

I N D E X

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S. No.	Date	Title	Page No.	Teacher's Sign/ Remarks
1	21-03-24	Import & Export data using Pandas library function	10	✓ 10/3/24 21-3-24
2	28-03-24	Demonstrate various data preprocessing techniques of dataset.	10	✓ 10/3/24 28-3-24
3.	04-04-24	Implement linear and Multi-linear regression algorithm using appropriate dataset.	10	✓ 10/4/24 04-4-24
4	18-04-24	Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new sample.	10	✓ 18/4/24 18-4-24
5	25-04-24	Build logistic Regression model for a given dataset.	10	✓ 25/4/24 25-4-24
6	09-05-2024	Build KNN Classification and SVM model for given dataset.	10	✓ 09/5/24 09-5-24
7	23-05-2024	Build Artificial Neural Network model with back propagation on a given dataset.	10	✓ 23/5/24 23-5-24
8	23-05-2024	a) Implement Random forest ensemble method on a given dataset. b) Implement Boosting ensemble method on a given dataset.	10	✓ 23/5/24 23-5-24

21/03/24

Lab - 1

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

→

```
import pandas as pd
```

```
airbnb_data = pd.read_csv("listing-austin.csv")  
airbnb_data.head()
```

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

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

(CSV file is now cleaned)

Output: (Cleaned Iris Data) creation

① id | name | host_id | host_name | neighbourhood | price

0	2265	Zen-East in the...	2466	Paddy	78702	179
---	------	--------------------	------	-------	-------	-----

1	5245	Eco friendly...	2466	Paddy	78702	114
---	------	-----------------	------	-------	-------	-----

(After removing duplicates)

width

② sepal-length-in-cm | sepal-in-cm | petal-length-in-cm | petal-width-in-cm

0	5.1	3.5	1.4	0.2
---	-----	-----	-----	-----

1	4.9	3.0	1.4	0.2
---	-----	-----	-----	-----

(After removing duplicates)

iris-setosa

iris-versicolor | iris-virginica

width

iris-setosa | iris-versicolor | iris-virginica

width | petal-length | petal-width

(After removing duplicates)

- Q) Demonstrate various data pre-processing techniques for a dataset.

→

2 Get the Data:

Download the Data: <https://raw.githubusercontent.com/ageron/handson-ml2/master/datasets/housing/housing.tgz>

```
import os
```

```
import tarfile
```

```
import urllib
```

```
DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml2/master/"
```

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

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

```
def fetch_housing_data(housing_url=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(url=housing_url, filename=tgz_path)
```

```
    housing_tgz = tarfile.open(name=tgz_path)
```

```
    housing_tgz.extractall(path=housing_path)
```

```
    housing_tgz.close()
```

```
fetch_housing_data()
```

```
import pandas as pd
```

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

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

```
    return pd.read_csv(data_path)
```

Quick look at the Data:

```
housing = load_housing_data()
```

```
housing.head()
```

```
housing.info()
```

```
housing.describe()
```

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

```
import seaborn as sns
```

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

```
plt.show()
```

Create a Test Set:

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

```
train_set, test_set = split_train_test(data=housing)
```

```
len(train_set), len(test_set)
```

(total * percentage) = length of training set + testing set

len(housing) * percentage = length of training set + testing set

(total * percentage) = training set

3 Discover & Visualize the Data to Gain Insights:

strat_train_set.shape, strat_test_set.shape

Visualizing Geographical Data

```
housing.plot(kind='scatter'; x='longitude'; y='latitude')
```

plt.show()

Looking for Correlations

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

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

([1, 0]) = significant (0, 1) = not significant = False

```
from pandas.plotting import scatter_matrix
```

```
attributes = ['median_house_value', 'median_income', 'total_rooms',
              'housing_median_age']
```

```
scatter_matrix(frame=housing[attributes], figsize=(12, 8))
```

plt.show()

```
housing['rooms_per_household'] = housing['total_rooms']/housing['households']
```

```
housing['age'] = housing['total_rooms']/housing['households']
```

