2019120006_DA_4

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1 Experiment 4: Linear Regression

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Class: BE EXTC Dataset Description: Given dataset is a climate change dataset which contains the yearly data of the amount of various gases and substances in the air and the temperature. Our task is to find out the correlation of all variables and build a linear regression model.

[ ]:
```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score
```

[ ]:
```
def get_corr_coef(data, col):
  for i in data.columns:
    if(i != col):
      r = np.corrcoef(data[col], data[i])
      print("The correlation coefficient of {} and {} is {}".format(col, i,␣
↪r[1][0]))
```

Custom function to calculate and print correlation coefficients of a variable with all other variables in a dataframe.

[ ]:
```
data = pd.read_csv("climate_change.csv")
data.head()
```

[ ]:
```
   Year  Month    MEI     CO2      CH4      N2O   CFC-11   CFC-12        TSI  \
0  1983      5  2.556  345.96  1638.59  303.677  191.324  350.113  1366.1024
1  1983      6  2.167  345.52  1633.71  303.746  192.057  351.848  1366.1208
2  1983      7  1.741  344.15  1633.22  303.795  192.818  353.725  1366.2850
3  1983      8  1.130  342.25  1631.35  303.839  193.602  355.633  1366.4202
4  1983      9  0.428  340.17  1648.40  303.901  194.392  357.465  1366.2335

   Aerosols   Temp
0    0.0863  0.109
```

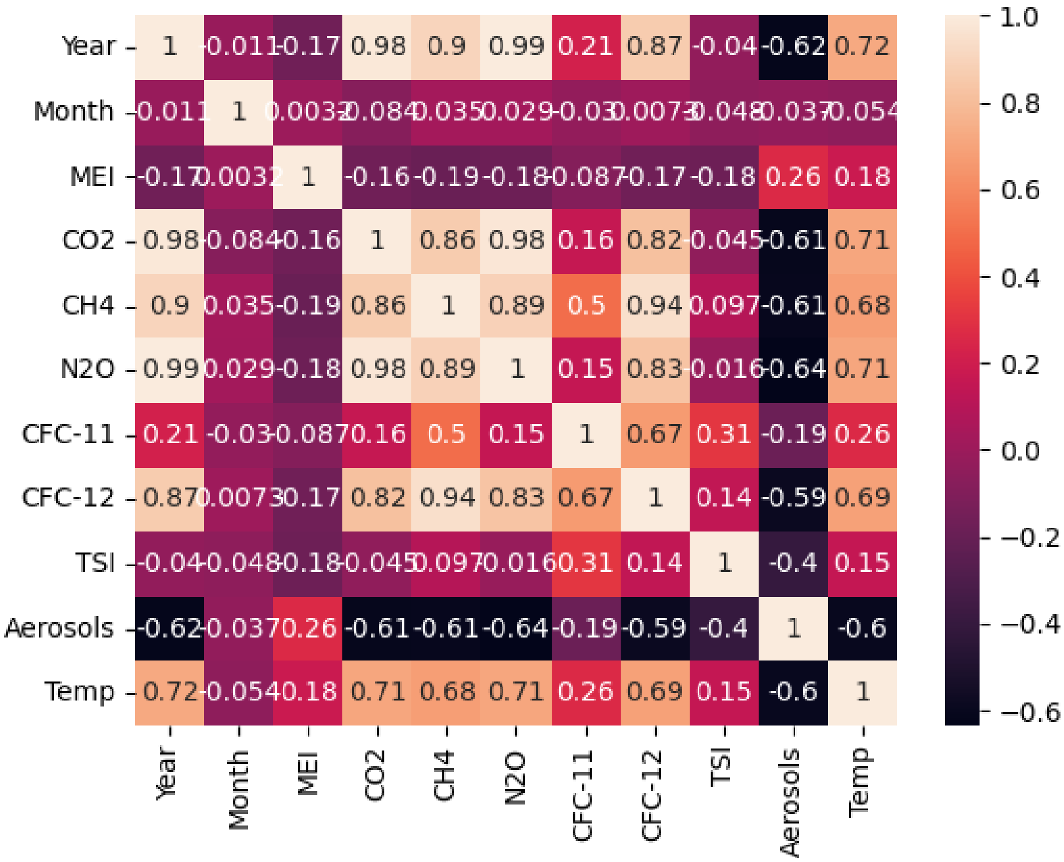
```
1     0.0794   0.118
2     0.0731   0.137
3     0.0673   0.176
4     0.0619   0.149
```

Importing the dataset and understanding the variables present.

