In [ ]:
```
#导入所需要的库
import numpy as np
#处理数据
import pandas as pd
pd.set_option('display.float_format', lambda x: '{:.2f}'.format(x))
#绘图更加美观
import seaborn as sns
color = sns.color_palette()
sns.set_style('darkgrid')
#绘图工具
import matplotlib.pyplot as plt
#jupyter的工具，让绘图更好看
%matplotlib inline

from scipy import stats
from scipy.special import boxcox1p
from scipy.stats import norm, skew

#忽略警告
import warnings
def ignore_warn(*args, **kwargs):
    pass
warnings.warn = ignore_warn
#机器学习工具
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import LabelEncoder
#划分数据集
from sklearn.model_selection import train_test_split
from pandas.plotting import scatter_matrix
#计算均方差
from sklearn.metrics import mean_squared_error
#用于数据标准化
from sklearn.preprocessing import StandardScaler
#决策树回归
from sklearn.tree import DecisionTreeRegressor
#梯度提升法
from sklearn import ensemble
#Lasso模型
from sklearn.linear_model import Lasso
#支持向量机
from sklearn.svm import SVR
#K折验证法
from sklearn.model_selection import cross_val_score
```

In [ ]:
```
#读取数据
df = pd.read_csv("housing.csv")
#拷贝一份数据，以免原有数据被破坏
df_copy = df.copy()
```

In [ ]:
```
#查看数据
#查看前五行
df.head()
```

Out[ ]:

	RM	LSTAT	PTRATIO	MEDV
0	6.58	4.98	15.30	504000.00
1	6.42	9.14	17.80	453600.00
2	7.18	4.03	17.80	728700.00
3	7.00	2.94	18.70	701400.00
4	7.15	5.33	18.70	760200.00

In [ ]:

```
#查看尾五行
df.tail()
```

Out[ ]:

	RM	LSTAT	PTRATIO	MEDV
484	6.59	9.67	21.00	470400.00
485	6.12	9.08	21.00	432600.00
486	6.98	5.64	21.00	501900.00
487	6.79	6.48	21.00	462000.00
488	6.03	7.88	21.00	249900.00

In [ ]:

```
#查看数据集属性描述,最好要有这一步!
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 489 entries, 0 to 488
Data columns (total 4 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   RM       489 non-null    float64
 1   LSTAT    489 non-null    float64
 2   PTRATIO  489 non-null    float64
 3   MEDV     489 non-null    float64
dtypes: float64(4)
memory usage: 15.4 KB
```

发现里面并没有空值，不用另外处理

In [ ]:

```
#查看数值属性列的最大值，最小值，均值等特征
df.describe()
```

Out[ ]:

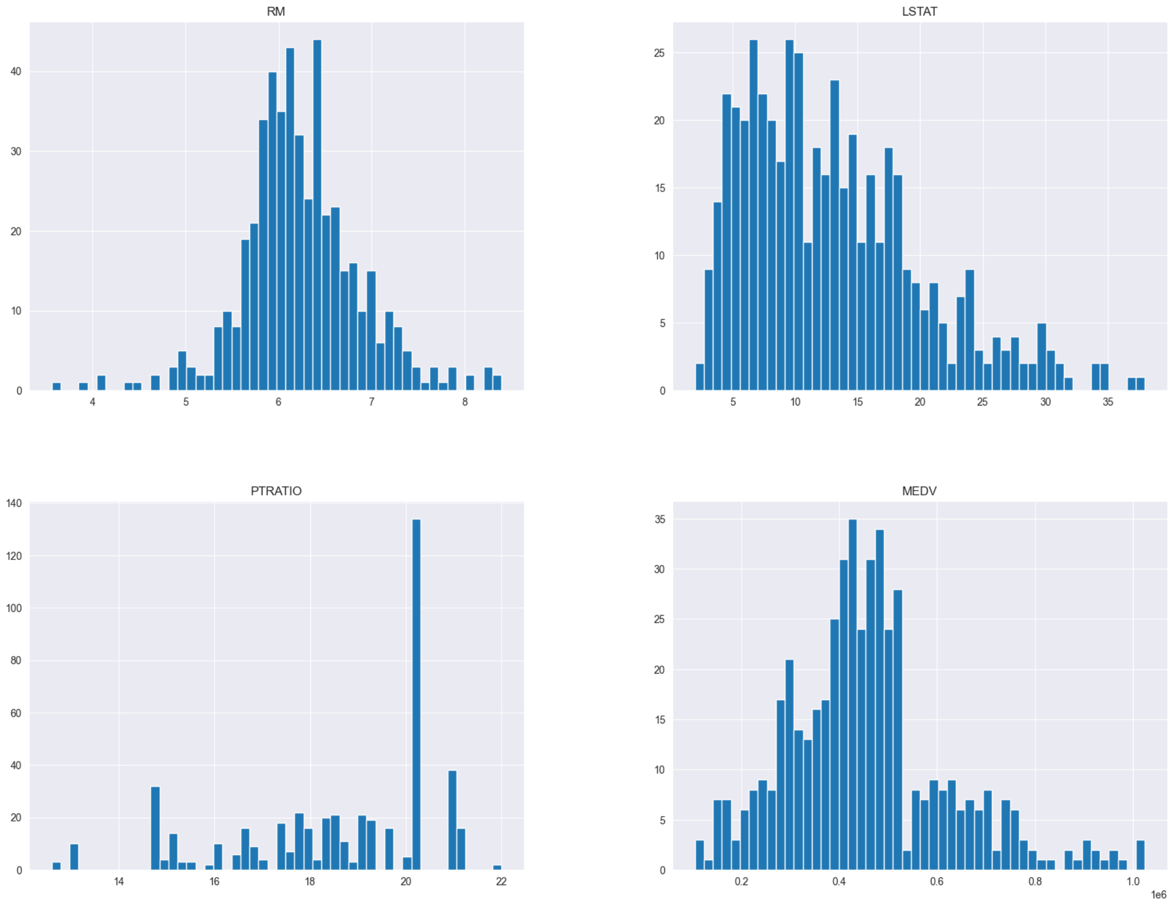
	RM	LSTAT	PTRATIO	MEDV
count	489.00	489.00	489.00	489.00
mean	6.24	12.94	18.52	454342.94
std	0.64	7.08	2.11	165340.28
min	3.56	1.98	12.60	105000.00
25%	5.88	7.37	17.40	350700.00
50%	6.18	11.69	19.10	438900.00
75%	6.58	17.12	20.20	518700.00
max	8.40	37.97	22.00	1024800.00

In [ ]:

```
#查看各属性的各自的分布图案
df.hist(bins=50, figsize=(20,15))#bins代表直方图分区数量，figsize代表图像的宽高
```

Out[ ]:

```
array([[<Axes: title={'center': 'RM'}>,
        <Axes: title={'center': 'LSTAT'}>],
       [<Axes: title={'center': 'PTRATIO'}>,
        <Axes: title={'center': 'MEDV'}>]], dtype=object)
```



In [ ]:

```
#采用留出法划分数据集
train_data, test_data = train_test_split(df,train_size = 0.8,test_size=0.2, rand
```

In [ ]:

```
#训练集
train_data.head()
```

Out[ ]:

	RM	LSTAT	PTRATIO	MEDV
325	5.87	9.80	20.20	409500.00
140	6.17	24.16	21.20	294000.00
433	6.75	17.44	20.20	281400.00
416	6.44	16.22	20.20	300300.00
487	6.79	6.48	21.00	462000.00

In [ ]:

```
#训练集
train_data.head()
```

Out[ ]:

	RM	LSTAT	PTRATIO	MEDV
325	5.87	9.80	20.20	409500.00
140	6.17	24.16	21.20	294000.00
433	6.75	17.44	20.20	281400.00
416	6.44	16.22	20.20	300300.00
487	6.79	6.48	21.00	462000.00

In [ ]:

```
#创建训练集的副本，防止原始训练集被伤害
train_copy = train_data.copy()
```

In [ ]:

```
#分析训练集的数据，PTRATIO,LSTAT,RM与MEDV的整体关系
#房价分布，s-蓝色-PTRATION，c-颜色-价格-（蓝-红）
train_data.plot(kind = "scatter", x = "RM", y = "LSTAT", alpha = 0.4,
             s = train_data["PTRATIO"]*3, label = "PTRATIO", figsize = (10,7),
             c = "MEDV", cmap = plt.get_cmap("jet"), colorbar = True,
            )
plt.legend()
```

Out[ ]:

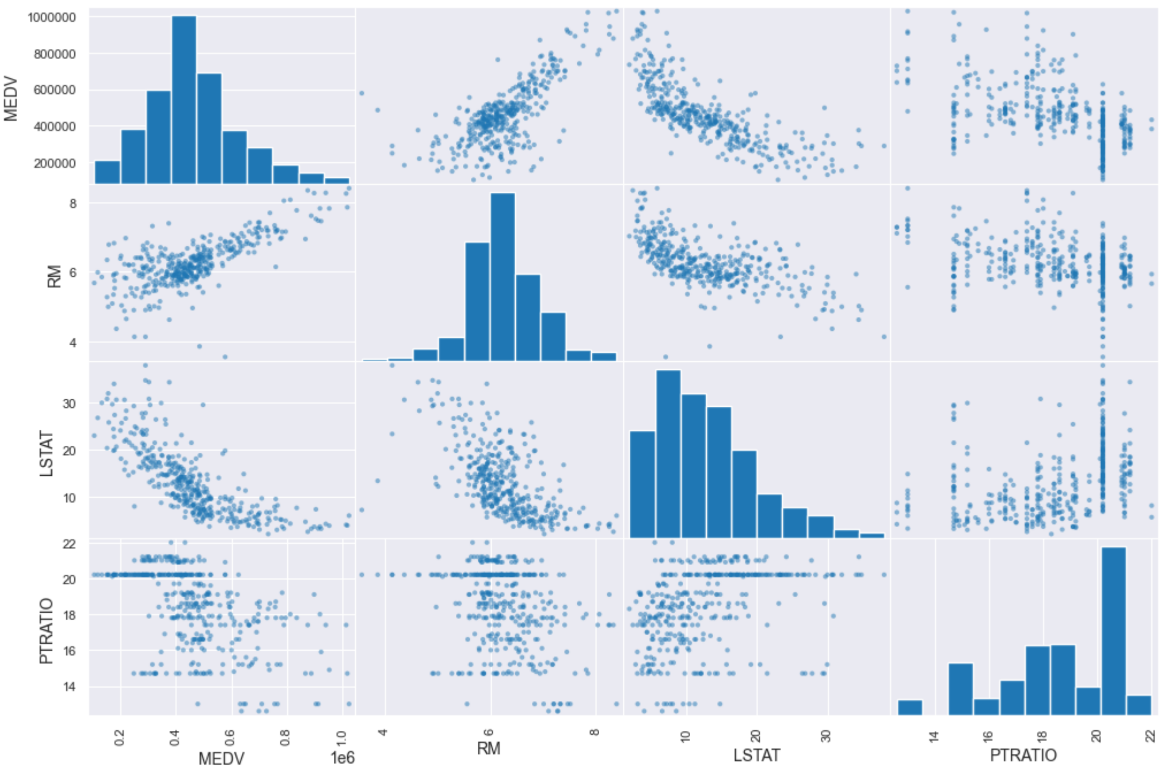
```
<matplotlib.legend.Legend at 0x2f2855de1d0>
```

In [ ]:
```
#计算每对属性的相关系数
corr_matrix = train_data.corr()
#每个属性与房价中位数的相关系数
corr_matrix["MEDV"].sort_values(ascending = False)
```

Out[ ]:
```
MEDV       1.00
RM         0.71
PTRATIO   -0.53
LSTAT     -0.76
Name: MEDV, dtype: float64
```

In [ ]:
```
#查看变量因变量两俩之间的关系
attributes = ["MEDV", "RM", "LSTAT", "PTRATIO"]
scatter_matrix(train_data[attributes], figsize = (12,8))
#从图中看出RM、LSTAT与MEDV相关性比较强，与之前的计算相近
```

Out[ ]:
```
array([[<Axes: xlabel='MEDV', ylabel='MEDV'>,
        <Axes: xlabel='RM', ylabel='MEDV'>,
        <Axes: xlabel='LSTAT', ylabel='MEDV'>,
        <Axes: xlabel='PTRATIO', ylabel='MEDV'>],
       [<Axes: xlabel='MEDV', ylabel='RM'>,
        <Axes: xlabel='RM', ylabel='RM'>,
        <Axes: xlabel='LSTAT', ylabel='RM'>,
        <Axes: xlabel='PTRATIO', ylabel='RM'>],
       [<Axes: xlabel='MEDV', ylabel='LSTAT'>,
        <Axes: xlabel='RM', ylabel='LSTAT'>,
        <Axes: xlabel='LSTAT', ylabel='LSTAT'>,
        <Axes: xlabel='PTRATIO', ylabel='LSTAT'>],
       [<Axes: xlabel='MEDV', ylabel='PTRATIO'>,
        <Axes: xlabel='RM', ylabel='PTRATIO'>,
        <Axes: xlabel='LSTAT', ylabel='PTRATIO'>,
        <Axes: xlabel='PTRATIO', ylabel='PTRATIO'>]], dtype=object)
```



In [ ]:
```
#进行数据清洗
#首先查看数据类型,都是数值类型特征
train_data.dtypes
```

Out[ ]:
```
RM         float64
LSTAT      float64
PTRATIO    float64
MEDV       float64
dtype: object
```

In [ ]:
```
#没有异常的值
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 391 entries, 325 to 102
Data columns (total 4 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   RM       391 non-null    float64
 1   LSTAT    391 non-null    float64
 2   PTRATIO  391 non-null    float64
 3   MEDV     391 non-null    float64
dtypes: float64(4)
memory usage: 15.3 KB
```

In [ ]:
```
#干净的训练集: 预测器和标签分开，因为两者进行数据转换的方式不同。
housing  = train_data.drop("MEDV", axis = 1)#housing数据副本 只包含预测器（3列）
housing_labels = train_data["MEDV"].copy()
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 391 entries, 325 to 102
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   RM       391 non-null    float64
 1   LSTAT    391 non-null    float64
 2   PTRATIO  391 non-null    float64
dtypes: float64(3)
memory usage: 12.2 KB
```

In [ ]:
```python
# 模型实例化
le = LinearRegression()
# 拟合过程，梯度下降法
le.fit(housing, housing_labels)
# 得到回归系数
coef1 = le.coef_  # 3个回归系数
```

In [ ]:
```python
#打印回归系数
print(coef1)
```

```
[ 87322.20361861 -10620.63731522 -19324.4102965 ]
```

In [ ]:
```python
#测试集的处理
housing_test = test_data.drop("MEDV",axis = 1)
housing_test_labels = test_data["MEDV"].copy()
```

In [ ]:
```python
#对测试集进行测试
predict1 = le.predict(housing_test)
```

In [ ]:
```python
#显示测试结果
predict1[:5]
```

Out[ ]:
```
array([342593.79029768, 506257.0916297 , 410499.93166174, 237792.7411537 ,
       327005.79653234])
```

In [ ]:
```python
#得分显示
#MSE （Mean Squared Error）是指预测值与实际值的平方差之和，公式为： MSE = ∑(y_hat
# 得分
print("Score: ", le.score(housing_test, housing_test_labels))
print("RSME: ", np.sqrt(mean_squared_error(housing_test_labels, predict1)))
```

```
Score:  0.6910934003098509
RSME:  82395.54332162568
```

In [ ]:
```python
#对应的回归系数
#创建一个空 DataFrame，并将其命名为 le_df，然后添加一个名为 'name' 的列，并填充 X
#接着添加 'coef' 列，并将 coef1 变成向量化的一维数组。最后返回的就是表格的形式
le_df = pd.DataFrame()

le_df["name"] = housing_test.columns.tolist()
le_df["coef"] = coef1.reshape(-1,1)#转换原来向量为矩阵

le_df
```

Out[ ]:

	name	coef
0	RM	87322.20
1	LSTAT	-10620.64
2	PTRATIO	-19324.41

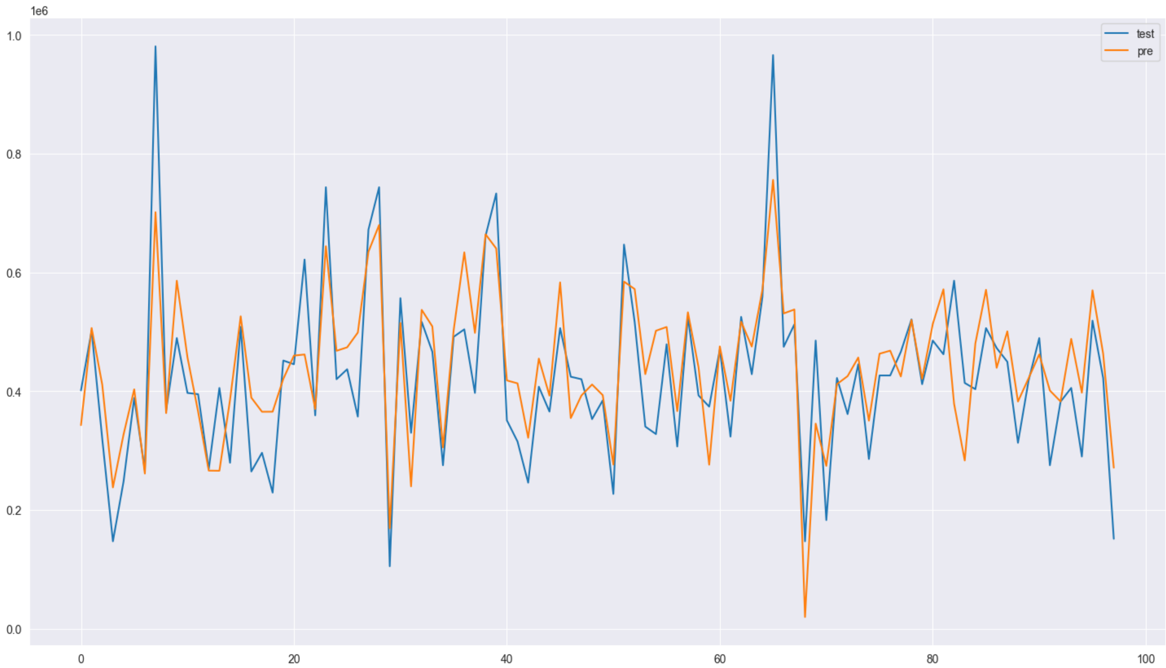
In [ ]:

```
#真实值与预测值的对比
train_test_comp = pd.DataFrame({"test": housing_test_labels.tolist(),
                                "pre": predict1.flatten()
                               })
print(train_test_comp)
```

```
        test       pre
0   401100.00 342593.79
1   501900.00 506257.09
2   319200.00 410499.93
3   147000.00 237792.74
4   247800.00 327005.80
..        ...       ...
93  405300.00 487964.06
94  289800.00 397345.91
95  518700.00 569811.90
96  422100.00 463015.87
97  151200.00 270976.11

[98 rows x 2 columns]
```

In [ ]:

```
#预测结果对比折线图
train_test_comp.plot(figsize=(18,10))
plt.show()
#下图蓝色的是预测值，黄色的是实际值
```



In [ ]:

```
#真实值 < 实际值
len(train_test_comp.query("test<pre")) / len(train_test_comp)
```

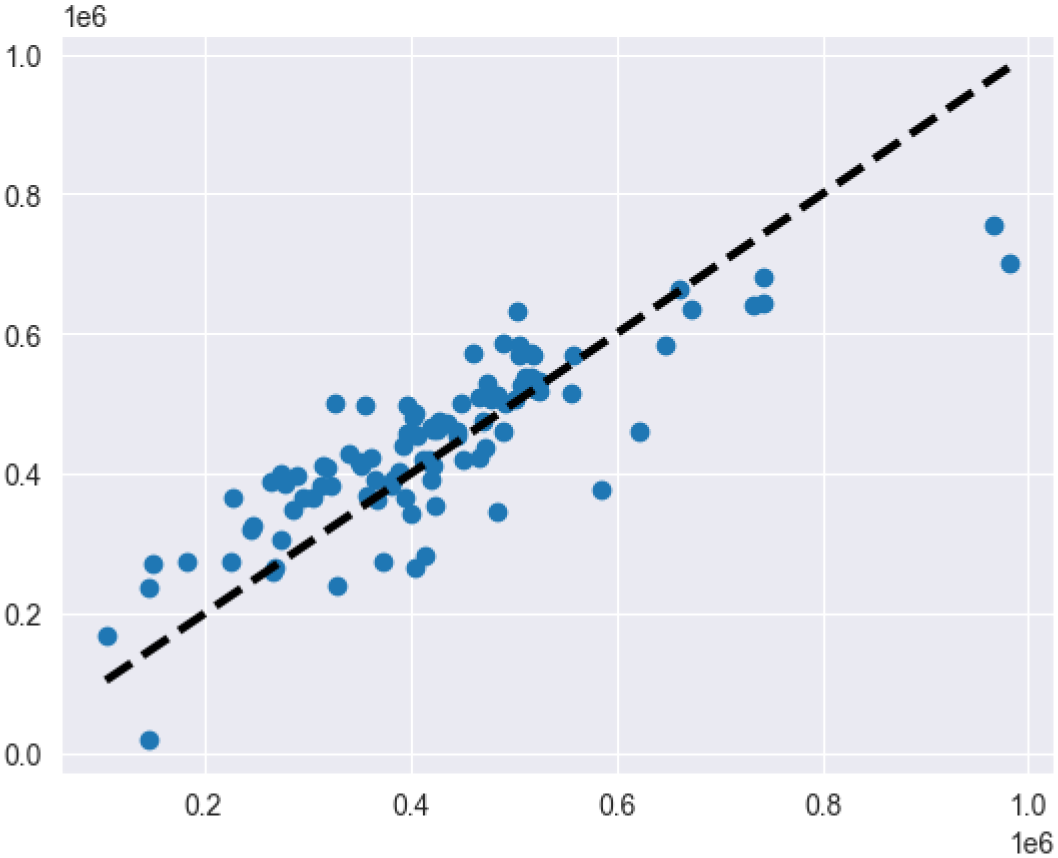
Out[ ]: 0.6938775510204082

In [ ]:

```
#阶段性结论
#发现模型预测的结果大约70%是测试房价大于实际房价
#房价的数据整体是很干净的没有过多噪音，比如值的格式错误，值缺失，没有较多涉及特征
```

In [ ]:

```
#模型评价
#在测试集上面的整体评价,将真实值和预测值的散点分布图画在坐标轴上
#横坐标housing_test_labels，纵坐标predict1
plt.scatter(housing_test_labels, predict1, label="test")
#绘制直线
plt.plot([housing_test_labels.min(), housing_test_labels.max()],
         [housing_test_labels.min(), housing_test_labels.max()],
         'k--',
         lw=3,
         label="predict"
        )

plt.show()
```



In [ ]:

```
#根据上图可以发现在0.2*10^6 ~ 0.6*10^6的范围内预测较为准确
#超过0.6*10^6之后， 预测值要比较小
```

In [ ]:

```
#整体数据集上面分析
all_data_x = df_copy.drop("MEDV",axis=1)
all_data_y = df_copy[["MEDV"]]
all_data_y.head()
```

Out[ ]:

	MEDV
0	504000.00
1	453600.00
2	728700.00
3	701400.00
4	760200.00

In [ ]:

```
#重新在整体上面建模
predict_all = le.predict(all_data_x)
print("Score: ", le.score(all_data_x,all_data_y ))  # 统一换成整体数据集
print("RSME: ", np.sqrt(mean_squared_error(all_data_y, predict_all)))
```

```
Score:  0.7171305906006962
RSME:  87847.04067318552
```

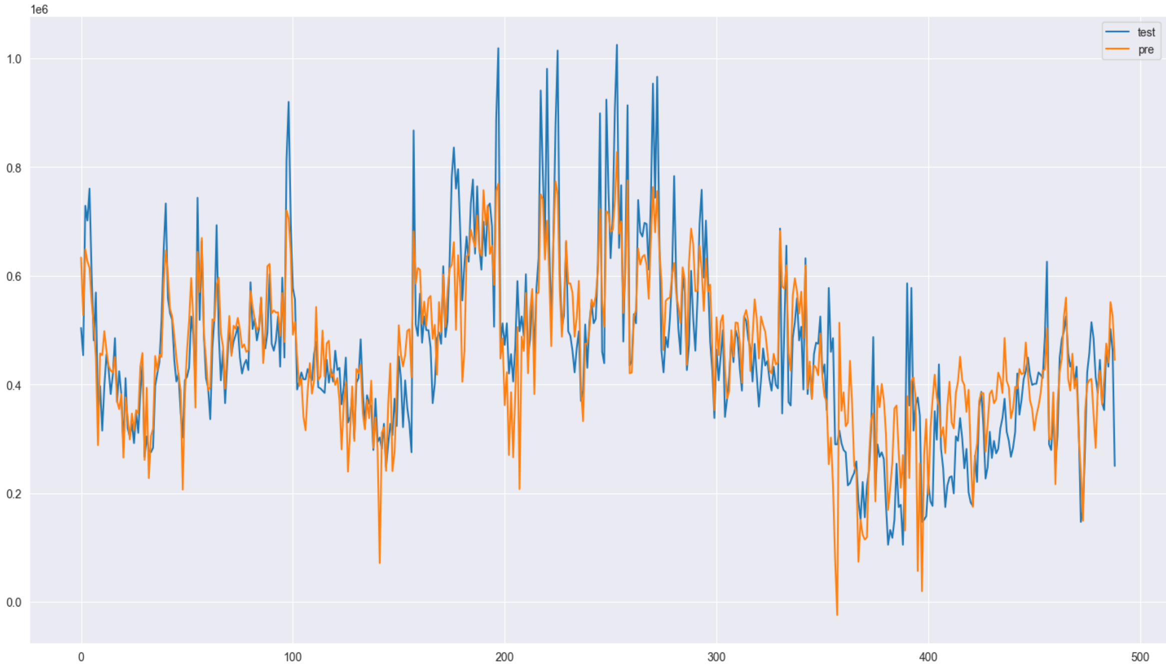
In [ ]:

```
#比较整体数据集上的真实值和预测值
all_pre = pd.DataFrame({"test": all_data_y["MEDV"].tolist(),
                         "pre": predict_all.flatten()
                        })
print(all_pre)
```

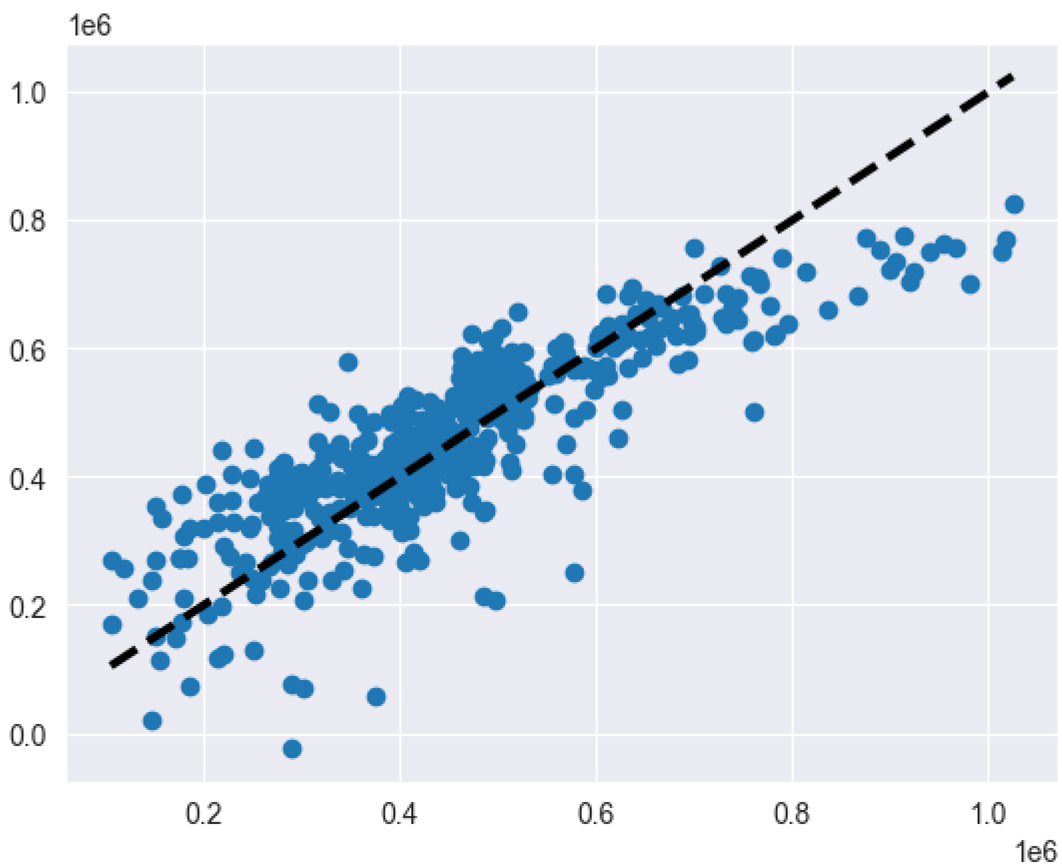
```
          test        pre
0    504000.00 633616.89
1    453600.00 527676.40
2    728700.00 648662.02
3    701400.00 626517.29
4    760200.00 614144.97
..         ...       ...
484  470400.00 475228.76
485  432600.00 440191.54
486  501900.00 551474.34
487  462000.00 526660.36
488  249900.00 445077.30

[489 rows x 2 columns]
```

In [ ]:

```
#折线图对比，更加清晰
all_pre.plot(figsize=(18,10))
plt.show()
```



In [ ]:
```
#同样把整体的真实值与预测值的散点图画出来
plt.scatter(all_data_y, predict_all, label="y_all")
plt.plot([all_data_y.min(), all_data_y.max()],
         [all_data_y.min(), all_data_y.max()],
         'k--',
         lw=3,
         label="all_predict"
        )

plt.show()
```



In [ ]:
```
#在整体上看来在0.2*10^6~0.7*10^6的范围内比较准确，超过0.7*10^6也是预测值比较小
```

In [ ]:
```
#模型的优化
#1、数据归一化。使用 sklearn 中的 StandardScaler 可以将数值特征归一化到 [-1, 1] 范
#要注意的是，当输入数据分布范围很大的时候可以使用归一化，以防止过大或过小的值影响到
#拉伸数据使其变化范围变大。
# 实例化
ss = StandardScaler()
# 特征数据
X = ss.fit_transform(all_data_x)
# 目标变量
y = ss.fit_transform(all_data_y)
# 先切分数据集
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

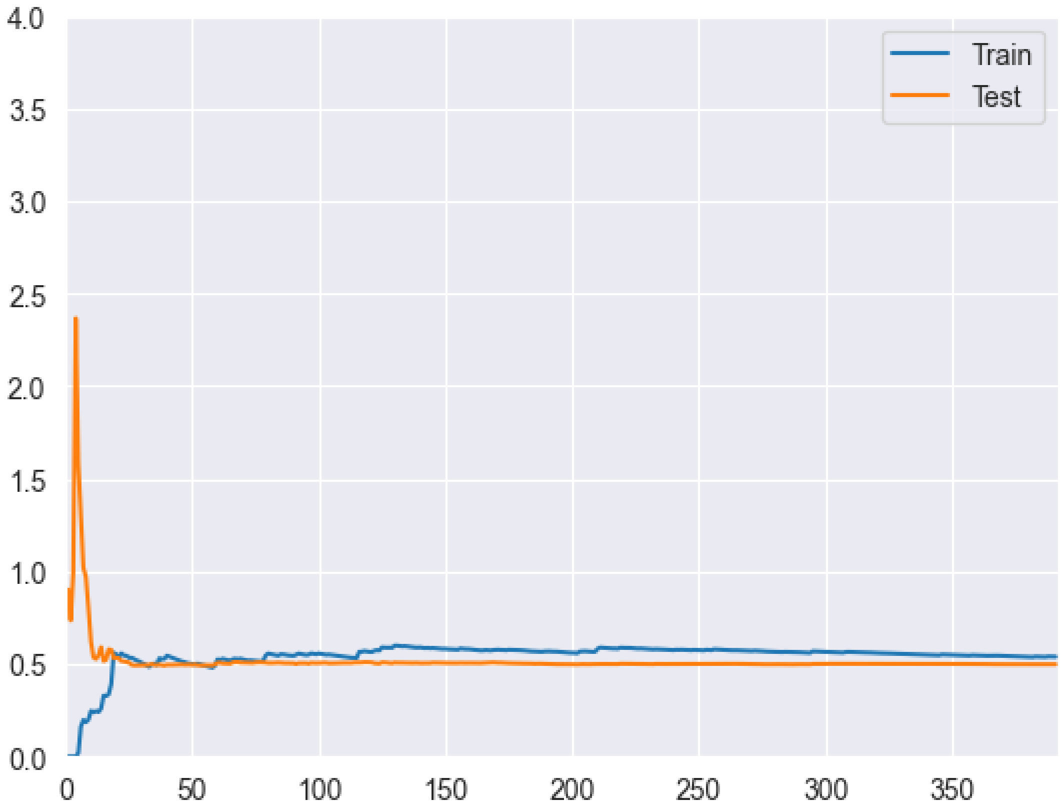
In [ ]:
```
#学习曲线
def plot_learning_curve(algo,X_train,X_test,y_train,y_test):
    train_score = []
    test_score = []

    for i in range(1,len(X_train)+1):
        algo.fit(X_train[:i],y_train[:i])
        y_train_predict = algo.predict(X_train[:i])
        train_score.append(mean_squared_error(y_train[:i],y_train_predict ))

        y_test_predict = algo.predict(X_test)
        test_score.append(mean_squared_error(y_test,y_test_predict))

    plt.plot([i for i in range(1,len(X_train)+1)], np.sqrt(train_score),label =
    plt.plot([i for i in range(1,len(X_train)+1)], np.sqrt(test_score),label = '
    plt.legend()
    plt.axis([0,len(X_train)+1,0,4])
    plt.show()
```

In [ ]:
```
#查看训练集
print(X_train)
```

```
[[-0.57743914 -0.44378023  0.79817433]
 [-0.10309369  1.58597496  1.2723085 ]
 [ 0.79116414  0.63611738  0.79817433]
 ...
 [-0.19951801 -0.03811189  0.79817433]
 [ 0.08819973  0.61208824  0.79817433]
 [ 0.25616467 -0.32646152  1.13006825]]
```

In [ ]:
```
#线性拟合,(较上面的补充学习曲线)
Le = LinearRegression()
Le.fit(X_train,y_train)
Le_pre = Le.predict(X_test)
# 模型评分
print('Score:{:.4f}'.format(Le.score(X_test, y_test)))
# RMSE(标准误差)
print('RMSE:{:.4f}'.format(np.sqrt(mean_squared_error(y_test,Le_pre))))
plot_learning_curve(Le,X_train,X_test,y_train,y_test)
```

```
Score:0.6911
RMSE:0.4988
```



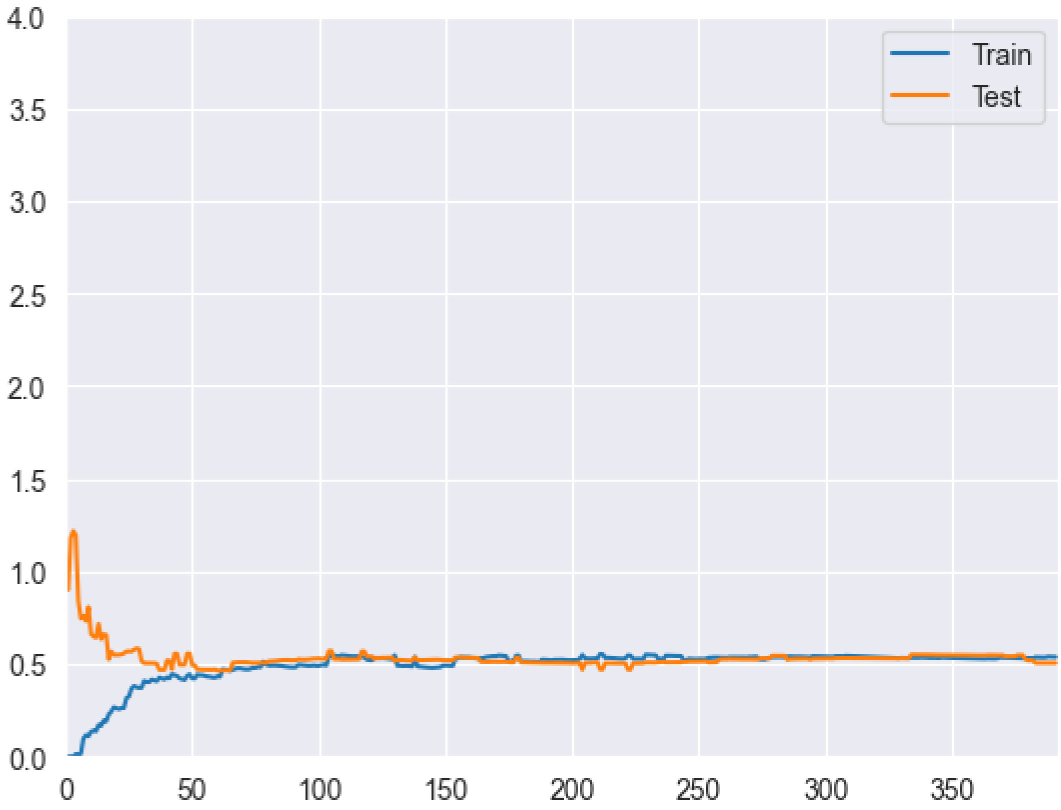
In [ ]:
```
#K折验证法
#评分函数
def display_scores(scores):
    print("Scores:")
    print(pd.Series(scores).mean())
#线性模型的评分:
lin_scores = cross_val_score(Le,X, y,scoring = "neg_mean_squared_error", cv = 10
lin_rmse_scores = np.sqrt(-lin_scores)
print("LinearRegression")
display_scores(lin_rmse_scores)
```

```
LinearRegression
Scores:
0.5558948933250007
```

In [ ]:
```
#决策树回归
tr = DecisionTreeRegressor(max_depth=2)
#进行拟合
tr.fit(X_train, y_train)
# 预测值
tr_pre = tr.predict(X_test)

# 模型评分
print('Score:{:.4f}'.format(tr.score(X_test, y_test)))
# RMSE(标准误差)
print('RMSE:{:.4f}'.format(np.sqrt(mean_squared_error(y_test,tr_pre))))
```

```
Score:0.6817
RMSE:0.5063
```

In [ ]:
```
plot_learning_curve(tr,X_train,X_test,y_train,y_test)
#横轴样本量, 纵轴RMSE
```



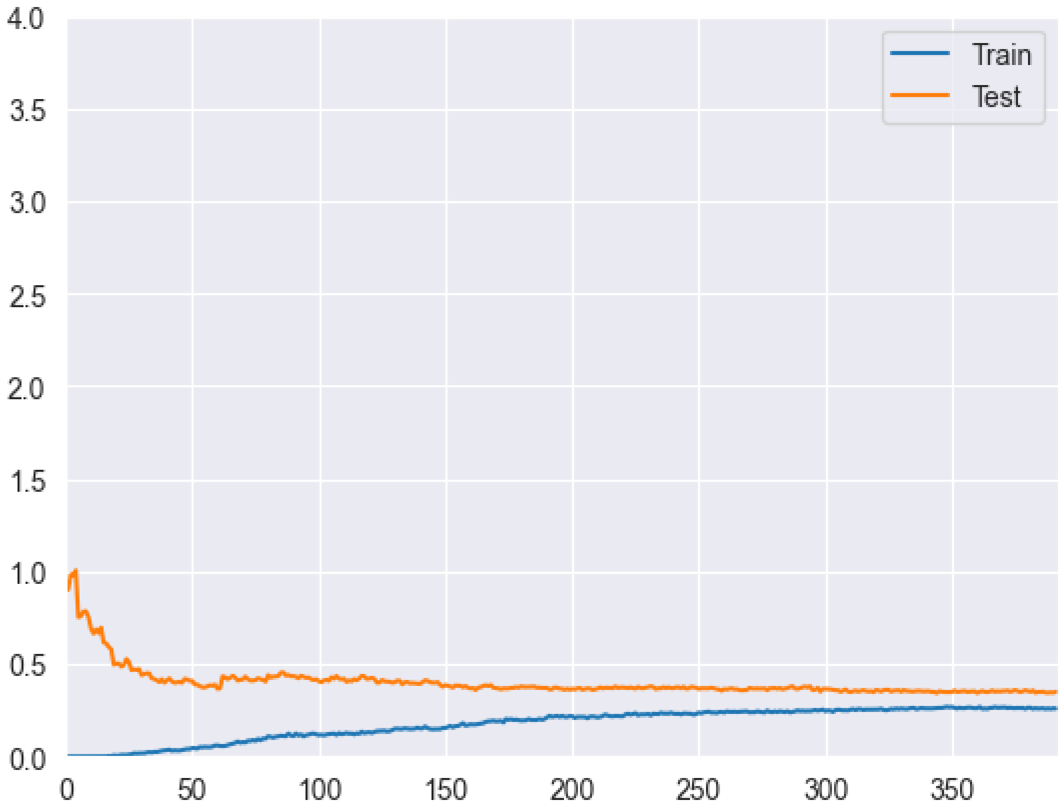
In [ ]:

```
#梯度提升法GradientBoosting
#对每个预测进行弱学习器的加权组合，形成更强的模型，由多个弱分类器组成。它通过梯度
gb = ensemble.GradientBoostingRegressor()

gb.fit(X_train, y_train)
gb_pre=gb.predict(X_test)

# 模型评分
print('Score:{:.4f}'.format(gb.score(X_test, y_test)))
# RMSE(标准误差)
print('RMSE:{:.4f}'.format(np.sqrt(mean_squared_error(y_test,gb_pre))))
```

```
Score:0.8476
RMSE:0.3504
```

In [ ]:

```
#梯度上升法的学习曲线
plot_learning_curve(gb,X_train,X_test,y_train,y_test)
```

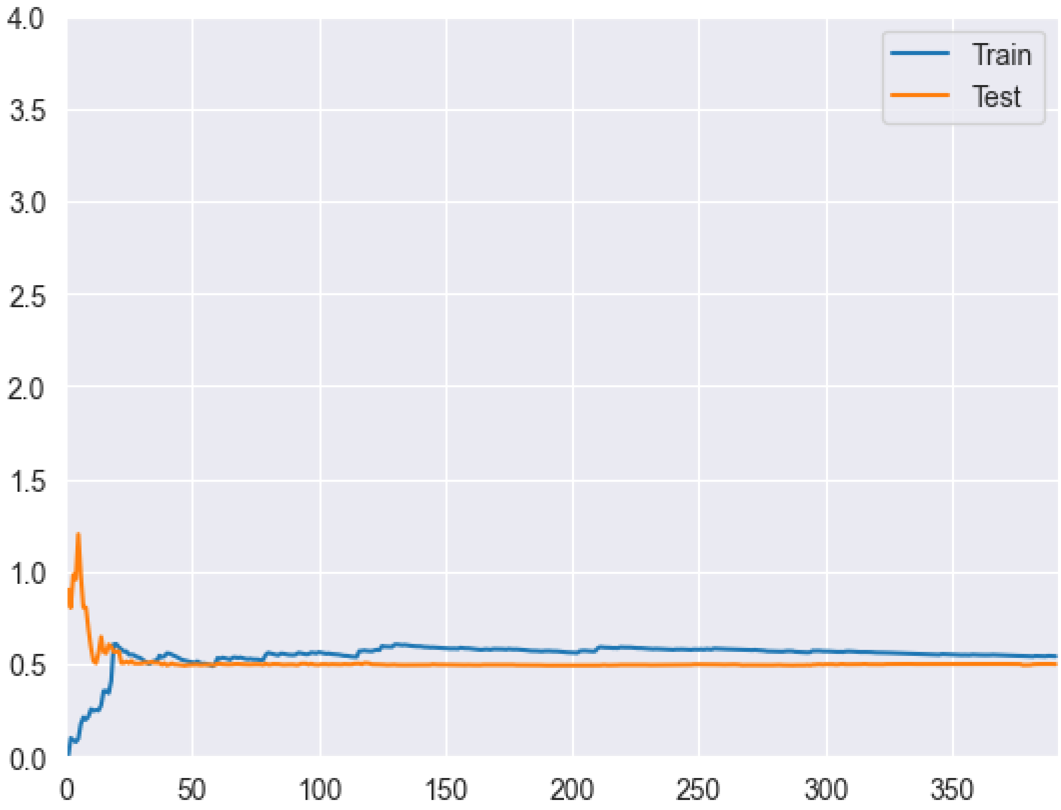


In [ ]:
```
#这个显而易见预测的效果更好
```

In [ ]:
```
#支持向量回归
linear_svr = SVR(kernel="linear")
linear_svr.fit(X_train, y_train)
linear_svr_pre = linear_svr.predict(X_test)

# 模型评分
print('Score:{:.4f}'.format(linear_svr.score(X_test, y_test)))
# RMSE(标准误差)
print('RMSE:{:.4f}'.format(np.sqrt(mean_squared_error(y_test,linear_svr_pre))))
```

```
Score:0.6903
RMSE:0.4995
```

In [ ]:
```
#这个的效果和梯度下降的多元回归模型相差不大
#学习曲线
plot_learning_curve(linear_svr,X_train,X_test,y_train,y_test)
```



In [ ]:
```
#采用不同模型进行建模后发现采用Gradient Boosting 算法的话，效果是最好的。最终的评
```