Energy Efficiency (Regression)

In [1]:

```
import pandas as pd
```

In [2]:

```
energy = pd.read_excel("ENB2012_data.xlsx")
energy.head()
```

Out[2]:

	X1	X2	X3	X4	X5	X6	X7	X8	Y1	Y2
0	0.98	514.5	294.0	110.25	7.0	2	0.0	0	15.55	21.33
1	0.98	514.5	294.0	110.25	7.0	3	0.0	0	15.55	21.33
2	0.98	514.5	294.0	110.25	7.0	4	0.0	0	15.55	21.33
3	0.98	514.5	294.0	110.25	7.0	5	0.0	0	15.55	21.33
4	0.90	563.5	318.5	122.50	7.0	2	0.0	0	20.84	28.28

In [3]:

```
energy.describe()
```

Out[3]:

	X1	X2	X3	X4	X5	X6	X7	X8	Y1	Y2
count	768.000000	768.000000	768.000000	768.000000	768.00000	768.000000	768.000000	768.00000	768.000000	768.000000
mean	0.764167	671.708333	318.500000	176.604167	5.25000	3.500000	0.234375	2.81250	22.307195	24.587760
std	0.105777	88.086116	43.626481	45.165950	1.75114	1.118763	0.133221	1.55096	10.090204	9.513306
min	0.620000	514.500000	245.000000	110.250000	3.50000	2.000000	0.000000	0.00000	6.010000	10.900000
25%	0.682500	606.375000	294.000000	140.875000	3.50000	2.750000	0.100000	1.75000	12.992500	15.620000
50%	0.750000	673.750000	318.500000	183.750000	5.25000	3.500000	0.250000	3.00000	18.950000	22.080000
75%	0.830000	741.125000	343.000000	220.500000	7.00000	4.250000	0.400000	4.00000	31.667500	33.132500
max	0.980000	808.500000	416.500000	220.500000	7.00000	5.000000	0.400000	5.00000	43.100000	48.030000

In [4]:

```
for col in energy.columns:
    print(col)
    print("*********************")
    print(energy[col].value_counts())
    print()
```

```
X1
*********************
0.98    64
0.90    64
0.86    64
0.82    64
0.79    64
0.76    64
0.74    64
0.71    64
0.69    64
0.66    64
0.64    64
0.62    64
Name: X1, dtype: int64

X2
*********************
514.5    64
563.5    64
588.0    64
612.5    64
637.0    64
661.5    64
686.0    64
710.5    64
735.0    64
759.5    64
784.0    64
808.5    64
Name: X2, dtype: int64

X3
*********************
294.0    192
318.5    192
343.0    128
416.5     64
245.0     64
269.5     64
367.5     64
Name: X3, dtype: int64
```

```
X4
********************
220.50    384
147.00    192
122.50    128
110.25     64
Name: X4, dtype: int64

X5
********************
7.0    384
3.5    384
Name: X5, dtype: int64

X6
********************
2    192
3    192
4    192
5    192
Name: X6, dtype: int64

X7
********************
0.10    240
0.25    240
0.40    240
0.00     48
Name: X7, dtype: int64

X8
********************
1    144
2    144
3    144
4    144
5    144
0     48
Name: X8, dtype: int64

Y1
********************
15.16    6
13.00    5
15.23    4
28.15    4
14.60    4
        ..
33.21    1
36.77    1
36.71    1
37.03    1
16.64    1
Name: Y1, Length: 587, dtype: int64

Y2
********************
21.33    4
29.79    4
14.27    4
17.20    4
14.28    4
        ..
14.65    1
14.54    1
14.39    1
14.46    1
17.11    1
Name: Y2, Length: 636, dtype: int64
```

In [5]:

```python
energy.isna().sum()
```

Out[5]:

```
X1    0
X2    0
X3    0
X4    0
X5    0
X6    0
X7    0
X8    0
Y1    0
Y2    0
dtype: int64
```

In [6]:

```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

In [7]:

```python
X = energy.drop(['Y1', 'Y2'], 1).to_numpy()
```

```
y = energy.drop(['X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X7', 'X8'], 1).to_numpy()

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)

scaler = StandardScaler()
scaler.fit(X)
X_train_s = scaler.transform(X_train)
X_test_s = scaler.transform(X_test)
```

