

计算方法上机实习二 实习报告

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计算方法上机实习二 实习报告

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一、分析报告

1.问题分析

给出平面上的20个点，要求：

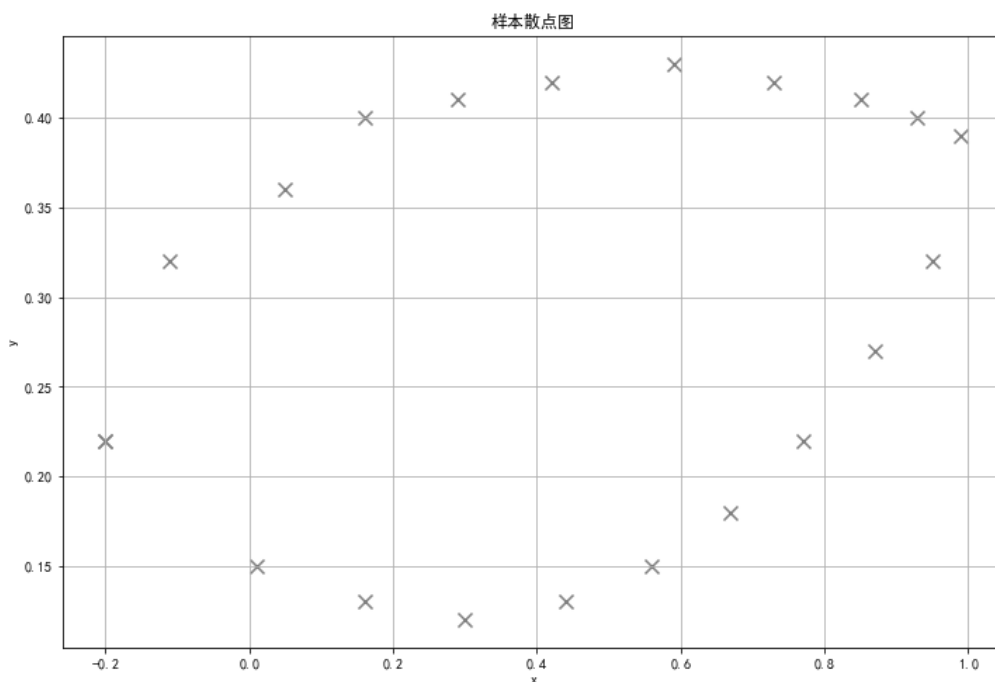
- a) 用三次样条插值构造出插值曲线；
- b) 用最小二乘法构造出拟合曲线，拟合方程为 $b_0 + b_1x + b_2y + b_3xy + b_4y^2 = x^2$.

20个点的坐标如下：

x	0.99	0.95	0.87	0.77	0.67	0.56	0.44	0.30	0.16	0.01
y	0.39	0.32	0.27	0.22	0.18	0.15	0.13	0.12	0.13	0.15

x	0.93	0.85	0.73	0.59	0.42	0.29	0.16	0.05	-0.11	-0.20
y	0.40	0.41	0.42	0.43	0.42	0.41	0.40	0.36	0.32	0.22

首先绘制出(x, y)的散点图，观察散点在平面上的分布情况.



从图中可以看出散点大致围出了一个闭合的区域，因此在进行三次样条插值时使用周期性边界条件.

2.算法细节

(1)三次样条插值的实现

使用三弯矩法计算各个区间上样条函数的系数.

给定函数 $y = f(x)$ 在区间 $[a, b]$ 上的一组节点 (x_k, y_k) ($k = 0, 1, 2, \dots, n$), 将 $[a, b]$ 划分为 n 个子区间 $[x_{i-1}, x_i]$ ($i = 1, 2, \dots, n$).

设样条函数为 $S(x)$, 每个区间上的样条函数为 $S_i(x) = a_i x^3 + b_i x^2 + c_i x + d_i$ ($i = 1, 2, \dots, n$).

记 $M_i = S''(x_i)$, $h_i = x_i - x_{i-1}$ ($i = 1, 2, \dots, n$).

计算得

$$S(x) = \frac{M_{i-1}}{6h_i}(x_i - x)^3 + \frac{M_i}{6h_i}(x - x_{i-1})^3 + \left(\frac{y_i}{h_i} - \frac{h_i M_i}{6}\right)(x - x_{i-1}) + \left(\frac{y_{i-1}}{h_i} - \frac{h_i M_{i-1}}{6}\right)(x_i - x)$$

$$x_{i-1} \leq x \leq x_i, i = 1, 2, \dots, n-1$$

不考虑边界条件时, 有如下的方程组

$$\begin{cases} \alpha_1 M_0 + 2M_1 + (1 - \alpha_1)M_2 = \beta_1 \\ \alpha_1 M_1 + 2M_2 + (1 - \alpha_2)M_3 = \beta_2 \\ \vdots \\ \alpha_{n-1} M_{n-2} + 2M_{n-1} + (1 - \alpha_{n-1})M_n = \beta_{n-1} \end{cases}$$

$$\alpha_i = \frac{h_i}{h_i + h_{i+1}}, \beta_i = \frac{6}{h_i + h_{i+1}} \left(\frac{y_{i+1} - y_i}{h_{i+1}} - \frac{y_i - y_{i-1}}{h_i} \right)$$

再加上周期性边界条件 $y_0 = y_n, y'_0 = y'_n, y''_0 = y''_n$.

由 $M_0 = M_n$ 和 $y'_0 = y'_n$, 得

$$\begin{cases} M_0 = M_n \\ \frac{h_1}{h_1 + h_n} M_1 - \frac{h_n}{h_1 + h_n} M_{n-1} + 2M_n = \frac{6}{h_1 + h_n} \left(\frac{y_1 - y_0}{h_1} - \frac{y_n - y_{n-1}}{h_n} \right) \end{cases}$$

以上两个方程组联立可解出 M_i , 进而求得 $S(x)$ 的系数.

