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CE475

Fundamentals and Applications of Machine Learning

Project Report

Identification and Significance of the Problem

In this project, the goal is to find the best model for first 100 row in the data which has response values and then predict the last 20 row's response values with that method.

Methodology

Multiple Linear Regression

I've tried backward elimination in MLR and eliminated features x1 and x4 based on their p_values. After that, to prove that I've eliminated right features, I compare the root mean squared errors with cross-validation of all subsets (2^n). Model without x1 and x4 has the best rmse value.

Polynomial Regression

In Polynomial Regression, I've tried to find the best degree. RMSE significantly increased after degree 3, so I choose degree 3 for my polynomial model. However, It was still high and it was close to the MLR model's rmse value.

Lasso

I’ve used Lasso since it enhances the prediction accuracy and interpretability of the statistical model it produces. LassoCV selects the best model with cross-validation. Since it’s rmse value is not satisfying, I’ve skipped to my next model.

Decision Tree Regressor

Decision tree builds regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes. I’ve used GridSearchCV to find best DTR model. RMSE value was better.

Random Forest Regressor

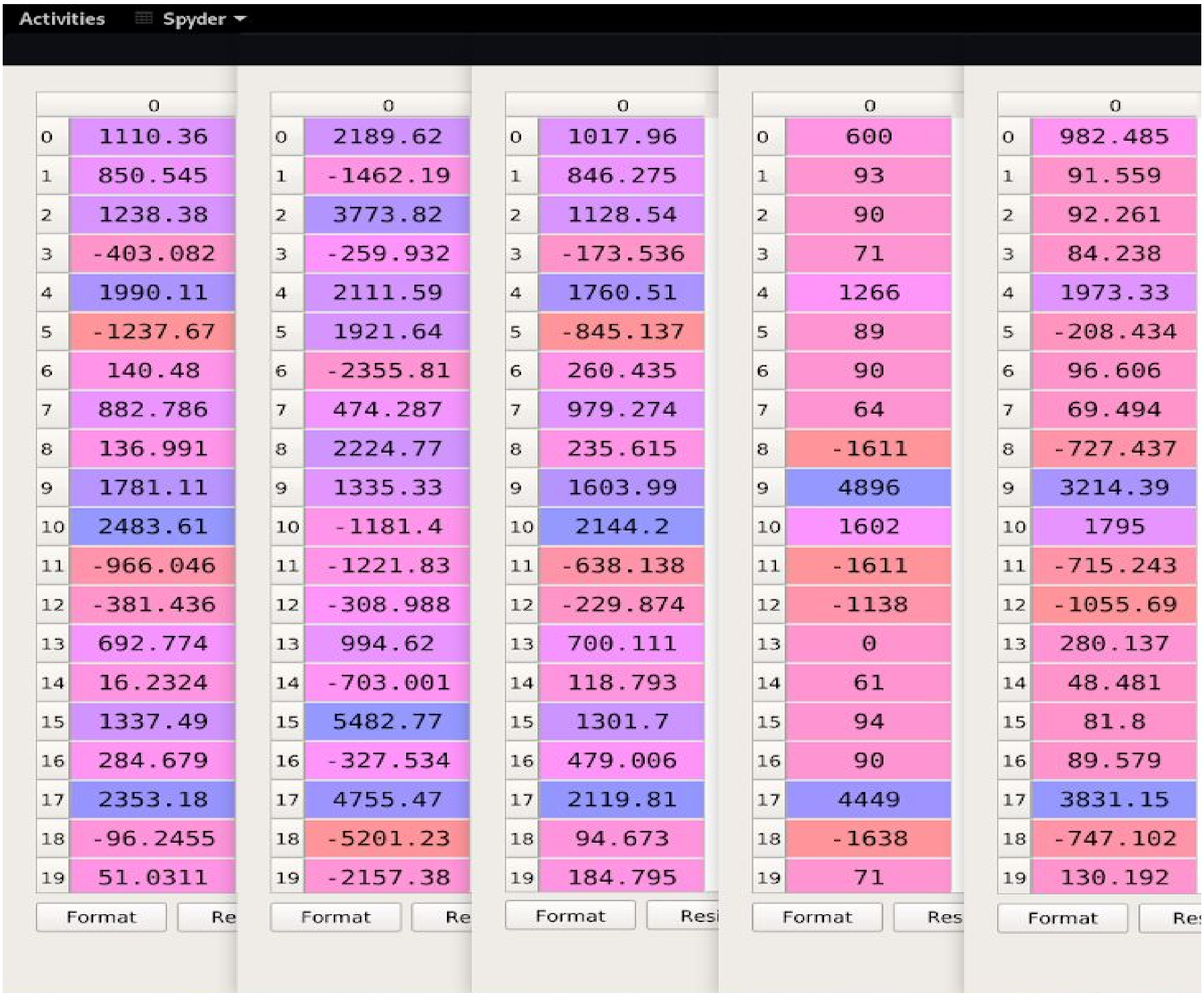
A random forest is a meta estimator that fits a number of classifying decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. I’ve used GridSearchCV with 1000 estimators. RMSE value is so much better so I decided to use Random Forest Regressor to predict last 20 rows.

