names = ["sepal_length_in_cm", "sepal_width_in_cm",
            "petal_length_in_cm", "petal_width_in_cm",
            "class"]
```

```
iris_data = pd.read_csv(url, names=col_names)
```

```
iris_data.head()
```

- Output

	sepal-length in cm	sepal-width in cm	petal-length in cm	petal-width in cm	class
0	5.1	3.5	1.4	0.2	iris-setosa
1	4.9	3	1.4	0.2	iris-setosa
2	4.7	3.2	1.3	0.2	iris-setosa
3	4.6	3.1	1.5	0.2	iris-setosa
4	5	3.6	1.4	0.2	iris-setosa

# Exporting data frame to a CSV file

```
iris_data.to_csv("cleaned_iris_data.csv")
```

Over  
110  
210

## Week-2

### 1. Download the data & look at the bigger picture

- The California census data is being used here.
- import os
- The important feature of the data are population, median income, median housing price for each block group in California.
- The block group has a population between 600 to 3000

### Selected Performance measure

→ Root mean Squared error

### Check the assumption

→ An example for assumption can be the months worked on the algorithm be 6 month, etc

### 2. Get the data

# We are importing the python libraries like os module, tarfile archive files and urllib (URL handling module)

import os

import tarfile

import urllib

# We are forming the download root for the data set  
Path & a URL is created

Download\_root = "https://raw.githubusercontent.com/mgordon/handson-m12/master/"

Housing\_path = os.path.join("data", "01")

Housing\_URL = Download\_root + "datasets/housing/housing.tgz"

# We now define a function to fetch the housing data by giving it Housing\_URL & Housing\_Path as parameters

```
def fetch_housing_data(Housing_URL, housing_path="Housing-path"):
```

os.makedirs(name=housing\_path, exist\_ok=True)

tgz\_path = os.path.join(housing\_path, "housing.tgz")

urllib.request.urlretrieve(Housing\_URL,

filename=tgz\_path)

housing\_tgz = tarfile.open(name=tgz\_path)

housing\_tgz.extractall(path=housing\_path)

housing\_tgz.close()

# Call the fetch\_housing\_data() function

```
fetch_housing_data()
```

# Importing pandas library

```
import pandas as pd
```

# defining a function to load the housing data

```
def load_housing_data(housing_path=Housing_path):
```

```
    data_path = os.path.join(housing_path, "housing.csv")
    return pd.read_csv(data_path)
```

# Loading the data into housing variable & displaying first 5 data rows

```
housing = load_housing_data()
```

```
housing.head()
```

# Visualizing the data using histogram. We use matplotlib library.

```
import matplotlib.pyplot as plt
```

```
housing.hist(bins=50, figsize=(20,15))
plt.show()
```

# Creating a train & test set using numpy library