4 Prepare the Data for Machine Learning Algorithms

Data Cleaning

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

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

```
housing_num = housing.drop('ocean_proximity', axis=1)
```

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

`import statistics`

`housing.num.median().values`

Handling Text & Categorical Attributes

from sklearn.preprocessing import OrdinalEncoder

`ordinal_encoder = OrdinalEncoder()`

`ordinal_encoder.categories_`

Select & Train a Model

Training & Evaluating on the Training Set

from sklearn.linear_model import LinearRegression

`lin_reg = LinearRegression()`

`lin_reg.fit(X = housing_prepared, y = housing_labels)`

($y = \text{linear_reg}(\text{X})$) by prediction

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)`~~

~~`lin_rmse = np.sqrt((sum((y - y_hat) ** 2) / len(y)))`~~

~~`np.sqrt(((y - y_hat) ** 2).sum() / len(y))`~~

~~`np.sqrt(((y - y_hat) ** 2).sum() / len(y))`~~

~~`train_x.describe().T['count']`~~

~~`train_x.describe().T['count']`~~

from sklearn.tree import DecisionTreeRegressor

tree-reg = DecisionTreeRegressor()

tree-reg.fit(X=housing_prepared, y=housing_labels)

Better Evaluation using Cross-Validation

from sklearn.model_selection import cross_val_score

scores = cross_val_score(estimator=tree-reg, X=housing_prepared, y=housing_labels, scoring='neg_mean_squared_error', cv=10)

tree_rmse_scores = np.sqrt(-scores)

from sklearn.ensemble import RandomForestRegressor

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_

cat-encoder = full-pipeline.named_transformers_[‘cat’]

final-model = grid-search.best_estimator_

x-test-prepared = full-pipeline.transform(X=x-test)

final_rmse = np.sqrt(final-mse)

final_rmse

04-04-29

Lab - 4

3. Implement Linear and Multi Linear Regression algorithm using appropriate dataset.

→

for Simple 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 pandas.core.common import random_state
from sklearn.linear_model import LinearRegression

df_sal = pd.read_csv('content/Salary-Data.csv')
df_sal.head() # (start=0) head(1) df[0:3].head() df[0:3]
(df.describe().round(2).head() == df).T.all().all()

df_sal.describe() # (start=0) df.describe() df[0:3].describe()
plt.title('Salary Distribution Plot')
sns.distplot(df_sal['Salary']) # (start=0) df[0:3].hist()
plt.show() # (start=0) plt.show() df[0:3].hist()

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

plt.title('Salary vs Experience') # (start=0) df[0:3].plot()
plt.xlabel('Years of Experience') # (start=0) df[0:3].xaxis
plt.ylabel('Salary') # (start=0) df[0:3].yaxis
plt.box(False)
plt.show() # (start=0) plt.show()

x=df_sal.iloc[:, :-1].values # (start=0) df[0:3].values
y=df_sal.iloc[:, -1:] # (start=0) df[0:3].values
```

`x-train, x-test, y-train, y-test = train-test-split(x, y, test_size=0.2, random_state=0)`

`regressor = LinearRegression()`

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

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

`y-pred-train = regressor.predict(x-train)`

`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 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()`

`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 OneHotEncoder
from sklearn.linear_model import LinearRegression
df_start = pd.read_csv('content/50_Startups.csv')
df_start.head()
df_start.describe()
plt.title('Profit Distribution Plot')
sns.distplot(df_start['Profit'])
plt.show()
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()
```

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

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

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

x = np.array(ct.fit_transform(x))

X-train, X-test, y-train, y-test = train_test_split(x, y,

test_size = 0.2, random_state=0)

regressor = LinearRegression()

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

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

np.set_printoptions(precision=2)

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

result

3. Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new sample.

