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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("C:/Users/Admin/Downloads/listings-austin.csv")
airbnb-data.head()
```

#output:

| | id | listing_url | Scrape_id | last_scraped |
|---|------|-----------------------------------|----------------|--------------|
| 0 | 2265 | https://www.airbnb.com/rooms/2265 | 20180710171409 | 2018-07-10 |
| 1 | 5245 | https://www.airbnb.com/rooms/5245 | 20180710171409 | 2018-07-10 |
| 2 | 5456 | https://www.airbnb.com/rooms/5456 | 20180710171409 | 2018-07-10 |
| 3 | 5769 | https://www.airbnb.com/rooms/5769 | 20180710171409 | 2018-07-10 |
| 4 | 6413 | https://www.airbnb.com/rooms/6413 | 20180710171409 | 2018-07-10 |

5 rows x 96 columns

2) Reading Data from URL:

Code:

```
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()
```

Output:

| | class | sepal-length | sepal-length | petal-length | petal-length |
|---|-------------|--------------|--------------|--------------|--------------|
| | | (in-cm) | (in-cm) | (in-cm) | (in-cm) |
| 0 | iris-setosa | 5.1 | 3.5 | 1.4 | 0.2 |
| 1 | iris-setosa | 4.9 | 3.0 | 1.4 | 0.2 |
| 2 | iris-setosa | 4.7 | 3.2 | 1.3 | 0.2 |
| 4 | iris-setosa | 4.6 | 3.1 | 1.5 | 0.2 |
| 5 | iris-setosa | 5.0 | 3.6 | 1.4 | 0.2 |

→ Export code:

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

Hadoop Certification (Pandas)

i) Creating, Reading and Writing.

- import pandas as pd

Creating data:

i) pd.DataFrame({'Yes': [50, 21], 'No': [131, 273]})

| | Yes | No |
|---|-----|-----|
| 0 | 50 | 131 |
| 1 | 21 | 273 |
| 2 | | |

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 | It was awful |
| Product B | Pretty good | Bland |

Reading Data Files.

1) wine_reviews = pd.read_csv("../input/winemag-data.csv")

2) wine_reviews.shape

(12997, 14)

3) wine_reviews.head()

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End to End hands on machine learning:

Get the data

data.head()

- Gives first five data entries.

data.info()

Output

| | column | Non-null count |
|---|---------------------|----------------|
| 0 | longitude | 20640 |
| 1 | latitude | 20640 |
| 2 | housing-age | 20640 |
| 3 | total-rooms | 20640 |
| 4 | total-bedrooms | 20640 |
| 5 | population | 20640 |
| 6 | households | 20640 |
| 7 | median-income | 20640 |
| 8 | median-house-income | 20640 |
| 9 | ocean-proximity | 20640 |

data['ocean-proximity'].value_counts()

data.describe()

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

Step 2: Discover and visualize the data to gain sight

data.plot(kind='scatter', x='longitude',
y='latitude')

plt.show()

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

```
plt.show()
```

```
data[['population', 'median-house-value']].corr()
corr_matrix = housing.corr()
```

```
corr_matrix['median-house-value'].sort_values
(ascending=False)
```

```
data.plot (kind='scatter', x='median-income',
y='median-house-value', figsize=(12,8)
alpha=0.1)
```

```
plt.show()
```

Step 3: Prepare the data for machine learning algorithms.

```
housing_num = data.drop(['ocean-proximity'],
axis=1)
```

```
housing_cat = housing[['ocean-proximity']]
```

```
housing_cat.head()
```

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

```
for train_index, test_index in split.split
```

```
(x=housing, y=housing['income-cat']):
```

```
strat_train_set = housing.loc[train_index]
```

```
strat_test_set = housing.loc[test_index]
```

```
housing = strat_train_set.copy()
```

5. Select and train model:

```
from sklearn.linear_model import LinearRegression  
lin-reg = LinearRegression()  
lin-reg.fit(x=housing['prepared'], y=housing['label'])  
some_data = housing.iloc[:5]  
print("Predictions:", lin-reg.predict(some_data))
```

```
from sklearn.metrics import mean_squared_error  
housing_prediction = lin-reg.predict(housing['prepared'])  
lin-mse = mean_squared_error(housing['label'], housing_prediction)
```

6. Fine-Tune your model:

```
from sklearn import RandomForestRegressor  
from sklearn.model_selection import GridSearchCV  
forest-reg = RandomForestRegressor()  
grid-search.fit(x=housing['prepared'],  
                 y=housing['label'])
```

```
grid-search.best_params_
```

```
grid-search.best_estimator_
```

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Week-3

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Simple Linear Regression

```
import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt  
import seaborn as sns  
from sklearn.linear_model import LinearRegression
```

```
df_sal = pd.read_csv('salary_data.csv')  
df_sal.head()  
plt.title("Salary plot")  
sns.distplot(df_sal['Salary'])  
plt.show()
```

```
plt.scatter(df_sal['Years Experience'],  
           df_sal['Salary'], color='lightcoral')  
plt.title('Salary vs experience')  
plt.show()
```

Split Data

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

split into train and 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)
```

```
y_pred_test = regressor.predict(x_test)
```

```
y_pred_train = regressor.predict(x_train)
```

Visual Predictions:

```
plt.scatter(x_train, y_train, color = 'lightcoral')
```

```
plt.plot(x_train, y_pred_train)
```

```
plt.show()
```

Coefficient and Intercept:

```
print(f'Coefficient: {regressor.coef_}')
```

```
print(f'Intercept: {regressor.intercept_}')
```

Output:

Coefficient: [(-9312.57512)]

Intercept: [26780.0991]

Multiple Linear Regression

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
```

```
df_start = pd.read_csv('startups.csv')
```

```
df_start.head()
```

```
df.describe()
```

```
df['Profit'].hist()
```

Distribution

```
plt.title('Profit distribution plot')
```

```
sns.distplot(df_start['Profit'])
```

```
plt.show()
```

Relationship between profit and RandD spend

```
plt.scatter(df_start['RandD Spend'], df_start['Profit'])
```

```
plt.show()
```

Split Data

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

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

split into train test data.

```
x_train, y_train, x_test, 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 Prediction:

```
nb.set.printOptions(precision=2)
```

```
result = nb.concatenate([y-pred.reshape(len(y-pred)), y-test.reshape(len(y-test)), 1])
```

```
print(result)
```

```
array([103015.2, 103282.38], [1032582.28, 144259.4], [132447.74, 146121.95], [1])
```

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Week-4

AI/ML/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(cif, filled=True, feature_names=iris_du  
feature_names, class_names=iris_data.
```

```
plt.show()
```

Output:

Accuracy 1.0

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Week-5

Build logistic regression model for given dataset

Code: Load Insurance dataset with

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

```
df = pd.read_csv("insData.csv")  
df.head()
```

| | 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
```

```
1.0
```

```
0.8
```

```
0.6
```

```
0.4
```

```
0.2
```

```
0.0
```

```
20 30 40 50 60
```

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x-train, x-test, y-train, y-test =
train-test-split(df[['age']], df['bought_insurance'],
train_size=0.8)

```
from sklearn.linear_model import LogisticRegression  
model = LogisticRegression()  
model.fit(x-train, y-train)
```

• LogisticRegression

LogisticRegression()

```
print(x-test)
```

| age | 30 | 30 |
|-----|----|----|
| 26 | 23 | 0 |
| 25 | 54 | 0 |
| 11 | 28 | 0 |
| 1 | 25 | 0 |
| 16 | 25 | 0 |
| 18 | 19 | 0 |

y-predicted = model.predict(x-test)

model.predict_proba(x-test)

model.score(x-test, y-test)

0.833333334

```
print(y-predicted)
```

[0 0 0 0 0]

Lab program no 6
Build KNN classification model for given dataset.

