# 1.Hyper-parameter Tuning

October 28, 2021

Hyperparameter Tuning for Multiple Regression

We will find optimal number of features using recursive feature elimination (RFE) and k-fold cross validation.

[56]:
```
# 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

[57]:
```
df = pd.read_csv('E:\\MY LECTURES\\DATA SCIENCE\\3.Programs\\dataset\\Housing.
↪csv')
df.head()
```

[57]:
```
      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
```

### 0.0.2 Step 2: Apply EDA

Univariate and bivariate analysis

### 0.0.3 Step 3. Pre-process and extract the features

[58]:
```python
# 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
df[binary_vars_list] = df[binary_vars_list].apply(binary_map)
df.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
0        furnished
1        furnished
2   semi-furnished
3        furnished
4        furnished
```

[59]:
```python
# '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(df['furnishingstatus'], drop_first = True)
status.head()
```

[59]:
```
   semi-furnished  unfurnished
0               0            0
1               0            0
2               1            0
3               0            0
```

```
4                0            0
```

[60]:
```
# concat the dummy variable df with the main df
df = pd.concat([df, status], axis = 1)
df.head()
```

[60]:
```
      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
```

[61]:
```
# remove 'furnishingstatus' since we alreday have the dummy vars
df.drop(['furnishingstatus'], axis = 1, inplace = True)
df.head()
```

[61]:
```
      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

   semi-furnished  unfurnished
0               0            0
```

```
1           0           0
2           1           0
3           0           0
4           0           0
```

[62]:
```
# extracting relevant features
numeric_vars = ['area', 'bedrooms', 'bathrooms', 'stories', 'parking','price']
temp = df[numeric_vars]
temp.head()
```

[62]:
```
   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
```

[63]:
```
# pre-process: Scale the values of those features between 0 and 1
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
temp1 = scaler.fit_transform(temp)
temp1 = pd.DataFrame(temp1,columns=['area', 'bedrooms', 'bathrooms', 'stories',␣
 ↪'parking','price'])
temp1.head()
```

[63]:
```
       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
```

[64]:
```
df1 = df[["mainroad","guestroom", "basement", "hotwaterheating",␣
 ↪"airconditioning", "prefarea", "semi-furnished"]]
df1.head()
```

[64]:
```
   mainroad  guestroom  basement  hotwaterheating  airconditioning  prefarea  \
0         1          0         0                0                1         1
1         1          0         0                0                1         0
2         1          0         1                0                0         1
3         1          0         1                0                1         1
4         1          1         1                0                1         0

   semi-furnished
0               0
1               0
2               1
```

```
3              0
4              0
```

[65]:
```
pre_processed_data = pd.concat([df1,temp1],axis=1)
pre_processed_data.head()
```

[65]:
```
   mainroad  guestroom  basement  hotwaterheating  airconditioning  prefarea  \
0         1          0         0                0                1         1
1         1          0         0                0                1         0
2         1          0         1                0                0         1
3         1          0         1                0                1         1
4         1          1         1                0                1         0

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

[66]:
```
pre_processed_data.shape
```

[66]:
```
(545, 13)
```

### 0.0.4 Step 4. Split the data for training and testing

[67]:
```
# split into train and test
from sklearn.model_selection import train_test_split
train, test = train_test_split(pre_processed_data, train_size = 0.8, test_size␣
↪= 0.2, random_state = 100)
```

[68]:
```
# 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
```

**Using RFE (recursive feature elimination ) to find optimal number of features** Now, we have 13 input features. To build the model using RFE, we need to tell RFE how many features we want in the final model. It then runs a feature elimination algorithm.

Note that the number of features to be used in the model is a **hyperparameter**.