考虑到给出的散点围住了一块闭合区域，无法使用一个样条函数 $S(x)$ 进行插值，所以考虑使用参数方程的形式进行插值.

设插值曲线的参数方程为

$$\begin{cases} x = \phi(u) \\ y = \psi(u) \end{cases} \quad (1 \leq u \leq 21)$$

然后分别对 (u_i, ϕ_i) 和 (u_i, ψ_i) 进行插值即可.

因为共有21个点（周期边界条件又加了一个点），所以使 u 的取值在1到21之间，插值节点可以简单地设 $u_i = i$ ，方便计算.

记样条插值函数为 $x = \Phi(u), y = \Psi(u)$ ，将它们联立即得到原问题的插值函数.

(2)最小二乘法的实现

将 $(x_i, y_i, x_i y_i, y_i^2)$ 看作特征变量， x_i^2 看作目标变量，通过最小二乘法来计算 $x^2 = b_0 + b_1 x + b_2 y + b_3 xy + b_4 y^2$ 中的参数 b_i .

由线性代数的相关知识可知，最小二乘解 $b = (b_0, b_1, b_2, b_3, b_4)^T$ 满足方程

$$A^T A b = A^T y$$
$$A = \begin{bmatrix} 1 & x_1 & y_1 & x_1 y_1 & y_1^2 \\ 1 & x_2 & y_2 & x_2 y_2 & y_2^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_m & y_m & x_m y_m & y_m^2 \end{bmatrix}, y = \begin{bmatrix} x_1^2 \\ x_2^2 \\ \vdots \\ x_m^2 \end{bmatrix}$$

解方程组即可求得 b_i .

(3)线性方程组的解法

使用高斯消元法解线性方程组.

对于线性方程组 $Ax = b$ ，构造增广矩阵 $B = [A \ b]$ ，对矩阵 B 进行初等变换，将 B 化成行阶梯矩阵，通过回代求出 x .

3.编程思路

程序主要分为5个模块，主程序jsff2，用来进行三次样条插值的子例程cubic_spline，用来进行线性回归的子例程linear_regression，用来解线性方程组的子例程gauss_elimination，以及用来输出调试信息的子例程print_matrix.

用变量 n 代表点的个数，注意一共有20个点，故 n 取20，但是周期边界条件要求第一个元素和最后一个元素相等，所以在数组末尾把第一个元素加进去，所以实际上一共有 $(n+1)$ 个点，三次样条插值的增广矩阵的维数为 $(n+1)*(n+2)$.

用变量 m 表示特征的个数，一共有四个特征 $(x_i, y_i, x_i y_i, y_i^2)$ ，故 m 取4，但是为了让拟合出来的方程有截距，把1加入到了特征当中，所以实际上有 $(m+1)$ 个特征， $A^T A$ 的维数为 $(m+1)*(m+1)$.

4.运行结果分析

(1)插值与拟合结果

所有分段插值函数如下， $\Phi_i(u), \Psi_i(u)$ 代表区间 $u \in [i, i+1]$ 上的插值函数：

$$\begin{aligned}
\Phi_1(u) &= -0.12242695552139u^3 + 0.620827425229071u^2 - 0.795493586822241u + 0.0970931171453089 \\
\Phi_2(u) &= 0.0450416545059086u^3 - 0.383984235119213u^2 + 1.2141297399838u - 1.24265577553802 \\
\Phi_3(u) &= -0.00773963751205065u^3 + 0.09104739304242u^2 - 0.210965163351066u + 0.182439165496785 \\
\Phi_4(u) &= -0.00408315310999727u^3 + 0.0471695802177794u^2 - 0.0354538822501808u - 0.0515759554439212 \\
\Phi_5(u) &= 0.00407229882784846u^3 - 0.0751621988499066u^2 + 0.576204994014763u - 1.07100735230721 \\
\Phi_6(u) &= -0.00220605173813974u^3 + 0.0378481113378809u^2 - 0.101856876648706u + 0.285116427166702 \\
\Phi_7(u) &= 0.00475184852006571u^3 - 0.108267794084433u^2 + 0.920954511375397u - 2.10144371187308 \\
\Phi_8(u) &= -0.00680123266957672u^3 + 0.169006154466985u^2 - 1.29723713664059u + 3.81373433406101 \\
\Phi_9(u) &= 0.00245298202243794u^3 - 0.0808576422174111u^2 + 0.951537074050127u - 2.93258854119811 \\
\Phi_{10}(u) &= -0.023010616742044u^3 + 0.683050320717046u^2 - 6.68754259344141u + 22.5310106047535 \\
\Phi_{11}(u) &= 0.0295894229569073u^3 - 1.05275098934835u^2 + 12.4062718411197u - 47.479642496811 \\
\Phi_{12}(u) &= -0.015347032170241u^3 + 0.564961395228992u^2 - 7.00627679288179u + 30.170552191783 \\
\Phi_{13}(u) &= 0.0117986651928982u^3 - 0.493720801933434u^2 + 6.75659179168742u - 29.4685451939834 \\
\Phi_{14}(u) &= -0.011847647674838u^3 + 0.499424338511485u^2 - 7.14744013401028u + 35.4169367476484 \\
\Phi_{15}(u) &= 0.0255920244501641u^3 - 1.18536090711361u^2 + 18.1243384919536u - 90.9419557980455 \\
\Phi_{16}(u) &= -0.0205205168830207u^3 + 1.02804107687926u^2 - 17.2900932435877u + 97.9350133691652 \\
\Phi_{17}(u) &= 0.016490051426569u^3 - 0.859497906909814u^2 + 14.7980694808266u - 83.8979087358491 \\
\Phi_{18}(u) &= -0.0254396892702901u^3 + 1.40470809072058u^2 - 25.9576384760735u + 160.636339000187 \\
\Phi_{19}(u) &= 0.0152687016312779u^3 - 0.915670190668801u^2 + 18.1295488747951u - 118.582514278605 \\
\Phi_{20}(u) &= 0.0843648837882596u^3 - 5.0614411200877u^2 + 101.0449674666u - 671.351971603004
\end{aligned}$$

