混凝土抗压能力研究

Concrete Compressive Strength

Contents

01. 课题意义

01. Project Significance

1.1 课题意义

1.1 Project description

课题简介

虽然现在传统水泥可以通过市场购买大量获得，然而在建筑需要高强度水泥的时，依旧需要建筑工根据经验与要求调配所需要的水泥。与传统水泥不同，高强度水泥的应用条件复杂且每次使用的量不是很大，使其无法批量生产， 而且其的成分更加复杂，成型后的各项属性要求严格，从而对各种成分的比例十分苛刻，对调配人员的技术有很大要求。引入机器学习，可以减小聘请专业人员而带来的开销，同时帮助开发出可以符合大多数条件的高性能水泥以实现量产。

02. 特征解释

02. Attributes Explaining

2 特征解释

2. Attributes Explaining

```
[ 0.49461925  0.13754964 -0.10396731 -0.2883762   0.36899962 -0.16778573
 -0.16479048  0.33073125  1.         ]
```

Cement (component 1)(kg in a m^3 mixture)： 水泥（Kg/m^3）
水泥作胶凝材料。水泥与水的配比共同决定混凝土强度。比值越大，强度越高。

Blast Furnace Slag(component 2)(kg in a m^3 mixture)：高炉矿渣（Kg/m^3）
会增加混凝土密度，使内部结构更加紧密以增强混凝土强度。

Fly Ash (component 3)(kg in a m^3 mixture)：飞灰（Kg/m^3）
增大混凝土强度。与其他因素关联性较小。

Water (component 4)(kg in a m^3 mixture)：水（Kg/m^3）
与水泥含量按照一定配比混合。

2 特征解释

2. Attributes Explaining

```
[ 0.49461925  0.13754964 -0.10396731 -0.2883762   0.36899962 -0.16778573
 -0.16479048  0.33073125  1.         ]
```

Superplasticizer (component 5)(kg in a m^3 mixture)：超增塑剂（Kg/m^3）
可在混凝土凝固之前增加其流动性及加工性，方便施工。同时也是减水剂，增加混凝土的强度。

Fine Aggregate (component 7)(kg in a m^3 mixture)：细骨料（Kg/m^3）
直径小于4.8mm，起骨架作用。作用同6。

Coarse Aggregate（component 6)(kg in a m^3 mixture)：粗骨料（Kg/m^3）（直径大于5mm）起骨架作用。在满足技术要求的前提下，粗骨料的最大粒径应尽量选大一些。与细骨料的比例以及各自的含量共同影响混凝土强度。

Age (day)：凝固时间时间（天）正相关，大约前四十天增长较快，之后增长缓慢。

03. 算法实现

03. Algorithm Implementation

3.1 最小二乘法

3.1 Least Square Method

In [52]:

```
import sys
import importlib
importlib.reload(sys)
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import statsmodels.api as sm
data = pd.read_csv('C:\\Users\longj\Desktop\winequality\\1.csv')
#print (data)
dataset = np.array(data)
######相关性分析
cor = np.corrcoef(dataset,rowvar=0)[:,-1]
######输出相关矩阵的第一列
print (cor)
#######筛选后的数据读取
data1 = pd.read_csv('C:\\Users\longj\Desktop\winequality\\1.csv')
dataset1 = np.array(data1)
######筛选后的变量######
X1 = dataset1[:,0:8]
Y1 = dataset1[:,-1]
est = sm.OLS(Y1, sm.add_constant(X1)).fit()
print (est.summary())
print(est.params) #系数
```

3.1 最小二乘法

3.1 Least Square Method

取绝对值后，0-0.09为没有相关性，0.3-弱，0.1-0.3为弱相关，0.3-0.5为中等相关，0.5-1.0为强相关。

```
[ 0.49461925  0.13754964 -0.10396731 -0.2883762   0.36899962 -0.16778573
 -0.16479048  0.33073125  1.        ]
```

3.1 最小二乘法

3.1 Least Square Method

OLS Regression Results

Dep. Variable:	y	R-squared:	0.615
Model:	OLS	Adj. R-squared:	0.612
Method:	Least Squares	F-statistic:	204.0
Date:	Tue, 24 Jul 2018	Prob (F-statistic):	1.20e-205
Time:	22:20:20	Log-Likelihood:	-3862.4
No. Observations:	1029	AIC:	7743.
Df Residuals:	1020	BIC:	7787.
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-26.6807	26.544	-1.005	0.315	-78.768	25.407
x1	0.1199	0.008	14.161	0.000	0.103	0.136
x2	0.1047	0.010	10.352	0.000	0.085	0.125
x3	0.0887	0.013	7.064	0.000	0.064	0.113
x4	-0.1432	0.040	-3.567	0.000	-0.222	-0.064
x5	0.3063	0.093	3.282	0.001	0.123	0.489
x6	0.0189	0.009	2.022	0.043	0.001	0.037
x7	0.0216	0.011	2.017	0.044	0.001	0.043
x8	0.1144	0.005	21.135	0.000	0.104	0.125