[69]:
```python
# num of max features
len(x_train.columns)
```

[69]:
```
12
```

**demanding 10 features**

[70]:
```python
# first model with an arbitrary choice of n_features (say 10) using Recursive␣
↪Feature Elimination (RFE)
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression

lm = LinearRegression()

rfe = RFE(lm, n_features_to_select = 10)

rfe = rfe.fit(x_train, y_train)
```

[71]:
```python
# tuples of (feature name, whether selected, ranking)
# note that the 'rank' is > 1 for non-selected features
list(zip(x_train.columns,rfe.support_,rfe.ranking_))
```

[71]:
```
[('mainroad', True, 1),
 ('guestroom', True, 1),
 ('basement', False, 2),
 ('hotwaterheating', True, 1),
 ('airconditioning', True, 1),
 ('prefarea', True, 1),
 ('semi-furnished', False, 3),
 ('area', True, 1),
 ('bedrooms', True, 1),
 ('bathrooms', True, 1),
 ('stories', True, 1),
 ('parking', True, 1)]
```

[72]:
```python
import sklearn.metrics

# predict prices of X_test
y_pred = rfe.predict(x_test)

# evaluate the model on test set
r2 = sklearn.metrics.r2_score(y_test, y_pred)
print("R2 score for 10 features is ", np.round(r2,2)*100,"%")
```

```
R2 score for 10 features is  66.0 %
```

**demanding 6 features**

[73]:
```
# try with another value of RFE

rfe = RFE(lm, n_features_to_select = 6)
rfe = rfe.fit(x_train, y_train)

# predict prices of X_test
y_pred = rfe.predict(x_test)

# evaluate the model on test set
r2 = sklearn.metrics.r2_score(y_test, y_pred)
print("R2 score for 6 features is ", np.round(r2,2)*100,"%")
```

```
R2 score for 6 features is  61.0 %
```

**Using k-fold cross-validation**

[74]:
```
# number of features in X_train
len(x_train.columns)
```

[74]: 12

[75]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV


# step-1: create a cross-validation scheme
folds = KFold(n_splits = 5, shuffle = True, random_state = 100)

# step-2: specify range of hyperparameters to tune
hyper_params = [{'n_features_to_select': list(range(1, 14))}]

# step-3: perform grid search
# 3.1 specify model
lm = LinearRegression()
rfe = RFE(lm)

# 3.2 call GridSearchCV()
model_cv = GridSearchCV(estimator = rfe, param_grid = hyper_params, scoring=␣
↪'r2', cv = folds, verbose = 1, return_train_score=True)

# fit the model
model_cv.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 13 candidates, totalling 65 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  65 out of  65 | elapsed:    0.6s finished
```

[75]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=100, shuffle=True),
             estimator=RFE(estimator=LinearRegression()),
             param_grid=[{'n_features_to_select': [1, 2, 3, 4, 5, 6, 7, 8, 9,
                                                   10, 11, 12, 13]}],
             return_train_score=True, scoring='r2', verbose=1)
```

[76]:
```
# cv results
cv_results = pd.DataFrame(model_cv.cv_results_)
cv_results
```

[76]:
```
    mean_fit_time  std_fit_time  mean_score_time  std_score_time  \
0        0.010394      0.001020         0.002399    4.893565e-04
1        0.010787      0.003189         0.002399    4.897265e-04
2        0.009394      0.001021         0.001999    6.315051e-04
3        0.008196      0.000748         0.001799    3.998047e-04
4        0.008156      0.003756         0.001208    9.861814e-04
5        0.009488      0.006468         0.001207    9.855652e-04
6        0.006742      0.005462         0.001599    7.997275e-04
7        0.005597      0.000489         0.001999    7.478899e-07
8        0.004523      0.000445         0.002399    4.898045e-04
9        0.004397      0.000489         0.001599    4.896873e-04
10       0.003399      0.000799         0.001599    4.894147e-04
11       0.002598      0.000490         0.001599    4.894537e-04
12       0.000999      0.001264         0.003924    5.917418e-03

   param_n_features_to_select                          params  \
0                           1   {'n_features_to_select': 1}
1                           2   {'n_features_to_select': 2}
2                           3   {'n_features_to_select': 3}
3                           4   {'n_features_to_select': 4}
4                           5   {'n_features_to_select': 5}
5                           6   {'n_features_to_select': 6}
6                           7   {'n_features_to_select': 7}
7                           8   {'n_features_to_select': 8}
8                           9   {'n_features_to_select': 9}
9                          10  {'n_features_to_select': 10}
10                         11  {'n_features_to_select': 11}
11                         12  {'n_features_to_select': 12}
12                         13  {'n_features_to_select': 13}

    split0_test_score  split1_test_score  split2_test_score  \
0            0.276949           0.387262           0.100131
1            0.429683           0.556214           0.406671
2            0.495335           0.585472           0.491629
3            0.533694           0.612475           0.481561
4            0.531246           0.625839           0.531517
5            0.548520           0.634265           0.550628
```

