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Roll No. _____ Subject ML LAB College _____

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Jan-3-24

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LAB - 1

Write a python program to import and export data using pandas library functions.

i) Download listings-austin.csv file.

Code :-

```
import pandas as pd  
airbnb-data = pd.read_csv("data/listings-austin.csv")  
airbnb-data.head()
```

Output:-

	id	name	host-id	host-name
0	2265	Zen-East in the Heart of Austin	2466	Paddy
1	5295	Eco friendly, Colorful, Clean	2466	Paddy
2	5456	Walk to 6th Rainey St and Co	8028	Sylvia
3	5769	NW Austin Room	8186	Elizabeth
4	6413	Term of a Studio near Down	13879	Todd

a) Reading data from URL

Webpage URL

```
url = "https://archive.ics.uci.edu/ml/machine-learning-  
databases/iris/iris.data"
```

Define the column names

```
col-names = ["sepal.length-in-cm", "sepal.width-in-cm",  
"petal.length-in-cm", "petal.width.in-cm",  
"class"]
```

Read data from URL

```
iris-data = pd.read_csv(url, names=col-names)
```

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iris - data. head().

Output :-

	sepal length(cm)	sepal width(cm)	petal length(cm)	petal width(cm)	class
0	5.1	3.5	1.4	0.2	iris-setosa
1	4.9	3.0	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	5.0	3.6	1.4	0.2	iris-setosa

Kaggle certification (Pandas).

i) Creating, Reading and writing

- import pandas as pd.

Creating data:

i) pd.DataFrame ({'Yes': [50, 21], 'No': [131, 27]})

	Yes	No
0	50	131
1	21	27

ii) pd.DataFrame ({'Bob': ['I liked it', 'It was awful'], 'Sue': ['Pretty good', 'Bland'], 'Index': ['Product A', 'Product B']})

	Bob	Sue
Product A	I liked it	Pretty good
Product B	It was awful	Bland

Reading Path (ptes): -

- 1) Wine - reviews = pd.read_csv("../input/.../winemag.csv")
- 2) wine_reviews.shape
(129971, 14)
- 3) wine_reviews.head.

1) Importing the required libraries and reading the file

WineReview from - wine_reviews

WineReview = pd.read_csv("../input/winemag-data-130k.csv")

WineReview.info() + WineReview.describe().T + WineReview.dtypes + WineReview

WEEK - 2

End-End ML Project

1. Get the data:-

import os

import tarfile

import urllib

DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-mlops/main/"

housing_mlops/master/

HOUSING_PATH = os.path.join("data", "01")

HOUSING_URL = DOWNLOAD_ROOT + "datasets/housing/housing.tgz"

```
def fetch_housing_data(housing_url=HOUSING_URL,
                      housing_path=HOUSING_PATH):
    os.makedirs(housing_path, exist_ok=True)
    tgz_path = os.path.join(housing_path, "housing.tgz")
    urllib.request.urlretrieve(url=housing_url,
                               filename=tgz_path)
    housing_tgz = tarfile.open(name=tgz_path)
    housing_tgz.extractall(path=housing_path)
    housing_tgz.close()
```

Download the data and call the function.

fetch_housing_data().

2. Discover & Visualize the data to gain insights.

latitude / longitude info can be represented using - plot()

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

To estimate densities, use 'alpha' parameter

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

To check the relation between two or more data
info, 'corr' method is used.

```
housing[['population', 'median_house_value']].corr()
```

This generates a weak correlation b/w the
specified parameters.

For a better correlation, we need to do

```
corr_matrix = housing.corr()
```

```
corr_matrix['median_house_value'].sort_values(ascending=False)
```

3. Prepare data for ML Algorithms

```
from sklearn.impute import SimpleImputer
```

```
imputer = SimpleImputer(strategy='median')
```

This can handle only numbers

```
housing_num = housing.drop("ocean-proximity", axis=1)
```

Now we fit imputer over our data.

Fitting is basically "training".

```
imputer.fit(housing_num)
```

Now we can use this to transform the numbers by replacing their missing values with corresponding medians.

```
X = imputer.transform(housing_num)
```

X is a numpy array with the transformed features. we add it back to the dataframe.

```
housing_tr = pd.DataFrame(data=X, index=housing_num
```

index,

columns=housing_num

columns).