Omnibus:	5.681	Durbin-Watson:	1.287
Prob(Omnibus):	0.058	Jarque-Bera (JB):	5.621
Skew:	-0.180	Prob(JB):	0.0602
Kurtosis:	3.038	Cond. No.	1.06e+05

3.2 梯度下降算法

3.2 Gradient descent algorithm

Cement (component 1)(kg in a m^3 mixture)	Blast Furnace Slag (component 2)(kg in a m^3 mixture)	Fly Ash (component 3)(kg in a m^3 mixture)	Water (component 4)(kg in a m^3 mixture)	Superplasticizer (component 5) (kg in a m^3 mixture)	Coarse Aggregate (component 6)(kg in a m^3 mixture)	Fine Aggregate (component 7)(kg in a m^3 mixture)	Age (day)	Concrete compressive strength(MPa, megapascals)
1.000000	0.000000	0.0	0.321086	0.07764	0.694767	0.205720	0.074176	0.967485
1.000000	0.000000	0.0	0.321086	0.07764	0.738372	0.205720	0.074176	0.741996
0.526256	0.396494	0.0	0.848243	0.00000	0.380814	0.000000	0.739011	0.472655
0.526256	0.396494	0.0	0.848243	0.00000	0.380814	0.000000	1.000000	0.482372
0.220548	0.368392	0.0	0.560703	0.00000	0.515698	0.580783	0.986264	0.522860

3.2 梯度下降算法

3.2 Gradient descent algorithm

```
CostFunction(X,Y,theta)
```

```
118735914.04274993
```

```
theta, cost = gradientDescent(X,Y,theta,0.001,5000)
theta
```

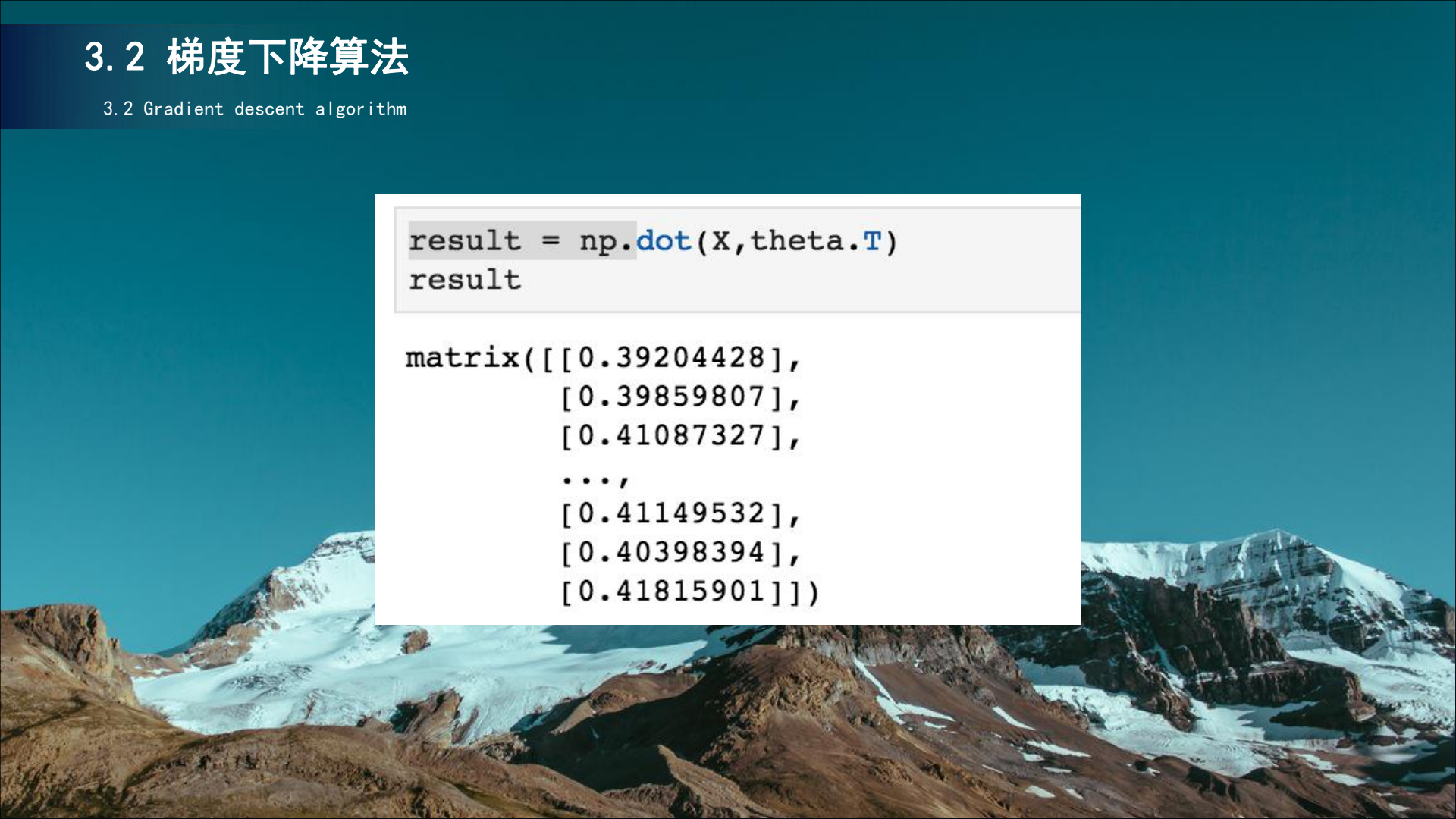
```
matrix([[0.16740689, 0.16142097, 0.10321284, 0.23149265, 0.04857272,
         0.15030017, 0.20218821, 0.00700069]])
```

