3.Poynomial Regression (SK Learn) for Multple Orders

October 28, 2021

Polynomial Regression (Non-Linear fitting)

Let us work on a real dataset with Sci-Kit (SK) Learn for Multiple Orders (1, 2, 3, 6, 10, 20)

[37]:
```
# Import necessary package
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings # supress warnings
warnings.filterwarnings('ignore')
```

0.0.1 Step 1: Load the dataset

[38]:
```
df = pd.read_csv('E:\\MY LECTURES\\DATA SCIENCE\\3.Programs\\dataset\\Housing.
↪csv')
df.head()
```

[38]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	\
0	13300000	7420	4	2	3	yes	no	no	
1	12250000	8960	4	4	4	yes	no	no	
2	12250000	9960	3	2	2	yes	no	yes	
3	12215000	7500	4	2	2	yes	no	yes	
4	11410000	7420	4	1	2	yes	yes	yes	

	hotwaterheating	airconditioning	parking	prefarea	furnishingstatus
0	no	yes	2	yes	furnished
1	no	yes	3	no	furnished
2	no	no	2	yes	semi-furnished
3	no	yes	3	yes	furnished
4	no	yes	2	no	furnished

[39]:
```
df.shape
```

[39]: (545, 13)

0.0.2 Step 2: Apply EDA

Univariate analysis

[40]:
```
# Statistics summary
df["area"].describe()
```

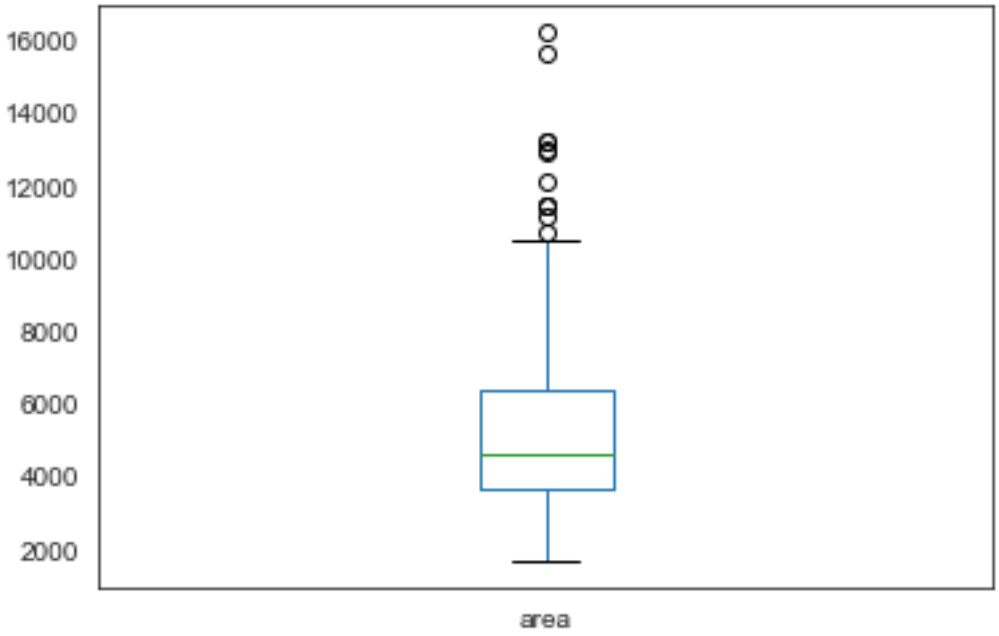
[40]:
```
count      545.000000
mean      5150.541284
std       2170.141023
min       1650.000000
25%       3600.000000
50%       4600.000000
75%       6360.000000
max      16200.000000
Name: area, dtype: float64
```

[41]:
```
df["price"].describe()
```

[41]:
```
count    5.450000e+02
mean     4.766729e+06
std      1.870440e+06
min      1.750000e+06
25%      3.430000e+06
50%      4.340000e+06
75%      5.740000e+06
max      1.330000e+07
Name: price, dtype: float64
```

