Stage B Project

June 13, 2023

1 Machine Learning: Regression - Predicting Energy Efficiency of Buildings

1.1 Stage B Project(Tag-Along Codes for the Graded Assessment)

By Raqib. Check my GitHub repo for more of my projects.

[1]:
```
# import libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style='white')

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import  LinearRegression, Ridge, Lasso
from sklearn.metrics import  mean_absolute_error, mean_squared_error, r2_score

import statsmodels.api as sm
```

[2]:
```
# read csv file
df = pd.read_csv('energydata_complete.csv')
df.head()
```

[2]:

	date	Appliances	lights	T1	RH_1	T2	RH_2	\
0	2016-01-11 17:00:00	60	30	19.89	47.596667	19.2	44.790000	
1	2016-01-11 17:10:00	60	30	19.89	46.693333	19.2	44.722500	
2	2016-01-11 17:20:00	50	30	19.89	46.300000	19.2	44.626667	
3	2016-01-11 17:30:00	50	40	19.89	46.066667	19.2	44.590000	
4	2016-01-11 17:40:00	60	40	19.89	46.333333	19.2	44.530000	

	T3	RH_3	T4	…	T9	RH_9	T_out	Press_mm_hg	\
0	19.79	44.730000	19.000000	…	17.033333	45.53	6.600000	733.5	
1	19.79	44.790000	19.000000	…	17.066667	45.56	6.483333	733.6	
2	19.79	44.933333	18.926667	…	17.000000	45.50	6.366667	733.7	
3	19.79	45.000000	18.890000	…	17.000000	45.40	6.250000	733.8	

```
4  19.79  45.000000  18.890000  …  17.000000  45.40  6.133333        733.9

   RH_out  Windspeed  Visibility  Tdewpoint        rv1        rv2
0    92.0   7.000000   63.000000        5.3  13.275433  13.275433
1    92.0   6.666667   59.166667        5.2  18.606195  18.606195
2    92.0   6.333333   55.333333        5.1  28.642668  28.642668
3    92.0   6.000000   51.500000        5.0  45.410389  45.410389
4    92.0   5.666667   47.666667        4.9  10.084097  10.084097

[5 rows x 29 columns]
```

[3]:
```
# summary of dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19735 entries, 0 to 19734
Data columns (total 29 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   date         19735 non-null  object
 1   Appliances   19735 non-null  int64
 2   lights       19735 non-null  int64
 3   T1           19735 non-null  float64
 4   RH_1         19735 non-null  float64
 5   T2           19735 non-null  float64
 6   RH_2         19735 non-null  float64
 7   T3           19735 non-null  float64
 8   RH_3         19735 non-null  float64
 9   T4           19735 non-null  float64
 10  RH_4         19735 non-null  float64
 11  T5           19735 non-null  float64
 12  RH_5         19735 non-null  float64
 13  T6           19735 non-null  float64
 14  RH_6         19735 non-null  float64
 15  T7           19735 non-null  float64
 16  RH_7         19735 non-null  float64
 17  T8           19735 non-null  float64
 18  RH_8         19735 non-null  float64
 19  T9           19735 non-null  float64
 20  RH_9         19735 non-null  float64
 21  T_out        19735 non-null  float64
 22  Press_mm_hg  19735 non-null  float64
 23  RH_out       19735 non-null  float64
 24  Windspeed    19735 non-null  float64
 25  Visibility   19735 non-null  float64
 26  Tdewpoint    19735 non-null  float64
 27  rv1          19735 non-null  float64
 28  rv2          19735 non-null  float64
```

```
dtypes: float64(26), int64(2), object(1)
memory usage: 4.4+ MB
```

[4]:
```
# chekcking for null values
df.isnull().sum()
```

[4]:
```
date           0
Appliances     0
lights         0
T1             0
RH_1           0
T2             0
RH_2           0
T3             0
RH_3           0
T4             0
RH_4           0
T5             0
RH_5           0
T6             0
RH_6           0
T7             0
RH_7           0
T8             0
RH_8           0
T9             0
RH_9           0
T_out          0
Press_mm_hg    0
RH_out         0
Windspeed      0
Visibility     0
Tdewpoint      0
rv1            0
rv2            0
dtype: int64
```

[5]:
```
# convert date to a datetime datatype
df['date'] = pd.to_datetime(df['date'])
df['date']
```