→

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
import seaborn as sns
```

From sklearn.datasets import load_iris

(2) iris_data = load_iris()

print(iris_data.describe)

features :

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, plot_tree
import matplotlib.pyplot as plt
```

```
clf = DecisionTreeClassifier()
```

```
clf.fit(x, y)
```

plt.figure(figsize=(12, 8))
plot_tree(clf, filled=True, feature_names=iris.data,
 feature_name, class_names=iris.target_names)
plt.show()

Output:

petal width(cm) <= 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) >= 1.75

gini = 0.512

samples = 100

values = [0, 50, 50]

class = versicolor

petal length(cm) <= 4.95

gini = 0.168

samples = 54

value = [0, 49, 5]

class = versicolor

petal length(cm) >= 4.95

gini = 0.043

samples = 46

value = [0, 1, 45]

class = virginica

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: output displayed from above result is given

Mean Accuracy : 0.9666

"vectorized version" (vec) -> 96%

(base-fit) -> 96%

Logistic regression -> test -> fit = LogisticRegression.fit(x, y)

Logistic regression -> fit, predict -> predict .fb

predict .fb (test -> x) -> true

predict .fb (test -> x) -> false

0.96

("vectorized version" -> 96%)

(vec) -> 96% (base-fit) -> 96%

(test -> x) -> 96% (base-fit) -> 96%

(base-fit) -> 96%

((test -> x) -> 96% (base-fit) -> 96%)

((test -> x) -> 96% (base-fit) -> 96%)

: output

7.9 -> 96% (base-fit) -> 96%

7.9 -> 96% (base-fit) -> 96% (base-fit) -> 96%

7.9 -> 96% (base-fit) -> 96% (base-fit) -> 96%

(5) example (fb)

((5) -> 96% (base-fit) -> 96%)

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(1))
```

```
x_train, x_test, y_train, y_test = Train-test-split(df[["age"]])
```

```
df.bought_insurance, test_size = 0.2
```

```
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 predi(age):
```

```
z = 0.042 * age - 1.53
```

```
y = sigmoid(z)
```

```
return y
```

`point(predi(35))` → F 5.9 with added points first time

`point(predi(43))` → F 5.9 with added points second time
by adding hospital

Output:

Prediction: array ((1, 0, 1, 0, 0, 0, 0, 1, 0)) hospital

Score: 0.8888

Linear Reg score: 0.584321

Predictions: 0.485

0.5685

(("upside", "23.2018"), 76 - 0.0002)

("d", "p" - 0.0002)

~~W~~ : (array) statement in 0.0, 0.0

[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0] = 0.000000

if 0.0 > 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 else 0.0

(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0)

if 0.0 > 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 else 0.0

(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0)

if 0.0 > 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 else 0.0

(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0)

: (array) statement in 0.0, 0.0

[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0] = 0.000000

if 0.0 > 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0 else 0.0

(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0)

(("front", "back", "left")) select 0.0

("front", "back", "left") select 0.0

(("back", "left")) select 0.0

(("back", "left", "right")) select 0.0

09/05/2024

Lab - 6 & 7

classmate

Date _____
Page _____

Build KNN Classification and SVM model for a given dataset



import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

import numpy as np

df = pd.read_csv("iris.csv")

df.head()

classes = df["Species"].unique()

colors = ['r', 'g', 'b']

for i, cls in enumerate(classes):

class_data = df[df["Species"] == cls]

plt.scatter(class_data["SepalLengthCm"], class_data["PetalLengthCm"], c=colors[i], label=cls)

plt.xlabel('Sepal Length [cm]')

plt.ylabel('Petal Length [cm]')

plt.legend()

plt.show()

for i, cls in enumerate(classes):

class_data = df[df["Species"] == cls]

plt.scatter(class_data["SepalWidthCm"], class_data["PetalWidthCm"], c=colors[i], label=cls)

plt.xlabel('Sepal Width [cm]')

plt.ylabel('Petal Width [cm]')

plt.legend()

plt.show()

Ques 15
7/3/24

3-dot

~~y = df["Species"]~~ ~~remove Species column~~
~~x = df.drop(["Species"], axis=1)~~ ~~no need for y~~

from sklearn.model_selection import train_test_split

x-train, x-test, y-train, y-test = train_test_split(x, y, test_size=0.2, random_state=0)

from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=3)

knn.fit(x-train, y-train)

y-pred = knn.predict(x-test)

y2 = knn.predict(x-train)

from sklearn.metrics import accuracy_score

score = accuracy_score(y-pred, y-test)

print(f"Training Accuracy: {score}")

score2 = accuracy_score(y2, y-train)

print(f"Training Accuracy: {score2}")

Output:

Training Accuracy: 1.0

Training Accuracy: 1.0

from sklearn.svm import SVC

model = SVC(kernel='linear', random_state=0, C=1.0)

model.fit(x-train, y-train)

y2 = model.predict(x-train)

from sklearn.metrics import accuracy_score

score = accuracy_score(y-pred, y-test)

print(f"Testing Accuracy: {score}")

score2 = accuracy_score(y2, y-train)

print(f"Training Accuracy: {score2}")

Output: Training Accuracy: 1.0

Training Accuracy: 1.0

Lab - 8

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)
```

```
X = X / np.amax(X, axis=0)
```

```
y = y / 100
```

```
epoch = 5000
```

```
lr = 0.1
```

```
input_layer_neurons = 2
```

```
hidden_layer_neurons = 3
```

```
output_neurons = 1
```

```
wh = np.random.uniform(size=(input_layer_neurons, hidden_layer_neurons))
```

```
bh = np.random.uniform(size=(1, hidden_layer_neurons))
```

```
wout = np.random.uniform(size=(hidden_layer_neurons, output_neurons))
```

```
bout = bh = np.random.uniform(size=(1, output_neurons))
```

```
def sigmoid(x):
```

