```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import RFE
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.feature_selection import SelectFromModel
In [2]:
#Load the data
data=pd.read_csv("daimonds(predict price).csv")
```

data.shape

In [3]:

#realize the data

Out[3]:

(53940, 12)

In [4]:

```
#glance the data
#第一col是多餘的(要刪掉)・第二col為編號・要預測為price
data.head()
```

Out[4]:

	Unnamed: 0	Unnamed: 0.1	carat	cut	color	clarity	depth	table	price	x	у	z
0	0	1	0.23	NaN	Е	SI2	61.5	55.0	326.0	3.95	3.98	2.43
1	1	2	0.21	Premium	Е	SI1	59.8	NaN	326.0	3.89	3.84	2.31
2	2	3	0.23	Good	Е	VS1	56.9	65.0	327.0	4.05	4.07	2.31
3	3	4	0.29	Premium	1	NaN	62.4	58.0	334.0	4.20	NaN	2.63
4	4	5	0.31	Good	J	SI2	63.3	58.0	335.0	4.34	4.35	2.75

In [5]: ▶

```
#刪除第一個col和編號
data=data_dron(["Unnamed: 0" "Unnamed: 0 1"] axi
```

data=data.drop(["Unnamed: 0","Unnamed: 0.1"],axis=1)

data

Out[5]:

	carat	cut	color	clarity	depth	table	price	x	у	z
0	0.23	NaN	E	SI2	61.5	55.0	326.0	3.95	3.98	2.43
1	0.21	Premium	Е	SI1	59.8	NaN	326.0	3.89	3.84	2.31
2	0.23	Good	Е	VS1	56.9	65.0	327.0	4.05	4.07	2.31
3	0.29	Premium	1	NaN	62.4	58.0	334.0	4.20	NaN	2.63
4	0.31	Good	J	SI2	63.3	58.0	335.0	4.34	4.35	2.75
53935	0.72	Ideal	D	SI1	60.8	57.0	2757.0	5.75	5.76	3.50
53936	0.72	Good	D	SI1	63.1	55.0	2757.0	5.69	5.75	3.61
53937	0.70	Very Good	D	SI1	62.8	60.0	2757.0	5.66	5.68	3.56
53938	0.86	Premium	Н	SI2	61.0	58.0	2757.0	6.15	6.12	3.74

In [6]:

#checking null data #資料集看起來夠大,可以刪除空值 print(data.isnull().sum())

carat 993 cut 989 color 992 clarity 995 depth 990 table 993 992 price Χ 991 997 У 992 Z dtype: int64

```
In [7]: ▶
```

```
data_drop=data.dropna()
data_drop
```

Out[7]:

	carat	cut	color	clarity	depth	table	price	x	у	z
2	0.23	Good	E	VS1	56.9	65.0	327.0	4.05	4.07	2.31
4	0.31	Good	J	SI2	63.3	58.0	335.0	4.34	4.35	2.75
5	0.24	Very Good	J	VVS2	62.8	57.0	336.0	3.94	3.96	2.48
6	0.24	Very Good	1	VVS1	62.3	57.0	336.0	3.95	3.98	2.47
7	0.26	Very Good	Н	SI1	61.9	55.0	337.0	4.07	4.11	2.53
53934	0.72	Premium	D	SI1	62.7	59.0	2757.0	5.69	5.73	3.58
53935	0.72	Ideal	D	SI1	60.8	57.0	2757.0	5.75	5.76	3.50
53936	0.72	Good	D	SI1	63.1	55.0	2757.0	5.69	5.75	3.61
53937	0.70	Very Good	D	SI1	62.8	60.0	2757.0	5.66	5.68	3.56
53938	0.86	Premium	Н	SI2	61.0	58.0	2757.0	6.15	6.12	3.74

44773 rows × 10 columns

```
In [8]: ▶
```

```
#check null data
#not null data
print(data_drop.isnull().sum())
```

```
carat
            0
            0
cut
            0
color
clarity
            0
depth
            0
table
            0
            0
price
            0
Х
            0
У
dtype: int64
```

