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TE COMPS A4

DWM
EXPERIMENT 3
LINEAR REGRESSION

AIM: Implementation of Linear Regression
1. Single Variate
2. Multi Variate

THEORY:
Linear Regression is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting. Different regression models differ based on – the kind of relationship between dependent and independent variables they are considering and the number of independent variables being used.
Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output). Hence, the name is Linear Regression.
In the figure above, X (input) is the work experience and Y (output) is the salary of a person. The regression line is the best fit line for our model.

Hypothesis function for Linear Regression :

$$y = \theta_1 + \theta_2 . x$$

While training the model we are given :
x: input training data (univariate – one input variable(parameter))
y: labels to data (supervised learning)
When training the model – it fits the best line to predict the value of y for a given value of x. The model gets the best regression fit line by finding the best θ1 and θ2 values.
θ1: intercept
θ2: coefficient of x

Once we find the best θ1 and θ2 values, we get the best fit line. So when we are finally using our model for prediction, it will predict the value of y for the input value of x.

Cost Function (J):

By achieving the best-fit regression line, the model aims to predict y value such that the error difference between predicted value and true value is minimum. So, it is very important to update the θ1 and θ2 values, to reach the best value that minimize the error between predicted y value (pred) and true y value (y).

$$minimize \frac{1}{n} \sum_{i=1}^{n} (pred_i - y_i)^2$$

$$J = \frac{1}{n} \sum_{i=1}^{n} (pred_i - y_i)^2$$

Cost function(J) of Linear Regression is the Root Mean Squared Error (RMSE) between predicted y value (pred) and true y value (y).

CODE:

```
import warnings
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plb
from sklearn.model_selection import train_test_split

sns.set()
warnings.simplefilter("ignore")

df = pd.read_csv("StudentsPerformance.csv")
df.head()

print(df.info())
```

```
df['final score'] = df.apply(lambda x : (x['math score'] + x['reading score'] + x['writing score'])
/ 3, axis=1)

df.head()
data2 = df.drop('final score', axis=1)
plt.figure(figsize=(16, 6))
sns.boxplot(data=data2)

df = df.apply(LabelEncoder().fit_transform)

# MULTIVARIATE

X = df.drop('final score', axis=1)
y = df['final score']
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.2)
lr = LinearRegression()
lr.fit(X_train, y_train)

pred = lr.predict(X_test)

lr.score(X_test, y_test)
accuracy = mean_squared_error(y_test, pred)
print('Mean Squared Error: ', accuracy)

# UNIVARIATE
sns.scatterplot(df["writing score"],df["final score"])
plt.savefig('scp-1', dpi=500)
m, b = np.polyfit(df["writing score"], df["final score"], 1)

plt.plot(df["writing score"], m*df["writing score"] + b)

X_uni = df['writing score']
y_uni = df['final score']
X_uni_train, X_uni_test, y_uni_train, y_uni_test = train_test_split(X_uni,y_uni,test_size = 0.2)

lr2 = LinearRegression()
X_uni_train = X_uni_train.reshape(-1,1)
X_uni_test = X_uni_test.values.reshape(-1,1)

lr2.fit(X_uni_train, y_uni_train)
pred_uni = lr2.predict(X_uni_test)
lr2.score(X_uni_test, y_uni_test)

accuracy_uni = mean_squared_error(y_uni_test, pred_uni)
print('Mean Squared Error: ', accuracy_uni)
```

OUTPUT:

```
head() of the database:
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score
0	female	group B	bachelor's degree	standard	none	72	72	74
1	female	group C	some college	standard	completed	69	90	88
2	female	group B	master's degree	standard	none	90	95	93
3	male	group A	associate's degree	free/reduced	none	47	57	44
4	male	group C	some college	standard	none	76	78	75