| | | | |
|---|---|---|---|
| 6 | 0.572115 | 0.669321 | 0.588741 |
| 7 | 0.582022 | 0.674105 | 0.616321 |
| 8 | 0.567159 | 0.678084 | 0.643983 |
| 9 | 0.595612 | 0.686668 | 0.660261 |
| 10 | 0.589047 | 0.695003 | 0.671007 |
| 11 | 0.592462 | 0.693810 | 0.672526 |
| 12 | 0.592462 | 0.693810 | 0.672526 |

| | split3_test_score | … | mean_test_score | std_test_score | rank_test_score | \ |
|---|---|---|---|---|---|---|
| 0 | 0.296618 | … | 0.251887 | 0.096787 | 13 | |
| 1 | 0.508769 | … | 0.462183 | 0.059862 | 12 | |
| 2 | 0.550714 | … | 0.523759 | 0.037856 | 11 | |
| 3 | 0.548044 | … | 0.536108 | 0.044583 | 10 | |
| 4 | 0.518539 | … | 0.542786 | 0.042524 | 9 | |
| 5 | 0.529404 | … | 0.552411 | 0.044890 | 8 | |
| 6 | 0.555967 | … | 0.596075 | 0.039000 | 7 | |
| 7 | 0.572281 | … | 0.608162 | 0.036143 | 6 | |
| 8 | 0.601480 | … | 0.617711 | 0.038855 | 5 | |
| 9 | 0.609489 | … | 0.632374 | 0.034953 | 4 | |
| 10 | 0.615245 | … | 0.636593 | 0.039712 | 3 | |
| 11 | 0.620823 | … | 0.637518 | 0.038926 | 1 | |
| 12 | 0.620823 | … | 0.637518 | 0.038926 | 1 | |

| | split0_train_score | split1_train_score | split2_train_score | \ |
|---|---|---|---|---|
| 0 | 0.280964 | 0.233348 | 0.315899 | |
| 1 | 0.491680 | 0.447678 | 0.492970 | |
| 2 | 0.549716 | 0.519267 | 0.546667 | |
| 3 | 0.597053 | 0.571504 | 0.551180 | |
| 4 | 0.600922 | 0.584481 | 0.596180 | |
| 5 | 0.623425 | 0.599596 | 0.606989 | |
| 6 | 0.632366 | 0.626130 | 0.634878 | |
| 7 | 0.641664 | 0.640590 | 0.644835 | |
| 8 | 0.661629 | 0.641990 | 0.654508 | |
| 9 | 0.680275 | 0.653070 | 0.663458 | |
| 10 | 0.687217 | 0.655536 | 0.666639 | |
| 11 | 0.687616 | 0.657890 | 0.667863 | |
| 12 | 0.687616 | 0.657890 | 0.667863 | |

| | split3_train_score | split4_train_score | mean_train_score | std_train_score |
|---|---|---|---|---|
| 0 | 0.270183 | 0.300176 | 0.280114 | 0.028176 |
| 1 | 0.471062 | 0.496231 | 0.479924 | 0.018399 |
| 2 | 0.533585 | 0.548466 | 0.539540 | 0.011666 |
| 3 | 0.540888 | 0.573760 | 0.566877 | 0.019500 |
| 4 | 0.604684 | 0.611186 | 0.599491 | 0.008967 |
| 5 | 0.635190 | 0.620695 | 0.617179 | 0.012560 |
| 6 | 0.647244 | 0.648303 | 0.637784 | 0.008646 |
| 7 | 0.658142 | 0.662905 | 0.649627 | 0.009131 |

