

Федеральное государственное бюджетное образовательное учреждение высшего образования «Новосибирский государственный технический университет»



Кафедра теоретической и прикладной информатики

Лабораторная работа N°6 по дисциплине «Статистические методы анализа данных»

Студенты ИВАНОВ ВЛАДИСЛАВ (92)

ОБЕРШТ ЕЛЕНА (93)

Вариант 5

Преподаватель ПОПОВ АЛЕКСАНДР АЛЕКСАНДРОВИЧ

Новосибирск, 2022

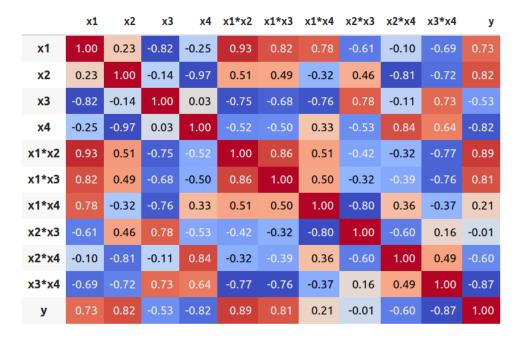
### 1 Постановка задачи

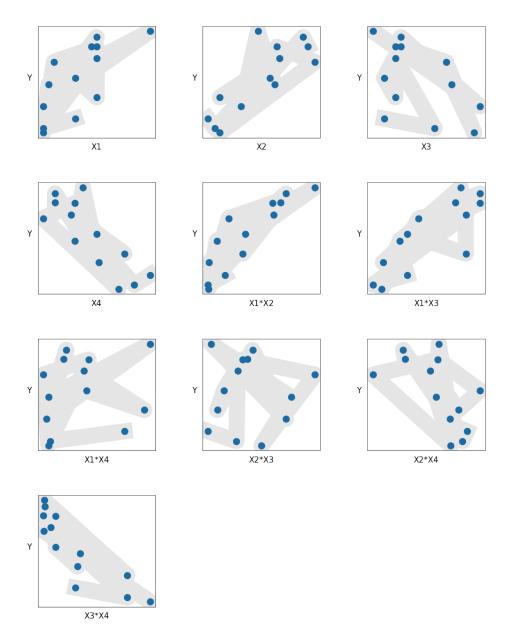
Модифицировать программу МНК-оценивания из ЛР №2 под реализацию алгоритма включения. Выбрать оптимальную модель для аппроксимации заданных экспериментальных данных.

	<b>x1</b>	<b>x2</b>	х3	<b>x4</b>	у
1	7.0	26.0	6.0	60.0	78.5
2	1.0	29.0	15.0	52.0	74.3
3	11.0	56.0	8.0	20.0	104.3
4	11.0	31.0	8.0	47.0	87.6
5	7.0	52.0	6.0	33.0	95.9
6	11.0	55.0	9.0	22.0	109.2
7	3.0	71.0	17.0	6.0	102.7
8	1.0	31.0	22.0	44.0	72.5
9	2.0	54.0	18.0	22.0	93.1
10	21.0	47.0	4.0	26.0	115.9
11	1.0	40.0	23.0	34.0	83.8
12	11.0	66.0	9.0	12.0	113.3
13	10.0	68.0	8.0	12.0	109.4

#### 2 Анализ взаимосвязей

Вычислим коэффициент корреляции Пирсона для каждой пары признаков и их взаимодействий, построим корреляционную матрицу и графики зависимостей:





По корреляционной таблице и графикам можно сделать вывод о том, что все зависимости, кроме X1\*X4 и X2\*X3, близки к линейным. В качестве класса допустимых решений F возьмем следующий:

$$f(x) = 1 + x_1 + x_2 + x_3 + x_4 + x_1x_2 + x_1x_3 + x_1x_4$$

$$n = 13$$

$$m = 8$$

# 3 Используемые критерии

$$C_{p} = \frac{RSS_{p}}{\hat{\sigma}^{2}} + 2 p - n \rightarrow min$$

$$R_{p}^{2} = \frac{\sum (\hat{y}_{ip} - \overline{\hat{y}}_{p})^{2}}{\sum (y_{i} - \overline{y})^{2}} \rightarrow 1$$

$$E_{p} = \frac{RSS_{p}}{n(n-p)} (1 + n + \frac{p(n+1)}{n-p-2}) \Rightarrow min$$

$$AEV_{p} = \frac{p \cdot RSS_{p}}{n(n-p)} \Rightarrow min$$

$$F_{ij} = \frac{v_{2}}{v_{1}} \cdot \frac{RSS_{ij} - RSS_{j}}{RSS_{i,j}}$$

$$RSS_{p} = (y - \hat{y}_{p})^{T} (y - \hat{y}_{p})$$

$$\hat{\sigma}^{2} = \frac{RSS}{n-m}$$

$$v_{1} = 1$$

$$v_{2} = n - m$$

### 4 Алгоритм включения

$$f_1(x) = (1)^T$$

$$p = 1$$

$$f_2(x) = (1, x_1 x_2)^T$$

$$p=2$$

$$f_3(x) = (1, x_4, x_1 x_2)^T$$

$$p=3$$

$$f_4(x) = (1, x_4, x_1 x_2, x_1 x_4)^T$$

$$p = 4$$
F11 F12 F13 F16

0 0.34 1.05 1.01 0.0

$$f_5(x) = (1, x_2, x_4, x_1x_2, x_1x_4)^T$$

$$p = 5$$
F11 F13 F16

0 0.47 0.01 0.01

$$f_6(x) = (1, x_1, x_2, x_4, x_1x_2, x_1x_4)^T$$

$$p = 6$$
F13 F16

0 0.01 0.18

$$f_7(x) = (1, x_1, x_2, x_4, x_1x_2, x_1x_3, x_1x_4)^T$$

$$p = 7$$
F13
0 0.18

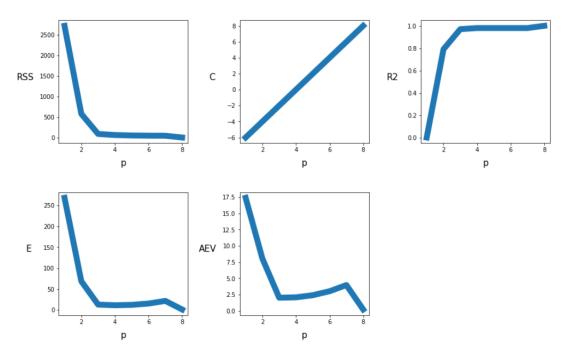
$$f_8(x) = (1, x_1, x_2, x_3, x_4, x_1x_2, x_1x_3, x_1x_4)^T$$

# 5 Исследование

Таблица значений критериев:

	RSS	C	R2	E	AEV
1	2715.76	-6.0	0.00	268.09	17.41
2	574.56	-4.0	0.79	68.75	8.04
3	87.63	-2.0	0.97	12.98	2.02
4	60.74	0.0	0.98	11.42	2.08
5	50.19	2.0	0.98	12.39	2.41
6	45.88	4.0	0.98	15.53	3.02
7	44.29	6.0	0.98	21.86	3.97
8	1.73	8.0	1.00	1.37	0.21

Графики зависимости значений критериев от шага:



Выберем лучшую модель:

$$f_4(x) = (1, x_4, x_1 x_2, x_1 x_4)^T$$
$$\hat{\theta} = (101.62, -0.58, 0.02, 0.01)^T$$

Сравним её предсказания с целевой переменной:

	у	y_hat	y - y_hat
1	78.5	77.032927	1.467073
2	74.3	72.619850	1.680150
3	104.3	106.708551	-2.408551
4	87.6	89.613044	-2.013044
5	95.9	93.813034	2.086966
6	109.2	105.645076	3.554924
7	102.7	103.006694	-0.306694
8	72.5	77.222237	-4.722237
9	93.1	91.772587	1.327413
10	115.9	116.352012	-0.452012
11	83.8	83.115939	0.684061
12	113.3	112.391284	0.908716
13	109.4	111.206767	-1.806767

## 6 Код программы

```
import pandas as pd
   import numpy as np
   import random
3
   import scipy.stats
   from matplotlib import pyplot as plt
   from statsmodels.stats.outliers_influence import
   → variance_inflation_factor
   np.set_printoptions(suppress=True)
   random.seed(42)
   x1 = [7.0, 1.0, 11.0, 11.0, 7.0, 11.0, 3.0, 1.0, 2.0, 21.0, 1.0, 11.0, 10.0]
10
   \mathbf{x2} = [26.0, 29.0, 56.0, 31.0, 52.0, 55.0, 71.0, 31.0, 54.0, 47.0, 40.0, 66.0, 68.0]
11
   x3 = [6.0, 15.0, 8.0, 8.0, 6.0, 9.0, 17.0, 22.0, 18.0, 4.0, 23.0, 9.0, 8.0]
12
   x4 = [60.0, 52.0, 20.0, 47.0, 33.0, 22.0, 6.0, 44.0, 22.0, 26.0, 34.0, 12.0, 12.0]
   y = [78.5, 74.3, 104.3, 87.6, 95.9, 109.2, 102.7, 72.5, 93.1, 115.9, 83.8, 113.3, 1]
    → 09.4]
15
   df = pd.DataFrame(list(zip(x1, x2, x3, x4, y)), columns=['x1', 'x2',
16
   \rightarrow 'x3', 'x4', 'y'])
   df.index += 1
17
   print(df)
18
   df2 = pd.DataFrame(list(zip(x1, x2, x3, x4, np.array(x1)*np.array(x2),
    \rightarrow np.array(x1)*np.array(x3), np.array(x1)*np.array(x4),
    \rightarrow np.array(x2)*np.array(x3), np.array(x2)*np.array(x4),
    \rightarrow np.array(x3)*np.array(x4), y)), columns=['x1', 'x2', 'x3', 'x4',
    → 'x1*x2', 'x1*x3', 'x1*x4', 'x2*x3', 'x2*x4', 'x3*x4', 'y'])
   corr = df2.corr()
   corr.style.background_gradient(cmap='coolwarm').set_precision(2)
23
   factors = [x1, x2, x3, x4, np.array(x1)*np.array(x2),
24
    \rightarrow np.array(x1)*np.array(x3), np.array(x1)*np.array(x4),
    \rightarrow np.array(x2)*np.array(x3), np.array(x2)*np.array(x4),
    \rightarrow np.array(x3)*np.array(x4)]
   factors_str = ['X1', 'X2', 'X3', 'X4', 'X1*X2', 'X1*X3', 'X1*X4',
    → 'X2*X3', 'X2*X4', 'X3*X4']
26
   fig = plt.figure(figsize=(15,20))
27
   fig.subplots_adjust(hspace=0.4, wspace=0.4)
28
   for i in range(1, len(factors)+1):
29
        ax = fig.add\_subplot(4, 3, i)
        ax.scatter(factors[i-1], y, s=150)
31
        ax.plot(factors[i-1], y, 'k', lw=30, alpha=0.1)
32
        ax.set(xlabel=factors_str[i-1], ylabel='Y')
33
        ax.yaxis.label.set_size(15)
34
        ax.xaxis.label.set_size(15)
35
        ax.yaxis.label.set_rotation(0)
36
```

```
ax.yaxis.labelpad = 15
37
       ax.xaxis.labelpad = 10
38
       plt.tick_params(which='both', bottom=False, left=False,
39
        → labelbottom=False, labelleft=False)
   RSS_list, C_list, R2_list, E_list, AEV_list = [], [], [], [], []
41
42
   n = len(y)
43
   m = 8
44
   nu1 = 1
45
   nu2 = n - m
46
   x0 = np.full((n,), 1.0)
47
48
   p = 1 # !!!
49
   F_list = []
50
   X = np.array([x0]).T # !!!
51
   theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
53
   y_hat = np.dot(X, theta)
54
   RSS = sum((y - y_hat)**2)
55
   sigma2 = RSS / nu2
56
   C = (RSS / sigma2) + 2 * p - n
57
   R2 = sum((y_hat - np.mean(y_hat))**2) / sum((y - np.mean(y))**2)
58
   E = (RSS / (n * (n - p))) * (1 + n + (p * (n + 1) / (n - p - 2)))
   AEV = (p * RSS) / (n * (n - p))
   RSS_list.append(round(RSS, 2)), C_list.append(round(C, 2)),

¬ R2_list.append(round(R2, 2)), E_list.append(round(E, 2)),
    → AEV_list.append(round(AEV, 2))
62
   for i in [x1, x2, x3, x4, np.array(x1)*np.array(x2),
63
    \rightarrow np.array(x1)*np.array(x3), np.array(x1)*np.array(x4)]: # !!!
       X = np.array([x0, i]).T # !!!
64
       theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
65
       RSS_{new} = sum((y - np.dot(X, theta))**2)
66
67
       F = (nu2 / nu1) * (RSS - RSS_new) / RSS_new
68
       F_list.append(round(F, 2))
69
70
   df = pd.DataFrame(F_list).T
71
   df.rename(columns={0: 'F11', 1: 'F12', 2: 'F13', 3: 'F14', 4: 'F15', 5:
72
    → 'F16', 6: 'F17'}, inplace=True) # !!!
   print(df)
73
74
   p = 2 # !!!
75
   F_{list} = []
76
   X = \text{np.array}([x0, \text{np.array}(x1)*\text{np.array}(x2)]).T \# !!!
77
   78
79
   y_hat = np.dot(X, theta)
80
```

```
RSS = sum((y - y_hat)**2)
81
   sigma2 = RSS / nu2
82
   C = (RSS / sigma2) + 2 * p - n
83
   R2 = sum((y_hat - np.mean(y_hat))**2) / sum((y - np.mean(y))**2)
84
   E = (RSS / (n * (n - p))) * (1 + n + (p * (n + 1) / (n - p - 2)))
85
   AEV = (p * RSS) / (n * (n - p))
86
   RSS_list.append(round(RSS, 2)), C_list.append(round(C, 2)),
87
    \rightarrow R2_list.append(round(R2, 2)), E_list.append(round(E, 2)),
      AEV_list.append(round(AEV, 2))
88
   for i in [x1, x2, x3, x4, np.array(x1)*np.array(x3),
89
    \rightarrow np.array(x1)*np.array(x4)]: # !!!
        X = \text{np.array}([x0, \text{np.array}(x1)*\text{np.array}(x2), i]).T # !!!
90
        theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
91
        RSS_new = sum((y - np.dot(X, theta))**2)
92
93
        F = (nu2 / nu1) * (RSS - RSS_new) / RSS_new
        F_list.append(round(F, 2))
95
96
   df = pd.DataFrame(F_list).T
97
   df.rename(columns={0: 'F11', 1: 'F12', 2: 'F13', 3: 'F14', 4: 'F16', 5:
98
    → 'F17'}, inplace=True) # !!!
   print(df)
99
   p = 3 # !!!
101
   F_list = []
102
   X = \text{np.array}([x0, x4, \text{np.array}(x1)*\text{np.array}(x2)]).T # !!!
103
   104
105
   y_hat = np.dot(X, theta)
106
   RSS = sum((y - y_hat)**2)
107
   sigma2 = RSS / nu2
108
   C = (RSS / sigma2) + 2 * p - n
109
   R2 = sum((y_hat - np.mean(y_hat))**2) / sum((y - np.mean(y))**2)
110
   E = (RSS / (n * (n - p))) * (1 + n + (p * (n + 1) / (n - p - 2)))
111
   AEV = (p * RSS) / (n * (n - p))
112
   RSS_list.append(round(RSS, 2)), C_list.append(round(C, 2)),
113

→ R2_list.append(round(R2, 2)), E_list.append(round(E, 2)),
      AEV_list.append(round(AEV, 2))
114
   for i in [x1, x2, x3, np.array(x1)*np.array(x3),
115
        np.array(x1)*np.array(x4)]: # !!!
        X = \text{np.array}([x0, x4, \text{np.array}(x1)*\text{np.array}(x2), i]).T # !!!
116
        theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
117
        RSS_{new} = sum((y - np.dot(X, theta))**2)
118
119
        F = (nu2 / nu1) * (RSS - RSS_new) / RSS_new
120
        F_list.append(round(F, 2))
121
122
```

```
df = pd.DataFrame(F_list).T
123
    df.rename(columns={0: 'F11', 1: 'F12', 2: 'F13', 3: 'F16', 4: 'F17'},
124
        inplace=True) # !!!
    print(df)
125
126
    p = 4 \# !!!
127
   F_list = []
128
   X = np.array([x0, x4, np.array(x1)*np.array(x2),
129
    \rightarrow np.array(x1)*np.array(x4)]).T # !!!
    theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
130
   y_hat = np.dot(X, theta)
132
   RSS = sum((y - y_hat)**2)
133
    sigma2 = RSS / nu2
134
    C = (RSS / sigma2) + 2 * p - n
135
    R2 = sum((y_hat - np.mean(y_hat))**2) / sum((y - np.mean(y))**2)
136
    E = (RSS / (n * (n - p))) * (1 + n + (p * (n + 1) / (n - p - 2)))
137
    AEV = (p * RSS) / (n * (n - p))
138
    RSS_list.append(round(RSS, 2)), C_list.append(round(C, 2)),
139

→ R2_list.append(round(R2, 2)), E_list.append(round(E, 2)),
       AEV_list.append(round(AEV, 2))
140
    for i in [x1, x2, x3, np.array(x1)*np.array(x3)]: # !!!
141
        X = np.array([x0, x4, np.array(x1)*np.array(x2),
142
         \rightarrow np.array(x1)*np.array(x4), i]).T # !!!
        theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
143
        RSS_{new} = sum((y - np.dot(X, theta))**2)
144
145
        F = (nu2 / nu1) * (RSS - RSS_new) / RSS_new
146
        F_list.append(round(F, 2))
147
148
    df = pd.DataFrame(F_list).T
149
    df.rename(columns={0: 'F11', 1: 'F12', 2: 'F13', 3: 'F16'},
150

    inplace=True) # !!!

    print(df)
151
152
   p = 5 # !!!
153
   F_{list} = []
154
   X = np.array([x0, x2, x4, np.array(x1)*np.array(x2),
155
    \rightarrow np.array(x1)*np.array(x4)]).T # !!!
    theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
156
157
    y_hat = np.dot(X, theta)
158
    RSS = sum((y - y_hat)**2)
159
    sigma2 = RSS / nu2
160
    C = (RSS / sigma2) + 2 * p - n
161
    R2 = sum((y_hat - np.mean(y_hat))**2) / sum((y - np.mean(y))**2)
162
    E = (RSS / (n * (n - p))) * (1 + n + (p * (n + 1) / (n - p - 2)))
163
   AEV = (p * RSS) / (n * (n - p))
164
```

```
RSS_list.append(round(RSS, 2)), C_list.append(round(C, 2)),
165
        R2_{list.append(round(R2, 2))}, E_{list.append(round(E, 2))},
        AEV_list.append(round(AEV, 2))
166
    for i in [x1, x3, np.array(x1)*np.array(x3)]: # !!!
167
        X = np.array([x0, x2, x4, np.array(x1)*np.array(x2),
168
         \rightarrow np.array(x1)*np.array(x4), i]).T # !!!
        theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
169
        RSS_{new} = sum((y - np.dot(X, theta))**2)
170
171
        F = (nu2 / nu1) * (RSS - RSS_new) / RSS_new
        F_{list.append(round(F, 2))}
173
174
    df = pd.DataFrame(F_list).T
175
    df.rename(columns={0: 'F11', 1: 'F13', 2: 'F16'}, inplace=True) # !!!
176
    print(df)
177
178
    p = 6 # !!!
179
    F_{list} = []
180
   X = \text{np.array}([x0, x1, x2, x4, \text{np.array}(x1)*\text{np.array}(x2),
181
    \rightarrow np.array(x1)*np.array(x4)]).T # !!!
    182
183
    y_hat = np.dot(X, theta)
184
    RSS = sum((y - y_hat)**2)
185
    sigma2 = RSS / nu2
    C = (RSS / sigma2) + 2 * p - n
187
    R2 = sum((y_hat - np.mean(y_hat))**2) / sum((y - np.mean(y))**2)
188
    E = (RSS / (n * (n - p))) * (1 + n + (p * (n + 1) / (n - p - 2)))
189
    AEV = (p * RSS) / (n * (n - p))
190
    RSS_list.append(round(RSS, 2)), C_list.append(round(C, 2)),
191

→ R2_list.append(round(R2, 2)), E_list.append(round(E, 2)),
    → AEV_list.append(round(AEV, 2))
192
    for i in [x3, np.array(x1)*np.array(x3)]: # !!!
193
        X = np.array([x0, x1, x2, x4, np.array(x1)*np.array(x2),
194
         \rightarrow np.array(x1)*np.array(x4), i]).T # !!!
        theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
        RSS_{new} = sum((y - np.dot(X, theta))**2)
196
197
        F = (nu2 / nu1) * (RSS - RSS_new) / RSS_new
198
        F_list.append(round(F, 2))
199
200
    df = pd.DataFrame(F_list).T
201
    df.rename(columns={0: 'F13', 1: 'F16'}, inplace=True) # !!!
202
    print(df)
203
204
    p = 7 # !!!
205
   F_{list} = []
206
```

```
X = np.array([x0, x1, x2, x4, np.array(x1)*np.array(x2),
207
    \rightarrow np.array(x1)*np.array(x3), np.array(x1)*np.array(x4)]).T # !!!
    theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
208
209
   y_hat = np.dot(X, theta)
210
    RSS = sum((y - y_hat)**2)
211
    sigma2 = RSS / nu2
212
    C = (RSS / sigma2) + 2 * p - n
213
    R2 = sum((y_hat - np.mean(y_hat))**2) / sum((y - np.mean(y))**2)
214
    E = (RSS / (n * (n - p))) * (1 + n + (p * (n + 1) / (n - p - 2)))
215
   AEV = (p * RSS) / (n * (n - p))
216
    RSS_list.append(round(RSS, 2)), C_list.append(round(C, 2)),
      R2_{list.append(round(R2, 2)), E_{list.append(round(E, 2)),}
       AEV_list.append(round(AEV, 2))
218
    for i in [x3]: # !!!
219
        X = np.array([x0, x1, x2, x4, np.array(x1)*np.array(x2),
220
         \rightarrow np.array(x1)*np.array(x3), np.array(x1)*np.array(x4), i]).T #
         theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
        RSS_{new} = sum((y - np.dot(X, theta))**2)
222
223
        F = (nu2 / nu1) * (RSS - RSS_new) / RSS_new
224
        F_{list.append(round(F, 2))}
    df = pd.DataFrame(F_list).T
227
    df.rename(columns={0: 'F13'}, inplace=True) # !!!
228
    print(df)
229
230
    p = 8 # !!!
231
   F_list = []
232
   X = np.array([x0, x1, x2, x3, x4, np.array(x1)*np.array(x2),
233
    \rightarrow np.array(x1)*np.array(x3), np.array(x1)*np.array(x4),
    \rightarrow np.array(x2)*np.array(x3), np.array(x2)*np.array(x4),
    \rightarrow np.array(x3)*np.array(x4)]).T # !!!
    theta = np.dot(np.linalg.inv(np.dot(X.T, X)), np.dot(X.T, y))
234
235
    y_hat = np.dot(X, theta)
236
    RSS = sum((y - y_hat)**2)
237
    sigma2 = RSS / nu2
238
    C = (RSS / sigma2) + 2 * p - n
239
    R2 = sum((y_hat - np.mean(y_hat))**2) / sum((y - np.mean(y))**2)
240
    E = RSS / (n * (n - p)) * (1 + n + p * (n + 1) / (n - p - 2))
241
    AEV = (p * RSS) / (n * (n - p))
242
    RSS_list.append(round(RSS, 2)), C_list.append(round(C, 2)),

¬ R2_list.append(round(R2, 2)), E_list.append(round(E, 2)),
      AEV_list.append(round(AEV, 2))
244
   df = pd.DataFrame(list(zip(RSS_list, C_list, R2_list, E_list,
245
    → AEV_list)), columns=['RSS', 'C', 'R2', 'E', 'AEV'])
```

```
df.index += 1
246
    print(df)
247
248
    lists = [RSS_list, C_list, R2_list, E_list, AEV_list]
249
    lists_str = ['RSS', 'C', 'R2', 'E', 'AEV']
250
    p_list = [1,2,3,4,5,6,7,8]
251
252
    fig = plt.figure(figsize=(15,20))
253
    fig.subplots_adjust(hspace=0.4, wspace=0.4)
254
    for i in range(1, len(lists)+1):
255
        ax2 = fig.add\_subplot(4, 3, i)
256
        ax2.plot(p_list, lists[i-1], lw=10, alpha=1)
257
        ax2.set(xlabel='p', ylabel=lists_str[i-1])
258
        ax2.yaxis.label.set_size(15)
259
        ax2.xaxis.label.set_size(15)
260
        ax2.yaxis.label.set_rotation(∅)
261
        ax2.yaxis.labelpad = 25
262
        ax2.xaxis.labelpad = 10
263
264
    X_best = np.array([x0, x4, np.array(x1)*np.array(x2),
265
    \rightarrow np.array(x1)*np.array(x4)]).T
    theta_best = np.dot(np.linalg.inv(np.dot(X_best.T, X_best)),
266
    → np.dot(X_best.T, y))
    y_hat_best = np.dot(X_best, theta_best)
267
    residuals_best = y - y_hat_best
268
269
    print('theta_best =', theta_best)
270
    df = pd.DataFrame(list(zip(y, y_hat_best, residuals_best)),
271

    columns=['y', 'y_hat', 'y - y_hat'])
    df.index += 1
272
    df
273
```