```
In [1]:

1   import pandas as pd
2  import numpy as np
3  import matplotlib.pyplot as plt
4  %matplotlib inline
5  plt.style.use("seaborn")
```

In [2]: 1 csvpath='/home/ubuntu/桌面/Git/Deeplearning/Python课件/5-机器学习/J老师/others/USA_Housing.csv' 2 USAhousing = pd.read_csv(csvpath)

3 USAhousing.head()

Out[2]:

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.458574	5.682861	7.009188	4.09	23086.800503	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701
1	79248.642455	6.002900	6.730821	3.09	40173.072174	1.505891e+06	188 Johnson Views Suite 079\nLake Kathleen, CA
2	61287.067179	5.865890	8.512727	5.13	36882.159400	1.058988e+06	9127 Elizabeth Stravenue\nDanieltown, WI 06482
3	63345.240046	7.188236	5.586729	3.26	34310.242831	1.260617e+06	USS Barnett\nFPO AP 44820
4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	USNS Raymond\nFPO AE 09386

In [3]: 1 USAhousing.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):

#	Column	Non-Null Count	Dtype
0	Avg. Area Income	5000 non-null	float64
1	Avg. Area House Age	5000 non-null	float64
2	Avg. Area Number of Rooms	5000 non-null	float64
3	Avg. Area Number of Bedrooms	5000 non-null	float64
4	Area Population	5000 non-null	float64
5	Price	5000 non-null	float64
6	Address	5000 non-null	object

dtypes: float64(6), object(1)
memory usage: 273.6+ KB

数据处理

```
In [4]: ▼ 1 # 判断哪些列存在数据缺失
2 USAhousing.isna().sum()
```

Out[4]: Avg. Area Income

Avg. Area House Age

Avg. Area Number of Rooms

Avg. Area Number of Bedrooms

Area Population

Price

Address

dtype: int64

In [5]: ▼ 1 # 判断DataFrame中是否有重复的行
2 USAhousing.duplicated().value_counts() # 注意value_counts是函数Series的函数

Out[5]: False 5000

In [6]: ▼ 1

1 # 仅针对数值型特征做分析

2 USAhousing.describe() # 平均值与中位数相同或相似说明符合正态分布

Out[6]:

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5.000000e+03
mean	68583.108984	5.977222	6.987792	3.981330	36163.516039	1.232073e+06
std	10657.991214	0.991456	1.005833	1.234137	9925.650114	3.531176e+05
min	17796.631190	2.644304	3.236194	2.000000	172.610686	1.593866e+04
25%	61480.562388	5.322283	6.299250	3.140000	29403.928702	9.975771e+05
50%	68804.286404	5.970429	7.002902	4.050000	36199.406689	1.232669e+06
75%	75783.338666	6.650808	7.665871	4.490000	42861.290769	1.471210e+06
max	107701.748378	9.519088	10.759588	6.500000	69621.713378	2.469066e+06

In [7]: ▼ 1 # 分析object类型的Address是否可以作为特征

2 USAhousing.describe(include=[object]) # 显然不行,可以提取有用信息后去掉此列

Out[7]:

	Address
count	5000
unique	5000
top	208 Michael Ferry Apt. 674\nLaurabury, NE 3701
freq	1

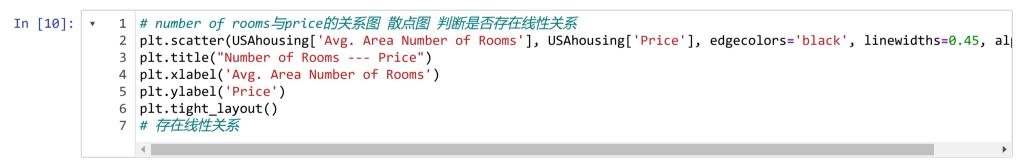
可视化分析

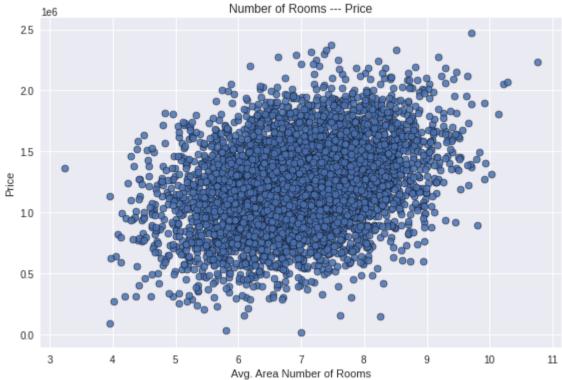
```
In [8]: # income与price的关系图 散点图 判断是否存在线性关系
2 plt.scatter(USAhousing['Avg. Area Income'], USAhousing['Price'], edgecolors='black', linewidths=0.45, alpha=0.85)
3 plt.title("Income --- Price")
4 plt.xlabel('Avg. Area Income')
5 plt.ylabel('Price')
6 plt.tight_layout()
7 # 存在线性关系
```



```
In [9]: # house age与price的关系图 散点图 判断是否存在线性关系
2 plt.scatter(USAhousing['Avg. Area House Age'], USAhousing['Price'], edgecolors='black', linewidths=0.45, alpha=0.3
3 plt.title("House Age --- Price")
4 plt.xlabel('Avg. Area House Age')
5 plt.ylabel('Price')
6 plt.tight_layout()
7 # 存在线性关系
```







```
In [11]: # number of bedrooms与price的关系图 散点图 判断是否存在线性关系
plt.scatter(USAhousing['Avg. Area Number of Bedrooms'], USAhousing['Price'], edgecolors='black', linewidths=0.45,
plt.title("Number of Bedrooms --- Price")
plt.xlabel('Avg. Area Number of Bedrooms')
plt.ylabel('Price')
plt.tight_layout()
# 可能存在一定的线性关系
```



```
In [12]: * 1 # number of rooms与price的关系图 散点图 判断是否存在线性关系
2 plt.scatter(USAhousing['Area Population'], USAhousing['Price'], edgecolors='black', linewidths=0.45, alpha=0.85)
3 plt.title("Area Population --- Price")
4 plt.xlabel('Area Population')
5 plt.ylabel('Price')
6 plt.tight_layout()
7 # 存在线性关系
```



▼ 建立模型

```
In [15]:
          1 # 特征缩放:数据集归一化
          2 from sklearn.preprocessing import StandardScaler # 数据预处理类
          3
          4 | # 归一化方法: 标准差标准化(zero-mean) 转化函数: x = (x-mean) / std
           | # 经过处理后得到的数据集符合标准正态分布,即均值为0,标准差为1
          5
           # 适用于本身服从正态分布的数据
          6
          7
          8 scaler = StandardScaler()
          9
         10 # 下面两行代码是固定用法,不能颠倒顺序
         11 X_train = scaler.fit_transform(X_train) # 求得 训练集 的平均值和方差并应用在 训练集 上,同时也会保存
                                          # 用保存的 训练集 的平均值和方差来应用在 测试集 上
         12 X_test = scaler.transform(X_test)
         13
         14 # 数据预处理中的方法:
         15
         16 # - fit():
         17 # 解释:简单来说,就是求得训练集X的均值啊,方差啊,最大值啊,最小值,这些训练集X固有的属性。可以理解为一个训练过程
         19 # - transform():
         20 # 解释:在Fit的基础上,进行标准化,降维,归一化等操作(看具体用的是哪个工具,如PCA,StandardScaler等)
         21
         22 # - fit_transform():
         23 # 解释: fit_transform是fit和transform的组合,既包括了训练又包含了转换
```

```
In [16]: v 1 # 模型训练
2 from sklearn.linear_model import LinearRegression
3 lin_reg_model = LinearRegression()
5 lin_reg_model.fit(X_train, y_train) #fit生成权重系数coefficient
```

Out[16]: v LinearRegression LinearRegression()

```
In [17]: ▼ 1 # 输出截距
2 print(lin_reg_model.intercept_)
```

1228219.1492415662

```
In [18]: v 1 # 特征权重
2 coeff_df = pd.DataFrame(lin_reg_model.coef_, X.columns, columns=['Coefficient'])
3 coeff_df.sort_values(by='Coefficient', ascending=False)
```

Out[18]:

```
Avg. Area Income 232679.724643

Avg. Area House Age 163841.046593

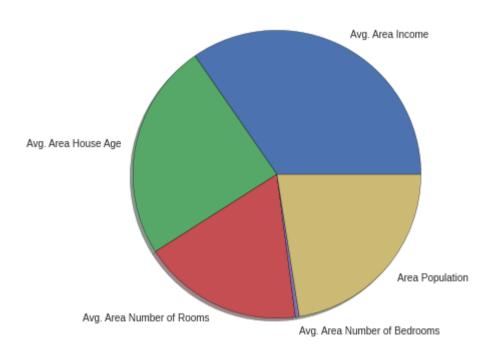
Area Population 151252.342377

Avg. Area Number of Rooms 121110.555478

Avg. Area Number of Bedrooms 2892.815119
```

```
In [19]: v 1 # 特征权重可视化
2 plt.pie(lin_reg_model.coef_, labels=X.columns, shadow=True, wedgeprops={'edgecolor':'black'})
3 plt.title("Coefficient Pie")
4 plt.tight_layout()
```

Coefficient Pie



, 模型评估

```
In [20]:
             1 from sklearn import metrics
             3 # 模型评估函数
             4 | def print_evaluate(y_test, y_predict):
                    mse = metrics.mean_squared_error(y_test, y_predict) #MSE
                    mae = metrics.mean_absolute_error(y_test, y_predict) #MAE
             6
             7
                    rmse = np.sqrt(mse) #RMSE
                    r2 = metrics.r2_score(y_test, y_predict) #R2 Square
             8
                    print(f'MSE: \{mse\} \setminus \{mse\} \setminus \{mae\} \setminus \{r2\} \setminus \{r2\} \setminus \{n'\})
            10
            11 # 模型预测 输出评估结果
            12 | test_pred = lin_reg_model.predict(X_test)
            14 print("测试集计算结果: \n_
            15 print_evaluate(y_test, test_pred)
```

测试集计算结果:

MSE: 10068422551.40088 RMSE: 100341.52954485436 MAE: 81135.56609336878 R2: 0.9146818498754016

```
In [21]: 
# 预测与真实结果可视化

2 plt.scatter(y_test.index, y_test, label='Reality')

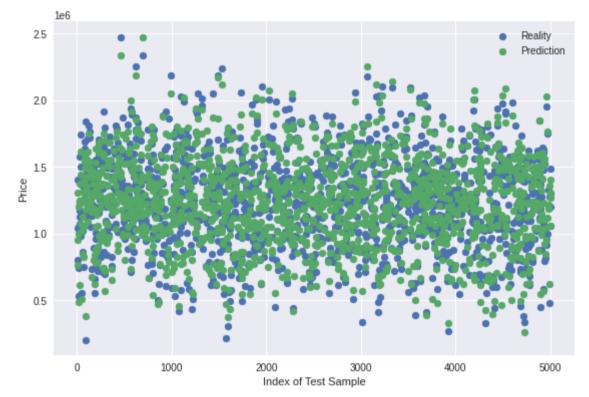
3 plt.scatter(y_test.index, test_pred, label='Prediction')

4 plt.legend()

5 plt.xlabel('Index of Test Sample')

6 plt.ylabel('Price')

7 plt.tight_layout()
```



```
In [22]: 

# 保存模型
import pickle

scalerfile = './scaler.sav'
pickle.dump(scaler, open(scalerfile, 'wb')) # 参数
pickle.dump(lin_reg_model, open('./HousingModel.pkl', 'wb')) # 模型
```