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

```
def derivatives_sigmoid(z):
```

```
    return z * (1 - z)
```

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

```
    hinp1 = np.dot(X, wh) + bh
```

```
    hinp = hinp1 + b1
```

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

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

```
    outinp = outinp1 + b2
```

$$\text{outImp} = \text{outImp} + \text{bout}$$

$$\text{output} = \text{sigmoid}(\text{outImp})$$

$$\text{EO} = \text{y} - \text{output}$$

$$\text{outgrad} = \text{derivatives_sigmoid}(\text{output})$$

$$\text{d_output} = \text{EO} * \text{outgrad}$$

$$\text{EH} = \text{d_output}, \text{dot}(\text{wout}, \text{T})$$

$$\text{hiddengrad} = \text{derivatives_sigmoid}(\text{layer_act})$$

$$\text{d_hiddenlayer} = \text{EH} * \text{hiddengrad}$$

$$\text{wout} = \text{layer_act}, \text{dot}(\text{d_output}) * \text{lr}$$

$$\text{wh} + \text{x}, \text{dot}(\text{d_hiddenlayer}) * \text{lr}$$

$$\text{print}("Input: " + \text{str}(\text{x}))$$

$$\text{print}("Actual Output: " + \text{str}(\text{y}))$$

$$\text{print}("Predicted Output: " + \text{str}(\text{output}))$$

$$(\text{y}, \text{x}) \rightarrow \text{y} = \text{f}(\text{x})$$

$$\text{Output: } \text{a sigmoid}$$

$$\text{Input: } [\text{0.666667}, 1]$$

$$[\text{0.333333}, \text{0.666667}]$$

$$[0.5 = [1, 0.666667]]$$

$$\text{Actual Output: } [0.92]$$

$$[0.86]$$

$$[0.89]$$

$$\text{Predicted output: } [0.8915061]$$

$$[0.88519821]$$

$$[0.88962179]$$

$$[0.88962179]$$

$$[0.88962179]$$

$$[0.88962179]$$

$$[0.88962179]$$

$$[0.88962179]$$

$$[0.88962179]$$

$$[0.88962179]$$

$$[0.88962179]$$

$$[0.88962179]$$

$$[0.88962179]$$

Lab - 9

- q) a) Implement Random forest ensemble method on a given dataset
 b) Implement Boosting ensemble method on a given dataset.