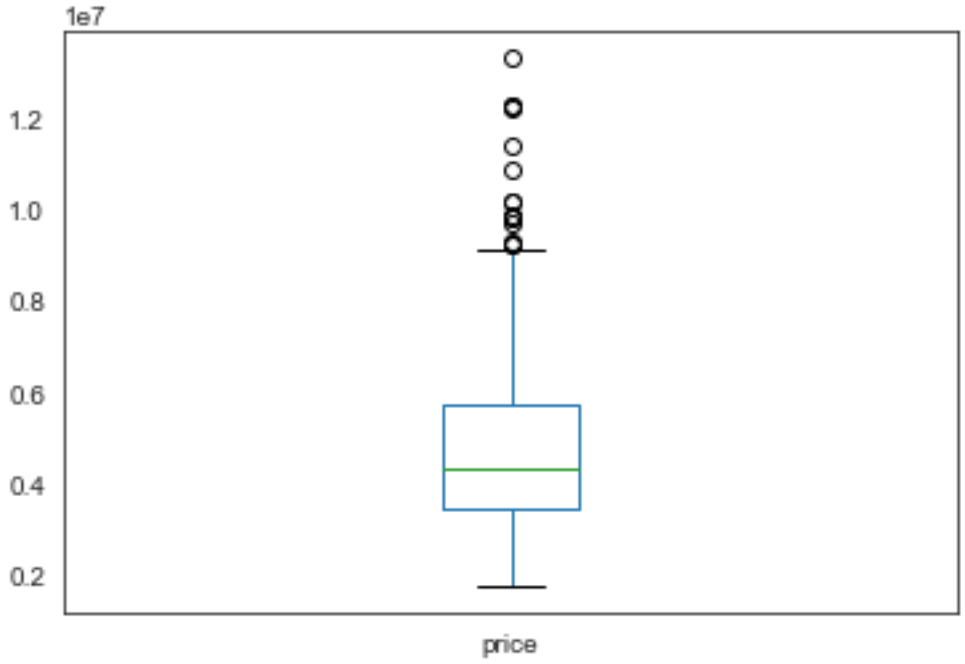
[42]:
```
# Univariate Analysis using Boxplot
sns.set_style(style='white')
df.boxplot(column =['area'], grid = False)
```

[42]:
```
<AxesSubplot:>
```



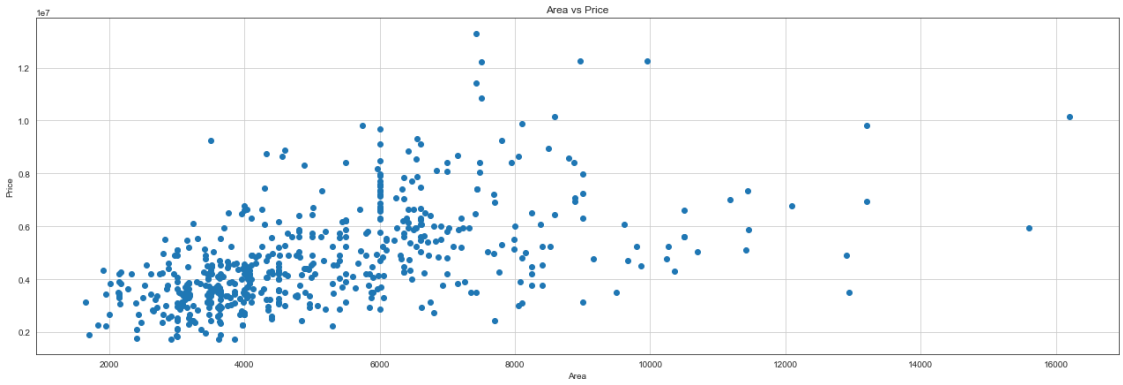
[43]:
```
sns.set_style(style='white')
df.boxplot(column =['price'], grid = False)
```

[43]: <AxesSubplot:>



Bivariate analysis

[44]:
```
# Scatter plot
sns.set_style(style='white')
fig = plt.figure(figsize=(22,7))
plt.scatter(df["area"],df["price"])
plt.grid(b=None)
plt.xlabel("Area")
plt.ylabel("Price")
plt.title("Area vs Price")
plt.show()
```



[45]:
```
# Correlation
r = df["area"].corr(df["price"])
print("Correlation value : ",round(r,2)*100,"%")
# Spearman's rho
# df["area"].corr(df["price"], method='spearman')
# Kendall's tau
# df["area"].corr(df["price"], method='kendall')
```

```
Correlation value :  54.0 %
```

Applying linear regression may not be helpful, so lets try to fit non-linear models.