1.0.1 Data Preprocessing

[ ]:
```python
#finding inter quartile range to remove outliers
Q1 = data.quantile(0.25)
Q3 = data.quantile(0.75)
IQR = Q3 - Q1
data = data[~((data < (Q1 - 1.5 * IQR)) |(data > (Q3 + 1.5 * IQR))).any(axis=1)]
```

[ ]:
```python
sns.heatmap(data.corr(), annot=True);
```



The heatmap shows that CO2, CH4, N2O and CFC-12 are highly correlated with temperature.

[ ]:
```python
data.columns
```

[ ]: Index(['Year', 'Month', 'MEI', 'CO2', 'CH4', 'N2O', 'CFC-11', 'CFC-12', 'TSI',
       'Aerosols', 'Temp'],
      dtype='object')

[ ]:
```python
import statsmodels.api as sm
x = data[['MEI', 'CO2', 'CH4', 'N2O', 'CFC-11', 'CFC-12', 'TSI',
       'Aerosols']]
y = data[['Temp']]
X2 = sm.add_constant(x)
est = sm.OLS(y, X2)
est2 = est.fit()
print(est2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   Temp   R-squared:                       0.703
Model:                            OLS   Adj. R-squared:                  0.692
Method:                 Least Squares   F-statistic:                     69.11
Date:                Sat, 19 Nov 2022   Prob (F-statistic):           2.36e-57
Time:                        16:20:30   Log-Likelihood:                 251.36
No. Observations:                 243   AIC:                            -484.7
Df Residuals:                     234   BIC:                            -453.3
Df Model:                           8
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        -60.8378     23.736     -2.563      0.011    -107.600     -14.075
MEI            0.0665      0.007      9.650      0.000       0.053       0.080
CO2            0.0033      0.002      1.389      0.166      -0.001       0.008
CH4           -0.0005      0.001     -0.895      0.372      -0.002       0.001
N2O           -0.0033      0.010     -0.319      0.750      -0.023       0.017
CFC-11        -0.0032      0.002     -1.319      0.188      -0.008       0.002
CFC-12         0.0027      0.001      2.173      0.031       0.000       0.005
TSI            0.0449      0.018      2.532      0.012       0.010       0.080
Aerosols      -8.2339      2.042     -4.032      0.000     -12.257      -4.211
==============================================================================
Omnibus:                        3.269   Durbin-Watson:                   1.015
Prob(Omnibus):                  0.195   Jarque-Bera (JB):                2.996
Skew:                           0.194   Prob(JB):                        0.224
Kurtosis:                       3.381   Cond. No.                     9.94e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 9.94e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Attributes with p-values less than 0.05 are MEI, CFC-12, TSI and Aerosols.

[ ]:
```
train_data = data[data.iloc[:,0]<=2006]
train_data.head()
```

[ ]:
```
    Year  Month    MEI     CO2      CH4      N2O   CFC-11   CFC-12        TSI  \
29  1985     10 -0.140  343.08  1681.56  305.395  215.327  390.676  1365.5269
30  1985     11 -0.050  344.40  1680.68  305.530  216.282  392.714  1365.6289
31  1985     12 -0.293  345.82  1677.99  305.653  217.326  394.539  1365.6794
32  1986      1 -0.307  346.54  1675.82  305.775  218.382  396.082  1365.6746
33  1986      2 -0.191  347.13  1666.83  305.911  219.379  397.345  1365.5475