a) → import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

import numpy as np

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

`df.head()`

`y = df["Species"]`

`x = df.drop(["Species"], axis=1)`

`from sklearn.model_selection import train_test_split`

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

`test_size = 0.3, random_state=42)`

`from sklearn.ensemble import RandomForestClassifier`

`clf = RandomForestClassifier(n_estimators = 100)`

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

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

`y2 = clf.predict(X-train)`

`from sklearn.metrics import accuracy_score`

`score = accuracy_score(y-pred, y-test)`

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

`score2 = accuracy_score(y2, y-train)`

`print(f"Training Accuracy : {score2} ^")`

Output :

Testing Accuracy : 1.0

Training Accuracy : 1.0

from sklearn.linear_model import LogisticRegression

lrm = LogisticRegression()

adbhp = AdaBoost

b) → from sklearn.ensemble import AdaBoostClassifier

adb = AdaBoostClassifier()

adb.model_ = adb.fit(X_train, y_train)

y_pred = adb.predict(X_test)

y2 = adb.predict(X_train)

from sklearn.metrics import accuracy_score

score = accuracy_score(y_pred, y_test)

print("Testing Accuracy : {score}")

score2 = accuracy_score(y2, y_train)

print("Training Accuracy: {score2}")

Output: Testing Accuracy : 0.977777

Training Accuracy : 1.0

from sklearn.linear_model import LogisticRegression

lrm = LogisticRegression()

adbhp = AdaBoostClassifier(n_estimators=150, estimator=lrm, learning_rate=1)

model = adbhp.fit(X_train, y_train)

y_pred = model.predict(X_test)

y2 = model.predict(X_train)

from sklearn.metrics import accuracy_score

score = accuracy_score(y_pred, y_test)

print("Testing Accuracy: {score}")

score2 = accuracy_score(y2, y_train)

print("Training Accuracy: {score2}")

~~Output: temporary, based on behavior, words, emotions, etc.~~

Testing Accuracy: 1.0

Training Accuracy: 1.0

Initial goal: 1.0

Final goal: 1.0

Lab-10

- 10 Build k-Means algorithm to cluster a set of data stored in .CSV file.

→

```

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, columns=['Sepal-length',
                                      'Sepal-width', 'petal-length', 'petal-width'])
y = pd.DataFrame(iris.target, columns=['Targets'])

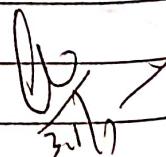
model = KMeans(n_clusters=3)
model.fit(x)

plt.figure(figsize=(14, 14))
colormap = np.array(['red', 'lime', 'black'])

plt.subplot(2, 2, 1)
plt.scatter(x['Petal-length'], x['Petalwidth'],
            c=colormap[y['Targets']], s=40)
plt.title('Real Clusters')
plt.xlabel('Petal length')
plt.ylabel('Petal width')

plt.subplot(2, 2, 2)
plt.scatter(x['Petal-length'], x['Petal-width'],
            c=colormap[model.labels_], s=40)
plt.title('k-Means clustering')
plt.xlabel('Petal length')
plt.ylabel('Petal width')
plt.show()

```



Lab-11a

Date _____
Page _____

11 Implement Dimensionality reduction using PCA Method

12 Use k-Means algorithm to cluster a set of data stored in a CSV file.

→ 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()

(['data', 'target', 'target_names', 'feature_names', 'DESCR', 'filename'])

df = pd.DataFrame(cancer['data'], columns=cancer['feature_names'])

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

scaler.fit(df)

scaled_data = scaler.transform(df)

([('scaled_data', 'target', 'target_names', 'feature_names', 'DESCR', 'filename')])

from sklearn.decomposition import PCA

pca = PCA(n_components=2)

pca.fit(scaled_data)

x_pca = pca.transform(scaled_data)

scaled_data.shape

x_pca.shape

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')

(x_min - 10, x_max + 10)

(y_min - 10, y_max + 10)

(x_min - 10, x_max + 10)

(y_min - 10, y_max + 10)