```
import numpy as np
```

```
def split_train_test(data, test_ratio=0.2):
```

```
shuffled_indices = np.random.permutation(len(data))
```

```
test_set_size = int(len(data) * test_ratio)
```

```
test_indices = shuffled_indices[:test_set_size]
```

```
train_indices = shuffled_indices[test_set_size:]
```

```
train_indices = shuffled_indices[:test_set_size]
```

```
return data.iloc[train_indices], data.iloc[test_indices]
```

```
+train_set, test_set = split_train_test(data = data, test_ratio=0.2)
```

3. Discover & visualizing the data to gain insights  
train set. shape, test set. shape

### visualizing

housing.plot (kind = 'scatter', x = 'longitude',  
y = 'latitude'), alpha = 0.1)  
plt.show()

### correlation

corr\_matrix = housing.corr()

corr\_matrix ['median\_house\_value']

sort\_values (ascending = False)

from pandas import plotting import ScatterMatrix

attributes = ['median\_house\_value',  
'median\_income']

scatter\_matrix [frame = housing [attribute],  
jigsize = 12, 8])

plt.show()

housing ['rooms per household'] =

housing ['total\_rooms'] / housing ['  
households']

4. Prepare the data for machine learning  
algorithms

from sklearn import simpleImputer  
imputer = simpleImputer(strategy =  
'median')

housing\_num = housing.drop ("ocean-  
proximity", axis = 1) (housing\_num)

## Computer Statistics

housing.num.median().values

- from sklearn.preprocessing import OrdinalEncoder
   
ordinal\_encoder = OrdinalEncoder()
   
ordinal\_encoder.categories\_
   
other\_encoder = combined\_attributes['ocean\_proximity'].values
   
ocean\_proximity = other\_encoder

housing.extra\_attribs = other\_encoder
   
transform(housing.values)

- from sklearn.compose import ColumnTransformer
   
num\_attributes = housing.num.columns.tolist()

### 5. Select and train a model:

- from sklearn.linear\_model import LinearRegression
   
lin\_reg = LinearRegression()
   
lin\_reg.fit(X=housing\_prepared,
 y=housing\_labels)
- housing\_predictions = lin\_reg.predict(housing\_prepared)
- lin\_mse = mean\_squared\_error(housing\_labels, housing\_predictions)
   
lin\_rmse = np.sqrt(lin\_mse)

- from sklearn.tree import DecisionTreeRegressor
   
tree\_reg = DecisionTreeRegressor()
   
tree\_reg.fit(X=housing\_prepared,
 y=housing\_labels)
- forest\_reg = RandomForestRegressor()
   
forest\_reg.fit(X=housing\_prepared,
 y=housing\_labels)

## 6. Fine-tune Your Model:

- grid-search-best params.
- grid-search-best estimator  
 $\text{est encoder} = \text{full\_pipeline}.named\_transformer_['cat']$
- final\_model = grid-search-best estimator
- $x_{\text{test\_prepared}} = \text{full\_pipeline}.\text{transform}(x=x_{\text{test}})$   
 $\text{final\_xmse} = \text{np}.sqrt(\text{final\_mse})$   
 $\text{final\_ymse}$
- Squared - errors =  $(y_{\text{test}} - \text{final\_predictions})^2$

## 7. Launch, Monitor and Maintain your system

100  
44%  
44%

Week-4

## Simple linear regression

Code:

```
def estimate_coeff(x, y):
    n = np.size(x)
    m_x = np.mean(x)
    m_y = np.mean(y)
```

$$SS_{xy} = np.sum(y * x) = n * m_y * m_x$$

$$SS_{xx} = np.sum(x * x) = n * m_x * m_x$$

$$b_1 = SS_{xy} / SS_{xx}$$

$$b_0 = m_y - b_1 * m_x$$

return (b\_0, b\_1)

```
def plot_regression_line(x, y, b):
```

```
plt.scatter(x, y, color = "m", marker = "o", s=30)
```

$$y_{pred} = b[0] + b[1] * x$$

```
plt.plot(x, y_pred, color = "g")
```

```
plt.xlabel('x')
```

```
plt.ylabel('y')
```

```
def main():
```

```
n = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```
y = np.array([1, 3, 2, 5, 7, 8, 3, 9, 10, 12])
```

```
b = estimate_coef(x, y)
```

```
print ("Estimated coefficients:\nb_0 = {}  
b_1 = {}".format(b))
```

Step 1

```
import pandas as pd
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

```
from sklearn.model_selection import train_test_split
```

```
from pandas.core.common import
```

```
from sklearn.linear_model import LinearRegression
```

```
df_scl = pd.read_csv('~/content/salary_Data.csv')
```

```
df_scl.head()
```

```
df_scl.describe()
```

```
plt.title('Salary Distribution Plot')
```

```
sns.distplot(df_scl['Salary'])
```

```
plt.show()
```

```
plt.scatter(df_scl['Years Experience'],  
           df_scl['Salary'], color='lightcoral')
```

```
plt.title('Salary vs experience')
```

```
plt.xlabel('Years of experience')
```

```
plt.ylabel('Salary')
```

```
plt.box(False)
```

```
plt.show()
```

$$x = df\_sal - iloc[:, :-1]$$

$$y = df\_sal.iloc[:, -1:]$$

$x\_train, x\_test, y\_train, y\_test =$   
 $\text{train\_test\_split}(x, y, \text{test\_size} = 0.2, \text{random\_state} = 0)$

regressor = regressor.predict(~~x-test~~)  
 $y\_pred\_test = \text{regressor}.predict(x\_test)$   
 $y\_pred\_train = \text{regressor}.predict(x\_train)$

$y\_pred\_test = \text{regressor}.predict(x\_test)$   
 $y\_pred\_train = \text{regressor}.predict(x\_train)$

plt.scatter(x\_train, y\_train, color='light coral')

plt.plot(x\_train, y\_pred\_train, color='firebrick')  
 $\text{plt.xlabel('Years of Experience')}$

plt.ylabel('Salary')

plt.legend(['X\_train / Pred(y-test)', 'X\_train / y\_train'], title='Salary/Exp', loc='best', fontsize='white')

plt.box(False)

plt.show()

plt.scatter(x\_test, y\_test, color='light coral')

plt.plot(x\_train, y\_pred\_train, color='firebrick')