Implementation

In the implementation part, I’ve used spyder as my integrated development environment since I like using it’s variable explorer feature and the jupyter notebook for presentation purposes. I’ve also used the scikit-learn library, pandas, numpy and seaborn. Implementation process can be seen below in appended the jupyter notebook.

Results

MLR Polynomial R. Lasso DTR RFR



	MLR (0)	Polynomial R. (0)	Lasso (0)	DTR (0)	RFR (0)
0	1110.36	2189.62	1017.96	600	982.485
1	850.545	-1462.19	846.275	93	91.559
2	1238.38	3773.82	1128.54	90	92.261
3	-403.082	-259.932	-173.536	71	84.238
4	1990.11	2111.59	1760.51	1266	1973.33
5	-1237.67	1921.64	-845.137	89	-208.434
6	140.48	-2355.81	260.435	90	96.606
7	882.786	474.287	979.274	64	69.494
8	136.991	2224.77	235.615	-1611	-727.437
9	1781.11	1335.33	1603.99	4896	3214.39
10	2483.61	-1181.4	2144.2	1602	1795
11	-966.046	-1221.83	-638.138	-1611	-715.243
12	-381.436	-308.988	-229.874	-1138	-1055.69
13	692.774	994.62	700.111	0	280.137
14	16.2324	-703.001	118.793	61	48.481
15	1337.49	5482.77	1301.7	94	81.8
16	284.679	-327.534	479.006	90	89.579
17	2353.18	4755.47	2119.81	4449	3831.15
18	-96.2455	-5201.23	94.673	-1638	-747.102
19	51.0311	-2157.38	184.795	71	130.192

Conclusion

To conclude, I've used various models and choose the one with the lowest root mean squared error value. In this case, it was Random Forest Regression for me.

There are a couple of lessons I've learned during the process. I've always forget to train my data at the end with all the data and use a model built upon training data from train_test_split.

I've also learned I've to %reset my ipython to not get confused with variables related to the previous model.

Sometimes DataFrame gets the previous row as a header and the code hard to debug if I don't notice it early on.

I have to pay more attention to documentation, for example, I've tried to build over 200 polynomial features on my own because I thought PolynomialFeatures is doing something else rather than that.

And I've learned that train_test_split is not enough, I've to use cross-validation if I can.

In [1]:

```
# %% Import Libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import make_scorer
from sklearn.ensemble import RandomForestRegressor

import warnings
warnings.filterwarnings('ignore')
```

```
/opt/anaconda/anaconda3/lib/python3.7/site-packages/sklearn/ensemble/weight_boosting.py:29: Deprecat
ionWarning: numpy.core.umath_tests is an internal NumPy module and should not be imported. It will b
e removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

In [2]:

```
# %% Read CSV
df = pd.read_csv('data.csv', index_col=0, nrows=100)
df.index = np.arange(0, len(df))
willbepredicted = pd.read_csv('data.csv', index_col=0, skiprows=range(1, 101), nrows=20)

feature_cols = ['x1', 'x2', 'x3', 'x4', 'x5']