    Aerosols   Temp
29    0.0101 -0.008
30    0.0097 -0.093
31    0.0122 -0.002
32    0.0146  0.121
33    0.0158  0.065
```

Creating a training data dataframe by selecting data upto 2006.

[ ]:
```
test_data = data[data.iloc[:,0]>2006]
test_data.head()
```

[ ]:
```
     Year  Month    MEI     CO2      CH4      N2O   CFC-11   CFC-12  \
284  2007      1  0.974  382.93  1799.66  320.561  248.372  539.206
285  2007      2  0.510  383.81  1803.08  320.571  248.264  538.973
286  2007      3  0.074  384.56  1803.10  320.548  247.997  538.811
287  2007      4 -0.049  386.40  1802.11  320.518  247.574  538.586
288  2007      5  0.183  386.58  1795.65  320.445  247.224  538.130

           TSI  Aerosols   Temp
284  1365.7173    0.0054  0.601
285  1365.7145    0.0051  0.498
286  1365.7544    0.0045  0.435
287  1365.7228    0.0045  0.466
288  1365.6932    0.0041  0.372
```

Creating a testing data dataframe by selecting data after 2006.

[ ]:
```
x = data[['MEI', 'CO2', 'CH4', 'N2O', 'CFC-11', 'CFC-12', 'TSI', 'Aerosols']]
y = data['Temp']
```

[ ]:
```
x_train = train_data[['MEI','CO2', 'CH4', 'N2O', 'CFC-11', 'CFC-12', 'TSI',␣
 ↪'Aerosols']]
y_train = train_data['Temp']
x_test = test_data[['MEI', 'CO2', 'CH4', 'N2O', 'CFC-11',  'CFC-12', 'TSI',␣
 ↪'Aerosols']]
y_test = test_data['Temp']
```

Separating the variables and target into two dataframes.

```
[ ]: X2_train = sm.add_constant(x_train)
     est_train = sm.OLS(y_train, X2_train)
     est2 = est_train.fit()
     print(est2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   Temp   R-squared:                       0.722
Model:                            OLS   Adj. R-squared:                  0.711
Method:                 Least Squares   F-statistic:                     68.15
Date:                Sat, 19 Nov 2022   Prob (F-statistic):           3.37e-54
Time:                        16:20:30   Log-Likelihood:                 229.49
No. Observations:                 219   AIC:                            -441.0
Df Residuals:                     210   BIC:                            -410.5
Df Model:                           8
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        -51.0320     24.469     -2.086      0.038     -99.268      -2.796
MEI            0.0622      0.007      8.508      0.000       0.048       0.077
CO2            0.0050      0.002      1.995      0.047    5.82e-05       0.010
CH4           -0.0004      0.001     -0.689      0.491      -0.001       0.001
N2O            0.0018      0.012      0.156      0.876      -0.021       0.025
CFC-11        -0.0011      0.003     -0.406      0.685      -0.007       0.004
CFC-12         0.0014      0.001      0.940      0.348      -0.002       0.004
TSI            0.0360      0.019      1.931      0.055      -0.001       0.073
Aerosols      -8.4359      2.024     -4.167      0.000     -12.427      -4.445
==============================================================================
Omnibus:                        6.330   Durbin-Watson:                   0.994
Prob(Omnibus):                  0.042   Jarque-Bera (JB):                6.027
Skew:                           0.363   Prob(JB):                       0.0491
Kurtosis:                       3.366   Cond. No.                     9.82e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 9.82e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
[ ]: from sklearn.linear_model import LinearRegression
     clf = LinearRegression()
     clf.fit(x_train, y_train)
```

```
[ ]: LinearRegression()
```

Creating a Linear Regression model using the Scikit-Learn API

[ ]:
```
print("Intercept: ", clf.intercept_)
print("Coefficients:")
list(zip(x_train, clf.coef_))
```

```
Intercept:  -51.03196915985813
Coefficients:
```

[ ]:
```
[('MEI', 0.0622356977730238),
 ('CO2', 0.004960698794040838),
 ('CH4', -0.0003881072780236086),
 ('N2O', 0.001826241931154713),
 ('CFC-11', -0.001134499328455555),
 ('CFC-12', 0.00140132770320733),
 ('TSI', 0.03604734063953123),
 ('Aerosols', -8.435947559286046)]
```

Printing the y-intercept of the best fit line and the regression coefficients of all variables.

[ ]:
```
y_pred= clf.predict(x_test)
print("Prediction for test set: {}".format(y_pred))
```

