Sardar Patel Institute of Technology, Mumbai
Department of Electronics and Telecommunication Engineering
B.E. Sem-VII

Experiment : Linear Regression

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Objective: Building Linear Regression model for given dataset..
Platform : Google Colab

Data Set Link: https://www.kaggle.com/datasets/econdata/climate-change

Code and ouput:

```
import pandas as pd
import numpy as np
import seaborn as sns

data=pd.read_csv('/content/climate_change.csv')
data_train=data[data.Year<=2006]
data_test=data[data.Year>2006]

data.head()
```

	Year	Month	MEI	CO2	CH4	N2O	CFC-11	CFC-12	TSI	Aerosols	Temp
0	1983	5	2.556	345.96	1638.59	303.677	191.324	350.113	1366.1024	0.0863	0.109
1	1983	6	2.167	345.52	1633.71	303.746	192.057	351.848	1366.1208	0.0794	0.118
2	1983	7	1.741	344.15	1633.22	303.795	192.818	353.725	1366.2850	0.0731	0.137
3	1983	8	1.130	342.25	1631.35	303.839	193.602	355.633	1366.4202	0.0673	0.176
4	1983	9	0.428	340.17	1648.40	303.901	194.392	357.465	1366.2335	0.0619	0.149

```
data=data.drop(['Year','Month'],axis=1)
data_train=data_train.drop(['Year','Month'],axis=1)
data_test=data_test.drop(['Year','Month'],axis=1)
```

The above parameter splits the data and test data.

```
data.describe()
```

	MEI	CO2	CH4	N2O	CFC-11	CFC-12	TSI	Aerosols	Temp
count	308.000000	308.000000	308.000000	308.000000	308.000000	308.000000	308.000000	308.000000	308.000000
mean	0.275555	363.226753	1749.824513	312.391834	251.973068	497.524782	1366.070759	0.016657	0.256776
std	0.937918	12.647125	46.051678	5.225131	20.231783	57.826899	0.399610	0.029050	0.179090
min	-1.635000	340.170000	1629.890000	303.677000	191.324000	350.113000	1365.426100	0.001600	-0.282000
25%	-0.398750	353.020000	1722.182500	308.111500	246.295500	472.410750	1365.717050	0.002800	0.121750
50%	0.237500	361.735000	1764.040000	311.507000	258.344000	528.356000	1365.980900	0.005750	0.248000
75%	0.830500	373.455000	1786.885000	316.979000	267.031000	540.524250	1366.363250	0.012600	0.407250
max	3.001000	388.500000	1814.180000	322.182000	271.494000	543.813000	1367.316200	0.149400	0.739000

data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 308 entries, 0 to 307
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   MEI       308 non-null    float64
 1   CO2       308 non-null    float64
 2   CH4       308 non-null    float64
 3   N2O       308 non-null    float64
 4   CFC-11    308 non-null    float64
 5   CFC-12    308 non-null    float64
 6   TSI       308 non-null    float64
 7   Aerosols  308 non-null    float64
 8   Temp      308 non-null    float64
dtypes: float64(9)
memory usage: 21.8 KB
```

data.nunique()

```
MEI         294
CO2         298
CH4         303
N2O         304
CFC-11      307
CFC-12      307
TSI         302
Aerosols    155
Temp        242
dtype: int64
```

data.isnull().sum()