X = df[feature_cols]
y = df.Y
x_find = willbepredicted[feature_cols]
```

In [3]:

```
# %% Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.20, random_state=0)
```

In [4]:

```
linreg = LinearRegression()

linreg.fit(X, y)
y_pred = linreg.predict(X)
```

In [5]:

```
print("x1: ", linreg.coef_[0])
print("x2: ", linreg.coef_[1])
print("x3: ", linreg.coef_[2])
print("x4: ", linreg.coef_[3])
print("x5: ", linreg.coef_[4])
```

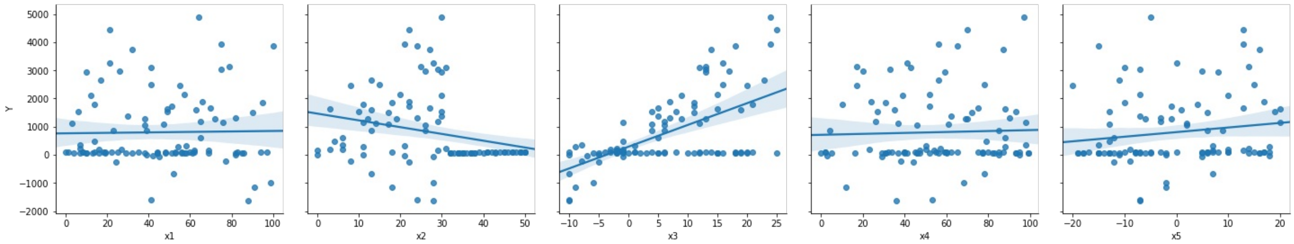
```
x1:  -0.14813529290736643
x2:  -32.1007066048948
x3:  82.67435716452609
x4:  0.5973716561125914
x5:  12.214009071344265
```

In [6]:

```
%matplotlib inline
sns.pairplot(df, x_vars=['x1', 'x2', 'x3', 'x4', 'x5'], y_vars='Y', height=4, aspect=1.0, kind='reg')
```

Out[6]:

```
<seaborn.axisgrid.PairGrid at 0x7fe4771c92e8>
```



In [7]:

```
# Building the optimal model using Backward Elimination
import statsmodels.formula.api as sm
X.insert(0, "x0", 1)

X_opt = X[['x0', 'x1', 'x2', 'x3', 'x4', 'x5']]
regressor_OLS = sm.OLS(endog = y, exog = X_opt).fit()
regressor_OLS.summary()
```

Out[7]:

OLS Regression Results

Dep. Variable:	Y	**R-squared:**	0.467
Model:	OLS	**Adj. R-squared:**	0.439
Method:	Least Squares	**F-statistic:**	16.47
Date:	Tue, 04 Dec 2018	**Prob (F-statistic):**	1.20e-11
Time:	10:43:37	**Log-Likelihood:**	-825.21
No. Observations:	100	**AIC:**	1662.
Df Residuals:	94	**BIC:**	1678.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x0	1113.1040	349.862	3.182	0.002	418.446	1807.762
x1	-0.1481	3.556	-0.042	0.967	-7.208	6.911
x2	-32.1007	7.468	-4.298	0.000	-46.929	-17.272
x3	82.6744	10.004	8.264	0.000	62.810	102.538
x4	0.5974	3.631	0.165	0.870	-6.612	7.807
x5	12.2140	8.437	1.448	0.151	-4.538	28.966

Omnibus:	6.029	**Durbin-Watson:**	1.890
Prob(Omnibus):	0.049	**Jarque-Bera (JB):**	5.501
Skew:	0.555	**Prob(JB):**	0.0639
Kurtosis:	3.298	**Cond. No.**	296.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

p value of x1 is 0.967 and it's greater than my SL. I've eliminated x1

In [8]:

```
X_opt = X[['x0', 'x2', 'x3', 'x4', 'x5']]
regressor_OLS = sm.OLS(endog = y, exog = X_opt).fit()
regressor_OLS.summary()
```

Out[8]:

OLS Regression Results

Dep. Variable:	Y	**R-squared:**	0.467
Model:	OLS	**Adj. R-squared:**	0.444
Method:	Least Squares	**F-statistic:**	20.80
Date:	Tue, 04 Dec 2018	**Prob (F-statistic):**	2.44e-12
Time:	10:43:37	**Log-Likelihood:**	-825.21
No. Observations:	100	**AIC:**	1660.
Df Residuals:	95	**BIC:**	1673.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
x0	1106.7271	312.948	3.536	0.001	485.447	1728.008
x2	-32.0779	7.409	-4.330	0.000	-46.787	-17.369
x3	82.6731	9.952	8.307	0.000	62.916	102.430
x4	0.5788	3.585	0.161	0.872	-6.538	7.696
x5	12.2223	8.390	1.457	0.148	-4.434	28.879

Omnibus:	5.964	**Durbin-Watson:**	1.889
Prob(Omnibus):	0.051	**Jarque-Bera (JB):**	5.432
Skew:	0.552	**Prob(JB):**	0.0661
Kurtosis:	3.295	**Cond. No.**	217.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

x4's p value (0.872) is greater than my SL. I've eliminated x4

In [9]:

```
X_opt = X[['x0', 'x2', 'x3', 'x5']]
regressor_OLS = sm.OLS(endog = y, exog = X_opt).fit()
regressor_OLS.summary()
```

Out[9]:

OLS Regression Results

Dep. Variable:	Y	**R-squared:**	0.467
Model:	OLS	**Adj. R-squared:**	0.450
Method:	Least Squares	**F-statistic:**	28.01
Date:	Tue, 04 Dec 2018	**Prob (F-statistic):**	4.24e-13
Time:	10:43:37	**Log-Likelihood:**	-825.22
No. Observations:	100	**AIC:**	1658.
Df Residuals:	96	**BIC:**	1669.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x0	1141.8474	223.861	5.101	0.000	697.486	1586.209
x2	-32.2098	7.326	-4.396	0.000	-46.753	-17.667
x3	82.6821	9.901	8.351	0.000	63.029	102.335
x5	12.1522	8.336	1.458	0.148	-4.395	28.700

Omnibus:	6.187	**Durbin-Watson:**	1.884
Prob(Omnibus):	0.045	**Jarque-Bera (JB):**	5.662
Skew:	0.562	**Prob(JB):**	0.0589
Kurtosis:	3.310	**Cond. No.**	73.9

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

remaining features' p values are less than my significance level 0.05

In [10]:

```
feature_cols = [ 'x2', 'x3', 'x5' ]
X_train = df[feature_cols]
y_train = df.Y

X_test = willbepredicted[feature_cols]

linreg.fit(X_train, y_train)
y_pred = linreg.predict(X_test)

print(y_pred)
```

```
[ 1110.36291321   850.545366    1238.37578502  -403.08248109
  1990.10754432 -1237.67131187   140.48020518   882.78590327
   136.99100333  1781.10677895  2483.61099772  -966.04607179
  -381.43565364   692.77445583    16.23241308  1337.48754781
   284.67917056  2353.1827379    -96.24550126    51.03107948]
```

then I've decided find all the subsets of my data, and compare their rmse values to understand the effects of my features on my model

In [11]:

```
scores = cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')

# fix the sign of MSE scores
mse_scores = -scores

# convert from MSE to RMSE
rmse_scores = np.sqrt(mse_scores)

# calculate the average RMSE
print("Mean of rmse with all features included: " , rmse_scores.mean())
```

```
Mean of rmse with all features included:  1000.0719831858908
```

Let's find rmse for all subsets of our features

['x5'], ['x4'], ['x4', 'x5'],['x3'],['x3', 'x5'],['x3', 'x4'],['x3', 'x4', 'x5'],['x2'],['x2', 'x5'],['x2', 'x4'],['x2', 'x4', 'x5'],['x2', 'x3'],['x2', 'x3', 'x5'],['x2', 'x3', 'x4'],['x2', 'x3', 'x4', 'x5'],['x1'],['x1', 'x5'],['x1', 'x4'],['x1', 'x4', 'x5'],['x1', 'x3'],['x1', 'x3', 'x5'],['x1', 'x3', 'x4'],['x1', 'x3', 'x4', 'x5'],['x1', 'x2'],['x1', 'x2', 'x5'],['x1', 'x2', 'x4'],['x1', 'x2', 'x4', 'x5'],['x1', 'x2', 'x3'],['x1', 'x2', 'x3', 'x5'],['x1', 'x2', 'x3', 'x4'],['x1', 'x2', 'x3', 'x4', 'x5']

In [12]:

```
feature_cols = [ 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error'))
.mean())

feature_cols = [ 'x4' ]
X = df[feature_cols]
print("Mean of rmse [ 'x4' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error'))
.mean())

feature_cols = [ 'x4', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x4', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_er
ror')).mean())

feature_cols = [ 'x3' ]
X = df[feature_cols]
print("Mean of rmse [ 'x3' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error'))
.mean())

feature_cols = [ 'x3', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x3', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_er
ror')).mean())

feature_cols = [ 'x3', 'x4' ]
X = df[feature_cols]
print("Mean of rmse [ 'x3', 'x4' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_er
ror')).mean())

feature_cols = [ 'x3', 'x4', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x3', 'x4', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squa
red_error')).mean())

feature_cols = [ 'x2' ]
X = df[feature_cols]
print("Mean of rmse [ 'x2' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error'))
.mean())

feature_cols = [ 'x2', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x2', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_er
ror')).mean())

feature_cols = [ 'x2', 'x4' ]
X = df[feature_cols]
print("Mean of rmse [ 'x2', 'x4' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_er
ror')).mean())

feature_cols = [ 'x2', 'x4', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x2', 'x4', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squa
red_error')).mean())

feature_cols = [ 'x2', 'x3' ]
X = df[feature_cols]
print("Mean of rmse [ 'x2', 'x3' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_er
```

```
ror')).mean())

feature_cols = [ 'x2', 'x3', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x2', 'x3', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x2', 'x3', 'x4' ]
X = df[feature_cols]
print("Mean of rmse [ 'x2', 'x3', 'x4' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x2', 'x3', 'x4', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x2', 'x3', 'x4', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x4' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x4' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x4', 'x5']
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x4', 'x5']: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x3' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x3' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x3', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x3', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x3', 'x4' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x3', 'x4' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x3', 'x4', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x3', 'x4', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x2' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x2' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x2', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x2', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x2', 'x4' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x2', 'x4' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x2', 'x4', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x2', 'x4', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x2', 'x3' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x2', 'x3' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mean_squared_error')).mean())

feature_cols = [ 'x1', 'x2', 'x3', 'x5' ]
```

```
X = df[feature_cols]

print("Mean of rmse [ 'x1', 'x2', 'x3', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mea
n_squared_error')).mean())

feature_cols = [ 'x1', 'x2', 'x3', 'x4' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x2', 'x3', 'x4' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='neg_mea
n_squared_error')).mean())

feature_cols = [ 'x1', 'x2', 'x3', 'x4', 'x5' ]
X = df[feature_cols]
print("Mean of rmse [ 'x1', 'x2', 'x3', 'x4', 'x5' ]: ", np.sqrt(-cross_val_score(linreg, X, y, cv=10, scoring='n
eg_mean_squared_error')).mean())
```

```
Mean of rmse [ 'x5' ]:  1233.816965091099
Mean of rmse [ 'x4' ]:  1262.2824118519077
Mean of rmse [ 'x4', 'x5' ]:  1254.3868143284667
Mean of rmse [ 'x3' ]:  1044.8402437111006
Mean of rmse [ 'x3', 'x5' ]:  1045.5269498128887
Mean of rmse [ 'x3', 'x4' ]:  1073.407916205778
Mean of rmse [ 'x3', 'x4', 'x5' ]:  1074.0602249108588
Mean of rmse [ 'x2' ]:  1206.1829154024713
Mean of rmse [ 'x2', 'x5' ]:  1198.3669975919577
Mean of rmse [ 'x2', 'x4' ]:  1224.3957612088545
Mean of rmse [ 'x2', 'x4', 'x5' ]:  1216.4591428441017
Mean of rmse [ 'x2', 'x3' ]:  963.3214406915713
Mean of rmse [ 'x2', 'x3', 'x5' ]:  962.5889085840488
Mean of rmse [ 'x2', 'x3', 'x4' ]:  992.1879646685354
Mean of rmse [ 'x2', 'x3', 'x4', 'x5' ]:  991.8323083830168
Mean of rmse [ 'x1' ]:  1252.0266242901002
Mean of rmse [ 'x1', 'x5' ]:  1243.8427178517418
Mean of rmse [ 'x1', 'x4' ]:  1275.1254642411577
Mean of rmse [ 'x1', 'x4', 'x5']:  1266.5025472346201
Mean of rmse [ 'x1', 'x3' ]:  1058.7370593626356
Mean of rmse [ 'x1', 'x3', 'x5' ]:  1058.5477092551932
Mean of rmse [ 'x1', 'x3', 'x4' ]:  1089.3511823080048
Mean of rmse [ 'x1', 'x3', 'x4', 'x5' ]:  1089.4269954875585
Mean of rmse [ 'x1', 'x2' ]:  1214.777753151737
Mean of rmse [ 'x1', 'x2', 'x5' ]:  1206.7205443053754
Mean of rmse [ 'x1', 'x2', 'x4' ]:  1234.172616251501
Mean of rmse [ 'x1', 'x2', 'x4', 'x5' ]:  1225.8884062809059
Mean of rmse [ 'x1', 'x2', 'x3' ]:  969.9825044197854
Mean of rmse [ 'x1', 'x2', 'x3', 'x5' ]:  969.5297732894338
Mean of rmse [ 'x1', 'x2', 'x3', 'x4' ]:  1000.131410389532
Mean of rmse [ 'x1', 'x2', 'x3', 'x4', 'x5' ]:  1000.0719831858908
```

now y_mlr contains my Multiple Linear Regression predictions

In [13]:

```
feature_cols = [ 'x2', 'x3', 'x5' ]
X = df[feature_cols]
y = df.Y

X_test = willbepredicted[feature_cols]

linreg.fit(X, y)
y_mlr = linreg.predict(X_test)
```

after that I've tried decision tree regression, random forest regression and lasso method.

In [14]:

```
X = df[feature_cols]
y = df.Y
x_find = willbepredicted[feature_cols]

# %% Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.20, random_state=0)
```

In [15]:

```
from sklearn.preprocessing import PolynomialFeatures
for i in range(1, 7):
    poly_reg = PolynomialFeatures(degree = i)
    X_poly = poly_reg.fit_transform(X)
    X_train_poly = poly_reg.fit_transform(X_train)
    lin_reg = LinearRegression()
    lin_reg.fit(X_train_poly, y_train)
    pol_scores = np.sqrt(-cross_val_score(lin_reg, X_poly, y, cv = 10, scoring='neg_mean_squared_error'))
    print("mean cross validation score(degree {}): {}".format(i,np.mean(pol_scores)))
    print("RMSE without CV(degree {}): {}".format(i,np.sqrt(np.sum(np.square(y_test - lin_reg.predict(poly_reg.fi
t_transform(X_test))))/len(X_test))))
    print("")
```

```
mean cross validation score(degree 1): 962.5889085840487
RMSE without CV(degree 1): 828.3654902357964

mean cross validation score(degree 2): 929.3727870100718
RMSE without CV(degree 2): 847.7239333513262

mean cross validation score(degree 3): 994.7451650509689
RMSE without CV(degree 3): 771.7619208312487

mean cross validation score(degree 4): 1923.619778983891
RMSE without CV(degree 4): 1171.0306116996853

mean cross validation score(degree 5): 4671.6716115755935
RMSE without CV(degree 5): 4169.884535249694

mean cross validation score(degree 6): 37001.83191438672
RMSE without CV(degree 6): 28568.331650381257
```

RMSE increases after degree 3, so I choose degree 3 for my polynomial model

In [16]:

```
poly_reg = PolynomialFeatures(degree = 3)
X_poly = poly_reg.fit_transform(X)
lin_reg = LinearRegression()
lin_reg.fit(X_poly, y)
y_pol = lin_reg.predict(poly_reg.fit_transform(x_find))
```

In [17]:

```
# %% Decision Tree Regressor Model
dt = DecisionTreeRegressor(random_state=0, criterion="mse")
dt_fit = dt.fit(X_train, y_train)

# dt_scores now consist RMSE
dt_scores = np.sqrt(-cross_val_score(dt_fit, X, y, cv = 10, scoring='neg_mean_squared_error'))
print("mean cross validation score: {}".format(np.mean(dt_scores)))

# RMSE without cross-validation
print("score without cv: {}".format(np.sqrt(np.sum(np.square(y_test - dt_fit.predict(X_test)))/len(X_test))))

# GridSearchCV

from sklearn.metrics import mean_squared_error
scoring = make_scorer(mean_squared_error)
g_cv = GridSearchCV(DecisionTreeRegressor(random_state=0),
              param_grid={'min_samples_split': range(2, 10)},
              scoring=scoring, cv=10, refit=True)

g_cv.fit(X_train, y_train)
g_cv.best_params_

result = g_cv.cv_results_

# RMSE of GridSearchCV
print("RMSE of best estimator: {}".format(np.sqrt(np.sum(np.square(y_test - g_cv.best_estimator_.predict(X_test))
)/len(X_test))))

# fit all data before prediction
g_cv.fit(X, y)
# Prediction of last 20 row by Decision Tree Regressor Model
y_dtr = g_cv.best_estimator_.predict(x_find)
```

```
mean cross validation score: 547.5454703092869
score without cv: 853.5270353070254
RMSE of best estimator: 853.5270353070254
```

In [18]:

```
# %% Random Forest Regression

rfr = RandomForestRegressor(random_state=0, criterion="mse")
rfr_fit = rfr.fit(X_train, y_train)

# rfr_scores now consist RMSE
rfr_scores = np.sqrt(-cross_val_score(rfr_fit, X, y, cv = 10, scoring='neg_mean_squared_error'))
print("mean cross validation score: {}".format(np.mean(rfr_scores)))

# RMSE without cross-validation
print("score without cv: {}".format(np.sqrt(np.sum(np.square(y_test - rfr_fit.predict(X_test)))/len(X_test))))

# RMSE of GridSearchCV
from sklearn.metrics import mean_squared_error
param_grid = {
    'n_estimators': [1000]
}

scoring = make_scorer(mean_squared_error)
g_cv = GridSearchCV(RandomForestRegressor(random_state=0),
              param_grid=param_grid,
              scoring=scoring, cv=10, refit=True)

g_cv.fit(X_train, y_train)
g_cv.best_params_

result = g_cv.cv_results_
# print(result)
print("RMSE of best estimator: {}".format(np.sqrt(np.sum(np.square(y_test - g_cv.best_estimator_.predict(X_test))
)/len(X_test))))
# fit all data before prediction
g_cv.fit(X, y)
y_rfr = g_cv.best_estimator_.predict(x_find)
```

```
mean cross validation score: 497.7086291841295
score without cv: 572.635035166379
RMSE of best estimator: 585.0795790109667
```

In [19]:

```
# %% Lasso

from sklearn.linear_model import LassoCV
reg = LassoCV(cv=5, random_state=0).fit(X_train, y_train)

lasso_scores = np.sqrt(-cross_val_score(reg, X, y, cv = 10, scoring='neg_mean_squared_error'))
print("mean cross validation score: {}".format(np.mean(lasso_scores)))

# RMSE without cross-validation
print("score without cv: {}".format(np.sqrt(np.sum(np.square(y_test - reg.predict(X_test)))/len(X_test))))
# fit all data before prediction
reg.fit(X, y)
y_lasso = reg.predict(x_find)
```

```
mean cross validation score: 962.9765376122477
score without cv: 828.0371207159719
```