3.2 梯度下降算法

3.2 Gradient descent algorithm

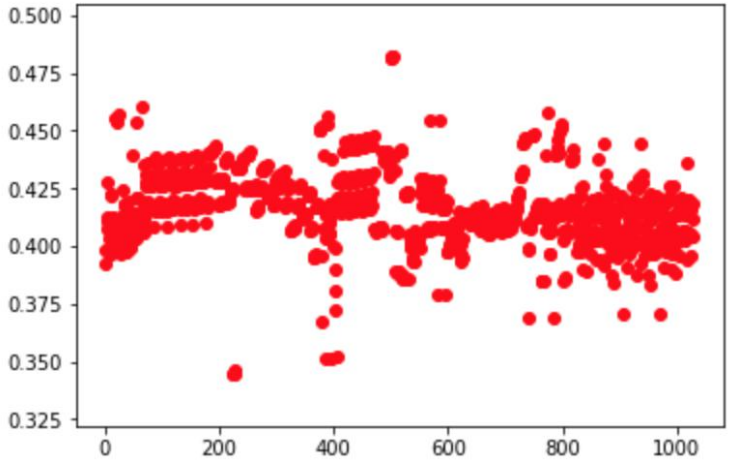
```
result = np.dot(X,theta.T)
result
```

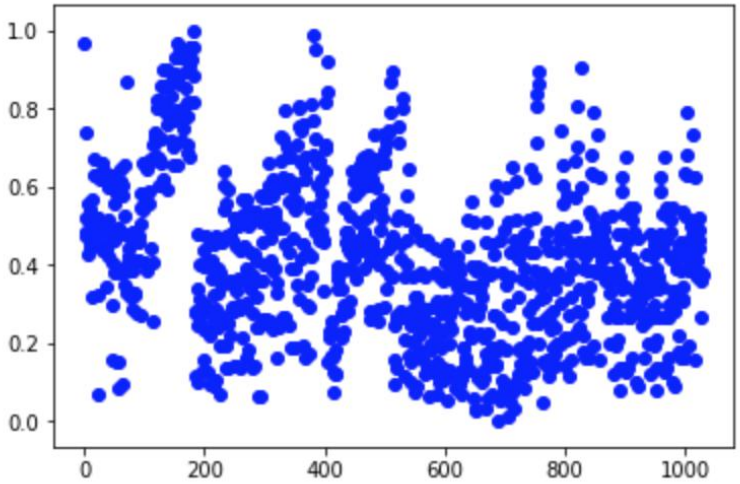
```
matrix([[0.39204428],
        [0.39859807],
        [0.41087327],
        ...,
        [0.41149532],
        [0.40398394],
        [0.41815901]])
```



3.2 梯度下降算法

3.2 Gradient descent algorit





3.2 梯度下降算法

3.2 Gradient descent algorithm

调用sklearn包得到的结果：

```
0.6155198704142721
```

```
model.coef_
```

```
array([[ 0.65372242,  0.46504761,  0.2192059 , -0.23383314,  0.11722477,
         0.07750913,  0.10026005,  0.51796229]])
```

自己写算法得到的结果：

```
theta, cost = gradientDescent(X,Y,theta,0.001,5000)
theta
```

```
matrix([[0.16740689, 0.16142097, 0.10321284, 0.23149265, 0.04857272,
         0.15030017, 0.20218821, 0.00700069]])
```