$$\begin{aligned}
\Psi_1(u) &= 0.0129196424100381u^3 - 0.0385118820961294u^2 - 0.0449018505818788u + 0.29049409026797 \\
\Psi_2(u) &= -0.015092320199554u^3 + 0.129559893561424u^2 - 0.381045384015591u + 0.51458975538192 \\
\Psi_3(u) &= 0.00744966908457009u^3 - 0.0733180099956936u^2 + 0.227588313840762u - 0.0940439168444352 \\
\Psi_4(u) &= -0.00470637312605011u^3 + 0.0725544965317488u^2 - 0.355901708096683u + 0.683942767945957 \\
\Psi_5(u) &= 0.00137584040695409u^3 - 0.0186787064633142u^2 + 0.100264294063634u - 0.0763338596045747 \\
\Psi_6(u) &= -0.000797010853508062u^3 + 0.0204326162250046u^2 - 0.134403632529536u + 0.393001955434792 \\
\Psi_7(u) &= 0.00181220300707815u^3 - 0.0343608748473059u^2 + 0.249150814513381u - 0.501958465503483 \\
\Psi_8(u) &= -0.00645177137248217u^3 + 0.163974510262142u^2 - 1.33753228662778u + 3.72919657895604 \\
\Psi_9(u) &= 0.0139948324149489u^3 - 0.388083791998497u^2 + 3.63099246352029u - 11.1763778503021 \\
\Psi_{10}(u) &= -0.029527517756155u^3 + 0.917586713134619u^2 - 9.42571259853971u + 32.3459724280901 \\
\Psi_{11}(u) &= 0.0241152552989715u^3 - 0.852624797684555u^2 + 10.0466139930531u - 39.0525582066838 \\
\Psi_{12}(u) &= -0.00693356066019014u^3 + 0.265132576845265u^2 - 3.36647447150244u + 14.5997954131197 \\
\Psi_{13}(u) &= 0.00361901714411142u^3 - 0.146417957522496u^2 + 1.98368247527845u - 8.58421802293079 \\
\Psi_{14}(u) &= -0.00754247811393316u^3 + 0.322364843315376u^2 - 4.57927676625408u + 22.042925382376 \\
\Psi_{15}(u) &= 0.00655082497814037u^3 - 0.311833795827933u^2 + 4.9337028614267u - 25.5219731613395 \\
\Psi_{16}(u) &= 0.00133924853485252u^3 - 0.0616781265501159u^2 + 0.931212123179315u - 4.1753555727953 \\
\Psi_{17}(u) &= -0.0119078489198728u^3 + 0.613923843640878u^2 - 10.5540213700676u + 60.9076342222704 \\
\Psi_{18}(u) &= 0.0162921459525459u^3 - 0.908875879469737u^2 + 16.8563736471156u - 103.554735895134 \\
\Psi_{19}(u) &= -0.0232607635005404u^3 + 1.34563995935619u^2 - 25.9794272607746u + 167.738669477342 \\
\Psi_{20}(u) &= 0.0167509652700748u^3 - 1.05506376688073u^2 + 22.0346472365455u - 152.355160139217
\end{aligned}$$

拟合出的系数 b 和回归方程如下:

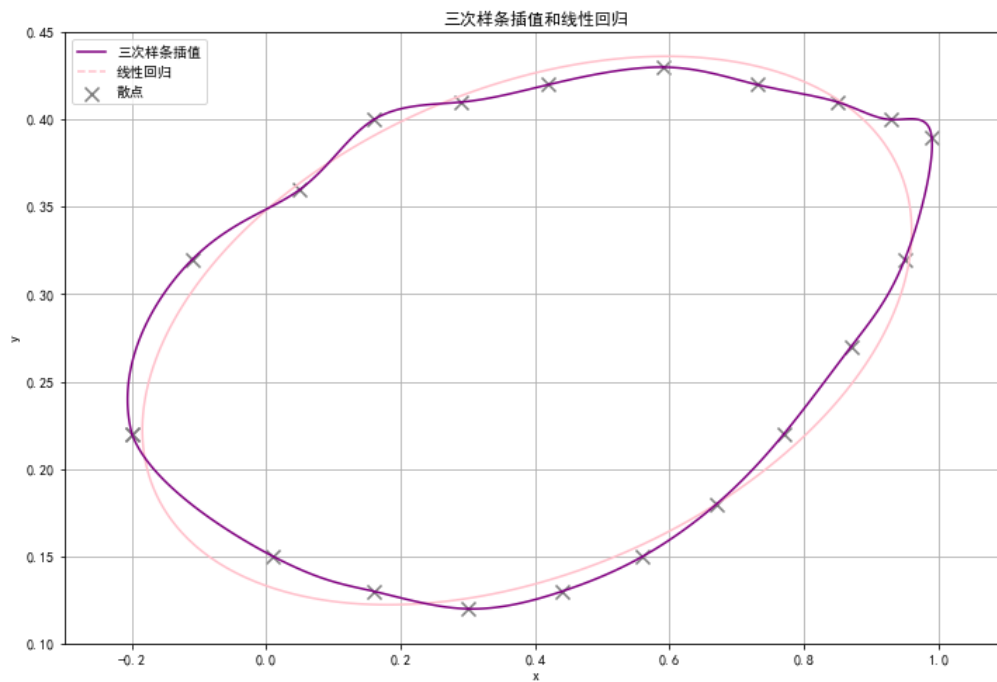
$$\begin{aligned}
b_0 &= -0.61675402721062844 \\
b_1 &= 0.037372895747393553 \\
b_2 &= 6.4038200357358814 \\
b_3 &= 2.6440756536123722 \\
b_4 &= -13.302206388291150 \\
x^2 &= -0.616754 + 0.0373729x + 6.40382y + 2.64408xy - 13.3022y^2
\end{aligned}$$

拟合函数的误差平方和Q, 复相关系数R如下:

$$\begin{aligned}
Q &= 0.018993061877819149 \\
R &= 0.99573520194623211
\end{aligned}$$

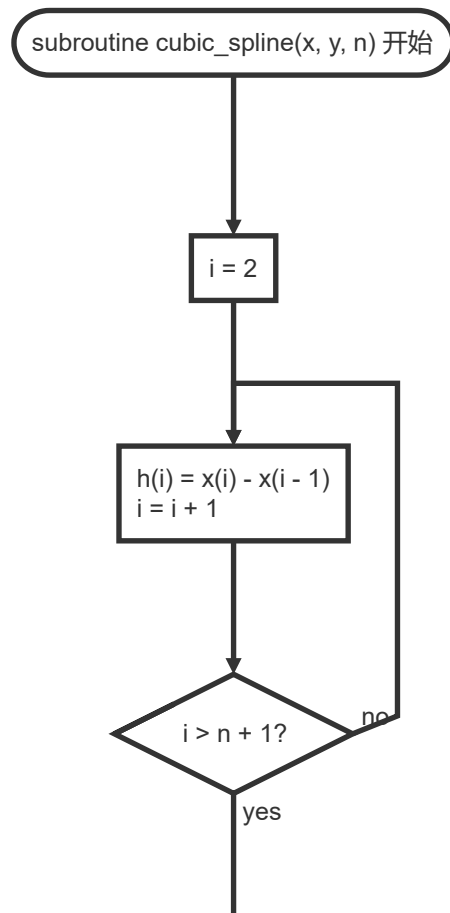
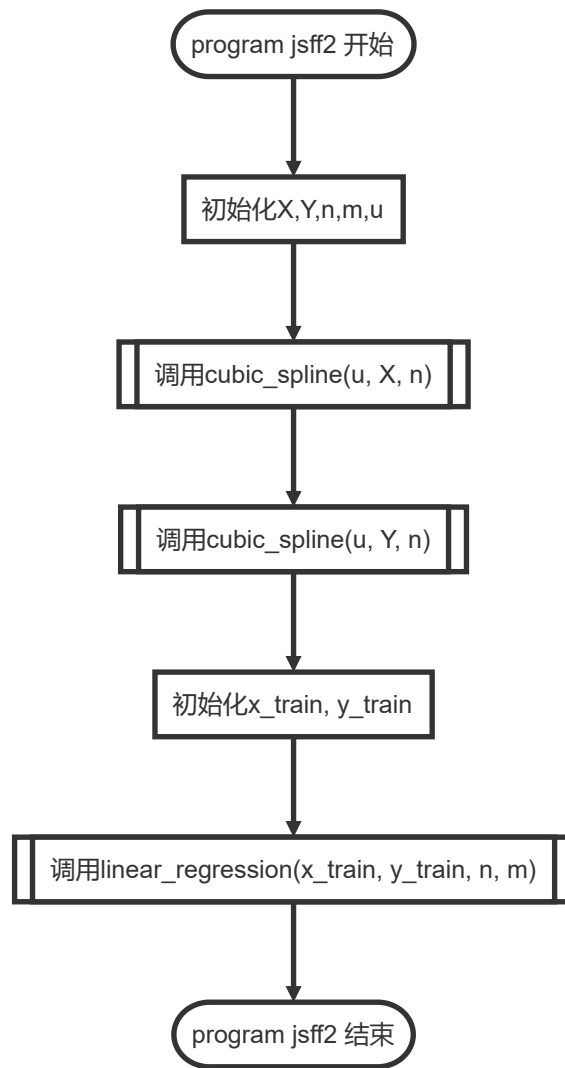
可以看到Q较小，R很接近1，说明拟合效果较好。

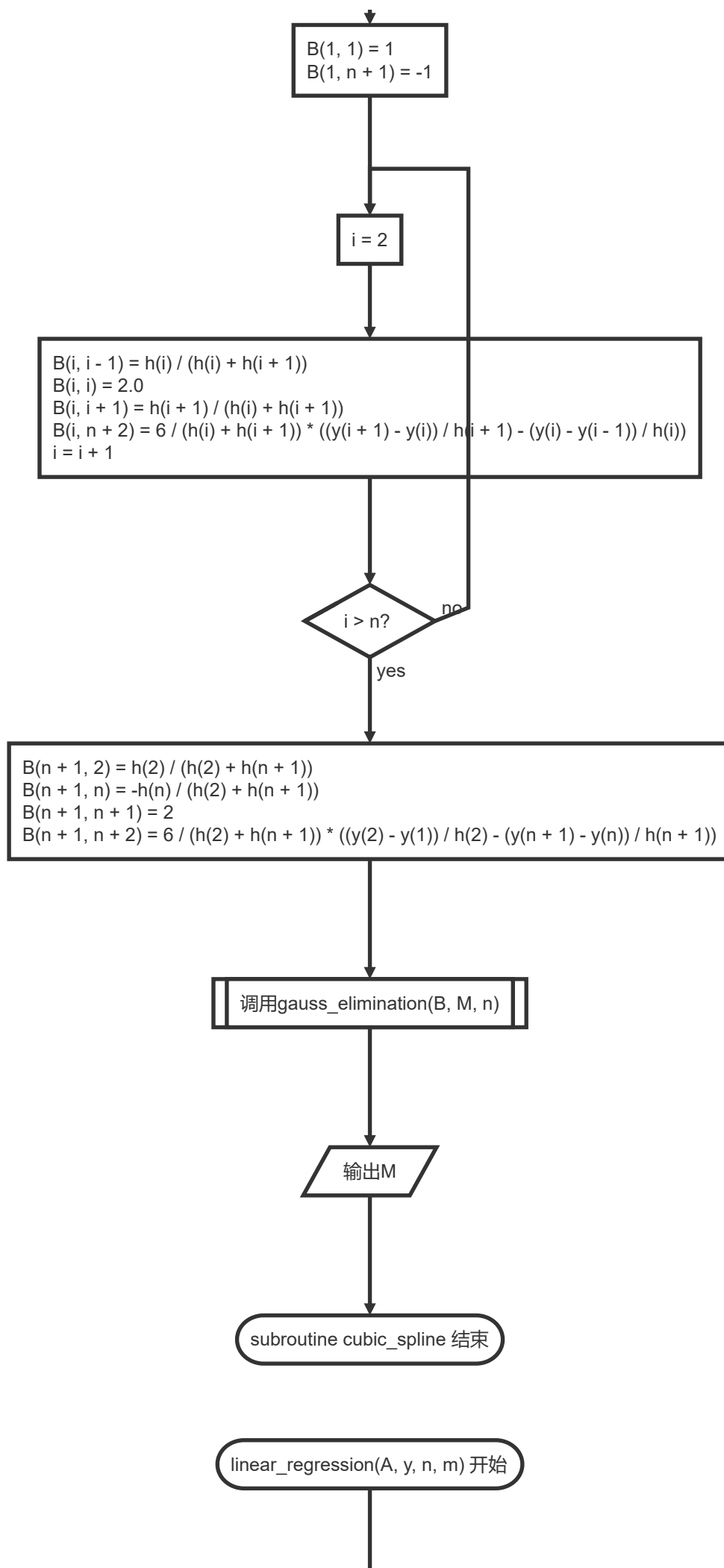
(2)曲线图

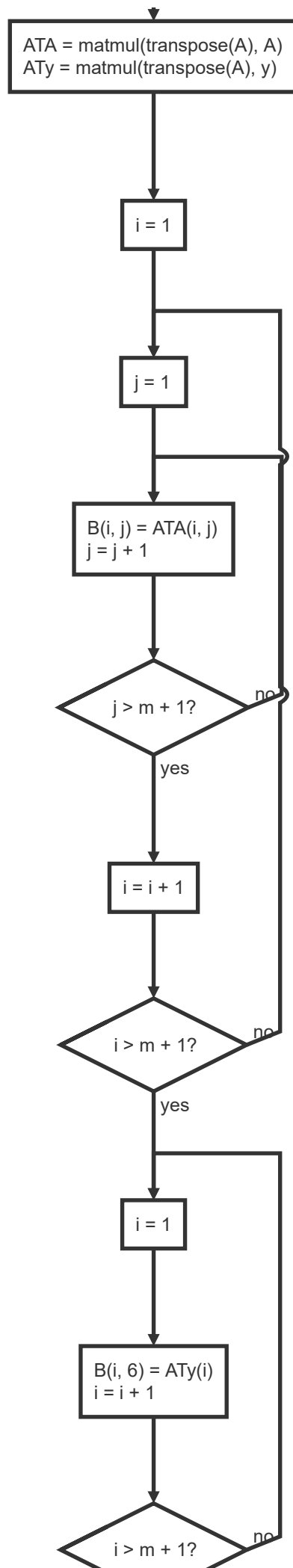


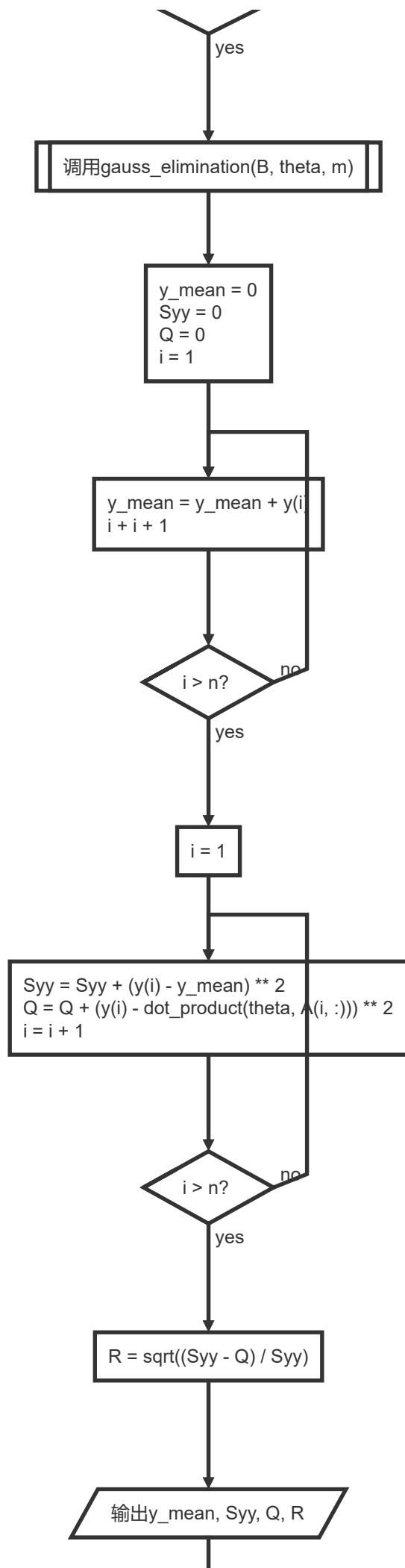
从上图可以看出，插值函数经过了每一个样本点，形状较为曲折，在训练集中的误差平方和为0；拟合函数为一个椭圆，刻画了样本点的分布趋势，在训练集中的误差平方和不为0。

二、编程流程图









linear_regression 结束

三、源代码

Fortran主程序

```
1  program jsff2
2      ! homework2 of Numerical Methods
3      ! arthor : zzy
4
5      implicit none
6      ! X : x coordinates, Y : y coordinates
7      ! X(1) = X(21), Y(1) = Y(21) inorder to apply periodical boundary conditions
8      real(8), dimension(21) :: X = [-0.20, 0.01, 0.16, 0.30, 0.44, 0.56, 0.67, 0.77,
9      0.87, 0.95,&
10                                     0.99, 0.93, 0.85, 0.73, 0.59, 0.42, 0.29, 0.16,
11      0.05, -0.11, -0.20]
12      real(8), dimension(21) :: Y = [0.22, 0.15, 0.13, 0.12, 0.13, 0.15, 0.18, 0.22,
13      0.27, 0.32,&
14                                     0.39, 0.4, 0.41, 0.42, 0.43, 0.42, 0.41, 0.4,
15      0.36, 0.32, 0.22]
16      ! u : the parameter of the curve X = X(u), Y = Y(u)
17      real(8), dimension(21) :: u
18      ! x_train : character variables in linear regression
19      real(8), dimension(20, 5) :: x_train
20      ! y_train : target variables in linear regression
21      real(8), dimension(20) :: y_train
22      ! i : loop variable, n : the number of samples, m : the number of chracters
23      ! 20 + 1 points are used in cubic spline
24      ! 20 points and 4 characters(x, y, x*y, y^2) are used in linear regression
25      integer(4) :: i, n = 20, m = 4
26
27      ! initialize u
28      do i = 1, n + 1
29          u(i) = dble(i)
30      end do
31      print *, 'Mx : '
32      call cubic_spline(u, X, n)
33      print *, 'My : '
34      call cubic_spline(u, Y, n)
35
36      ! initialize x_train and y_train
37      do i = 1, n
38          x_train(i, 1) = 1
39          x_train(i, 2) = X(i)
40          x_train(i, 3) = Y(i)
41          x_train(i, 4) = X(i) * Y(i)
42          x_train(i, 5) = Y(i) * Y(i)
43          y_train(i) = X(i) * X(i)
44      end do
45
46      call linear_regression(x_train, y_train, n, m)
47
48  end program jsff2
49
50  subroutine cubic_spline(x, y, n)
51      ! apply cubic spline interpolation algorithm
52      ! parameters: x, y : coordinates of the points to be interpolated
53      ! n : the number of the points to be interpolated
```

```

50      ! author: zzy
51
52      implicit none
53      integer(4), intent(in) :: n
54      integer(4) :: i
55      real(8), intent(in), dimension(n + 1) :: x
56      real(8), intent(in), dimension(n + 1) :: y
57      ! B : augmented matrix, B's shape is (n + 1, n + 2) since there are (n + 1) points
58      real(8), dimension(n + 1, n + 2) :: B
59      ! M : second derivative of spline functions in each interval
60      real(8), dimension(n + 1) :: M
61      ! h : h(i) = x(i) - x(i - 1)
62      real(8), dimension(n) :: h
63
64      ! calculate h
65      do i = 2, n + 1
66          h(i) = x(i) - x(i - 1)
67      end do
68
69      ! calculate B according to three-moment method and periodical boundary condition
70
71      ! M(1) == M(n + 1), periodical boundary condition
72      B(1, 1) = 1
73      B(1, n + 1) = -1
74
75      do i = 2, n
76          ! alpha(i) * M(i - 1) + 2 * M(i) + (1 - alpha(i)) * M(i + 2) == beta(i)
77          B(i, i - 1) = h(i) / (h(i) + h(i + 1))
78          B(i, i) = 2.0
79          B(i, i + 1) = h(i + 1) / (h(i) + h(i + 1))
80          B(i, n + 2) = 6 / (h(i) + h(i + 1)) * ((y(i + 1) - y(i)) / h(i + 1) - (y(i) -
y(i - 1)) / h(i))
81      end do
82
83      ! periodical boundary condition
84      B(n + 1, 2) = h(2) / (h(2) + h(n + 1))
85      B(n + 1, n) = -h(n) / (h(2) + h(n + 1))
86      B(n + 1, n + 1) = 2
87      B(n + 1, n + 2) = 6 / (h(2) + h(n + 1)) * ((y(2) - y(1)) / h(2) - (y(n + 1) -
y(n)) / h(n + 1))
88
89      call gauss_elimination(B, M, n)
90
91      print *, M
92
93  end subroutine cubic_spline
94
95  subroutine linear_regression(A, y, n, m)
96      ! apply linear regression algorithm
97      ! parameters: A : matrix of character variables, shape is (n, m + 1)
98      !               y : vector of target variables
99      !               n : the number of (x, y)
100     !               m : the number of characters
101     ! author: zzy
102
103     implicit none
104     integer(4), intent(in) :: n, m
105     real(8), dimension(n, m + 1) :: A
106     ! ATA : result of transpose(A) * A
107     real(8), dimension(m + 1, m + 1) :: ATA
108     ! B : augmented matrix
109     real(8), dimension(m + 1, m + 2) :: B
110     real(8), dimension(n) :: y
111     ! ATy : result of transpose(A) * y

```

```

112     real(8), dimension(m + 1) :: ATy
113     ! theta : solution of ATA*b == ATy
114     real(8), dimension(m + 1) :: theta
115     ! y_mean : mean value of y, Syy : variance of y, Q : sum of squared error (SSE), R
: multiple correlation coefficient
116     real(8) :: y_mean, Syy, Q, R
117     integer(4) :: i, j
118
119     ! call print_matrix(A, n, m + 1)
120     ! call print_matrix(y, m + 1, 1)
121
122     ATA = matmul(transpose(A), A)
123     ATy = matmul(transpose(A), y)
124
125     ! call print_matrix(ATA, m + 1, m + 1)
126     ! call print_matrix(ATy, m + 1, 1)
127
128     ! initialize augmented matrix
129     do i = 1, m + 1
130         do j = 1, m + 1
131             B(i, j) = ATA(i, j)
132         end do
133     end do
134
135     do i = 1, m + 1
136         B(i, 6) = ATy(i)
137     end do
138
139     ! call print_matrix(B, m + 1, m + 2)
140
141     ! solve the equation ATA*b == ATy
142     call gauss_elimination(B, theta, m)
143
144     print *, 'b :', theta
145
146     ! calculate y_mean, Syy, Q, R
147     y_mean = 0
148     Syy = 0
149     Q = 0
150
151     do i = 1, n
152         y_mean = y_mean + y(i)
153     end do
154     y_mean = y_mean / dble(n)
155
156     do i = 1, n
157         Syy = Syy + (y(i) - y_mean) ** 2
158         Q = Q + (y(i) - dot_product(theta, A(i, :))) ** 2
159     end do
160
161     R = sqrt((Syy - Q) / Syy)
162
163     print *, 'y_mean :', y_mean
164     print *, 'Syy :', Syy
165     print *, 'Q :', Q
166     print *, 'R :', R
167
168 end subroutine linear_regression
169
170 subroutine gauss_elimination(B, theta, n)
171     ! apply gauss elimination algorithm
172     ! parameters: B : augmented matrix
173     !             theta : solution of linear equations
174     !             n : the length of theta is (n + 1)

```

```

175      ! author: zzy
176
177      implicit none
178      integer(4), intent(in) :: n
179      real(8), intent(in out), dimension(n + 1, n + 2) :: B
180      real(8), intent(in out), dimension(n + 1) :: theta
181      integer(4) :: i, j, k
182
183      ! use elementary transformation to transform B into upper triangular matrix
184      do i = 1, n + 1 ! ii : rows
185          do j = i + 1, n + 2 ! j : columns
186              B(i, j) = B(i, j) / B(i, i)
187          end do
188          B(i, i) = 1
189          do j = i + 1, n + 1 ! j : rows
190              do k = i + 1, n + 2 ! k : columns
191                  B(j, k) = B(j, k) - B(j, i) * B(i, k)
192              end do
193              B(j, i) = 0
194          end do
195      end do
196
197      ! solve theta by transform B(1:n+1, 1:n+1) into diagonal matrix
198      do i = n + 1, 1, -1
199          do j = i + 1, n + 1
200              B(i, n + 2) = B(i, n + 2) - theta(j) * B(i, j)
201          end do
202          theta(i) = B(i, n + 2);
203      end do
204
205  end subroutine gauss_elimination
206
207  subroutine print_matrix(A, m, n)
208      ! debug function, print a matrix
209      ! parameters: A : matrix to be printed
210      !              (m, n) : shape of matrix
211      ! author: zzy
212
213      implicit none
214      integer(4) :: m, n, i
215      real(8), dimension(m, n) :: A
216
217      do i = 1, m
218          print *, A(i, :)
219      end do
220
221  end subroutine print_matrix

```

Python绘图程序

```

1  import matplotlib.pyplot as plt
2  import scipy.interpolate as spi
3  from sklearn.linear_model import LinearRegression as LR
4  import numpy as np
5  import pandas as pd
6  import sympy as sy
7  plt.rcParams['font.sans-serif']=['SimHei'] # 用来正常显示中文标签
8  plt.rcParams['axes.unicode_minus'] = False # 用来正常显示负号
9
10 # 初始化, x、y为坐标, Mx、My为Fortran计算出的二阶导数值, theta为Fortran计算出的线性拟合参数b
11 n = 20
12 x = [-0.2, 0.01, 0.16, 0.3, 0.44, 0.56, 0.67, 0.77, 0.87, 0.95, 0.99, 0.93, 0.85, 0.73,
0.59, 0.42, 0.29, 0.16, 0.05, -0.11, -0.2]

```

```

13 y = [0.22, 0.15, 0.13, 0.12, 0.13, 0.15, 0.18, 0.22, 0.27, 0.32, 0.39, 0.4, 0.41, 0.42,
14 0.43, 0.42, 0.41, 0.4, 0.36, 0.32, 0.22]
15 Mx = [0.50709311714530891, -0.22746861616752340, 4.2781310867928156E-002,
-3.6565142043757702E-003, -2.8155432864359401E-002, -3.7216398972686393E-003,
-1.6957950326107054E-002, 1.1553140794287205E-002, -2.9254255223173112E-002,
-1.4536363088545445E-002, -0.15260006354080916, 2.4936474200634589E-002,
-6.7145718820811259E-002, 3.6462723365777105E-003, -6.7439613712450261E-002,
8.6112532988534593E-002, -3.7010568309589723E-002, 6.1929740249824290E-002,
-9.0708395371916439E-002, 9.0381441575125630E-004, 0.50709311714530891]
16 My = [4.9409026797001335E-004, 7.8011944728198723E-002, -1.2541976469125507E-002,
3.2156038038295066E-002, 3.9177992819944257E-003, 1.2172841723718993E-002,
7.3907766026706191E-003, 1.8263994645139545E-002, -2.0446633589753450E-002,
6.3522360899939928E-002, -0.11364274563698991, 3.1048786156839283E-002,
-1.0552577804301562E-002, 1.1161525060366965E-002, -3.4093343623231971E-002,
5.2116062456102332E-003, 1.3247097454725363E-002, -5.8199996064511685E-002,
3.9552879650763990E-002, -0.10001170135247860, 4.9409026797001335E-004]
17 theta = [-0.61675402721062844, 3.7372895747393553E-002, 6.4038200357358814,
2.6440756536123722, -13.302206388291150]
18 # 通过Mx,My计算各个区间上的分段插值函数
19 U = sy.symbols('U')
20 xu, yu= [], [] # 储存分段插值函数
21 xu_coeffs, yu_coeffs = [], [] # 储存分段插值函数的系数
22 for i in range(1, n + 1):
23     phi = sy.simplify(Mx[i - 1] / 6 * (i + 1 - U) ** 3 + Mx[i] / 6 * (U - i) ** 3 +
(x[i] - Mx[i] / 6) * (U - i) + (x[i - 1] - Mx[i - 1] / 6) * (i + 1 - U))
24     psi = sy.simplify(My[i - 1] / 6 * (i + 1 - U) ** 3 + My[i] / 6 * (U - i) ** 3 +
(y[i] - My[i] / 6) * (U - i) + (y[i - 1] - My[i - 1] / 6) * (i + 1 - U))
25     phi = sy.Poly(phi)
26     psi = sy.Poly(psi)
27     xu.append(np.poly1d(phi.coeffs()))
28     yu.append(np.poly1d(psi.coeffs()))
29     xu_coeffs.append(phi.coeffs())
30     yu_coeffs.append(psi.coeffs())
31
32 # 开始画图, 在一张图中绘制插值曲线和拟合曲线
33 fig, ax = plt.subplots(figsize=(12, 8))
34
35 # 分段绘制插值曲线
36 for i in range(n):
37     u = np.linspace(i + 1, i + 2, 100)
38     if i == n - 1:
39         plt.plot(xu[i](u), yu[i](u), color='purple', label='三次样条插值')
40     else:
41         plt.plot(xu[i](u), yu[i](u), color='purple')
42
43 # 利用等高线绘制拟合曲线
44 xx = np.linspace(-0.3, 1.1, 100)
45 yy = np.linspace(0.1, 0.45, 100)
46 xx, yy = np.meshgrid(xx, yy)
47 zz = theta[0] + theta[1] * xx + theta[2] * yy + theta[3] * np.multiply(xx, yy) +
theta[4] * np.multiply(yy, yy) - np.multiply(xx, xx)
48 CS = ax.contour(xx, yy, zz, 0, colors='pink')
49 CS.collections[0].set_label('线性回归')
50
51 # 绘制散点图
52 ax.scatter(x, y, c='gray', marker='x', s=100, label='散点')
53
54 # 图片细节调整
55 ax.grid()
56 ax.set_xlabel('x')
57 ax.set_ylabel('y')
58 plt.legend(loc='upper left')
59 plt.title('三次样条插值和线性回归')

```

```
60 plt.show()
61 plt.close()
```

四、运行结果

```
shenye@shenye-virtual-machine:~/FortranPrograms$ gfortran jsff2.f90 -o jsff2 && ./jsff2
Mx :
0.50709311714530891      -0.22746861616752340      4.2781310867928156E-002      -3.6565142043757694E-003      -2.8155432864359405E-002
-3.7216398972686384E-003      -1.6957950326107057E-002      1.1553140794287204E-002      -2.9254255223173108E-002      -1.4536363088545449E-002
-0.15260006354080916      2.4936474200634585E-002      -6.7145718820811245E-002      3.6462723365777061E-003      -6.7439613712450261E-002
8.6112532988534593E-002      -3.7010568309589723E-002      6.1929740249824290E-002      -9.0708395371916425E-002      9.0381441575124177E-004
0.50709311714530891
My :
0.54284566866118333      -7.2460376492327445E-002      2.9155454261828601E-002      2.0614643203788051E-002      7.1090710492157285E-003
1.1291279168918538E-002      7.6340818456360699E-003      1.8196899987278390E-002      -2.0428142040654965E-002      6.3517252959952766E-002
-0.11364127798094577      3.1048150093328578E-002      -1.0551535134211474E-002      1.1157999534473027E-002      -3.4080286625660552E-002
5.1629044339197580E-003      1.3428847529025081E-002      -5.8878294503158242E-002      4.2084323318493912E-002      -0.10945917758138719
3.5752551515874427E-002
b : -0.61675402721062844      3.7372895747393553E-002      6.4038200357358814      2.6440756536123722      -13.302206388291150
y_mean : 0.35566500194840145
Syy : 2.2314830588593790
Q : 1.8993061877819140E-002
R : 0.99573520194623211
```

结果解释：

Mx为 x 对 u 插值所得到的各个区间上的分段插值函数的二阶导数值.

My为 y 对 u 插值所得到的各个区间上的分段插值函数的二阶导数值.

根据 Mx 可以构造出 x-u 插值函数 $x = \Phi(u)$, 根据 M 可以构造出 y-u 插值函数 $y = \Psi(u)$.

b 为向量 $(b_0, b_1, b_2, b_3, b_4)^T$, 是线性回归的拟合方程 $b_0 + b_1x + b_2y + b_3xy + b_4y^2 = x^2$ 的系数.

y_mean为目标变量(x^2)的平均值, Syy为目标变量的总平方和 (SST), Q为目标变量的误差平方和 (SSE), R为复相关系数.