~~plt.show()~~

print(f'Coefficient : {regressor.coef\_}')

print(f'Intercept : {regressor.intercept\_}')

## Multiple - linear Regression

```
import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt  
import seaborn as sns  
from sklearn.model_selection import train_test_split  
from sklearn.compose import ColumnTransformer  
from sklearn.preprocessing import StandardScaler
```

```
df_start = pd.read_csv('content/50_Startups.csv')  
df_start.head()
```

```
df_start.describe()
```

```
plt.title('Profit distribution plot')  
sns.set()  
plt.xlabel('R&D Spend')  
plt.ylabel('Profit')  
plt.box(False)  
plt.show()
```

```
x = df_start.iloc[:, :-1].values  
y = df_start.iloc[:, -1].values
```

```
ColumnTransformer(transformers = [ ('encoder', OneHotEncoder(), [3]), 'remainder', 'passthrough' ])
```

~~```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state = 42)
```~~

regressor = LinearRegression()

regressor.fit(x\_train, y\_train)

y\_pred = regressor.predict(x\_test)

np.set\_printoption(precision=2)

result = np.concatenate((y\_pred, y\_test), axis=1)

result

v1)

## Week-3 4

Use an appropriate data set for building the decision and apply this knowledge to classify a new some

```
import pandas as pd
```

```
import matplotlib.pyplot as plt
```

```
from sklearn.datasets import load_iris
```

```
import seaborn as sns
```

```
iris_data = load_iris()
```

```
print(iris_data.data)
```

```
X = iris_data.data
```

```
Y = iris_data.target
```

```
print("Shape of X:", X.shape)
```

```
print("Shape of Y:", Y.shape)
```

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.33, random_state=42)
```

```
from sklearn.tree import DecisionTreeClassifier
```

```
tree_model = DecisionTreeClassifier()
```

~~```
tree_model.fit(X_train, y_train)
```~~~~```
DecisionTreeClassifier()
```~~

from sklearn.tree import DecisionTreeClassifier  
 from sklearn import tree  
 import matplotlib.pyplot as plt

clf = DecisionTreeClassifier(max\_depth=3)

y\_f = clf(x, y)

plt.figure(figsize=(12, 8))  
 tree.plot\_tree(clf, filled=True, feature\_names=  
 feature\_names, class\_names=iris\_data.target)  
 plt.show()

Output:



petal width (cm)  $\alpha = 0.8$

gini = 0.667

Samples = 150

Values = [50, 50, 50]

class = setosa

gini = 0.0  
 samples = 50  
 values [50, 0, 0]  
 class = setosa



petal width (cm)  $\alpha = 1.75$   
 gini = 0.5  
 Samples = 100  
 Values = [0, 50, 50]  
 class = virginica



petal length (cm)  $\alpha = 1.95$   
 gini = 0.168  
 samples = 54  
 values = [0, 4, 4, 5]  
 class = virginicolor

petal length (cm)  $\alpha = 4.85$   
 gini = 0.043

Samples = 46  
 Values = [0, 1, 45]  
 class = virginica

state = 42)

from sklearn.model\_selection import  
cross\_val\_score

scores = cross\_val\_score (clf, X, y, cv=5)  
accuracy = scores.mean()

print ("Mean Accuracy:", accuracy)

Output

Mean Accuracy : 0.966

0.966

25/4/24

Week 5

5. Build logistic Regression model for a given dataset

```
import pandas as pd
```

```
from matplotlib import pyplot as plt
```

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.linear_model import LogisticRegression
```

```
df = pd.read_csv("insurance_data.csv")
```

```
print(df.head(2))
```

```
X_train, X_test, y_train, y_test = train_test_split(df[['age']],
```

```
df['bought_insurance'], test_size=0.3)
```

```
print("X-test")
```

```
print(X_test)
```

```
model = LogisticRegression()
```

```
model.fit(X_train, y_train)
```

```
y_pred = model.predict(X_test)
```

```
print(y_pred)
```

```
print(model.predict_proba(X_test))
```

```
print(model.score(X_test, y_test))
```

Output:

Accuracy = 0.5

```
import math
```

```
def sigmoid(z)
```

```
return 1 / (1 + math.exp(-z))
```

def predict(age):

$$z = 0.642 * \text{age} - 1.53$$

$$y = \text{sigmoid}(z)$$

return y

print(predict(35))

print(predict(43))

Output:

Prediction: array([1, 0, 1, 0, 0, 0, 0, 1, 0])

Score: 0.8888

Linear Reg score: 0.5843?

Predictions: 0.485

0.5685

~~WV~~

~~5~~

9/5/24 Week 6

g) Build KNN classification model for a dataset

Code:

```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt
import seaborn as sns
```

iris = load\_iris()

X = iris.data

y = iris.target

iris\_df = pd.DataFrame(X, columns=iris.feature\_names)

iris\_df['target'] = y

sns.pairplot(iris\_df, hue='target')

x\_train, x\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

k = 3

KNN\_knn\_classifier = KNeighborsClassifier(n\_neighbors=k)

knn\_classifier.fit(x\_train, y\_train)

KNearestClassifier

KNearestClassifier (n\_neighbors=3)

y\_pred = knn\_classifier.predict(X\_test)

accuracy = accuracy\_score

print(f"Accuracy: {accuracy}; score")

Output: Accuracy: 0.9833

- Q. Build support vector machine model for a given dataset.

Code:

```
import pandas as pd  
from sklearn.svm
```

```
from sklearn.svm import SVC
```

```
model = SVC(kernel='linear', random_state=0, C=1)  
model.fit(X_train, y_train)
```

```
y_pred = model.predict(X_test)
```

```
from sklearn.metrics import accuracy_score
```

```
score = accuracy_score(y_pred, y_test)
```

```
print(f"Testing accuracy: {score}")
```

```
score2 = accuracy_score(y2, y2_pred)
```

```
print(f"Training accuracy: {score2}")
```

```
Output =
```

Training Accuracy = 1.0

Testing Accuracy = 1.0

23/5/24 Week -7

- Q Build artificial neural network model with back propagation on a given dataset

import numpy as np

x = np.array([[2, 9], [1, 5], [3, 6]], dtype=float)

y = np.array([92, 86, 89], dtype=float)

y = y/100

epoch = 5000

lr = 0.1

inputlayer\_neurons = 2

hiddenlayer\_neurons = 3

output\_neurons = 1

wh = np.random.uniform(size=(inputlayer\_neurons, hiddenlayer\_neurons))

bh = np.random.uniform(size=(1, hiddenlayer\_neurons))

wout = np.random.uniform(size=(hiddenlayer\_neurons, output\_neurons))

bout = bh = np.random.uniform(size=(1, output\_neurons))

bout = bh = np.random.uniform(size=(1, output\_neurons))

def sigmoid(x):

return 1 / (1 + np.exp(-x))

def derivatives\_sigmoid(x):

return x \* (1 - x)

for i in range(epoch):

hinpl = np.dot(x, wh)

hinp = hinpl + bh

layer\_act = sigmoid(hinp)

outinp = outinp + bact

output = sigmoid(outinp)

E0 = y - output

outgrad = derivative\_sigmoid(output)

d\_output = E0 \* outgrad

EH = d\_output . dot (wout, T)

hiddergrad = derivative\_sigmoid(hlayer\_act)

d\_hiddenlayer = EH \* hiddergrad

wout += hlayer\_act.T.dot(d\_hiddenlayer)

print ("Input : " + str(x))

print ("Actual Output : " + str(y))

print ("Predicted Output : " + str(output))

Output :

[0.666666667 : 1. 0.3333333 0.66666667]

[0.92]

[0.86]

[0.87]

Predicted Output:

[0.8913061]

[0.8851982]

[0.88962179]

Mar 12  
2015

## Lab - 7

## Artificial Neural Network:

```
import numpy as np
```

 $x = np.array([[[2, 9], [1, 5], [3, 6]]], dtype=float)$ 
 $y = np.array([[[92], [86], [89]]], dtype=float)$ 
 $x = x / np.max(x, axis=0)$ 
 $y = y / 100$ 
 $epoch = 5000$ 
 $lt = 0.1$ 

input layer neurons = 3

hidden layer = 3

output neurons = 1

 $Wb = np.random.uniform(size=(\text{input layer neurons}, \text{hidden layer neurons}))$ 
 $bh = np.random.uniform(size=(1, \text{hidden layer}))$ 
 $wout = np.random.uniform(size=(\text{hidden layer neurons}, \text{output neurons}))$ 
 $bout = np.random.uniform(size=(1, \text{output neurons}))$ 

## # Sigmoid function

 $\text{def sigmoid}(x)$ 
 $\text{return } 1 / (1 + np.exp(-x))$ 
 $\epsilon b = y - output$ 
 $\text{output\_derivative} = derivative \cdot \text{sigmoid}(\text{output})$ 
 $\epsilon l - output = \epsilon_b * output$

$$E_H = d \cdot \text{output}_H \cdot (w_{H,T})$$

hidden prod = divisor sigmoid (hidden)

d - hiddenprod =  $E_H \otimes$  hiddsigprod

wout +  $\hat{y}$  = layer.out.  $I \cdot d \cdot \text{output}_H$

print ("Input" + str(x))

print ("actual output" + str(y))

print ("predicted output", output)

actual output = [0.92] [0.86] [0.89]

predicted output : [0.86] [0.85] [0.87]

Qvar  
f124  
30

Lab - 8  
Program

## 9a. Random Forest:

```
import numpy as np
import random as rd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
classification_report
```

```
data = pd.read_csv('content/spam  
data.csv')
```

```
x = data['Body']
y = data['label']
```

```
vectorizer = CountVectorizer()
```

```
x = vectorizer.fit_transform(x)
```

~~x\_train, x\_test, y\_train, y\_test =  
train\_test\_split(x, y, test\_size=0.2)  
random\_state=42)~~

~~print(classification\_report(y\_test, y\_pred))~~  
~~accuracy = 0.9731.~~

Q1  
30/07/2024

lab - 9

9b Adab east

import penetree es pd

import newborn signs

```
import matplotlib.pyplot as plt
```

`df = pd.read_csv('~/content/resos.csv');`  
`df.head()`

$$y = df([Species], axes=1)$$

from sklearn, model selection import  
train\_test\_split.

$x_{\text{train}}, x_{\text{test}}, y_{\text{train}}, y_{\text{test}} = \text{train}$   
 $x, y, \text{test\_size} \in 0.3, \text{test-split(0)}$

from sklearn.ensemble import  
AdaBoostClassifier()

$$\begin{aligned} \text{d}_1 \text{ ngs} &= \text{cabs} \cdot \text{product}(X - \text{test}) \\ y_2 &= \text{cabs} \cdot \text{product}(X - \text{teach}) \end{aligned}$$

geom. scholar - Metters import  
Surveying

Ex. Score = accuracy \* score (v. pref. Vtest)

point (accuracy score)

$$= 0.977$$

UV 267nm

30/9/24

lab - 10

## K-Means algorithms

Code :

```

import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import pandas as pd
import numpy as np

iris = datasets.load_iris()
X = pd.DataFrame(iris.data)
X.columns = ['Sepal_Length', 'Sepal_Width', 'Petal_Length',
             'Petal_Width']
y = pd.DataFrame(iris.target)
y.columns = ['Targets']

model = KMeans(n_clusters=3)
model.fit(X)

plt.figure(figsize=(14, 6))
cmap = np.array(['red', 'lime', 'blue'])

plt.subplot(2, 2, 1)
plt.scatter(X.Petal_Length, X.Petal_Width,
            c=cmap[y.Targets], s=40)
plt.title('Raw Clusters')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')

```

```
plt.subplot(2, 2, 2)
```

```
plt.scatter(x.PetalLength, x.PetalWidth,  
           c = colormap(modal_labels), s=40)
```

```
plt.title('K-Means Clustering')
```

```
plt.xlabel('Petal length')
```

```
plt.ylabel('Petal width')
```

```
plt.show()
```

W  
3=1/V

3/7/24 Lab - 10

## Principle component analysis

```
import matplotlib.pyplot as plt
```

```
import pandas as pd
```

```
import numpy as np
```

```
import seaborn as sns
```

```
%matplotlib inline
```

```
from sklearn.datasets import load_breast_cancer
```

```
cancer = load_breast_cancer()
```

```
cancer.keys()
```

```
df = pd.DataFrame(cancer['data'], columns=cancer['feature names'])
```

```
from sklearn.preprocessing import StandardScaler
```

```
scaler = StandardScaler()
```

```
scaler.fit(df)
```

```
scaled_data = scaler.transform(df)
```

~~from sklearn.decomposition import PCA~~
~~pcr = PCA(n\_components=2)~~
~~pcr.fit(scaled\_data)~~
~~x\_pca = pcr.transform(scaled\_data)~~

Scaled data shape

x\_pca.shape

plt.figure(figsize=(8, 6))

plt.scatter(x\_pro[0], x\_per[0], c='cyan')  
[ 'target' ], (cmap = 'plasma')  
plt.xlabel('First Principal component')  
plt.ylabel('Second principal component')

W  
JAN