Python code

```
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
```

label-mapping

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

```
iris_data.head()
```

```
[[1, 5.1, 3.5, 1.4, 0.2], [2, 4.9, 3.0, 1.4, 0.2], [3, 4.7, 3.2, 1.3, 0.2], [4, 4.6, 3.1, 1.5, 0.2], [5, 5.0, 3.6, 1.4, 0.2]]
```

| | Id | Sepal length | Sepal width | Petal length | Petal width | 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 |

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

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

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```
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()

iris_data['species'].unique()
Output:
array([1, 2, 3], dtype=int64)

iris_data.drop('Id', inplace=True, axis=1)
X = iris_data.drop('species', axis=1)
y = iris_data['species']

X_train, X_test, y_train, y_test
= train_test_split(X, y, test_size=0.4, random_state=42)

knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
Output:
Accuracy: 0.983333
```

Week no-7

Implementation of ANN using back Propagation for given values.

(Code :

```
import numpy as np
```

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

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

```
x1 = x / np.amax(x, axis=0)
```

```
y1 = y / 100
```

variable initialization

```
epoch = 5000 # training iterations.
```

```
lr = 0.1 # learning rate
```

```
input_layer_neurons = 2 # input layer neurons
```

```
hidden_layer_neurons = 3 # hidden layer neurons
```

```
output_neurons = 1 # output layer neurons
```

weight and bias initialization

```
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 = 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)
```

```
for i in range(epoch):  
    hinp1 = np.dot(X, wh)  
    hinp = hinp1 + bh  
    hlayer_act = sigmoid(hinp)  
    outinp1 = np.dot(hlayer_act, wout)  
    outinp = outinp1 + bout  
    output = sigmoid(outinp)
```

$E_0 = y - \text{output}$

```
outgrad = derivatives_sigmoid(output)
```

```
d_output =  $E_0 * \text{outgrad}$ 
```

```
EH = d_output . dot(wout.T)
```

```
hiddengrad = derivatives_sigmoid(hlayer_act)
```

```
d_hiddenlayer = EH * hiddengrad
```

```
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 " + str(output))
```

X Output:

Input:

```
[0.666667, 0.333333, 0.555556,  
 1.0, 0.666667]]
```

Actual Output:

 $[0.92]$ $[0.86]$ $[0.89]$

NP output

Predicted output

 $[0.8855471]$ $[0.88108002]$ $[0.88579557]$ $[0.8855471]$ $[0.88108002]$ $[0.88579557]$ $[0.8855471]$ $[0.88108002]$ $[0.88579557]$ $[0.8855471]$ $[0.88108002]$ $[0.88579557]$ $[0.8855471]$ $[0.88108002]$ $[0.88579557]$ $[0.8855471]$ $[0.88108002]$ $[0.88579557]$ $[0.8855471]$ $[0.88108002]$ $[0.88579557]$ $[0.8855471]$ $[0.88108002]$ $[0.88579557]$ $[0.8855471]$ $[0.88108002]$ $[0.88579557]$

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Program - 9a

```
from sklearn.ensemble import RandomForestClassifier  
import pandas as pd  
from sklearn.metrics import accuracy_score  
  
df = pd.read_csv("melb-data.csv")  
melbourne_data = df.dropna(axis=0)  
y = melbourne_data.Price  
melbourne_features = ['Rooms', 'Bathroom',  
                      'Landsize', 'BuildingArea',  
                      'YearBuilt', 'Latitude',  
                      'Longitude']  
X = melbourne_data[melbourne_features]
```

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

Output:

```
RandomForestClassifier()
```

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

```
accuracy = accuracy_score(y_predicted, y_test)  
print(accuracy)
```

Output:

```
0.9935483870967742
```

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k means Clustering Algorithm

implementation 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)
```

Output

```
KMeans
KMeans(n_clusters=3)
```

```
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)
plt.title('K-Means Clustering')
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-1], s=40)
plt.title('K-means clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal width')
```

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PCA visualization:

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

```
scaler = StandardScaler()
scaler.fit(df)
```

Output:

```
StandardScaler(copy=True, with_mean=True,
                with_std=True)
```

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

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

```
pca = PCA(n_components=2)
pca.fit(scaled_data)
```

Output:

```
PCA(copy=True, n_components=2, whiten=False)
```

```
x_pca = pca.transform(scaled_data)
```

scaled_data.shape

(569, 30)

x_pca.shape

(569, 2)

```
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')

Figure 1: First two principal components

Principal component = choose best

orthogonal basis

length

first vector from PCA (part) - first eigenvalue
of correlation matrix

second vector orthogonal to first

third vector orthogonal to first, second

fourth vector orthogonal to first, second, third

... etc. basis

length

first principal component = first eigenvector

second principal component = second eigenvector

import plt as plt

(x,y)

standardise x, y

PCA