```
C:\Users\Seneca\AppData\Local\Temp/ipykernel_6068/2382515809.py:1: FutureWarning: In a future version of pandas all arguments of D
ataFrame.drop except for the argument 'labels' will be keyword-only
  X = energy.drop(['Y1', 'Y2'], 1).to_numpy()
C:\Users\Seneca\AppData\Local\Temp/ipykernel_6068/2382515809.py:2: FutureWarning: In a future version of pandas all arguments of D
ataFrame.drop except for the argument 'labels' will be keyword-only
  y = energy.drop(['X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X7', 'X8'], 1).to_numpy()
```

Linear & Polynomial Regression

In [8]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, explained_variance_score
from sklearn.preprocessing import PolynomialFeatures
import matplotlib.pyplot as plt
```

Find best polynomial degree

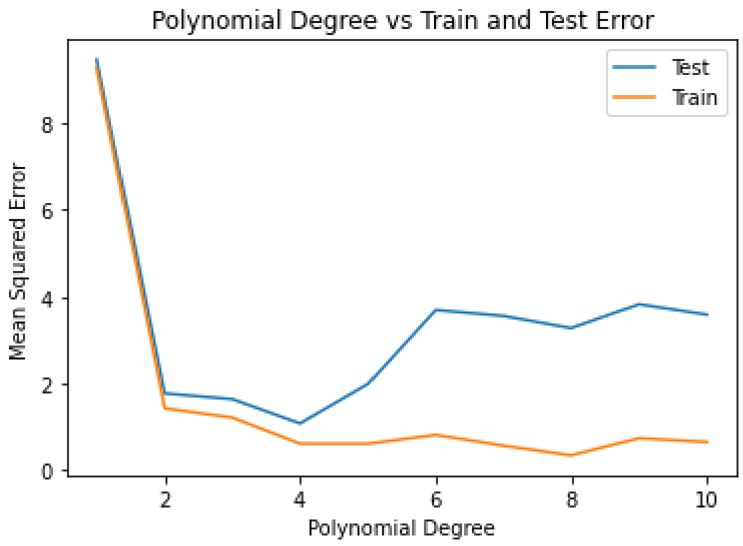
In [30]:

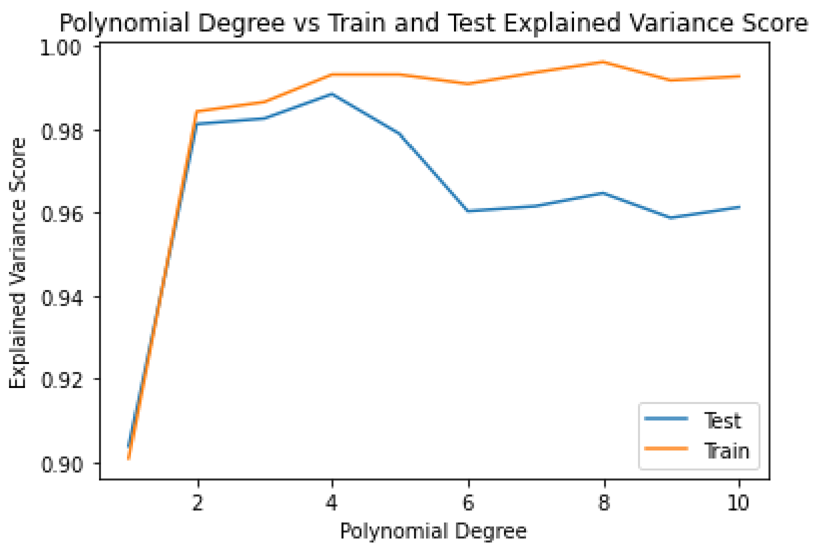
```
def run_polynomial_reg(X_tr, X_te):
    test_error = []
    test_var = []
    train_error = []
    train_var = []
    degrees = list(range(1, 11))

    # linear regression
    print("Degree: 1")
    lin_reg = LinearRegression()
    lin_reg = lin_reg.fit(X_tr, y_train)
    y_pred = lin_reg.predict(X_te)
    test_error.append(mean_squared_error(y_test, y_pred))
    test_var.append(explained_variance_score(y_test, y_pred))
    print("Test MSE: ", mean_squared_error(y_test, y_pred))
    print("Test Explained Variance: ", explained_variance_score(y_test, y_pred))

    y_pred = lin_reg.predict(X_tr)
    train_error.append(mean_squared_error(y_train, y_pred))
    train_var.append(explained_variance_score(y_train, y_pred))

    # polynomial regression
    for k in range (2, 11):
        print("Degree: ", k)
        pol = PolynomialFeatures(k)
        X_train_pol = pol.fit_transform(X_tr)
        X_test_pol = pol.fit_transform(X_te)

        # Train
        lin_reg = LinearRegression()
        lin_reg = lin_reg.fit(X_train_pol, y_train)

        # Test error
        y_pred = lin_reg.predict(X_test_pol)
        test_error.append(mean_squared_error(y_test, y_pred))
        test_var.append(explained_variance_score(y_test, y_pred))
        print("Test MSE: ", mean_squared_error(y_test, y_pred))
        print("Test Explained Variance: ", explained_variance_score(y_test, y_pred))

        # Train error
        y_pred = lin_reg.predict(X_train_pol)
        train_error.append(mean_squared_error(y_train, y_pred))
        train_var.append(explained_variance_score(y_train, y_pred))

    # make error plot
    plt.plot(degrees, test_error, label="Test")
    plt.plot(degrees, train_error, label="Train")
    plt.title("Polynomial Degree vs Train and Test Error")
    plt.xlabel("Polynomial Degree")
    plt.ylabel("Mean Squared Error")
    plt.legend()
    plt.show()

    # make explained variance plot
    plt.plot(degrees, test_var, label="Test")
    plt.plot(degrees, train_var, label="Train")
    plt.title("Polynomial Degree vs Train and Test Explained Variance Score")
    plt.xlabel("Polynomial Degree")
    plt.ylabel("Explained Variance Score")
    plt.legend()
    plt.show()
```

