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2	28/03/24	week -2 (Ch-2 logistic)		B
3	4/4/24	linear & Multiple Regression		
4	18/4/24	Decision Tree		
5	25/4/24	Logistic Regression (week-5)		
6	09/5/24	Knn classifier, SVM (week -6)		
7	23/5/24	Prog 8, Prog qa, qb (week-7)		
8	30/5/24	prog 10 (k-mans) prog 11 (PCA)		

21/03/24

A2-3-M

Week - 1

- Q) Write a python prog to import and export data using pandas library functions
i/p:

```
import pandas as pd
```

```
iris_data = pd.read_csv(r'C:\Users\Admin\Downloads\iris.csv')
```

```
iris_data.head()
```

O/P:

	5.1	3.5	1.4	0.2	Iris-setosa
0	4.9	3.0	1.4	0.2	Iris-setosa
1	4.7	3.2	1.3	0.2	Iris-setosa
2	4.6	3.1	1.5	0.2	Iris-setosa
3	5.0	3.6	1.4	0.2	Iris-setosa
4	5.4	3.9	1.7	0.4	Iris-setosa

Using URL

i/p:

```
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()
```

O/P: Same as the previous.

Kaggle:

Creating Dataframe:

1) Dataframe:

Eg: pd.DataFrame({ 'yes': [50, 21],
'No': [31, 2] })

	yes	No
0	50	131
1	21	2

2) Series:

Eg: pd.Series([1, 2, 3, 4, 5])

0	1	2	3	4	5
1	2	3	4	5	6
2	3	4	5	6	7
3	4	5	6	7	8
4	5	6	7	8	9

Reading Data:

Eg: data = pd.read_csv("college_data.csv")

data.head() → returns first five data values of dataset.

28/03/24

Wk 2/3/24

Week - 2

Chapter - 2

2) Get the data.

- import os
 - import tarfile
 - import urllib
- Download the data
→ take a quick look at the DST
→ create a test set

fetch_housing_data()

def load_housing_data(housing_path =
Housing_PATH):

1) Look at the big Picture.

- ↳ frame the problem
- ↳ select a performance measure
- ↳ check the assumptions

3) Discover & visualize the data to gain insights:

→ Put the test set aside, explore only the training set.

Strat_train_set.shape, Strat-test-set.shape

-

housing = Strat-train-set.copy(); housing.shape

→ Visualizing Geographical Data

since latitude / longitude info is there
we use `matplotlib plot` method of pandas.

`housing.plot()`

`housing.plot(kind='Scatter', x='longitude',
y='latitude')`

`plt.show()`

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

`plt.show()`

→ looking for correlations:

`corr_matrix = housing.corr()`

→ Experimenting with attribute combinations:

4) prepare the data for M.L. Algorithm

`housing Strat-train -> Set.drop("median_house_value")`

`housing_labels = Strat-train -> Set("median_house_value")`

`housing.shape, housing_labels.shape`

Data cleaning:

from sklearn import impute

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

`housing_mn = housing.drop("classproximity", axis=1)`

5) Select & Train Model

```
from sklearn.linear_model import LinearRegression  
lin-reg = LinearRegression()  
lin-reg.fit(x=housing_prepared, y=housing_labels)
```

Cross-validation

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

6) Time frame your model:

```
param_grid = [  
    {'n_estimators': [3, 10, 30], 'max_features':  
        [2, 4, 6, 8]}, {'bootstrap': [False],  
    'n_estimators': [3, 10], 'max_features':  
        [2, 3, 4]}]
```

```
forest-reg = RandomForestRegressor()
```

```
grid_search = GridSearchCV(estimator=forest-reg,  
                           param_grid, scoring='neg_mean_squared_error', cv=5, return_train-  
                           score=True, n_jobs=-1)
```

```
grid_search.fit(x=housing_prepared, y=housing_labels)
```

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Week - 3

Linear Regression

- ① df - sal = pd.read_csv('C:/Users/STUDENT.../Salary.csv')
df - sal - head()
- ② plt.title('Salary Distribution plot')
sns.distplot(df['Salary'])
plt.show()
- ③ plt.scatter(df['yearsExperience'], df['Salary'], color = 'lightcoral')
plt.xlabel('years of exp')
plt.ylabel('Salary')
plt.box(False)
plt.show()
- ④ Splitting variables
 $x = df['Salary'].iloc[:, :-1]$
 $y = df['Salary'].iloc[:, -1]$
- ⑤ x-train, x-test, y-train, y-test = train-test-split(y)
test.size = 0.2, random_state = 0
- ⑥ regressor.fit(x-train, y-train)
- ⑦ Prediction

$$y\text{-pred-test} = \text{regressor.predict}(x\text{-test})$$
$$y\text{-pred-train} = \text{regressor.predict}(x\text{-train})$$