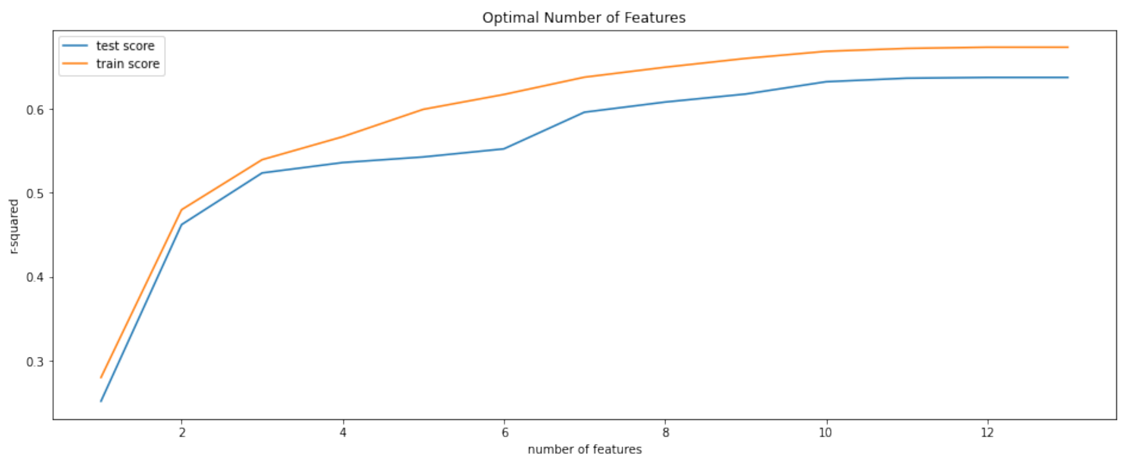
| | | | | |
|---|---|---|---|---|
| 8 | 0.666207 | 0.676354 | 0.660138 | 0.011516 |
| 9 | 0.667128 | 0.679152 | 0.668617 | 0.010173 |
| 10 | 0.671415 | 0.679437 | 0.672049 | 0.010835 |
| 11 | 0.672042 | 0.681946 | 0.673471 | 0.010470 |
| 12 | 0.672042 | 0.681946 | 0.673471 | 0.010470 |

[13 rows x 21 columns]

[77]:
```
# plotting cv results
plt.figure(figsize=(16,6))

plt.plot(cv_results["param_n_features_to_select"],␣
 ↪cv_results["mean_test_score"])
plt.plot(cv_results["param_n_features_to_select"],␣
 ↪cv_results["mean_train_score"])
plt.xlabel('number of features')
plt.ylabel('r-squared')
plt.title("Optimal Number of Features")
plt.legend(['test score', 'train score'], loc='upper left')
```

[77]: <matplotlib.legend.Legend at 0x1a2c3c6ba90>




From the graph above, we can observe that R_square value keeps increasing as we incrementally add features.

After adding 12 features, there is no much increase in the socre. Therefore, we can select first 10 features for building the model.

[78]:
```
# final model
n_features_optimal = 10

lm = LinearRegression()
```

```python
rfe = RFE(lm, n_features_to_select = n_features_optimal)
rfe = rfe.fit(x_train, y_train)

# predict prices of x_test
y_pred = rfe.predict(x_test)
r2 = sklearn.metrics.r2_score(y_test, y_pred)
print(r2)
```

```
0.656129343365103
```

Notice that the test score is very close to the 'mean test score' on the k-folds (about 60%). In general, the mean score estimated by CV will usually be a good estimate of the test score.