```
MEI          0
CO2          0
CH4          0
N2O          0
CFC-11       0
CFC-12       0
TSI          0
Aerosols     0
Temp         0
dtype: int64
```

Regression:

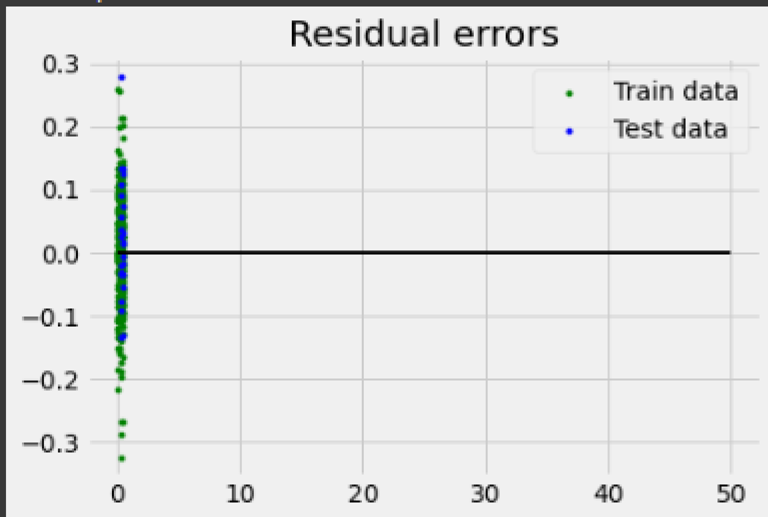
```
from sklearn import datasets, linear_model, metrics

import matplotlib.pyplot as plt
import numpy as np
from sklearn import datasets, linear_model, metrics
from sklearn.metrics import mean_squared_error

# load the boston dataset
# defining feature matrix(X) and response vector(y)

X_train = pd.DataFrame(data_train, columns=['MEI','CO2', 'CH4', 'N2O',
'CFC-11','CFC-12','TSI','Aerosols'])
y_train=data_train['Temp']
X_test = pd.DataFrame(data_test, columns=['MEI','CO2', 'CH4', 'N2O',
'CFC-11','CFC-12','TSI','Aerosols'])
y_test=data_test['Temp']
```

Linear regression model using Sk learn to predict the data

```
# create linear regression object
reg = linear_model.LinearRegression()

# train the model using the training sets
reg.fit(X_train, y_train)

# regression coefficients
print('Coefficients: ', reg.coef_)

# variance score: 1 means perfect prediction
print('Variance score: {}'.format(reg.score(X_train, y_train)))
```

```
y_pred = reg.predict(X_test)
errors = mean_squared_error(y_test,y_pred)
print("Mean Squared error: ",errors)

# plot for residual error

## setting plot style
plt.style.use('fivethirtyeight')

## plotting residual errors in training data
plt.scatter(reg.predict(X_train), reg.predict(X_train) - y_train,
            color = "green", s = 10, label = 'Train data')

## plotting residual errors in test data
plt.scatter(reg.predict(X_test), reg.predict(X_test) - y_test,
            color = "blue", s = 10, label = 'Test data')

## plotting line for zero residual error
plt.hlines(y = 0, xmin = 0, xmax = 50, linewidth = 2)

## plotting legend
plt.legend(loc = 'upper right')

## plot title
plt.title("Residual errors")

## method call for showing the plot
plt.show()
```

```
Coefficients:  [ 6.42053134e-02  6.45735927e-03  1.24041896e-04 -1.65280033e-02
 -6.63048889e-03  3.80810324e-03  9.31410835e-02 -1.53761324e+00]
Variance score: 0.7508932770523429
Mean Squared error:  0.009097810529180444
```



Problem 1.1 - Creating Our First Model

We are interested in how changes in these variables affect future temperatures, as well as how
well these variables explain temperature changes so far. To do this, first read the dataset climate_change.csv into Python.
Then, split the data into a training set, consisting of all the observations up to and including 2006, and a testing set consisting of the remaining years (hint: use subset). A training set refers
to the data that will be used to build the model, and a testing set refers to the data we will use to
test our predictive ability.
Next, build a linear regression model to predict the dependent variable Temp, using MEI, CO2,
CH4, N2O, CFC.11, CFC.12, TSI, and Aerosols as independent variables (Year and Month should NOT be used in the model). Use the training set to build the model.
Enter the model R2 (the "Multiple R-squared" value):

Answer:

The above output shows the coefficients and the error plot for the data.
The variance score [R2 value] is 0.7508
Mean squared error : 0.0909

Part 2:

```
import statsmodels.api as sm
# If p-value < 0.05 -->Significant
# If p-value > 0.05 -->Not Significant

x_incl_cons = sm.add_constant(X_train)
model = sm.OLS(y_train, x_incl_cons)  #ordinary least square
results = model.fit()  #regresssion results
# results.params
# results.pvalues
pd.DataFrame({'coef': results.params , 'pvalue': round(results.pvalues,3)})
```

	coef	pvalue
const	-124.594260	0.000
MEI	0.064205	0.000
CO2	0.006457	0.005
CH4	0.000124	0.810
N2O	-0.016528	0.055
CFC-11	-0.006630	0.000
CFC-12	0.003808	0.000
TSI	0.093141	0.000
Aerosols	-1.537613	0.000

Problem 1.2 - Creating Our First Model

Which variables are significant in the model? We will consider a variable signficant only if the p-value is below 0.05. (Select all that apply.)
a) MEI b) CO2 c) CH4 d) N2O e) CFC.11 f) CFC.12 g) TSI h) Aerosols

The p values for CH4 and N2O are greater than 0.05 hence indicating that these attributes are insignificant.
The sample size taken is the entire training sample.
P value for CH4 = 0.810
P value for N2O = 0.055
Hence,
a) MEI b) CO2 e) CFC.11 f) CFC.12 g) TSI h) Aerosols are significant

X_train.corr()

	MEI	CO2	CH4	N2O	CFC-11	CFC-12	TSI	Aerosols
MEI	1.000000	-0.041147	-0.033419	-0.050820	0.069000	0.008286	-0.154492	0.340238
CO2	-0.041147	1.000000	0.877280	0.976720	0.514060	0.852690	0.177429	-0.356155
CH4	-0.033419	0.877280	1.000000	0.899839	0.779904	0.963616	0.245528	-0.267809
N2O	-0.050820	0.976720	0.899839	1.000000	0.522477	0.867931	0.199757	-0.337055
CFC-11	0.069000	0.514060	0.779904	0.522477	1.000000	0.868985	0.272046	-0.043921
CFC-12	0.008286	0.852690	0.963616	0.867931	0.868985	1.000000	0.255303	-0.225131
TSI	-0.154492	0.177429	0.245528	0.199757	0.272046	0.255303	1.000000	0.052117
Aerosols	0.340238	-0.356155	-0.267809	-0.337055	-0.043921	-0.225131	0.052117	1.000000

The above matrix shows the correlation between different features with each other and with themselves.

Problem 2.1 - Understanding the Model

Current scientific opinion is that nitrous oxide and CFC-11 are greenhouse gases: gases that are able to trap heat from the sun and contribute to the heating of the Earth. However, the regression coefficients of both the N2O and CFC-11 variables are negative, indicating that increasing atmospheric concentrations of either of these two compounds is associated with lower global temperatures.

The possible explanations for the above statement are:

1. Climate scientists are wrong that N2O and CFC-11 are greenhouse gases - this regression analysis constitutes part of a disproof.

The above statement can be rejected since the data was fit using the model and the coefficients of each of the N2O and CH4 are found to be negative supporting the given argument.

2. There is not enough data, so the regression coefficients being estimated are not accurate

The above statement can be rejected given the model accuracy and the dataset used. The accuracy is quite high and the dataset used is large enough to support the argument.

3. .All of the gas concentration variables reflect human development - N2O and CFC.11 are correlated with other variables in the data set.

The above statement is true since the correlation matrix shows N2O and CFC 11 are highly correlated with the other features of the dataset since the coefficient values are quite high.

Inference:

1. The data shows good accuracy when predicted with a linear regression model.

2. The model shows the p values of each attribute thus indicating the significance of those attributes.
3. According to the P values, the gases CH4 and N2O have high p values indicating their insignificance.
4. Thus these attributes can be dropped for further analysis.
5. The reason N2O and CFC 11 have negative values and the temperatures rise, is because the two attributes are highly correlated with other variables. Thus, due to the effect of other gases the temperatures rise eventually.