- ① import libraries
- ② import data
- ③ Analyze data
- ④ Split data
- ⑤ Predict results
- ⑥ Visualize prediction

Multiple Linear Regression

- ① df_start = pd.read_csv('content/SD-startup.csv')
df_start.head()
 - ② plt.title('Profit distribution plot')
sns.distplot(df_start['Profit'])
plt.show()
 - ③ splitting
 $x = df_start.iloc[:, :-1].values$
 $y = df_start.iloc[:, -1].values$
 - ④ x_train, x_test, y_train, y_test = train_test_split
(x, y, test_size=0.2, random_state=0)
 - ⑤ regressor = LinearRegression()
regressor.fit(x_train, y_train)
 - ⑥ Predict.
y_pred = regressor.predict(x_test)
- Steps:
- 1) Import libraries
 - 2) Import data
 - 3) Analyze data
 - 4) Split into Independent / Dependent variables.
 - 5) Predict results.
 - 6) compare predictions.

18/4/24

Week - 4

Decision Tree

- ① $\text{cols} = \text{df. columns}[0:-1]$
for i in $\text{cols}:$
 $\text{sns. boxplot}(y=\text{df}(i))$
 plt. show()
- ② $\text{dt} = \text{DecisionTreeClassifier}(\text{max_depth}=3, \text{min_samples_}$
 $\text{leaf}=10, \text{random_state}=1)$
 $\text{dt. fit}(x, y)$
 $x = \text{df. drop}("Species", \text{axis}=1)$
 $y = \text{df}["Species"]$
- ③ $\text{features} = x\text{-columns.}$
 $\text{dot_data} = \text{export_graphviz(dt, out_files=None,}$
 $\text{feature_names=features})$
 $\text{graph} = \text{pydotplus.graph_from_dot_data(dot_data)}$
 $\text{Image(graph.create_png())}$
- ④ $\text{dt} = \text{DecisionTreeClassifier}(\text{random_state}=1)$
 $\text{dt. fit}(x\text{-train}, y\text{-train})$
 $y\text{-pred-train} = \text{dt. predict}(x\text{-train})$
 $y\text{-pred} = \text{dt. predict}(x\text{-test})$
 $y\text{-prob} = \text{dt. predict_proba}(x\text{-test})$
- ⑤ $\text{print("Accuracy of Decision Tree-Train!:", accuracy_score($
 $y\text{-pred-train}, y\text{-train}))}$
 $\text{print("Accuracy of Decision Tree-Test!:", accuracy_score($
 $y\text{-pred}, y\text{-test}))}$

Petal-width (cm) ≤ 0.8
 $\text{gini} = 0.666$
 Samples = 146
 Value = [47, 49, 50]

T
 $\text{gini} = 0.0$
 Samples = 47
 Value = [47, 0, 0]

F
 Petal-width (cm) ≤ 1.75
 $\text{gini} = 0.5$
 Samples = 99
 Value = [0, 49, 50]

Petal length (cm) ≤ 4.65
 $\text{gini} = 0.171$
 Samples = 53
 Value = [0, 4, 8, 5]

T
 F
 Sepal length (cm) ≤ 6.25
 $\text{gini} = 0.043$
 Samples = 46
 Value = [0, 1, 4, 5]

\downarrow
 $\text{gini} = 0.05$
 Samples = 39
 Value = [0, 38, 1]

\downarrow
 $\text{gini} = 0.408$
 Samples = 14
 Value = [0, 10, 4]

\downarrow
 $\text{gini} = 0.165$
 Samples = 11
 Value = [0, 1, 10]

\downarrow
 $\text{gini} = 0.0$
 Samples = 35
 Value = [0, 0, 35]

Logistic Regression

```
import pandas as pd
from matplotlib import pyplot as plt.
%matplotlib inline.
```

```
file_path = r"C:\Users\...csv"
df = pd.read_csv(file_path)
df.head()
```

```
from sklearn.model_selection import train_test_split
plt.scatter(df.age, df.bought_insurance, marker='+',
            color='red')
```