0.0.3 Step 3. Pre-process and extract the features

[46]:
```
# Load only area and price features
extracted = df.loc[:, ['area', 'price']]
extracted.head()
```

[46]:

	area	price
0	7420	13300000
1	8960	12250000
2	9960	12250000

```
3  7500  12215000
4  7420  11410000
```

[47]:
```
# pre-process: Scale the values of those features between 0 and 1
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
temp = scaler.fit_transform(extracted)
temp
```

[47]:
```
array([[0.39656357, 1.        ],
       [0.5024055 , 0.90909091],
       [0.57113402, 0.90909091],
       …,
       [0.13539519, 0.        ],
       [0.08659794, 0.        ],
       [0.15120275, 0.        ]])
```

[48]:
```
pre_processed = pd.DataFrame(temp,columns=["area","price"])
pre_processed.head()
```

[48]:

	area	price
0	0.396564	1.000000
1	0.502405	0.909091
2	0.571134	0.909091
3	0.402062	0.906061
4	0.396564	0.836364

[49]:
```
# visualise area-price relationship
sns.set_style(style='white')
fig = plt.figure(figsize=(22,7))
sns.regplot(x="area", y="price", data=pre_processed, fit_reg=False)
plt.grid(b=None)
plt.xlabel("Area")
plt.ylabel("Price")
plt.title("Area vs Price")
plt.show()
```

0.0.4 Step 4. Split the data for training and testing

[50]:
```
# split into train and test
from sklearn.model_selection import train_test_split
train, test = train_test_split(pre_processed, train_size = 0.8, test_size = 0.
↪2, random_state = 10)
```

[51]:
```
# split into x and y for both train and test sets
x_train = train['area'].values.reshape(-1, 1)
y_train = train['price']

x_test = test['area'].values.reshape(-1, 1)
y_test = test['price']
```

0.0.5 Step 5: Training and Testing for polynomial model with order 1, 2, 3, 6, 10, 20

Let's now predict the output value (for both train and test sets) and store the predictions in a table. Each row of the table is one data point, each column is a value of n (degree).

degree-1

degree-2

degree-3

...

degree-n

x1

x2

x3

...