```
Prediction for test set: [0.47395865 0.4503635  0.43347525 0.43430288 0.45407379
0.42558192
 0.4256269  0.40086034 0.34299562 0.34452906 0.34506256 0.3546125
 0.37297068 0.35481019 0.34472978 0.3962589  0.43969896 0.46681556
 0.45350739 0.42400764 0.38408517 0.36584435 0.38171572 0.3874683 ]
```

Printing the predictions from the model.

[ ]:
```
clf_diff = pd.DataFrame({'Actual value': y_test, 'Predicted value': y_pred})
clf_diff.head()
```

[ ]:

	Actual value	Predicted value
284	0.601	0.473959
285	0.498	0.450364
286	0.435	0.433475
287	0.466	0.434303
288	0.372	0.454074

Creating a dataframe with the actual and predicted values and displaying them.

[ ]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
meanAbErr = mean_absolute_error(y_test, y_pred)
meanSqErr = mean_squared_error(y_test, y_pred)
rootMeanSqErr = np.sqrt(meanSqErr)
print('R squared: {:.2f}'.format(clf.score(x,y)*100))
print('Mean Absolute Error:', meanAbErr)
print('Mean Square Error:', meanSqErr)
```

```python
print('Root Mean Square Error:', rootMeanSqErr)
```

```
R squared: 69.69
Mean Absolute Error: 0.0788135826026659
Mean Square Error: 0.010625956456136834
Root Mean Square Error: 0.10308228002977443
```

[ ]:
```python
get_corr_coef(data= train_data, col='N2O')
```

```
The correlation coefficient of N2O and Year is 0.9929762349866345
The correlation coefficient of N2O and Month is 0.031195858034826104
The correlation coefficient of N2O and MEI is -0.06177124908370094
The correlation coefficient of N2O and CO2 is 0.9749926361365616
The correlation coefficient of N2O and CH4 is 0.8903124993701754
The correlation coefficient of N2O and CFC-11 is 0.32738915672104657
The correlation coefficient of N2O and CFC-12 is 0.8645200386566593
The correlation coefficient of N2O and TSI is 0.15958759016062257
The correlation coefficient of N2O and Aerosols is -0.6609381809526802
The correlation coefficient of N2O and Temp is 0.7707514627632467
```

Printing correlation coefficient of N2O with all other variables.

[ ]:
```python
get_corr_coef(data= train_data, col='CFC-11')
```

```
The correlation coefficient of CFC-11 and Year is 0.39066011285143837
The correlation coefficient of CFC-11 and Month is -0.027567549452848228
The correlation coefficient of CFC-11 and MEI is -0.16610201966431876
The correlation coefficient of CFC-11 and CO2 is 0.3415448214852587
The correlation coefficient of CFC-11 and CH4 is 0.6279137878980163
The correlation coefficient of CFC-11 and N2O is 0.32738915672104657
The correlation coefficient of CFC-11 and CFC-12 is 0.7493680735584558
The correlation coefficient of CFC-11 and TSI is 0.2571940874708529
The correlation coefficient of CFC-11 and Aerosols is -0.23054354377641412
The correlation coefficient of CFC-11 and Temp is 0.3095061888348851
```

Printing correlation coefficient of CFC-11 with all other variables.

1.0.2 Training the model with N2O, MEI, TSI and Aerosols only

[ ]:
```python
x_train_1 = train_data[['MEI', 'N2O', 'TSI', 'Aerosols']]
y_train_1 = train_data['Temp']
x_test_1 = test_data[['MEI', 'N2O', 'TSI', 'Aerosols']]
y_test_1 = test_data['Temp']
x_1 = data[['MEI', 'N2O', 'TSI', 'Aerosols']]
y_1 = data[['Temp']]
```