$x\text{-train}$, $x\text{-test}$, $y\text{-train}$, $y\text{-test}$ = train-test-split
 $(df['age'])$, $df\text{.bought_insurance}$

```
print(x-train)
model = LogisticRegression()
model.fit(x-train, y-train)
print("co-efficient(m): ", model.coef_)
print("Intercept(b): ", model.intercept_)
```

df sigmoid(x):

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

$x=0$

sigmoid_value = sigmoid(0)

print("sigmoid value at x=0:", sigmoid_value)

df sigmoid(x):

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

def prediction_function(age):

$$m = 0.042$$

$$b = -1.53$$

$$z = m * \text{age} + b$$

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

return y.

predicted probability = prediction_function(35)

print("Predicted probability of buying insurance
for age 35: ", predicted_probability).

new.(1-new).model.grb.b = x
new.(1-new).fb = y

programs with else-labour-model and
tjg2-test-alot

= lotge, north, test-x, north-x

= acce-test, (x) judge + test, north
(x-acce-test), x = start-model

and personal programs ergebnis-model and
models

(r, i) known.y = result.y

((modelyear) r, i) known.y = result.y, north

((modelyear) r, i) known.y = result.y, test
(north-p, north-v) fib-n

(north-p, north-v) start-model = 57 programs - north

(start-p, test-x) start-model = 97 programs - test

09/05/24

week-6

KNN classifier:

①

```
import numpy as np  
import pandas as pd  
import matplotlib.pyplot as plt  
plt.style.use('seaborn')
```

②

```
data = pd.read_csv('diabetes.csv')  
df.head  
df.shape
```

③

```
X = df.drop(['Outcome'], axis=1).values  
y = df['Outcome'].values.
```

④

```
from sklearn.model_selection import  
train_test_split  
x_train, x_test, y_train, y_test =  
train_test_split(x, y, test_size=0.4,  
random_state=42, stratify=y)
```

⑤

```
from sklearn.neighbors import KNeighborsClassifier
```

```
neighbours = np.arange(1, 9)
```

```
train_accuracy = np.empty(len(neighbours))
```

```
test_accuracy = np.empty(len(neighbours))
```

```
Knn = KNeighborsClassifier(n_neighbors=1)
```

```
Knn.fit(x_train, y_train)
```

```
train_accuracy[0] = Knn.score(x_train, y_train)
```

```
test_accuracy[0] = Knn.score(x_test, y_test)
```

⑥ plt.plot(neighbors, train_accuracy, label='train')

plt.plot(neighbors, test_accuracy, label='test')
plt.show()

⑦ plt.scatter(neighbors, train_accuracy, color='r')
plt.show()

⑧ knn.fit(x_train, y_train)

knn.score(x_test, y_test)

Output Accuracy = 0.7398

(train) = (100%) $\sqrt{2} \approx 1.414$ = 1.41

(test) = (100%) $\sqrt{2} \approx 1.414$ = 1.41

200knn trogus model work

((trog-p-knn)) more accurate - 200knn) trog

((trog-p-knn)) more accurate - 200knn) trog

((trog-p-knn)) more - 200knn) trog

200knn model trogus

((trog-p-knn)) more accurate - 200knn) trog

[trogus more - 200knn] ((trog-p-knn)) more - 200

200knn . ffp

200knn . ffp

SVM

```
from sklearn import datasets  
cancer = datasets.load_breast_cancer()  
# enter features to print.  
print(cancer.target)
```

```
from sklearn.model_selection import train_test_split  
X_train, X_test, y_train, y_test =  
    train_test_split(cancer.data, cancer.target,  
                      test_size=0.3, random_state=109)
```

```
from sklearn import svm  
df = svm.SVC(kernel='linear')  
y_pred = df.predict(X_test)
```

```
from sklearn import metrics  
print(metrics.accuracy_score(y_test, y_pred))  
print(metrics.precision_score(y_test, y_pred))  
print(metrics.recall_score(y_test, y_pred))
```

```
import seaborn as sns  
sns.scatterplot(x=cancer.data[:, 0],  
                 y=cancer.data[:, 1], hue=cancer.target)  
plt.show()
```