4. Select & Train a Model:-

```
from sklearn.linear_model import LinearRegression  
lin-reg = LinearRegression()  
lin-reg.fit(X=housing_prepared, y=housing_labels)  
some_data = housing.iloc[:5] // Let's take small  
some_labels = housing_labels.iloc[:5] amount of the data  
some_data_prepared = full_pipeline.transform(some_data)  
lin-reg.predict(some_data_prepared)
```

Some-labels.to list() is not accurate, so we use another method.

```
from sklearn.metrics import mean_squared_error  
housing_predictions = lin-reg.predict(housing_prepared)  
lin-mse = mean_squared_error(housing_labels, housing_predictions)  
lin-rmse = np.sqrt(lin-mse) # This is the root mean squared error which is more accurate.
```

linear regression has better performance but lower accuracy when compared to Decision tree & Random forest.

Linear regression is represented as $y = mx + c$
// Random Forest is a combination of multiple decision trees
So it is better at capturing non-linear relationships.

Simple Linear Regression

~~Practical~~

```

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 random_state
from sklearn.linear_model import LinearRegression

df_sal = pd.read_csv('Content/Salary-Data.csv')
df_sal.head()
df_sal.describe()
plt.title('Salary Distribution Plot')
sns.distplot(df_sal['Salary'])
plt.show()

plt.scatter(df_sal['YearsExperience'], df_sal['Salary'],
            color='lightcoral')
plt.title('Salary vs Experience')
plt.xlabel('Years of experience')
plt.ylabel('Salary')
plt.ylim(0)
plt.show()

```

Split data

```

x = df_sal.iloc[:, 1:]
y = df_sal.iloc[:, 1:]

```

Split into Train test sets

$X\text{-train}, X\text{-test}, y\text{-train}, y\text{-test} = \text{train-test-split}$
 $(X, y), \text{test-size} = 0.2,$
 $\text{random_state} = 0$)

Train model

regressor = LinearRegression()

regressor.fit(X-train, y-train)

Predict results

y-pred-test = regressor.predict(X-test)

y-pred-train = regressor.predict(X-train)

Visualize predictions

plt.scatter(X-train, y-train, color='lightcoral')

plt.plot(X-train, y-pred-train, color='firebrick')

plt.title('Salary vs Experience (Training set)'),

plt.xlabel('Years of Experience')

plt.ylabel('Salary')

plt.legend(['X-train / Pred(y-test)',

'X-train / y-train'])

title='Sal(Exp)', loc='best', facecolor='white')

plt.box(False)

plt.show()

plt.scatter(X-test, y-test, color='lightcoral')

plt.plot(X-train, y-pred-train, color='firebrick')

plt.title('Salary vs Experience (Test set)'),

plt.xlabel('Years of Exp')

plt.ylabel('Salary')

plt.show()

```
coefficients and intercept  
print(f'Coefficient : {regressor.coef_}'')  
print(f'Intercept : {regressor.intercept_}'')
```

Coefficient : [9.31257]

Intercept : [26780.099]

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.linear_model import LinearRegression
```

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

```
df_start.describe()
```

Distribution

```
plt.title('Profit Distribution Plot')  
sns.distplot(df_start['Profit'])  
plt.show()
```

Relation between Profit and R&D spend

```
plt.scatter(df_start['R&D spend'], df_start['Profit'],  
           color = 'lightcoral')  
plt.title('Profit vs R&D spend')
```

```
plt.xlabel ('R&D Spend')
```

```
plt.ylabel ('Profit')
```

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

```
plt.show()
```

Split into Independent / Dependent variables.

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

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

One-hot encoding

```
ct = ColumnTransformer (transformers = [ ('encoder', OneHotEncoder (), [3]), ], remainder = 'pass through')
```

```
X = np.array (ct . fit_transform (X))
```

Split into Train / Test sets

```
X-train, X-test, y-train, y-test = train-test-split (X, y,
```

```
test_size = 0.2, random_state = 0)
```

Train model

```
regressor = LinearRegression ()
```

```
regressor . fit (X-train, y-train)
```

Predict results

```
y-pred = regressor . predict (X-test)
```

Compare predictions

```
np . set_printoptions (precision = 2)
```

```
result = np . concatenate ([y-pred . reshape (len (y-pred), 1),
```

(y-test . reshape (len (y-test), 1), 1)

WEEK - 4

GPA 10/10/24

Decision Tree:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score
```

Load iris dataset

iris_data = load_iris()

X = iris_data.data

y = iris_data.target

Split dataset into training and testing sets.

```
X-train, X-test, y-train, y-test = train_test_split(X, y,
                                                test_size=0.2,
                                                random_state=42)
```

Initialize decision tree classifier

clf = DecisionTreeClassifier()

Fit classifier to the training data

clf.fit(X-train, y-train)

Output:

DecisionTreeClassifier()

y-pred = clf.predict(X-test)

```
# Calculate Accuracy:  
accuracy = accuracy_score(y-test, y-pred)  
print("Accuracy:", accuracy)  
  
# plot decision Tree  
plt.figure(figsize=(12,8))  
plot_tree(clf, filled=True, feature_names=iris.data  
          .columns, class_names=iris.data  
          .target_name)  
plt.show()  
output:  
Accuracy 1.0
```

WEEK - 5

Build logistic regression model for given dataset

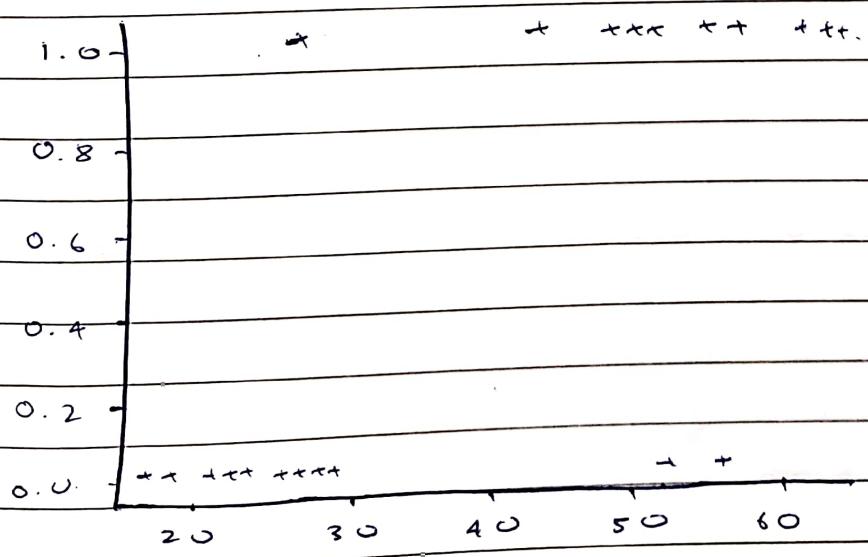
Code:-

```
import pandas as pd
from matplotlib import pyplot as plt
%matplotlib inline
df = pd.read_csv("insurance_data.csv")
df.head()
```

OUTPUT:-

	age	bought_insurance
0	22	0
1	25	0
2	47	1
3	52	0
4	46	1

```
plt.scatter(df.age, df.bought_insurance, marker='+', color='red')
```



```
from sklearn.model_selection import train_test_split  
X-train, X-test, y-train, y-test = train_test_split (df['age'],  
df.bought_insurance, train_size=0.2)  
from sklearn.linear_model import LogisticRegression  
model = LogisticRegression()  
model.fit(X-train, y-train)  
y-predicted = model.predict(X-test)  
model.predict_proba(X-test)  
model.score(X-test, y-test)
```

OUTPUT:-

0.8333

print(y-predicted)
[0 1 0 0 0 0]

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WEEK - 6

I) Build KNN classification model for Iris dataset

1) Importing necessary libraries

```
import pandas as pd  
from sklearn.model_selection import train_test_split  
from sklearn.metrics import accuracy_score  
from sklearn.neighbors import KNeighborsClassifier  
from sklearn.tree import plot_tree  
import matplotlib.pyplot as plt.
```

a> load data

```
iris_data = pd.read_csv('Iris.csv')
```

3> display sample of dataset

```
iris_data.head()
```

	ID	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

a> encoding the y values into numbers

```
label_mapping = {'Iris-setosa': 1, 'Iris-versicolor': 2, 'Iris-virginica': 3}
```

```
iris_data['Species'] = iris_data['Species'].map(label_mapping)
```

PTC



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5> creating a scatter plot

```
plt.scatter(iris_data['Sepal Length(cm)'], iris_data['Sepal Width(cm)'],
            c=iris_data['Species'], cmap='viridis')
plt.xlabel('Sepal Length (cm)')
plt.ylabel('Sepal Width (cm)')
plt.title('Scatter Plot of Iris Dataset (Sepal Features)')
plt.colorbar(label='Species')
plt.show()
```

6> Splitting the dataset into X and y

where X contains input features and y
contains the target label.

```
iris_data.drop('Id', inplace=True, axis=1)
```

```
X = iris_data.drop('Species', axis=1)
```

```
y = iris_data['Species']
```

7> Splitting the X and y into X-test, X-train,
y-train, y-test

X-train, X-test, y-train, y-test = train-test-split

```
(X,y, test_size=0.4,  
random_state=42)
```

8> Creating a KNN model

```
knn = KNeighborsClassifier(n_neighbors=5)
```

9> fitting the d model

```
knn.fit(X, y)
```

```
y-pred = knn.predict(X-test)
acc = accuracy_score(y-pred, y-test)
print(acc)
→ 1.0
```