[5]:
```
0       2016-01-11 17:00:00
1       2016-01-11 17:10:00
2       2016-01-11 17:20:00
3       2016-01-11 17:30:00
4       2016-01-11 17:40:00
                   …
19730   2016-05-27 17:20:00
```

```
19731   2016-05-27 17:30:00
19732   2016-05-27 17:40:00
19733   2016-05-27 17:50:00
19734   2016-05-27 18:00:00
Name: date, Length: 19735, dtype: datetime64[ns]
```

Question: From the dataset, fit a linear model on the relationship between the temperature in the living room in Celsius (x = T2) and the temperature outside the building (y = T6). What is the R^2 value in two d.p.?

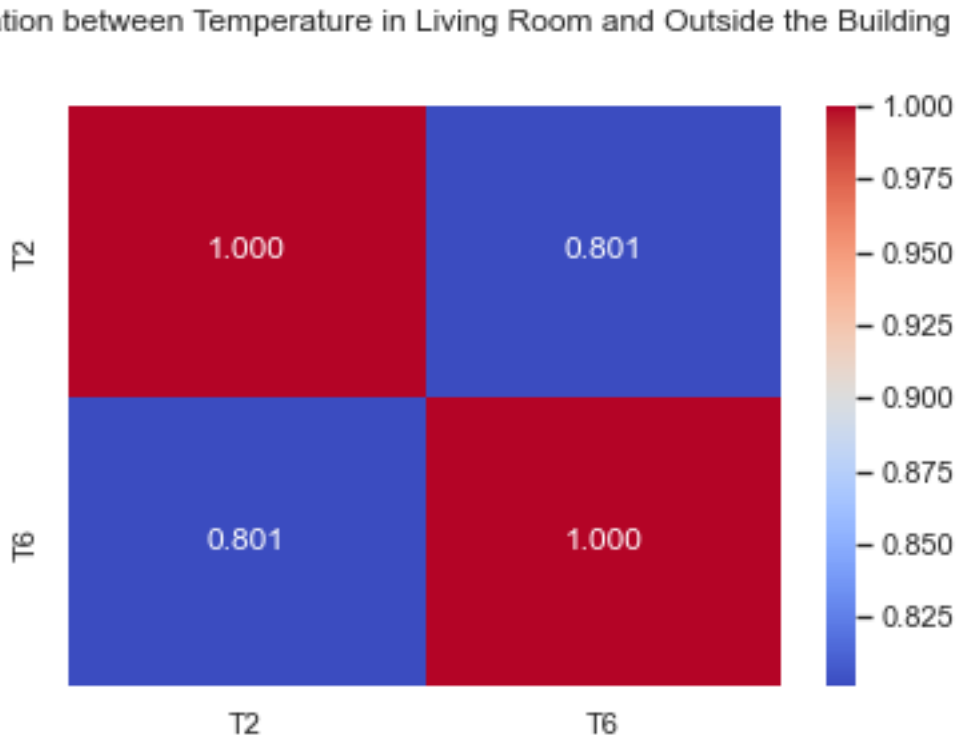
[6]:
```
x = df['T2']
y = df['T6']

# check first 5 rows of data
print(x.iloc[:5])
print()
print(y.iloc[:5])
```

```
0    19.2
1    19.2
2    19.2
3    19.2
4    19.2
Name: T2, dtype: float64

0    7.026667
1    6.833333
2    6.560000
3    6.433333
4    6.366667
Name: T6, dtype: float64
```

[7]:
```
x = df['T2']
y = df['T6']

x = sm.add_constant(x)
model = sm.OLS(y, x).fit()
r_squared = model.rsquared
print(f"The R-squared value is: {r_squared:.2f}")
```

```
The R-squared value is: 0.64
```

[8]:
```
corr = df[['T2', 'T6']]
sns.heatmap(corr.corr(), annot=True, fmt='.3f', cmap='coolwarm')
plt.title('Correlation between Temperature in Living Room and Outside the␣
 ↪Building', y=1.1)
plt.show();
```



1.1.1 Questions

Normalize the dataset using the MinMaxScaler after removing the following columns: ["date", "lights"]. The target variable is "Appliances". Use a 70-30 train-test set split with a random state of 42 (for reproducibility). Run a multiple linear regression using the training set and evaluate your model on the test set. Answer the following questions:

What is the Mean Absolute Error (in two decimal places)?