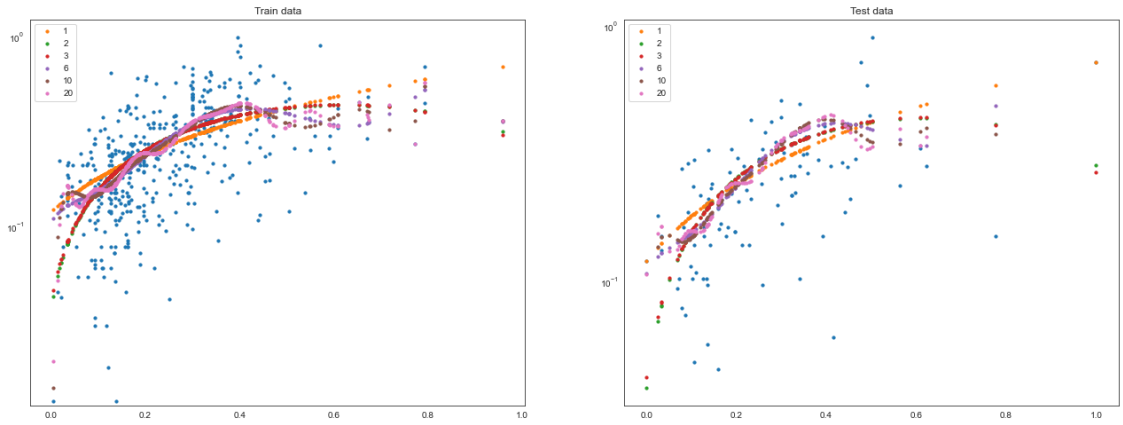
xn

[52]:
```
# fit multiple polynomial features
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import LinearRegression

degrees = [1, 2, 3, 6, 10, 20]

y_train_pred = np.zeros((len(x_train), len(degrees)))
y_test_pred = np.zeros((len(x_test), len(degrees)))
```

```
for i, degree in enumerate(degrees):

    # make pipeline: create features, then feed them to linear_reg model
    model = make_pipeline(PolynomialFeatures(degree), LinearRegression())
    model.fit(x_train, y_train)

    # predict on test and train data
    # store the predictions of each degree in the corresponding column
    y_train_pred[:, i] = model.predict(x_train)
    y_test_pred[:, i] = model.predict(x_test)
```

[53]:
```
# visualise train and test predictions, note that the y axis is on a log scale
plt.figure(figsize=(22, 8))

# train data
plt.subplot(121)
plt.scatter(x_train, y_train, s=10)
for i, degree in enumerate(degrees):
    plt.scatter(x_train, y_train_pred[:, i], s=10, label=str(degree))
    plt.legend(loc='upper left')
plt.yscale('log')
plt.title("Train data")


# test data
plt.subplot(122)
plt.scatter(x_test, y_test, s=10)
for i, degree in enumerate(degrees):
    plt.scatter(x_test, y_test_pred[:, i], s=10, label=str(degree))
    plt.legend(loc='upper left')
plt.yscale('log')
plt.title("Test data")
```

[53]:
```
Text(0.5, 1.0, 'Test data')
```



[54]:
```
# compare r2 for train and test sets (for all polynomial fits)
import sklearn.metrics

print("R-squared values: \n")
for i, degree in enumerate(degrees):
    train_r2 = round(sklearn.metrics.r2_score(y_train, y_train_pred[:, i]), 2)
    test_r2 = round(sklearn.metrics.r2_score(y_test, y_test_pred[:, i]), 2)
    print("Polynomial degree {0}: train score={1}, test score={2}".
 ↪format(degree, train_r2, test_r2))
```

```
R-squared values:

Polynomial degree 1: train score=0.28, test score=0.3
Polynomial degree 2: train score=0.33, test score=0.26
Polynomial degree 3: train score=0.33, test score=0.25
Polynomial degree 6: train score=0.36, test score=-0.04
Polynomial degree 10: train score=0.37, test score=-218.78
Polynomial degree 20: train score=0.37, test score=-102340492580.92
```

0.1 Building Multiple Linear Regression Model Without Cross-Validation

0.1.1 Step 1: Load the dataset

[55]:
```
df1 = pd.read_csv('E:\\MY LECTURES\\DATA SCIENCE\\3.Programs\\dataset\\Housing.
 ↪csv')
df1.head()
```

[55]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	\
0	13300000	7420	4	2	3	yes	no	no	
1	12250000	8960	4	4	4	yes	no	no	
2	12250000	9960	3	2	2	yes	no	yes	

```
3  12215000  7500         4          2        2      yes        no      yes
4  11410000  7420         4          1        2      yes       yes      yes

  hotwaterheating airconditioning  parking prefarea furnishingstatus
0              no             yes        2      yes        furnished
1              no             yes        3       no        furnished
2              no              no        2      yes   semi-furnished
3              no             yes        3      yes        furnished
4              no             yes        2       no        furnished
```

0.1.2 Step 2: Apply EDA

Univariate and bivariate analysis

0.1.3 Step 3. Pre-process and extract the features

[56]:
```
# data preparation - list of all the "yes-no" binary categorical variables
# we will map yes to 1 and no to 0
binary_vars_list =  ['mainroad', 'guestroom', 'basement', 'hotwaterheating',␣
 ↪'airconditioning', 'prefarea']

# defining the map function
def binary_map(x):
    return x.map({'yes': 1, "no": 0})

# applying the function to the housing variables list
df1[binary_vars_list] = df1[binary_vars_list].apply(binary_map)
df1.head()
```