In [9]:

```
#有feature是文字·將其轉換成數字
#依照鑽石的等級分類表
#先觀察每一個feature(cut,color,clarity)的value_counts
```

```
H
In [10]:
#cut
data_drop["cut"].value_counts()
Out[10]:
Ideal
             17852
Premium
             11502
Very Good
               9978
Good
               4096
Fair
               1345
Name: cut, dtype: int64
                                                                                               H
In [11]:
#color
data_drop["color"].value_counts()
Out[11]:
     9405
G
Ε
     8076
F
     7973
Н
     6919
     5593
D
Ι
     4496
J
     2311
Name: color, dtype: int64
In [12]:
                                                                                               H
#clarity
data_drop["clarity"].value_counts()
Out[12]:
        10854
SI1
VS2
        10191
SI2
         7626
VS1
         6800
VVS2
         4192
         3009
VVS1
IF
         1495
          606
I1
Name: clarity, dtype: int64
```

In [13]:

```
#將所有的轉換成數值
cut_mapping = {
    'Fair':1.0,
    'Good':2.0,
    'Very Good':3.0,
    'Premium':4.0,
    'Ideal':5.0
data_drop['cut']=data_drop['cut'].map(cut_mapping)
color mapping = {
    'J':1.0,
    'I':2.0,
    'H':3.0,
    'G':4.0,
    'F':5.0,
    'E':6.0,
    'D':7.0
data_drop['color']=data_drop['color'].map(color_mapping)
clarity_mapping = {
    'I1':1.0,
    'SI2':2.0,
    'SI1':3.0,
    'VS2':4.0,
    'VS1':5.0,
    'VVS2':6.0,
    'VVS1':7.0,
    'IF':8.0
data_drop['clarity']=data_drop['clarity'].map(clarity_mapping)
data_drop
```

```
<ipython-input-13-7b12959132d0>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  data drop['cut']=data drop['cut'].map(cut mapping)
<ipython-input-13-7b12959132d0>:19: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#returni
ng-a-view-versus-a-copy)
  data_drop['color']=data_drop['color'].map(color_mapping)
<ipython-input-13-7b12959132d0>:30: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
```

```
ng-a-view-versus-a-copy)
```

data_drop['clarity']=data_drop['clarity'].map(clarity_mapping)



Out[13]:

	carat	cut	color	clarity	depth	table	price	x	у	z
2	0.23	2.0	6.0	5.0	56.9	65.0	327.0	4.05	4.07	2.31
4	0.31	2.0	1.0	2.0	63.3	58.0	335.0	4.34	4.35	2.75
5	0.24	3.0	1.0	6.0	62.8	57.0	336.0	3.94	3.96	2.48
6	0.24	3.0	2.0	7.0	62.3	57.0	336.0	3.95	3.98	2.47
7	0.26	3.0	3.0	3.0	61.9	55.0	337.0	4.07	4.11	2.53
53934	0.72	4.0	7.0	3.0	62.7	59.0	2757.0	5.69	5.73	3.58
53935	0.72	5.0	7.0	3.0	60.8	57.0	2757.0	5.75	5.76	3.50
53936	0.72	2.0	7.0	3.0	63.1	55.0	2757.0	5.69	5.75	3.61
53937	0.70	3.0	7.0	3.0	62.8	60.0	2757.0	5.66	5.68	3.56
53938	0.86	4.0	3.0	2.0	61.0	58.0	2757.0	6.15	6.12	3.74

44773 rows × 10 columns

```
In [14]:

##區分出預測值和feature
y=data_drop["price"]
```

```
x=data_drop.drop(["price"],axis=1)
```

```
In [15]: ▶
```

```
columns = x.columns
```

```
In [16]:
```

```
#將x標準化
```

```
from sklearn import preprocessing
```

x = preprocessing.scale(x)

In [17]:

```
x_pd = pd.DataFrame(x,columns=columns)
x pd
```

Out[17]:

	carat	cut	color	clarity	depth	table	x	у	z
0	-1.201147	-1.702967	0.940515	0.576862	-3.371648	3.370086	-1.500724	-1.452156	-1.737904
1	-1.031920	-1.702967	-2.004794	-1.246023	1.079742	0.241853	-1.241903	-1.207954	-1.115649
2	-1.179994	-0.807976	-2.004794	1.184491	0.731977	-0.205038	-1.598897	-1.548093	-1.497487
3	-1.179994	-0.807976	-1.415732	1.792120	0.384212	-0.205038	-1.589972	-1.530650	-1.511629
4	-1.137687	-0.807976	-0.826670	-0.638395	0.106000	-1.098819	-1.482874	-1.417270	-1.426776
44768	-0.164628	0.087014	1.529576	-0.638395	0.662424	0.688743	-0.037046	-0.004387	0.058151
44769	-0.164628	0.982005	1.529576	-0.638395	-0.659082	-0.205038	0.016503	0.021778	-0.054986
44770	-0.164628	-1.702967	1.529576	-0.638395	0.940636	-1.098819	-0.037046	0.013056	0.100578
44771	-0.206935	-0.807976	1.529576	-0.638395	0.731977	1.135633	-0.063821	-0.047994	0.029867