```
After running df.info()
```

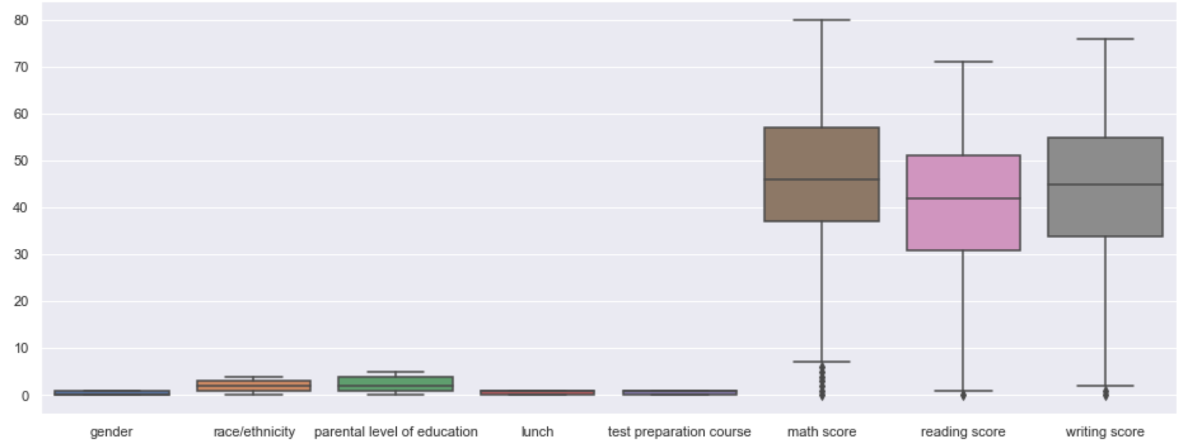
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   gender                       1000 non-null   object
 1   race/ethnicity               1000 non-null   object
 2   parental level of education  1000 non-null   object
 3   lunch                        1000 non-null   object
 4   test preparation course      1000 non-null   object
 5   math score                   1000 non-null   int64 
 6   reading score                1000 non-null   int64 
 7   writing score                1000 non-null   int64 
dtypes: int64(3), object(5)
memory usage: 62.6+ KB
None
```

```
df.head() after adding a final score column
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score	final score
0	female	group B	bachelor's degree	standard	none	72	72	74	72.666667
1	female	group C	some college	standard	completed	69	90	88	82.333333
2	female	group B	master's degree	standard	none	90	95	93	92.666667
3	male	group A	associate's degree	free/reduced	none	47	57	44	49.333333
4	male	group C	some college	standard	none	76	78	75	76.333333

```
Boxplot of the features
```

<AxesSubplot:>




```
df.head() after applying LabelEncoder to the dataset
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score	final score
0	0	1	1	1	1	52	44	50	118
1	0	2	4	1	0	49	62	64	147
2	0	1	3	1	1	70	67	69	178
3	1	0	0	0	1	27	29	20	48
4	1	2	4	1	1	56	50	51	129

```
df.info() after applying LabelEncoder to the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   gender                       1000 non-null   int64
 1   race/ethnicity               1000 non-null   int64
 2   parental level of education  1000 non-null   int64
 3   lunch                        1000 non-null   int64
 4   test preparation course      1000 non-null   int64
 5   math score                   1000 non-null   int64
 6   reading score                1000 non-null   int64
 7   writing score                1000 non-null   int64
 8   final score                  1000 non-null   int64
dtypes: int64(9)
memory usage: 70.4 KB
None
```

Considering Multivariate Linear Regression

```
Prediction Score of MultiVariate Linear Regression
```

```
lr.score(X_test, y_test)

0.9992194766540022
```

```
Mean Square Error of MultiVariate Linear Regression
```

```
print('Mean Squared Error: ', accuracy)

Mean Squared Error:  1.692171227952071
```

Now considering Univariate Linear Regression with Writing Score as the feature

```
Scatter Plot of the dataset
```

```
[<matplotlib.lines.Line2D at 0x2119c6f7e20>]
```


```
Prediction Score of Univariate LR
```

```
lr2.score(X_uni_test, y_uni_test)
```

```
0.9421228773316737
```

```
Mean Square Error of Univariate LR
```

```
accuracy_uni = mean_squared_error(y_uni_test, pred_uni)
print('Mean Squared Error: ', accuracy_uni)
```

```
Mean Squared Error:  109.48409107917793
```

CONCLUSION: We have implemented Multivariate and Univariate Linear Regression on a dataset and have observed the differences in their Accuracy Score and Mean Squared Errors. We observe 99.92% accuracy in the case of Multivariate with a Mean Squared Error of 1.62 whereas in the case of Univariate, the accuracy score is 94.21% and the Mean Squared Error is 109.48. Therefore we can conclude that using Multivariate Linear Regression is better than using Univariate but nevertheless the efficiency of Univariate is still great.