What is the Coefficient of Determination (in two decimal places)?

What is the Residual Sum of Squares (in two decimal places)?

What is the Root Mean Squared Error (in three decimal places)?

What is the Coefficient of Determination (in two decimal places)?

[9]:
```
# drop date, lights and Appliances from independent variable, X
X = df.drop(['date', 'lights', 'Appliances'], axis=1)
y  = df['Appliances']

# Normalize the dataset using the MinMaxScaler
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
X_df = pd.DataFrame(X_scaled, columns=X.columns)
```

```
# Use a 70-30 train-test set split with a random state of 42
X_train, X_test, y_train, y_test = train_test_split(X_df, y, test_size=0.3,␣
 ↪random_state=42)
```

[10]:
```
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

MAE = mean_absolute_error(y_test, y_pred)
print('The Mean Absolute error is = {}'.format(MAE))

print('Residual Sum of Squares: {}'.format(r2_score(y_pred, y_test)))
print(' Root Mean Squared Error: {}'.format(np.sqrt(mean_squared_error(y_test,␣
 ↪y_pred))))
```

```
The Mean Absolute error is = 53.64297765584961
Residual Sum of Squares: -4.4118937472949
 Root Mean Squared Error: 93.6404609399803
```

1.1.2 Question

Obtain the feature weights from your linear model above. Which features have the lowest and highest weights respectively?

[11]:
```
# Get the feature weights
feature_weights = model.coef_

# Create a DataFrame with feature names and weights
weights_df = pd.DataFrame({'Feature': X_train.columns, 'Weight':␣
 ↪feature_weights})

# Sort the DataFrame by weights in ascending order
weights_df_sorted = weights_df.sort_values('Weight')

# Extract the feature with the lowest weight
lowest_weight_feature = weights_df_sorted['Feature'].iloc[0]

# Extract the feature with the highest weight
highest_weight_feature = weights_df_sorted['Feature'].iloc[-1]

print(f"Feature with the lowest weight: {lowest_weight_feature}")
print(f"Feature with the highest weight: {highest_weight_feature}")
```

```
Feature with the lowest weight: RH_2
Feature with the highest weight: RH_1
```

1.1.3 Question

Train a ridge regression model with an alpha value of 0.4. Is there any change to the root mean squared error (RMSE) when evaluated on the test set?

[12]:
```
# Initialize and train the Ridge regression model
ridge_model = Ridge(alpha=0.4)
ridge_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = ridge_model.predict(X_test)

# Calculate RMSE before Ridge regression
rmse_before = np.sqrt(mean_squared_error(y_test, y_pred))

# Calculate RMSE after Ridge regression
ridge_model.fit(X_train, y_train)
y_pred_ridge = ridge_model.predict(X_test)
rmse_after = np.sqrt(mean_squared_error(y_test, y_pred_ridge))

# Compare the RMSE values
print(f"RMSE before Ridge regression: {rmse_before:.2f}")
print(f"RMSE after Ridge regression: {rmse_after:.2f}")
```

```
RMSE before Ridge regression: 93.66
RMSE after Ridge regression: 93.66
```

1.1.4 Question

Train a ridge regression model with an alpha value of 0.4. Is there any change to the root mean squared error (RMSE) when evaluated on the test set?

[13]:
```
# Initialize and train the Lasso regression model with an alpha value of 0.001
lasso_model = Lasso(alpha=0.001)
lasso_model.fit(X_train, y_train)

# Get the feature weights
feature_weights = lasso_model.coef_

# Count the number of features with non-zero weights
non_zero_features = sum(feature_weights != 0)

print(f"Number of features with non-zero weights: {non_zero_features}")
```

```
Number of features with non-zero weights: 25
```

1.1.5 Question

What is the new RMSE with the lasso regression? (Answer should be in three (3) decimal places)

[14]:
```
# Initialize and train the Lasso regression model
lasso_model = Lasso(alpha=0.001)
lasso_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = lasso_model.predict(X_test)

# Calculate the RMSE
rmse = mean_squared_error(y_test, y_pred, squared=False)

print(f"RMSE with Lasso regression: {rmse:.3f}")
```

```
RMSE with Lasso regression: 93.641
```

[ ]: