Forecasting price

Description

In the dataset 'sample.csv' there are 7 features and 1 target variable ('price'). In this project I will try to make a machine learning model that will forecast the price.

Data Handling

In [1]:
```
# Loading and looking at the data
import pandas as pd
data = pd.read_csv('sample.csv')
```

In [2]:
```
data.head()
```

Out[2]:

	loc1	loc2	para1	dow	para2	para3	para4	price
0	0	01	1	Mon	662	3000.0	3.8	73.49
1	9	99	1	Thu	340	2760.0	9.2	300.00
2	0	04	0	Mon	16	2700.0	3.0	130.00
3	4	40	1	Mon	17	12320.0	6.4	365.00
4	5	50	1	Thu	610	2117.0	10.8	357.50

There is at least one parameter that will have to be changed later - 'dow'.

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   loc1    10000 non-null  object 
 1   loc2    10000 non-null  object 
 2   para1   10000 non-null  int64  
 3   dow     10000 non-null  object 
 4   para2   10000 non-null  int64  
 5   para3   10000 non-null  float64
 6   para4   10000 non-null  float64
 7   price   10000 non-null  float64
dtypes: float64(3), int64(2), object(3)
memory usage: 625.1+ KB
```

From first columns it seems that the first two features are numeric, but they are in the string format in the dataset and this will have to be changed. Apart from that there are no null entries, which is good.

```
In [4]: # Changing the datatypes of the first two features
        try:
            data['loc1'] = data['loc1'].astype(int)
        except:
            print('There are non-integer values present')
```

```
There are non-integer values present
```

```
In [5]: try:
            data['loc2'] = data['loc2'].astype(int)
        except:
            print('There are non-integer values present')
```

```
There are non-integer values present
```

There is an error in the columns - some of the values are not numeric and have letters in them.

```
In [6]: # Thus, these features might not have any meaningful relationships and dropping the
        data.drop(columns=['loc1','loc2'],inplace=True)
```

```
In [7]: data.describe()
```

Out[7]:

	para1	para2	para3	para4	price
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	1.380800	447.384000	9547.989920	8.459522	433.733056
std	3.500831	221.005861	8022.814037	4.613526	277.435947
min	0.000000	16.000000	200.000000	1.000000	50.730000
25%	1.000000	301.000000	2898.000000	4.000000	250.000000
50%	1.000000	434.000000	6447.000000	7.200000	370.000000
75%	1.000000	582.000000	15000.000000	13.600000	550.000000
max	337.000000	2554.000000	34782.000000	27.200000	5700.000000

The ranges in most variables are relatively huge - some models will need scaling to be done

```
In [8]: # Changing the 'dow' feature into weekdays (0) and weekens (1)
        week = {'Mon':0,'Tue':0,'Wed':0,'Thu':0,'Fri':0,'Sat':1,'Sun':1}
        for i in week:
            data['dow'].replace(to_replace=i,value=week[i],inplace=True)
```