[ ]:
```python
X2_train_1 = sm.add_constant(x_train_1)
est_train_1 = sm.OLS(y_train_1, X2_train_1)
est2_1 = est_train_1.fit()
print(est2_1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   Temp   R-squared:                       0.706
Model:                            OLS   Adj. R-squared:                  0.701
Method:                 Least Squares   F-statistic:                     128.7
Date:                Sat, 19 Nov 2022   Prob (F-statistic):           8.92e-56
Time:                        16:20:31   Log-Likelihood:                 223.51
No. Observations:                 219   AIC:                            -437.0
Df Residuals:                     214   BIC:                            -420.1
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        -53.1366     23.146     -2.296      0.023     -98.759      -7.514
MEI            0.0606      0.007      8.212      0.000       0.046       0.075
N2O            0.0217      0.002     12.113      0.000       0.018       0.025
TSI            0.0342      0.017      2.028      0.044       0.001       0.067
Aerosols      -8.3714      1.995     -4.197      0.000     -12.303      -4.439
==============================================================================
Omnibus:                        9.543   Durbin-Watson:                   0.940
Prob(Omnibus):                  0.008   Jarque-Bera (JB):               10.250
Skew:                           0.407   Prob(JB):                      0.00595
Kurtosis:                       3.678   Cond. No.                     5.45e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.45e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[ ]:
```
clf = LinearRegression()
clf.fit(x_train_1, y_train_1)
```

[ ]:
```
LinearRegression()
```

[ ]:
```
print("Intercept: ", clf.intercept_)
print("Coefficients:")
list(zip(x_1, clf.coef_))
```

```
Intercept:  -53.13657186298022
Coefficients:
```

[ ]:
```
[('MEI', 0.0605710056491394),
 ('N2O', 0.02174196466857027),
 ('TSI', 0.03415981688806211),
 ('Aerosols', -8.37144911641541)]
```

[ ]:
```
y_pred_1= clf.predict(x_test_1)
print("Prediction for test set: {}".format(y_pred_1))
```

```
Prediction for test set: [0.4994973  0.47402556 0.45350238 0.44432044 0.4591232
0.42707112
 0.4311838  0.42411848 0.38135484 0.38933851 0.38846345 0.39489663
 0.4093001  0.38835418 0.3726421  0.41817244 0.45693594 0.48525866
 0.47434819 0.45574824 0.43001199 0.42539002 0.43910982 0.44125798]
```

[ ]:
```
clf_diff_1 = pd.DataFrame({'Actual value': y_test_1, 'Predicted value':␣
 ↪y_pred_1})
clf_diff_1.head()
```

[ ]:

	Actual value	Predicted value
284	0.601	0.499497
285	0.498	0.474026
286	0.435	0.453502
287	0.466	0.444320
288	0.372	0.459123

[ ]:
```
meanAbErr = mean_absolute_error(y_test_1, y_pred_1)
meanSqErr = mean_squared_error(y_test_1, y_pred_1)
rootMeanSqErr = np.sqrt(meanSqErr)
print('R squared: {:.2f}'.format(clf.score(x_1,y_1)*100))
print('Mean Absolute Error:', meanAbErr)
print('Mean Square Error:', meanSqErr)
print('Root Mean Square Error:', rootMeanSqErr)
```

```
R squared: 67.00
Mean Absolute Error: 0.09020686837753299
Mean Square Error: 0.01371761845998247
Root Mean Square Error: 0.1171222372565623
```

The R2 value obtained is reduced to 67 from the previously obtained 69.69.

1.0.3 Conclusion:

1. Variables with p-value less than 0.05 are MEI, CFC-12, TSI and Aerosols.
2. R2 score for the model with all variables is 69.69.
3. N2O is correlated with CO2, CH4 and CFC-12 as their respective correlation coefficients are above 0.7.
4. CFC-11 is correlated with CFC-12 as their correlation coefficient is above 0.7.

Statements 4 and 5 justify statement III from the lab document.

5. In the model with only MEI, N2O, TSI and Aerosols:
    - Regression coefficient of N2O is 0.0217 as compared to 0.0018 in the previous model. This indicates the increased influence of N2O on this model.
    - The R2 score for this model is 67, a decrease from the previous model.