Linear and Polynomial Regression Without Scaling

In [31]:
```
run_polynomial_reg(X_train, X_test)
```

```
Degree: 1
Test MSE:  9.473928887107558
Test Explained Variance:  0.9039367329631596
Degree:  2
Test MSE:  1.776666517087284
Test Explained Variance:  0.9812194450573242
Degree:  3
Test MSE:  1.6434598349914515
Test Explained Variance:  0.982552314074946
Degree:  4
Test MSE:  1.082644402129154
Test Explained Variance:  0.9884413310144932
Degree:  5
Test MSE:  1.9903321686464723
Test Explained Variance:  0.9788519320756142
Degree:  6
Test MSE:  3.7020169584381586
Test Explained Variance:  0.9603563709879839
Degree:  7
Test MSE:  3.5652840333426123
Test Explained Variance:  0.9615661401947476
Degree:  8
Test MSE:  3.283734404865018
Test Explained Variance:  0.9647114917427451
Degree:  9
Test MSE:  3.8333183965856357
Test Explained Variance:  0.9587680677234443
Degree:  10
Test MSE:  3.5961897774523846
Test Explained Variance:  0.9613200920313656
```



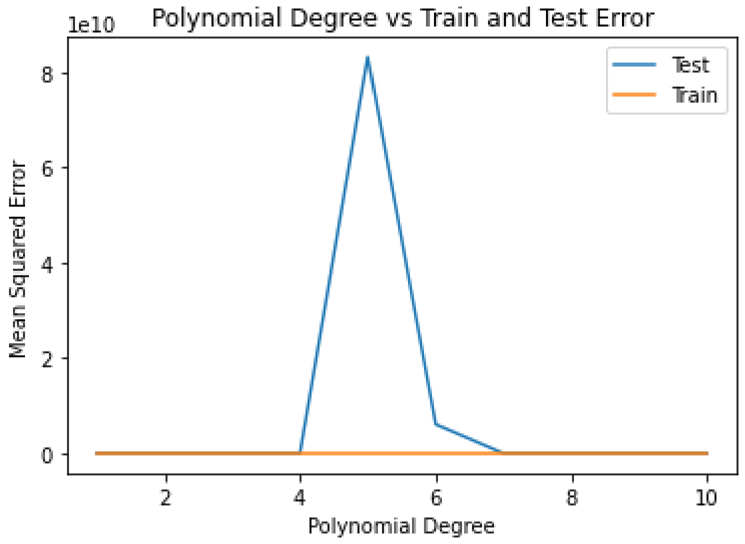


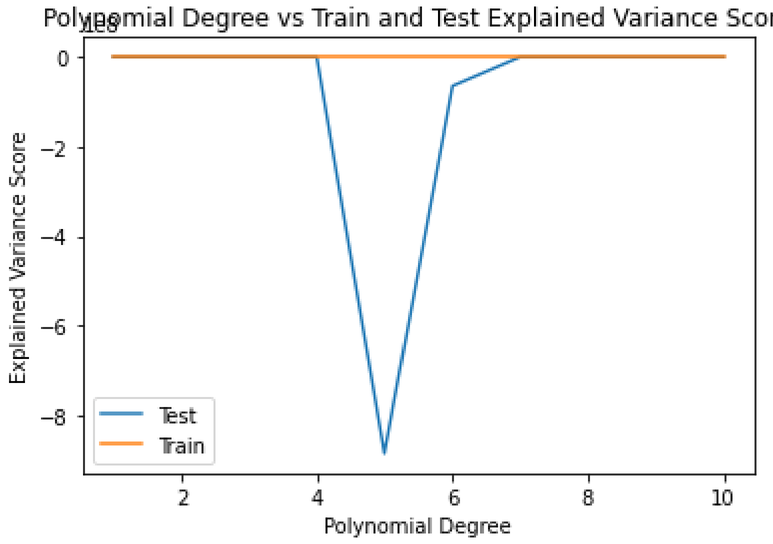
Linear and Polynomial Regression With Scaling