In [18]:

y.index=x_pd.index

y.index

Out[18]:

RangeIndex(start=0, stop=44773, step=1)

In [19]:

data=pd.concat([y,x_pd],axis=1)
data

Out[19]:

	price	carat	cut	color	clarity	depth	table	x	у	
0	327.0	-1.201147	-1.702967	0.940515	0.576862	-3.371648	3.370086	-1.500724	-1.452156	-1.737
1	335.0	-1.031920	-1.702967	-2.004794	-1.246023	1.079742	0.241853	-1.241903	-1.207954	-1.115
2	336.0	-1.179994	-0.807976	-2.004794	1.184491	0.731977	-0.205038	-1.598897	-1.548093	-1.497
3	336.0	-1.179994	-0.807976	-1.415732	1.792120	0.384212	-0.205038	-1.589972	-1.530650	-1.51
4	337.0	-1.137687	-0.807976	-0.826670	-0.638395	0.106000	-1.098819	-1.482874	-1.417270	-1.426
44768	2757.0	-0.164628	0.087014	1.529576	-0.638395	0.662424	0.688743	-0.037046	-0.004387	0.058
44769	2757.0	-0.164628	0.982005	1.529576	-0.638395	-0.659082	-0.205038	0.016503	0.021778	-0.054
44770	2757.0	-0.164628	-1.702967	1.529576	-0.638395	0.940636	-1.098819	-0.037046	0.013056	0.100
44771	2757.0	-0.206935	-0.807976	1.529576	-0.638395	0.731977	1.135633	-0.063821	-0.047994	0.029

```
In [20]:
                                                                                                         H
y=data["price"]
x=data.drop(["price"],axis=1)
In [21]:
                                                                                                         H
#將資料區分為訓練集和測試集
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,random_state=42)
In [22]:
                                                                                                         H
x_train
Out[22]:
            carat
                        cut
                                color
                                         clarity
                                                    depth
                                                               table
                                                                             X
                                                                                       У
                                                                                                 z
  1281 -0.143474
                  -2.597958
                             0.351453
                                       0.576862
                                                 -2.189248
                                                            3.816976
                                                                      0.168226
                                                                                0.126436
                                                                                          -0.111555
 12071
        0.618050
                  -0.807976 -0.826670
                                       0.576862
                                                -1.076400
                                                            1.582524
                                                                      0.828666
                                                                                0.841599
                                                                                          0.680407
        0.554590
                  0.087014 -1.415732 -1.246023
  1163
                                                -0.172212
                                                           -0.205038
                                                                      0.748342
                                                                                0.658447
                                                                                          0.680407
 27057 -1.010766
                  0.982005
                             0.351453
                                       1.184491
                                                 -0.589529
                                                           -0.651928
                                                                     -1.152654
                                                                               -1.112018 -1.172217
  5633
       -0.841539
                  -0.807976
                             0.351453
                                      -1.246023
                                                 0.245106
                                                           -0.205038
                                                                     -0.920607
                                                                                -0.867816 -0.861090
                                                       ...
                                                                                      ...
              ...
                         ...
                                   ...
                                                                            ...
 11284
        1.168040
                  0.087014 -2.004794
                                      -0.638395
                                                 -0.589529
                                                            0.688743
                                                                      1.194585
                                                                                1.207902
                                                                                          1.104672
 44732 -0.206935
                  0.982005
                             0.351453
                                       0.576862
                                                 0.523318
                                                           -0.651928
                                                                     -0.001347
                                                                                -0.030551
                                                                                          0.044009
 38158 -0.503083
                                      -0.638395
                                                                               -0.370690 -0.450967
                  0.087014
                             1.529576
                                                -0.659082
                                                            1.135633
                                                                     -0.394041
   860 -0.122321 -1.702967
                             0.940515 -0.638395
                                                            1.582524
                                                                                          0.100578
                                                 0.731977
                                                                      0.007578
                                                                                0.021778
In [23]:
                                                                                                         H
y_train
Out[23]:
          3002.0
1281
12071
          5845.0
1163
          2968.0
27057
           800.0
           579.0
5633
            . . .
11284
          5546.0
44732
          2751.0
38158
          1723.0
          2906.0
860
15795
          7797.0
Name: price, Length: 31341, dtype: float64
```

```
In [24]:
#先觀察都沒做feature selection前的mode準確度
model = LinearRegression()
model.fit(x_train,y_train)
Out[24]:
LinearRegression()
In [25]:
                                                                                       H
#觀察迴歸模型的準確度
score = model.score(x_test, y_test)
print('Score: ', score)
print('Accuracy: ' + str(score*100) + '%')
Score: 0.907752783949035
Accuracy: 90.77527839490351%
                                                                                       M
In [26]:
#feature selection
#使用filter法中的皮爾森相關係數方法作為篩選
#設在相關係數前n大的數字
def feature_selection_n(n):
   featuresCorr = data.corr()
   targetCorr=abs(featuresCorr["price"])
   targetCorr = targetCorr.drop("price")
   result =pd.Series.argsort(-targetCorr)
   targetCorr=targetCorr[result]
   selectedFeatures=targetCorr[0:n]
   #print(f"Number of selected features: {len(selectedFeatures)} \n\nHighly relative featu
   return selectedFeatures
In [27]:
selectedFeatures=feature_selection_n(4)
selectedFeatures
Out[27]:
carat
        0.920902
        0.883254
Х
        0.860264
У
        0.857077
Z
Name: price, dtype: float64
```

```
In [28]:
                                                                                                     H
x_train=x_train[selectedFeatures.index]
data_new=pd.concat([y_train,x_train],axis=1)
data_new
Out[28]:
         price
                   carat
                                X
                                          у
                                                    Z
               -0.143474
                         0.168226
                                   0.126436
                                             -0.111555
  1281
       3002.0
 12071 5845.0
               0.618050
                         0.828666
                                   0.841599
                                             0.680407
  1163 2968.0
               0.554590
                         0.748342
                                   0.658447
                                             0.680407
 27057
         800.0 -1.010766
                         -1.152654
                                   -1.112018 -1.172217
  5633
         579.0 -0.841539
                         -0.920607
                                  -0.867816 -0.861090
 11284 5546.0
               1.168040
                         1.194585
                                   1.207902
                                             1.104672
 44732 2751.0 -0.206935
                         -0.001347
                                   -0.030551
                                             0.044009
 38158 1723.0 -0.503083
                         -0.394041
                                   -0.370690
                                            -0.450967
   860 2906.0 -0.122321
                         0.007578
                                   0.021778
                                             0.100578
In [29]:
data_new.to_csv('daimonds_HW1_train.csv')
                                                                                                     H
In [30]:
#觀察select後的準確度
In [31]:
                                                                                                     H
x=data_new.drop(["price"],axis=1)
y=data_new["price"]
In [32]:
model = LinearRegression()
model.fit(x_train,y_train)
Out[32]:
LinearRegression()
```

```
In [33]:
```

```
x_test=x_test[selectedFeatures.index]
data_test=pd.concat([y_test,x_test],axis=1)
data_test
```

Out[33]:

	price	carat	Х	У	Z
8304	4694.0	0.448823	0.605544	0.545068	0.623838
34038	1184.0	-0.820385	-0.867058	-0.832930	-0.875232
10458	5262.0	0.448823	0.587694	0.658447	0.623838
25228	726.0	-0.926152	-1.054480	-0.981195	-1.087364
6561	4303.0	0.702664	0.828666	0.780549	0.864255
42843	2392.0	0.491129	0.623394	0.588675	0.694549
15400	7528.0	0.639204	0.766192	0.780549	0.779402
13538	6488.0	0.300748	0.435972	0.466574	0.510701
39448	1865.0	-0.206935	-0.135219	-0.170095	0.128862
35025	1286.0	-0.630004	-0.661786	-0.702107	-0.620673

13432 rows × 5 columns

```
In [34]:
```

```
#這邊發現無論怎麼調整相關係數的值,只要少任何一個feature, accuracy就會降低,故匯出保留所有feature, score = model.score(x_test, y_test) print('Score: ', score) print('Accuracy: ' + str(score*100) + '%')
```

Score: 0.8536277743784209 Accuracy: 85.36277743784208%

```
In [35]:
```

```
data_test.to_csv('daimonds_HW1_test.csv')
```

```
In [ ]:
```