CSE 4020 - MACHINE LEARNING

Lab 29+30

Random Forest

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Question:

Use random forest regression as part of ensemble learning to predict the amount of petrol consumption by studying different traits of a particular place.

Dataset Used:

petrol_consumption.csv

Procedure:

- -Using pandas, we first import the dataset into our workspace.
- -Next we define the set of dependent and independent attributes.
- We then import the random forest regressor from sklean rn.ensemble and train our model using the independent and dependent attributes.
- Next, we have printed the results of independent set as predicted by our regressor.
- Lastly, To check for the performance of our dataset, we have printed all the evaluation metrics

Since it has less Number of Rows we haven't split the dataset

Code Snippets and Explanation:

```
In [1]: #Importing Libraries
  import pandas as pd
  import numpy as np
  import matplotlib.pyplot as plt
```

Here we are importing the required Libraries

```
In [2]: #Importing the Dataset
    dataset = pd.read_csv("petrol_consumption.csv")
```

Using Pandas we are importing the data

```
In [3]: #First few rows of our dataset
          dataset.head(10)
Out[3]:
             Petrol_tax Average_income Paved_Highways Population_Driver_licence(%) Petrol_Consumption
                                   3571
                                                    1976
                                                                                0.525
                    9.0
                                   4092
                                                    1250
                                                                                0.572
                                                                                                      524
                                   3865
                                                                                0.580
                                    4870
                                                    2351
                                                                                0.529
                                                                                                      414
                    8.0
                                   4399
                                                     431
                                                                                0.544
                                                                                                      410
                   10.0
                                   5342
                                                    1333
                                                                                0.571
                                                                                                      457
                    8.0
                                   5319
                                                    11868
                                                                                0.451
                                                                                                      344
                                                                                0.553
                    8.0
                                   5126
                                                    2138
                                                                                                      467
                    8.0
                                   4447
                                                    8577
                                                                                0.529
                                                                                                      464
                    7.0
                                   4512
                                                    8507
                                                                                0.552
                                                                                                      498
```

Printing the first few rows.

```
In [4]:
        #Checcking for null values
        print(dataset.info())
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 48 entries, 0 to 47
        Data columns (total 5 columns):
             Column
                                            Non-Null Count
                                                            Dtype
             Petrol_tax
                                            48 non-null
                                                            float64
         0
         1
             Average_income
                                            48 non-null
                                                            int64
             Paved_Highways
                                            48 non-null
                                                            int64
             Population_Driver_licence(%) 48 non-null
                                                            float64
             Petrol_Consumption
                                            48 non-null
                                                            int64
        dtypes: float64(2), int64(3)
        memory usage: 2.0 KB
        None
```

```
In [5]: #Set of independent and dependent attributes
    X = dataset.iloc[:, 0:4].values
    y = dataset.iloc[:, -1].values

In [6]: #Training our Random Forest Regression Model
    from sklearn.ensemble import RandomForestRegressor
    regressor = RandomForestRegressor(n_estimators=200, random_state=0)
    regressor.fit(X, y)
Out[6]: RandomForestRegressor(n estimators=200, random state=0)
```

We have Defined set of Dependent and Independent attributes. The n_estimators here indicate the number of decision trees that we are using to train our random forest regressor. Hence we are using 200 decision trees for prediction. For final value we have used the average value of each decision tree to find the final consumption of petrol of a particular region.

```
In [7]: #Predictions by Regressor
y_pred = regressor.predict(X)

In [8]: #Printing Mean Absolute Error
from sklearn.metrics import mean_absolute_error
mean_absolute_error(y, y_pred)

Out[8]: 16.542083333333327
```

Printing the Mean Absolute Error

```
In [9]: #Printing Mean Absolute Error
from sklearn.metrics import mean_squared_error
mean_squared_error(y, y_pred)
Out[9]: 676.4954427083334
```

Printing the Mean Squared Error

```
In [10]: #Printing Root Mean Squared Error
np.sqrt(mean_squared_error(y, y_pred))
Out[10]: 26.00952599930136
```

Printing the Root Mean Squared Error

Printing the Root Mean Sqaured Log Error

```
In [12]: #Printing R-square value
    from sklearn.metrics import r2_score
    r2_score(y, y_pred)
Out[12]: 0.9448102799874128
```

Printing the R-square value

Results and Conclusions:

Mean Absolute Error from cell8 is 16.5420833333333327 Mean absolute error from cell 9 is 676.4954427083334 Root Mean Squared Error from cell10 is 26.00952599930136 Root Mean Squared Log Error from cell11 is 3.25846285550 7552

R-square value from cell12 is 0.9448102799874128