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  - 官方网址：http://www.ibeifeng.com/

人工智能之机器学习

晚自习

主讲人：Gerry

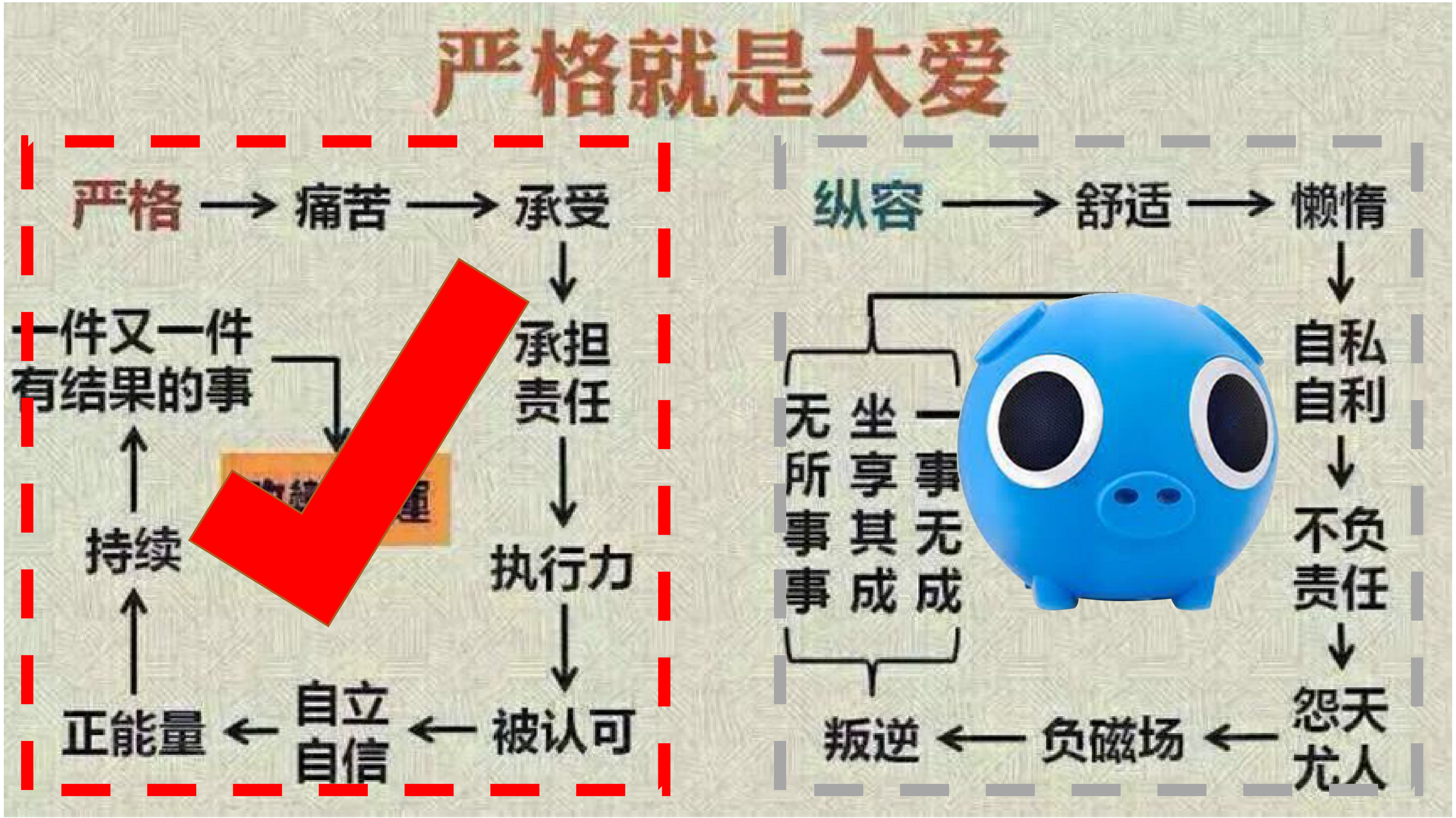
上海育创网络科技有限公司

IBEIFENG.COM

课程要求

- 课上课下“九字”真言
  - 认真听，善摘录，勤思考
  - **多温故，乐实践**，再发散
- 四不原则
  - 不懒散惰性，不迟到早退
  - 不请假旷课，不拖延作业
- 一点注意事项
  - 违反“四不原则”，不包就业和推荐就业

严格是大爱


严格就是大爱
严格 → 痛苦 → 承受
承担责任
执行力
被认可
自立自信
正能量
持续
一件又一件有结果的事
纵容 → 舒适 → 懒惰
自私自利
不负责任
怨天尤人
负磁场
叛逆
无所事事
坐享其成
一事无成

寄语

做别人不愿做的事，

做别人不敢做的事，

做别人做不到的事。

回归算法综合案例(二)：波士顿房屋租赁价格预测(作业)

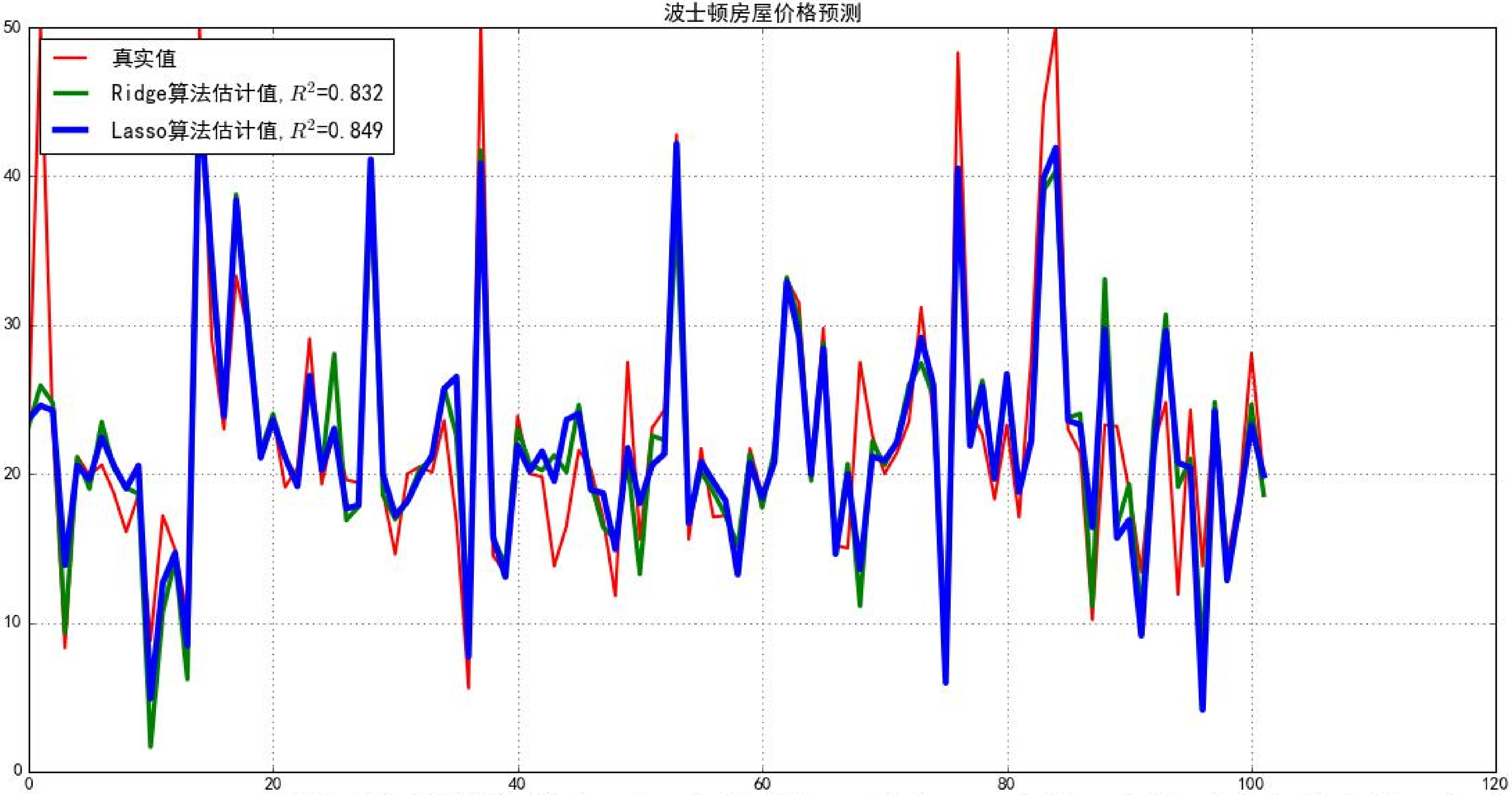
- 基于波士顿房屋租赁数据进行房屋租赁价格预测模型构建，分别使用Lasso回归、Ridge回两种回归算法构建模型；并分别构建2/3/4阶算法中的最优算法(参数)，并比较这两种回归算法的效果；另外使用lasso回归算法做特征选择(选择特征参数不为0的属性数据作为最终的特征属性，用这个选择出来的特征属性矩阵做Ridge回归)
  - 数据下载url: http://archive.ics.uci.edu/ml/datasets/Housing(现在没法下载啦)

Attribute Information:

1. CRIM: per capita crime rate by town
2. ZN: proportion of residential land zoned for lots over 25,000 sq.ft.
3. INDUS: proportion of non-retail business acres per town
4. CHAS: Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
5. NOX: nitric oxides concentration (parts per 10 million)
6. RM: average number of rooms per dwelling
7. AGE: proportion of owner-occupied units built prior to 1940
8. DIS: weighted distances to five Boston employment centres
9. RAD: index of accessibility to radial highways
10. TAX: full-value property-tax rate per $10,000
11. PTRATIO: pupil-teacher ratio by town
12. B: 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
13. LSTAT: % lower status of the population
14. MEDV: Median value of owner-occupied homes in $1000's

0.31533	0.00	6.200	0	0.5040	8.2660	78.30	2.8944	8	307.0	17.40	385.05	4.14	44.80
0.52693	0.00	6.200	0	0.5040	8.7250	83.00	2.8944	8	307.0	17.40	382.00	4.63	50.00
0.38214	0.00	6.200	0	0.5040	8.0400	86.50	3.2157	8	307.0	17.40	387.38	3.13	37.60
0.41238	0.00	6.200	0	0.5040	7.1630	79.90	3.2157	8	307.0	17.40	372.08	6.36	31.60
0.29819	0.00	6.200	0	0.5040	7.6860	17.00	3.3751	8	307.0	17.40	377.51	3.92	46.70
0.44178	0.00	6.200	0	0.5040	6.5520	21.40	3.3751	8	307.0	17.40	380.34	3.76	31.50
0.53700	0.00	6.200	0	0.5040	5.9810	68.10	3.6715	8	307.0	17.40	378.35	11.65	24.30
0.46296	0.00	6.200	0	0.5040	7.4120	76.90	3.6715	8	307.0	17.40	376.14	5.25	31.70
0.57529	0.00	6.200	0	0.5070	8.3370	73.30	3.8384	8	307.0	17.40	385.91	2.47	41.70
0.33147	0.00	6.200	0	0.5070	8.2470	70.40	3.6519	8	307.0	17.40	378.95	3.95	48.30
0.44791	0.00	6.200	1	0.5070	6.7260	66.50	3.6519	8	307.0	17.40	360.20	8.05	29.00
0.33045	0.00	6.200	0	0.5070	6.0860	61.50	3.6519	8	307.0	17.40	376.75	10.88	24.00
0.52058	0.00	6.200	1	0.5070	6.6310	76.50	4.1480	8	307.0	17.40	388.45	9.54	25.10
0.51183	0.00	6.200	0	0.5070	7.3580	71.60	4.1480	8	307.0	17.40	390.07	4.73	31.50
0.08244	30.00	4.930	0	0.4280	6.4810	18.50	6.1899	6	300.0	16.60	379.41	6.36	23.70
0.09252	30.00	4.930	0	0.4280	6.6060	42.20	6.1899	6	300.0	16.60	383.78	7.37	23.30
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

回归算法综合案例(二)：波士顿房屋租赁价格预测



Ridge算法:最优参数: {'poly__degree': 3, 'linear__fit_intercept': True, 'poly__include_bias': True, 'poly__interaction_only': True}
Ridge算法:R值=0.832
Lasso算法:最优参数: {'poly__degree': 3, 'linear__fit_intercept': False, 'poly__include_bias': True, 'poly__interaction_only': True}
Lasso算法:R值=0.849

回归算法综合案例(二)：波士顿房屋租赁价格预测

```
## 模型训练 ===> 单个Lasso模型（一阶特征选择）<2参数给定1阶情况的最优参数>
model = Pipeline([
            ('ss', StandardScaler()),
            ('poly', PolynomialFeatures(degree=1, include_bias=True, interaction_only=True)),
            ('linear', LassoCV(alphas=np.logspace(-3,1,20), fit_intercept=False))
        ])
# 模型训练
model.fit(x_train, y_train)


# 模型评测
## 数据输出
print "参数:", zip(names,model.get_params('linear')['linear'].coef_)
print "截距:", model.get_params('linear')['linear'].intercept_
```

```
参数: [('CRIM', 22.600592809201991), ('ZN', -0.93534557687414488), ('INDUS', 1.0202352850146854), ('CHAS', -0.0), ('NOX', 0.594831384154614
9), ('RM', -1.8002644875942369), ('AGE', 2.5861907995357281), ('DIS', -0.064956108249539249), ('RAD', -2.8017533936656509), ('TAX', 1.934332
9692037559), ('PTRATIO', -1.7218677875512203), ('B', -2.2762334623842988), ('LSTAT', 0.70288003005515387)]
截距: 0.0
```

CHAS列的数据对于LassoCV模型而言无用，所以在进行实际模型构建的时候，可以不考虑该特征

决策树案例二：波士顿房屋租赁价格预测(作业)

- 使用决策树算法API对波士顿房屋租赁数据进行回归操作，预测房屋的价格信息，并理解及进行决策树API的相关参数优化
- 数据来源：波士顿房屋租赁数据

Housing Data Set

Download: Data Folder, Data Set Description

Abstract: Taken from StatLib library

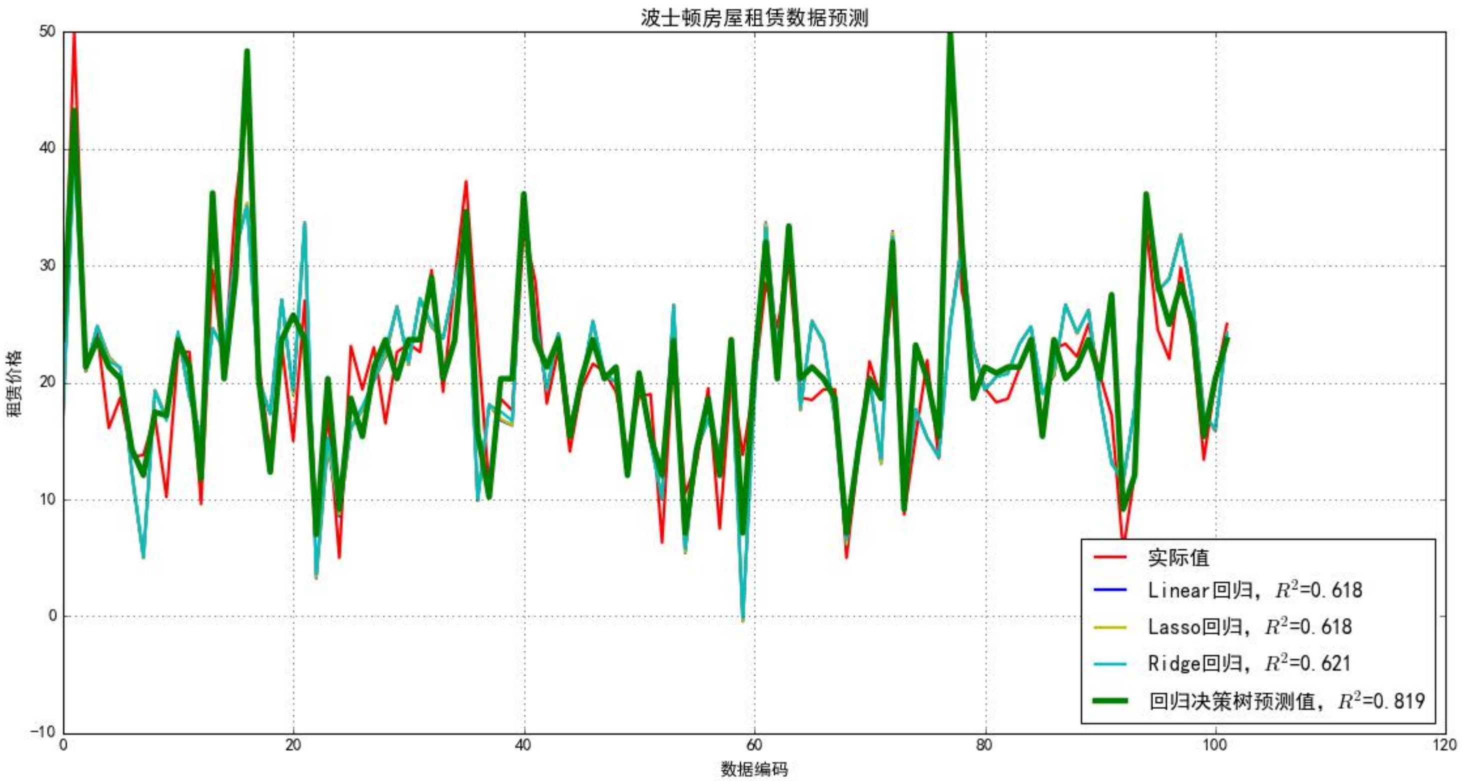
Data Set Characteristics:	Multivariate	**Number of Instances:**	506	**Area:**	N/A
Attribute Characteristics:	Categorical, Integer, Real	**Number of Attributes:**	14	**Date Donated**	1993-07-07
Associated Tasks:	Regression	**Missing Values?**	No	**Number of Web Hits:**	328263

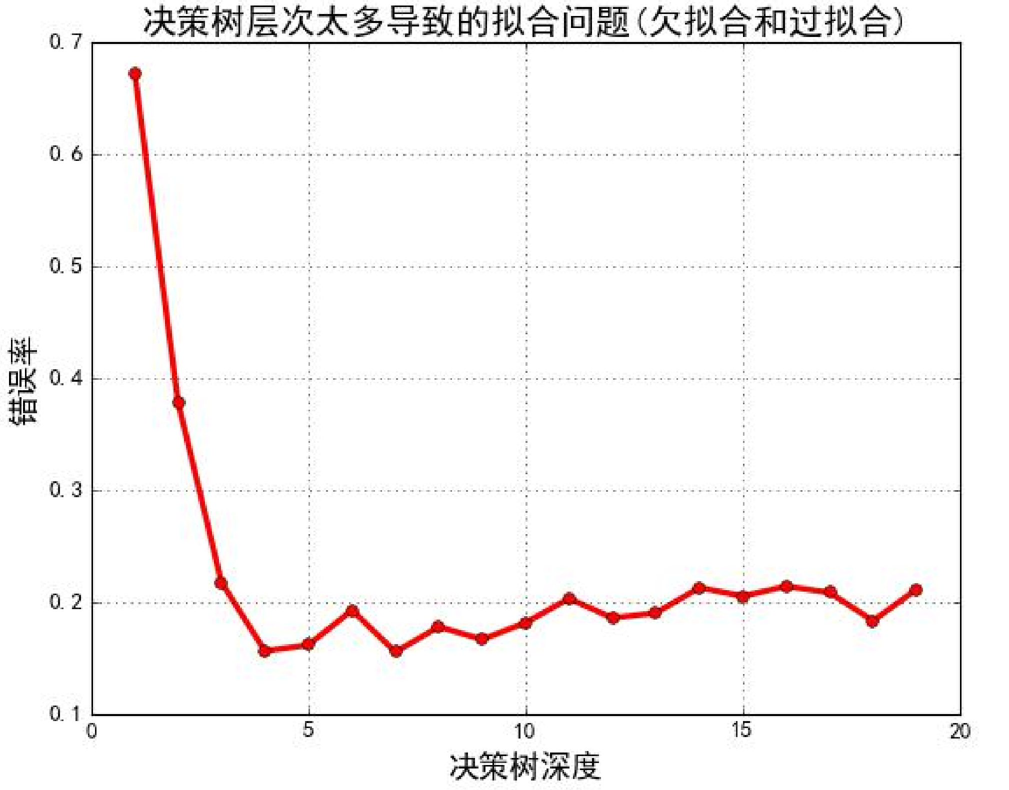
Attribute Information:

1. CRIM: per capita crime rate by town
2. ZN: proportion of residential land zoned for lots over 25,000 sq.ft.
3. INDUS: proportion of non-retail business acres per town
4. CHAS: Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
5. NOX: nitric oxides concentration (parts per 10 million)
6. RM: average number of rooms per dwelling
7. AGE: proportion of owner-occupied units built prior to 1940
8. DIS: weighted distances to five Boston employment centres
9. RAD: index of accessibility to radial highways
10. TAX: full-value property-tax rate per $10,000
11. PTRATIO: pupil-teacher ratio by town
12. B: 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
13. LSTAT: % lower status of the population
14. MEDV: Median value of owner-occupied homes in $1000's

```
class sklearn.tree.DecisionTreeRegressor(criterion='mse', splitter='best', max_depth=None, min_samples_split=2,
min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features=None, random_state=None,
max_leaf_nodes=None) ¶
```
[source]

决策树案例二：波士顿房屋租赁价格预测





GBDT回归案例：波士顿房屋租赁价格预测(作业)

- 基于波士顿房屋租赁数据进行房屋租赁价格预测模型构建，使用集成学习的算法方式对模型进行构建，比较基于GBDT的模型效果和单模型(单个线性回归、单个决策树)情况下的R2的评估值的比较。
  - 数据下载url: http://archive.ics.uci.edu/ml/datasets/Housing(现在没法下载啦)

Attribute Information: boston_housing.data

1. CRIM: per capita crime rate by town
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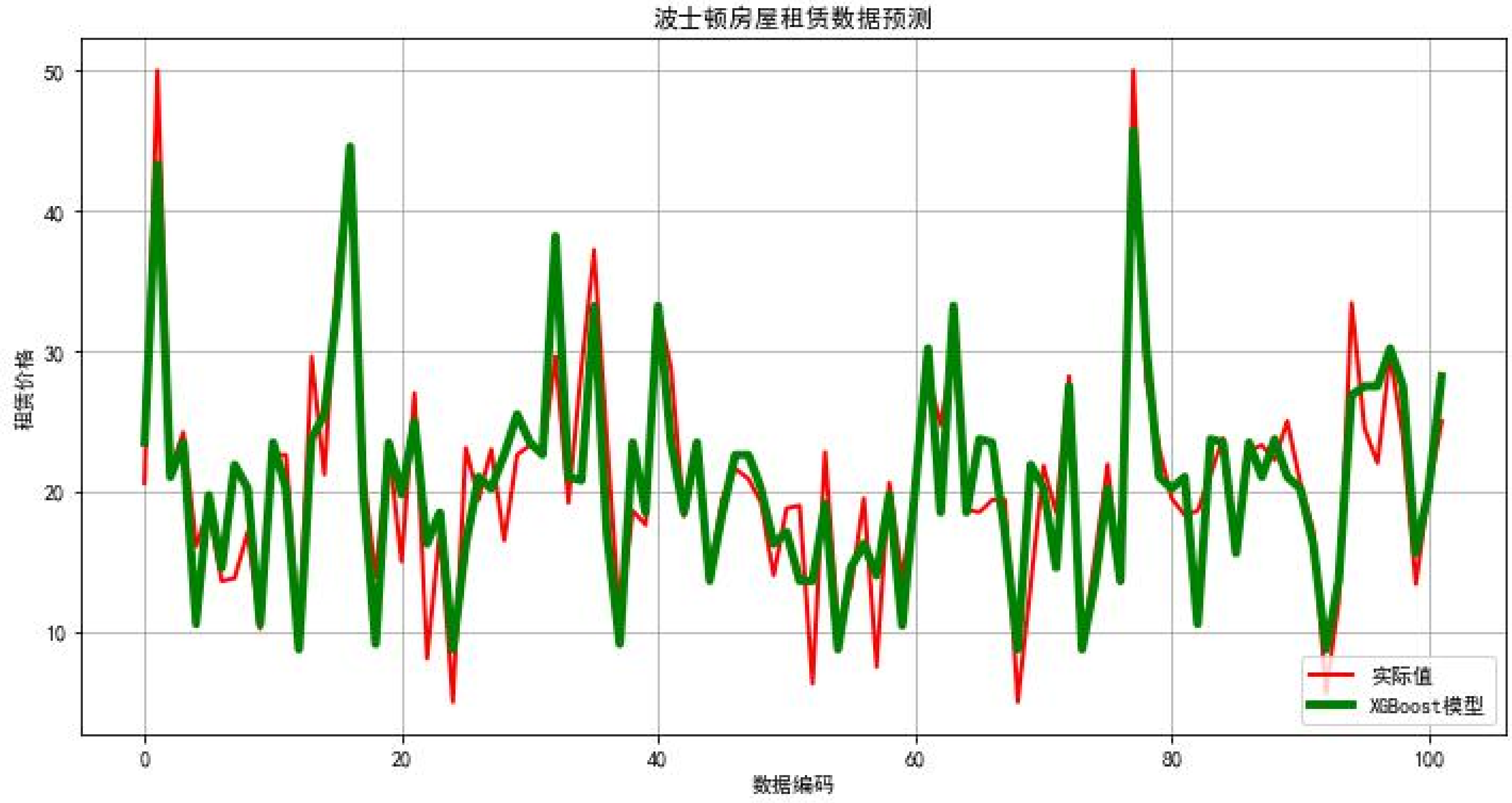
XGBoost案例(作业)

- 使用XGBoost相关算法API对波士顿房价进行预测，并最终输出R^2值；比较一下和GBDT的执行速度。



THANK YOU

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