[56]:
```
      price  area  bedrooms  bathrooms  stories  mainroad  guestroom  \
0  13300000  7420         4          2        3         1          0
1  12250000  8960         4          4        4         1          0
2  12250000  9960         3          2        2         1          0
3  12215000  7500         4          2        2         1          0
4  11410000  7420         4          1        2         1          1

   basement  hotwaterheating  airconditioning  parking  prefarea  \
0         0                0                1        2         1
1         0                0                1        3         0
2         1                0                0        2         1
3         1                0                1        3         1
4         1                0                1        2         0

  furnishingstatus
0        furnished
```

```
1        furnished
2   semi-furnished
3        furnished
4        furnished
```

[57]:
```
# 'dummy' variables
# get dummy variables for 'furnishingstatus'
# also, drop the first column of the resulting df (since n-1 dummy vars suffice)
status = pd.get_dummies(df1['furnishingstatus'], drop_first = True)
status.head()
```

[57]:
```
   semi-furnished  unfurnished
0               0            0
1               0            0
2               1            0
3               0            0
4               0            0
```

[58]:
```
# concat the dummy variable df with the main df
df1 = pd.concat([df1, status], axis = 1)
df1.head()
```

[58]:
```
      price  area  bedrooms  bathrooms  stories  mainroad  guestroom  \
0  13300000  7420         4          2        3         1          0
1  12250000  8960         4          4        4         1          0
2  12250000  9960         3          2        2         1          0
3  12215000  7500         4          2        2         1          0
4  11410000  7420         4          1        2         1          1

   basement  hotwaterheating  airconditioning  parking  prefarea  \
0         0                0                1        2         1
1         0                0                1        3         0
2         1                0                0        2         1
3         1                0                1        3         1
4         1                0                1        2         0

  furnishingstatus  semi-furnished  unfurnished
0        furnished               0            0
1        furnished               0            0
2   semi-furnished               1            0
3        furnished               0            0
4        furnished               0            0
```

[59]:
```
# remove 'furnishingstatus' since we alreday have the dummy vars
df1.drop(['furnishingstatus'], axis = 1, inplace = True)
df1.head()
```

[59]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditioning	parking	prefarea	semi-furnished	unfurnished
0	13300000	7420	4	2	3	1	0	0	0	1	2	1	0	0
1	12250000	8960	4	4	4	1	0	0	0	1	3	0	0	0
2	12250000	9960	3	2	2	1	0	1	0	0	2	1	1	0
3	12215000	7500	4	2	2	1	0	1	0	1	3	1	0	0
4	11410000	7420	4	1	2	1	1	1	0	1	2	0	0	0

[60]:
```
# extracting relevant features
numeric_vars = ['area', 'bedrooms', 'bathrooms', 'stories', 'parking','price']
temp = df1[numeric_vars]
temp.head()
```

[60]:

	area	bedrooms	bathrooms	stories	parking	price
0	7420	4	2	3	2	13300000
1	8960	4	4	4	3	12250000
2	9960	3	2	2	2	12250000
3	7500	4	2	2	3	12215000
4	7420	4	1	2	2	11410000

[61]:
```
# rescale the features between 0 to 1
scaler = MinMaxScaler()
temp1 = scaler.fit_transform(temp)
temp1 = pd.DataFrame(temp1,columns=['area', 'bedrooms', 'bathrooms', 'stories',␣
↪'parking','price'])
temp1.head()
```

[61]:

	area	bedrooms	bathrooms	stories	parking	price
0	0.396564	0.6	0.333333	0.666667	0.666667	1.000000
1	0.502405	0.6	1.000000	1.000000	1.000000	0.909091
2	0.571134	0.4	0.333333	0.333333	0.666667	0.909091
3	0.402062	0.6	0.333333	0.333333	1.000000	0.906061
4	0.396564	0.6	0.000000	0.333333	0.666667	0.836364

[62]:
```
df2 = df1[["mainroad","guestroom", "basement", "hotwaterheating",␣
↪"airconditioning", "prefarea", "semi-furnished"]]
df2.head()
```