04. 总结及优化

04. Summary and Optimization

4.1总结

4.1 Summary

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[ 0.49461925  0.13754964 -0.10396731 -0.2883762   0.36899962 -0.16778573
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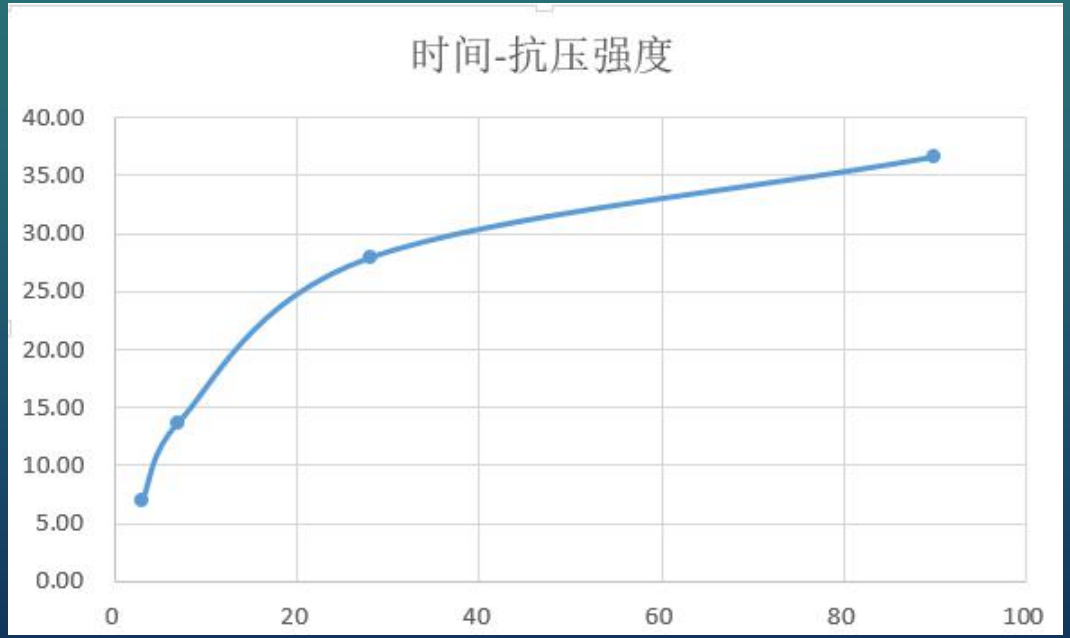
```

由相关系数可以得出，相关关系较弱，并不适合线性回归模型。
此后我们尝试了神经网络模型，由于时间关系，没有完全实现。

4.2 模型优化

4.2 Optimization



4.2 模型优化

4.2 Optimization

优化后

OLS Regression Results

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Df Residuals:	1020	BIC:	7787.
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
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x1	0.1199	0.008	14.161	0.000	0.103	0.136
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Omnibus:	5.681	Durbin-Watson:	1.287
Prob(Omnibus):	0.058	Jarque-Bera (JB):	5.621
Skew:	-0.180	Prob(JB):	0.0602
Kurtosis:	3.038	Cond. No.	1.06e+05

OLS Regression Results

Dep. Variable:	y	R-squared:	0.796
Model:	OLS	Adj. R-squared:	0.794
Method:	Least Squares	F-statistic:	361.2
Date:	Wed, 25 Jul 2018	Prob (F-statistic):	1.87e-249
Time:	00:47:22	Log-Likelihood:	-2502.7
No. Observations:	748	AIC:	5023.
Df Residuals:	739	BIC:	5065.
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-72.6915	21.370	-3.402	0.001	-114.645	-30.738
x1	0.1390	0.007	20.527	0.000	0.126	0.152
x2	0.1069	0.008	13.303	0.000	0.091	0.123
x3	0.0825	0.010	8.315	0.000	0.063	0.102
x4	-0.1068	0.031	-3.454	0.001	-0.167	-0.046
x5	0.0640	0.071	0.897	0.370	-0.076	0.204
x6	0.0290	0.008	3.828	0.000	0.014	0.044
x7	0.0374	0.009	4.287	0.000	0.020	0.055
x8	0.7592	0.025	30.262	0.000	0.710	0.808

Omnibus:	31.933	Durbin-Watson:	1.249
Prob(Omnibus):	0.000	Jarque-Bera (JB):	40.192
Skew:	0.423	Prob(JB):	1.87e-09
Kurtosis:	3.758	Cond. No.	1.09e+05

05. 小组分工

05. Work Distribution

5. 小组分工

5. Work Distribution

李鉴伦：梯度下降算法

易芳君：最小二乘法，ppt

杨柯：背景调查，整理

郜航：特征解释

李雨泽：总结优化，ppt

感谢大家观看！

Thanks for watching!