In [32]:
```
run_polynomial_reg(X_train_s, X_test_s)
```

```
Degree: 1
Test MSE:  9.494604383689417
Test Explained Variance:  0.903859607073465
Degree:  2
Test MSE:  1.7803196001673411
Test Explained Variance:  0.9811703714264455
Degree:  3
Test MSE:  1.8048407585068111
Test Explained Variance:  0.9807061614823389
Degree:  4
Test MSE:  1.163010164847321
Test Explained Variance:  0.9876269648293268
Degree:  5
Test MSE:  83188428505.0631
Test Explained Variance:  -884615746.5392985
Degree:  6
Test MSE:  6074869586.2866335
Test Explained Variance:  -64765644.66045452
```

```
Degree:  7
Test MSE:  519.0339146365108
Test Explained Variance:  -4.535582710096245
Degree:  8
Test MSE:  291.23574444429005
Test Explained Variance:  -2.1219878788028774
Degree:  9
Test MSE:  73.56289493848388
Test Explained Variance:  0.21533847054273098
Degree:  10
Test MSE:  151.6375396264335
Test Explained Variance:  -0.6204944250252705
```





Support Vector Machine

In [12]:
```
from sklearn.svm import LinearSVR
from sklearn.multioutput import MultiOutputRegressor
```

In [13]:
```
def run_svm(X_tr, X_te):
    svr = LinearSVR()
    multi_svr = MultiOutputRegressor(svr)
    multi_svr.fit(X_tr, y_train)
    y_pred = multi_svr.predict(X_te)
    print("Mean Squared Error: ", mean_squared_error(y_test, y_pred))
    print("Explained Variance Score: ", explained_variance_score(y_test, y_pred))
```

SVM Without Scaling

In [14]:
```
run_svm(X_train, X_test)
```

```
Mean Squared Error:  33.438587215816675
Explained Variance Score:  0.8251060837734372
```

```
C:\Users\Seneca\anaconda3\lib\site-packages\sklearn\svm\_base.py:985: ConvergenceWarning: Liblinear failed to converge, increase t
he number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
C:\Users\Seneca\anaconda3\lib\site-packages\sklearn\svm\_base.py:985: ConvergenceWarning: Liblinear failed to converge, increase t
he number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
```

SVM With Scaling

In [15]:
```
run_svm(X_train_s, X_test_s)
```

```
Mean Squared Error:  10.870072827441948
Explained Variance Score:  0.8948133892000907
```

Decision Tree

In [22]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [23]:
```
def run_dec_tree(X_tr, X_te):
    tree = DecisionTreeRegressor(random_state=42)
    tree.fit(X_tr, y_train)
    y_pred = tree.predict(X_te)
    print("Mean Squared Error: ", mean_squared_error(y_test, y_pred))
    print("Explained Variance Score: ", explained_variance_score(y_test, y_pred))
```

Decision Tree Without Scaling

In [24]:
```
run_dec_tree(X_train, X_test)
```

```
Mean Squared Error:  2.8324252677165345
Explained Variance Score:  0.9696445644623223
```

Decision Tree With Scaling

In [25]:
```
run_dec_tree(X_train_s, X_test_s)
```

```
Mean Squared Error:  2.879196094488188
Explained Variance Score:  0.9690379388604704
```

Random Forest Regression

In [26]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [27]:
```
def run_rand_forest(X_tr, X_te):
    rfr = RandomForestRegressor(random_state=42)
    rfr.fit(X_tr, y_train)
    y_pred = rfr.predict(X_te)
    print("Mean Squared Error: ", mean_squared_error(y_test, y_pred))
    print("Explained Variance Score: ", explained_variance_score(y_test, y_pred))
```

Random Forest Regression Without Scaling

In [28]:
```
run_rand_forest(X_train, X_test)
```

```
Mean Squared Error:  1.7338181172637772
Explained Variance Score:  0.981435199815003
```

Random Forest Regression With Scaling

In [29]:
```
run_rand_forest(X_train_s, X_test_s)
```

```
Mean Squared Error:  1.7540353284251966
Explained Variance Score:  0.9811876497266685
```