[62]:

	mainroad	guestroom	basement	hotwaterheating	airconditioning	prefarea	semi-furnished
0	1	0	0	0	1	1	0
1	1	0	0	0	1	0	0
2	1	0	1	0	0	1	1
3	1	0	1	0	1	1	0
4	1	1	1	0	1	0	0

[63]:
```
pre_processed_data = pd.concat([df2,temp1],axis=1)
pre_processed_data.head()
```

[63]:

	mainroad	guestroom	basement	hotwaterheating	airconditioning	prefarea	semi-furnished	area	bedrooms	bathrooms	stories	parking	price
0	1	0	0	0	1	1	0	0.396564	0.6	0.333333	0.666667	0.666667	1.000000
1	1	0	0	0	1	0	0	0.502405	0.6	1.000000	1.000000	1.000000	0.909091
2	1	0	1	0	0	1	1	0.571134	0.4	0.333333	0.333333	0.666667	0.909091
3	1	0	1	0	1	1	0	0.402062	0.6	0.333333	0.333333	1.000000	0.906061
4	1	1	1	0	1	0	0	0.396564	0.6	0.000000	0.333333	0.666667	0.836364

[64]:
```
pre_processed_data.shape
```

[64]:
```
(545, 13)
```

0.1.4 Step 4. Split the data for training and testing

[65]:
```
train, test = train_test_split(pre_processed_data, train_size = 0.8, test_size␣
↪= 0.2, random_state = 100)
```

[66]:
```
# divide into X_train, y_train, X_test, y_test
y_train = train.pop('price')
x_train = train

y_test = test.pop('price')
x_test = test
```

[67]:
```
# try with another value of RFE
lm = LinearRegression()
lm.fit(x_train, y_train)

# predict prices of X_test
y_pred = lm.predict(x_test)
```

0.1.5 R2 Score

[68]:
```
r2 = sklearn.metrics.r2_score(y_test, y_pred)
print(r2)
```

```
0.67767446576476
```

0.1.6 Problems in the Current Approach

In train-test split, we have three options: 1. **Simply split into train and test**: But that way tuning a hyperparameter makes the model 'see' the test data (i.e. knowledge of test data leaks into the model) 2. **Split into train, validation, test sets**: Then the validation data would eat into the training set 3. **Cross-validation**: Split into train and test, and train multiple models by sampling the train set. Finally, just test once on the test set.

0.2 Cross-Validation for Multiple Linear Regression

K-Fold Cross-Validation

[69]:
```
# k-fold CV (using all the 13 variables)
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
lm = LinearRegression()
scores = cross_val_score(lm, x_train, y_train, scoring='r2', cv=5)
scores
```

[69]:
```
array([0.64469087, 0.70115779, 0.61726174, 0.66130751, 0.59038153])
```

[70]:
```
# the other way of doing the same thing (more explicit)
# create a KFold object with 5 splits
folds = KFold(n_splits = 5, shuffle = True, random_state = 100)
scores = cross_val_score(lm, x_train, y_train, scoring='r2', cv=folds)
```

```
scores
```

[70]:
```
array([0.59246218, 0.69380963, 0.67252609, 0.62082293, 0.60796825])
```

[71]:
```
# can tune other metrics, such as MSE
scores = cross_val_score(lm, x_train, y_train,␣
 ↪scoring='neg_mean_squared_error', cv=5)
scores
```

[71]:
```
array([-0.01115667, -0.00765919, -0.00606751, -0.00748722, -0.01390484])
```

0.2.1 Types of Cross-Validation Schemes

1. **K-Fold** cross-validation: Most common
2. **Leave One Out (LOO)**: Takes each data point as the 'test sample' once, and trains the model on the rest n-1 data points. Thus, it trains n total models.
   - Advantage: Utilises the data well since each model is trained on n-1 samples
   - Disadvantage: Computationally expensive
3. **Leave P-Out (LPO)**: Creat all possible splits after leaving p samples out. For n data points, there are (nCp) possibile train-test splits.
4. (**For classification problems**) **Stratified K-Fold**: Ensures that the relative class proportion is approximately preserved in each train and validation fold. Important when ther eis huge class imbalance (e.g. 98% good customers, 2% bad).