SVM:

```
from sklearn.svm import SVC
model = SVC()
model.fit(X,y)
y-pred = model.predict(X-test)
acc = accuracy_score(y-pred, y-test)
print(acc)
→ 1.0
```

WEEK - 7

ANN:

8/25/2024

```

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.amax(X, axis=0)
y = y / 100
# Variable initialization
epoch = 5000
# Setting training iterations
# Setting learning rate
lr = 0.1
# input layer - neurons = 2
# number of features in data set
hiddenlayer - neurons = 3
# number of hidden layers neurons
output - neurons = 1
# number of neurons at output layer.
# weight and bias initialization
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))
bou = np.random.uniform(size=(1, output - neurons))

```

Sigmoid Function

```
def sigmoid(x):
    return 1 / (1 + np.exp(-x))
```

Derivative of Sigmoid Function

```
def derivatives_sigmoid(x):
    return x * (1 - x)
```

draws a random range of numbers uniformly of
dim X' Y for i in range(epoch):

Forward Propagation.

```
for i in range(epoch):
```

```
hinp = np.dot(X, wh)
```

```
hinp = hinp + bh
```

```
hlayer_act = sigmoid(hinp)
```

```
outinp1 = np.dot(hlayer_act, wout)
```

```
outinp = outinp1 + bout
```

```
output = sigmoid(outinp)
```

Back propagation

 ~~$E_0 = y - output$~~
 ~~$outgrad = derivatives_sigmoid(output)$~~
 ~~$d_output = E_0 * outgrad$~~
 ~~$EH = d_output \cdot dot(wout.T)$~~
 ~~$hidden_grad = derivatives_sigmoid(hlayer_act)$~~
 ~~$d_hidden_layer = EH * hidden_grad$~~

PTO

```

wout += hlayer - act. T. dot ( d - output ) * lr
wh += X. T. dot ( d - hiddenlayer ) * lr.
print ("Input : \n" + str (X))
print ("Actual output : \n" + str (y))
print ("Predicted output : \n", output)

```

OUTPUT:-

[[0.66666667 1. 1]]

[0.33333333 0.66666667]]

[1. 0.66666667]]

Actual output:

[[0.92]]

[0.80]]

[0.89]]

Predicted output:

[[0.79197201]]

[0.77476931]]

[0.79647277]]

Random Forest

```

1> from sklearn.ensemble import RandomForestClassifier
import pandas as pd
from sklearn.metrics import accuracy_score

2> df = pd.read_csv("C:/content/drive/")
melbourne_data = df.dropna(axis=0)
y = melbourne_data.Price
melbourne_features = ['Rooms', 'Bathroom', 'Landsize',
                      'BuildingArea', 'YearBuilt', 'Latitude', 'Longitude']
X = melbourne_data[melbourne_data.Features]

df.head()
3> from sklearn.model_selection import train_test_split
4> X_train, X_test, y_train, y_test = train_test_split(X, y,
train_size=0.8, random_state=0)
model = RandomForestClassifier()
model.fit(X, y)

y_predicted = model.predict(X_test)
accuracy = accuracy_score(y_predicted, y_test)
print(accuracy)
0.99

```

WEEK - 8

K-means.

1> Imports:-

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

2> Load Dataset:-

```
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']
```

3> K-Means Model

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

4> Plot the figures:-

```
plt.figure(figsize=(14,14))
colormap = np.array(['red', 'lime', 'black'])
plt.subplot(2,2,1)
plt.scatter(X.Petal-Length, X.Petal-Width, c=colormap[y.Targets], s=40)
plt.title('Real Clusters')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
```

H Plot the Model's Classification

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

```
plt.scatter(X.Petal_Length, X.Petal_Width, c = color_map  
[model.labels_], s=40)
```

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

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

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

PCA

1) Imports :-

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

```
import pandas as pd
```

```
import numpy as np
```

```
import seaborn as sns
```

```
%matplotlib inline
```

2) Import Dataset:-

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

```
cancer = load_breast_cancer()
```

```
cancer.keys()
```

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

3) PCA Visualization

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

```
scaler = StandardScaler()
```

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

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

```
from sklearn.decomposition import PCA
```

```
pca = PCA(n_components=2)
```

```
pca.fit(scaled_data)
```

$X_{-pca} = pca.\text{transform}(\text{scaled_data})$

scaled_data.shape

$X_{-pca}.\text{shape}$

Q) Plot the graph:

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

`plt.scatter(X_pca[:, 0], X_pca[:, 1], c=cancer['target'],
cmap='plasma')`

`plt.xlabel('First principal component')`

`plt.ylabel('Second principal component')`