```
In [9]: data.head()
```

Out[9]:

	para1	dow	para2	para3	para4	price
0	1	0	662	3000.0	3.8	73.49
1	1	0	340	2760.0	9.2	300.00
2	0	0	16	2700.0	3.0	130.00
3	1	0	17	12320.0	6.4	365.00
4	1	0	610	2117.0	10.8	357.50

Checking Outliers and Feature Correlation

In [10]:
```
# Getting rid of outliers for para2, para3 and target
iqr_para2 = 582 - 301
iqr_para3 = 15000 - 2898
iqr_target = 550 - 250
condition_para2 = (data['para2'] >= 301 - 1.5*iqr_para2) & (data['para2'] <= 582+1.
condition_para3 = (data['para3'] >= 2898 - 1.5*iqr_para3) & (data['para3'] <= 15000
condition_target = (data['price'] >= 250 - 1.5*iqr_target) & (data['price'] <= 550+
data = data[condition_para2 & condition_para3 & condition_target]
```

In [11]:
```
data.describe()
```

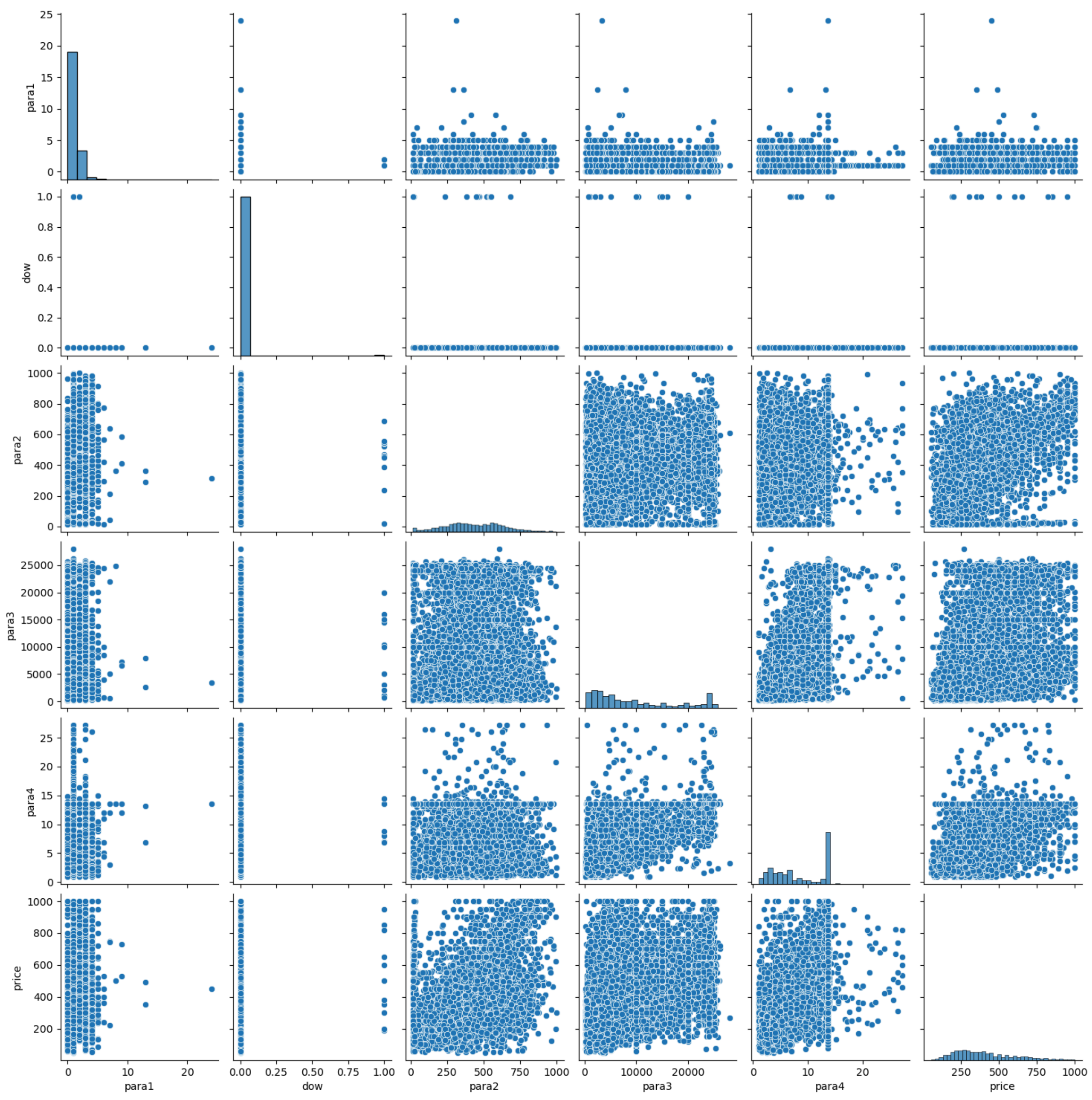
Out[11]:

	para1	dow	para2	para3	para4	price
count	9696.000000	9696.000000	9696.000000	9696.000000	9696.000000	9696.000000
mean	1.315285	0.001341	430.952764	9438.400505	8.359635	404.568833
std	0.969317	0.036594	187.388992	7990.290259	4.603430	198.662198
min	0.000000	0.000000	16.000000	200.000000	1.000000	50.730000
25%	1.000000	0.000000	298.000000	2838.250000	4.000000	250.000000
50%	1.000000	0.000000	425.000000	6299.500000	7.000000	360.000000
75%	1.000000	0.000000	572.000000	15000.000000	13.600000	525.000000
max	24.000000	1.000000	1002.000000	28000.000000	27.200000	1000.000000

In [12]:
```
# Visualizing the correlation among parameters
import matplotlib.pyplot as plt
import seaborn as sns
```

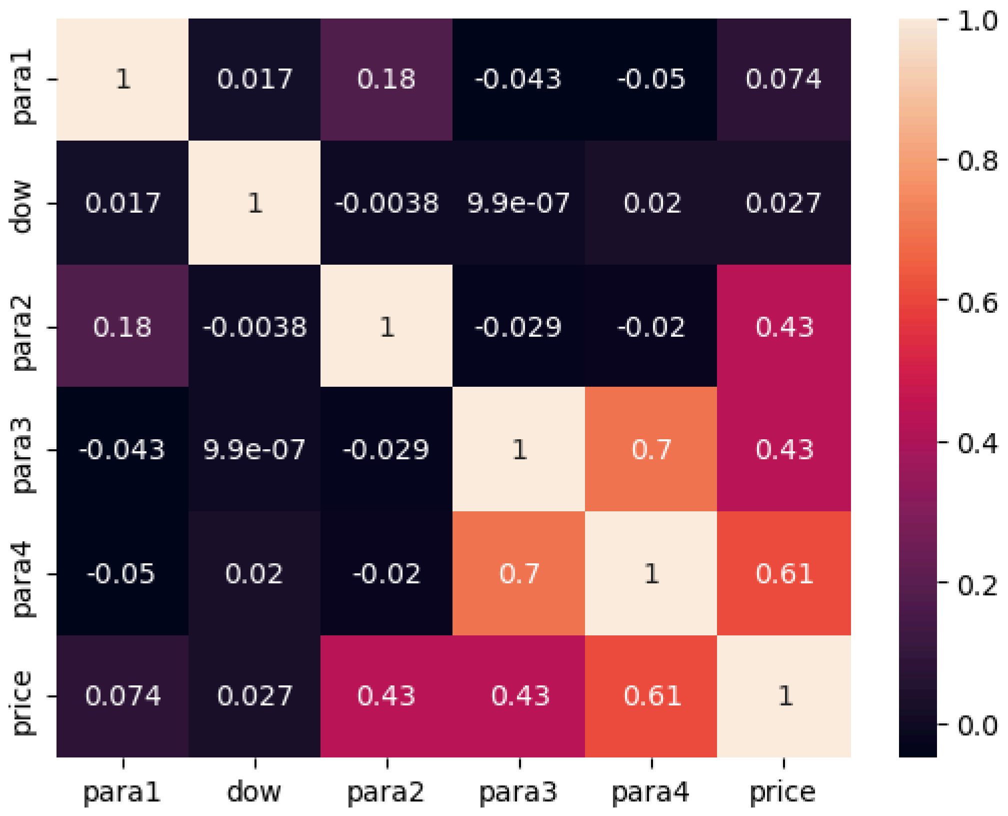
In [13]:
```
sns.pairplot(data)
plt.show()
```

```
C:\Users\azima\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The
figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



The multicollinearity here is hard to see, using another method to look at correlation should be better

```
In [14]: corr = data.corr(numeric_only=True)
         sns.heatmap(corr,annot=True)
         plt.show()
```



Feature Selection

The above correlation matrix shows that para1 almost does not affect the price, but has a correlation with days of week. Para3 and para4 have a strong correlation between each other and the impact on price almost corresponds with this correlation (0.43 ~ 0.61 * 0.71). Thus considering the stronger impact of para4, I will leave para4 and drop para3. Also days of week almost do not affect the price and can be dropped. Last, para1 can be dropped for two reasons: 1) minimal impact on price 2) there is a risk of correlation with para2 (0.074 ~ 0.43 * 0.18), which in turn poses a risk of multicollinearity.

In [15]:
```
data.drop(columns=['para1','para3','dow'],inplace=True)
```

In [16]:
```
data.head()
```

Out[16]:

	para2	para4	price
0	662	3.8	73.49
1	340	9.2	300.00
2	16	3.0	130.00
3	17	6.4	365.00
4	610	10.8	357.50

Assessing Relevant Models

Using various models for regression in accordance with the target context

In [17]:
```
from sklearn.metrics import mean_squared_error as MSE
from sklearn.metrics import r2_score

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import LinearRegression as LR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from statsmodels.regression.linear_model import OLS

from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
```

Ordinary-Least Squares

In [18]:
```
# Looking at the initial statistics of the dataset
model = OLS(data[['price']],data.drop(columns=['price']))
```

In [19]:
```
result=model.fit()
```

In [20]:
```
result.summary()
```

Out[20]:

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.917
Model:	OLS	**Adj. R-squared (uncentered):**	0.917
Method:	Least Squares	**F-statistic:**	5.330e+04
Date:	Mon, 29 Apr 2024	**Prob (F-statistic):**	0.00
Time:	16:00:32	**Log-Likelihood:**	-60963.
No. Observations:	9696	**AIC:**	1.219e+05
Df Residuals:	9694	**BIC:**	1.219e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
para2	0.4412	0.005	94.257	0.000	0.432	0.450
para4	25.9236	0.231	112.463	0.000	25.472	26.375

Omnibus:	987.685	**Durbin-Watson:**	1.972
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2300.592
Skew:	0.617	**Prob(JB):**	0.00
Kurtosis:	5.042	**Cond. No.**	82.0

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Preparing Data

In [21]:
```
# Splitting the data into train-test datasets
x_train,x_test,y_train,y_test = train_test_split(data.drop(columns=['price']),data[
```

In [22]:
```
# Using scaling immediately to be able to compare feature coefficients if need be
minmax = MinMaxScaler()
standard = StandardScaler()
x_train_mm = minmax.fit_transform(x_train)
x_train_ss = standard.fit_transform(x_train)
x_test_mm = minmax.transform(x_test)
x_test_ss = standard.transform(x_test)
```

```
In [23]: # Making the dataframes of the obtained results
x_train_mm = pd.DataFrame(x_train_mm,columns=x_train.columns)
x_train_ss = pd.DataFrame(x_train_ss,columns=x_train.columns)
x_test_mm = pd.DataFrame(x_test_mm,columns=x_train.columns)
x_test_ss = pd.DataFrame(x_test_ss,columns=x_train.columns)
```

I will use the RMSE measure for error comparison since this value should be closer in dimension to our price values and hence more convenient.

Linear Regression

```
In [24]: # LinReg MinMaxScaler
linreg1 = LR()
linreg1.fit(x_train_mm,y_train)
predict1 = linreg1.predict(x_test_mm)
MSE(y_test,predict1) ** (1/2), r2_score(y_test,predict1)
```

```
Out[24]: (131.6795396934365, 0.5700564898932159)
```

```
In [25]: # LinReg StandardScaler
linreg2 = LR()
linreg2.fit(x_train_ss,y_train)
predict2 = linreg2.predict(x_test_ss)
MSE(y_test,predict2) ** (1/2), r2_score(y_test,predict2)
```

```
Out[25]: (131.6795396934365, 0.5700564898932159)
```

The results came out to be identical. Overall the root mean squared error is acceptable considering the standard deviation and range of data, but more concept is needed to be sure about this, which for this dataset I do not have. There seems to be room for improving the R2-score. After this I am going to use MinMaxScaler results only for two reasons: 1) there are no negative values in our features and 2) I got rid of all the outliers to which MinMaxScaler is sensitive

```
In [26]: # Checking the model for any overfitting
predict1_tr = linreg1.predict(x_train_mm)
MSE(y_train,predict1_tr) ** (1/2), r2_score(y_train,predict1_tr)
```

```
Out[26]: (129.18589933318918, 0.5730427250738553)
```

Overfitting is negligible

Decision Tree Regressor

```
In [27]: # Trying the decision tree for which scaling is not necessary
# max_features only has 2 values for the dimensions of the final dataset
tree = DecisionTreeRegressor(random_state = 42)
params = {
         'max_depth': range(1,7),
          'max_features': [1,2]
         }
tree_search = GridSearchCV(estimator=tree,param_grid=params,scoring='neg_mean_squar
tree_search.fit(x_train,y_train)
prediction = tree_search.predict(x_test)
tree_search.best_estimator_
```

Out[27]:

```
DecisionTreeRegressor

DecisionTreeRegressor(max_depth=5, max_features=2, random_state=42)
```

In [28]:

```
# Just checking for overfitting
prediction_tr = tree_search.predict(x_train)
```

In [29]:

```
MSE(y_test,prediction) ** (0.5), MSE(y_train,prediction_tr) ** (0.5)
```

Out[29]:

```
(124.16018213219452, 117.59779771495799)
```

In [30]:

```
r2_score(y_test,prediction), r2_score(y_train,prediction_tr)
```

Out[30]:

```
(0.6177570533850889, 0.6462042843795808)
```

The error is lower than for linear regression. There is a slight overfitting.

Random Forest Regressor

In [31]:

```
import numpy as np
```

In [32]:

```
forest = RandomForestRegressor(random_state=42)
params = {'n_estimators': [100,200],
         'max_depth': range(1,7),
          'max_features': [1,2]
         }
forest_search = GridSearchCV(estimator=forest,param_grid=params,scoring='neg_mean_s
# Had to change the shape since it was in the form of a matrix for starters
forest_search.fit(x_train,np.reshape(y_train,(6787,)))
prediciton = forest_search.predict(x_test)
forest_search.best_estimator_
```

Out[32]:

```
RandomForestRegressor

RandomForestRegressor(max_depth=6, max_features=2, n_estimators=200,
                      random_state=42)
```

In [33]:

```
prediction_tr = forest_search.predict(x_train)
```

In [34]:

```
MSE(y_test,prediction) ** (0.5), MSE(y_train,prediction_tr) ** (0.5)
```

Out[34]:

```
(124.16018213219452, 111.36604181478275)
```

In [35]:
```
r2_score(y_test,prediction), r2_score(y_train,prediction_tr)
```
Out[35]:
```
(0.6177570533850889, 0.6827075337114792)
```

The error is comparable with the decision tree. Overfitting is more significant.

SVM

In [36]:
```
svm = SVR(kernel = 'poly')
params = {
    'degree' : range(2,7),
    'C' : [0.1,1,10]
}
svm_search = GridSearchCV(estimator=svm,param_grid=params,scoring='neg_mean_squared
# Using scaled data because of the dependency of the model on distance
svm_search.fit(x_train_mm,np.reshape(y_train,(6787,)))
svm_search.best_estimator_
```
Out[36]:
```
▾                  SVR
SVR(C=0.1, degree=2, kernel='poly')
```

In [37]:
```
prediction = svm_search.predict(x_test_mm)
prediction_tr = svm_search.predict(x_train_mm)
```
In [38]:
```
MSE(y_test,prediction) ** (0.5), MSE(y_train,prediction_tr) ** (0.5)
```
Out[38]:
```
(132.77445294714758, 127.64282216493353)
```
In [39]:
```
r2_score(y_test,prediction), r2_score(y_train,prediction_tr)
```
Out[39]:
```
(0.5628768173104466, 0.5831814987200192)
```

As can be seen the model with larger regularization happened to be better during hyperparameter selection. But the error in this case is significant (even worse than simple linear regression). It could be due to the greater regularizaion force that makes the model prefer a greater distance between planes.

K Nearest Neighbors

In [40]:
```
knn = KNeighborsRegressor()
params = {'n_neighbors':range(2,21),
         'weights':['uniform','distance']}
knn_search = GridSearchCV(estimator=knn,param_grid=params,scoring='neg_mean_squared
knn_search.fit(x_train_mm,y_train)
knn_search.best_estimator_
```

```
Out[40]:
▾        KNeighborsRegressor
KNeighborsRegressor(n_neighbors=20)
```

```
In [41]: # The following attribute was not displayed above, so I am looking at it here
knn_search.best_estimator_.weights
```

```
Out[41]: 'uniform'
```

```
In [42]: prediction = knn_search.predict(x_test_mm)
prediction_tr = knn_search.predict(x_train_mm)
```

```
In [43]: MSE(y_test,prediction) ** (0.5), MSE(y_train,prediction_tr) ** (0.5)
```

```
Out[43]: (123.06838181032771, 113.29021459437892)
```

```
In [44]: r2_score(y_test,prediction), r2_score(y_train,prediction_tr)
```

```
Out[44]: (0.6244499892366477, 0.6716485103282097)
```

The error here is minimal among the used models but there is a slight overfitting. Since the number of neighbors happened to be at the boundary (20), I will check greater numbers.

```
In [45]: knn = KNeighborsRegressor()
params = {'n_neighbors':range(20,41)}
knn_search = GridSearchCV(estimator=knn,param_grid=params,scoring='neg_mean_squared
knn_search.fit(x_train_mm,y_train)
knn_search.best_estimator_
```

```
Out[45]:
▾        KNeighborsRegressor
KNeighborsRegressor(n_neighbors=27)
```

```
In [46]: prediction = knn_search.predict(x_test_mm)
prediction_tr = knn_search.predict(x_train_mm)
```

```
In [47]: MSE(y_test,prediction) ** (0.5), MSE(y_train,prediction_tr) ** (0.5)
```

```
Out[47]: (122.4261134598076, 114.58895683976553)
```

```
In [48]: r2_score(y_test,prediction), r2_score(y_train,prediction_tr)
```

```
Out[48]: (0.6283595960080048, 0.6640770126898046)
```

New number of neighbors - 27. The error and overfitting in this case are even less.

Conclusion

Out of all the used models, the best one are the decision tree and K nearest neighbors if we consider error and overfitting. Overall, the best model is K Nearest Neighbors considering the speed of its use.