O/P: Accuracy: 0.9764

23/5/24

Week-7

A23-5-W

(ANN) Artificial neural network: (prog 8)

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_neurons = 2

hiddenlayer_neurons = 3

output_neurons = 1

wh = np.random.uniform(size=(input_neurons, hiddenlayer_neurons))

bh = np.random.uniform(size=(1, hiddenlayer_neurons))

def sigmoid(x):

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

def derivatives_sigmoid(x):

return x * (1 - x)

for i in range(epoch):

hinp = np.dot(ex, wh)

hinp = hinp + bh.

hlayer_act = sigmoid(hinp)

output = sigmoid(outinp)

E0 = y - output

out grad = derivatives_sigmoid(output)

E1 = d_output * dot(wout.T)

hidden grad - derivatives - sigmoid (layer-act)

$d_{\text{hiddenlayer}} = \text{EIT} * \text{hidden grad.}$

$n_{h+} = x \cdot T \cdot \text{dot}(d_{\text{hiddenlayer}}) * lr$

//print if p < o/p

o/p: Input:

$\begin{bmatrix} [0.66667] \\ [0.33333] \end{bmatrix}$

$\begin{bmatrix} 0.3333 & 0.55556 \end{bmatrix}$

$\begin{bmatrix} 1. & 0.66667 \end{bmatrix}$

Actual output:

$\begin{bmatrix} 0.92 \end{bmatrix}$

$\begin{bmatrix} 0.86 \end{bmatrix}$

$\begin{bmatrix} 0.89 \end{bmatrix}$

Predicted o/p:

$\begin{bmatrix} [0.8196977] \end{bmatrix}$

$\begin{bmatrix} [0.796237] \end{bmatrix}$

$\begin{bmatrix} [0.81616067] \end{bmatrix}$

Prog 9

9a) Random forest:

// import libraries

// import libraries

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

```
x = data.drop(columns = ['Species'])
```

```
y = data['Species']
```

x-train, x-test, y-train, y-test =

```
train-test_split(x,y, test_size = 0.2, random_state  
= 42)
```

```
rf_classifier = RandomForestClassifier(n_estimators = 100,
```

```
random_state = 42)
```

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

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

// print accuracy, classification report

feature-importances = rf_classifier.feature_importances
features = x.columns

```
importance-df = pd.DataFrame({'Feature': features,  
'Importance': feature-importances}).  
sort_values(by = 'Importance',  
ascending = False)
```

print(importance-df)

Op: Accuracy: 100.00%

9b) Ada boost

// import necessary libraries

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

```
x = data.drop(columns = ["species"])
```

```
y = data["Species"]
```

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

```
adaBoost_df = AdaBoostClassifier
```

```
(n_estimators = 150, learning_rate = 1)
```

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

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

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

```
// print Accuracy.
```

```
O/P: Accuracy: 1.0
```

30/05/24

week - 8
AO-5-24.

prog(0): K-means algorithm to cluster a set of data stored in a .csv file.

①

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

②

```
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

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

K-Means Clustering

④

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

orig class

⑤

```
plt.subplot(2,2,1)
plt.scatter(X.petal_length, X.petal_width, c=cmap[Y.targets], s=40)

plt.title('real clusters')
plt.xlabel('petal length')
plt.ylabel('petal width')
```

model
gen

8-100N

115-2-0-0-A

⑥ plt. subplot (2,2,2)

plt. scatter(x.petal_length, x.petal_width, c=colorsmap
(model.labels), s=40)

plt. title('k-means clustering')

plt.xlabel('petal length')

plt.ylabel('petal width')

Scatter plot showing petal length vs petal width

(0.273-0.92) < 0.25 (blue)

PCA

Dimensionality reduction using principle component analysis method.

① import matplotlib.pyplot as plt
import pandas as pd.
import numpy as np
import seaborn as sns
%matplotlib inline.

② from sklearn.datasets import load_breast_cancer
cancer = load_breast_cancer()
df = pd.DataFrame(cancer['data'], columns=
cancer['feature_names'])

③ from sklearn.preprocessing import StandardScaler as ss
scaler = ss()
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.transform(scaled_data)
scaled_data.shape
x_pca.shape

plot
⑤

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

plt.scatter(x_pca[:, 0], x_pca[:, 1],

c=cancer['target'], cmap='Plasma')

plt.xlabel('first principle component')

plt.ylabel('second principle component')