DATA SMOOTHING

EXERCISE 3

Data Smoothing Report

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1 Introduction

This exercise asks to use the linearly independent basis function:

$$\phi_{3,i}(x) = \binom{3}{i} x^i (1-x)^{3-i} \qquad i = 0, 1, 2, 3$$

to find the optimal combination

$$\phi(x) = \lambda_0 \phi_{3,0}(x) + \lambda_1 \phi_{3,1}(x) + \lambda_2 \phi_{3,2}(x) + \lambda_3 \phi_{3,3}(x)$$

that minimizes the Euclidean norm

$$\sqrt{\sum_{j=0}^{19} (\phi(x_j) - y_j)^2}$$

for the 20 data points (x_j, y_j) given in

j	x_j	y_j
0	0.0	-0.80
1	0.6	-0.34
2	1.5	0.59
3	1.7	0.59
4	1.9	0.23
5	2.1	0.10
6	2.3	0.28
7	2.6	1.03
8	2.8	1.50
9	3.0	1.44
10	3.6	0.74
11	4.7	-0.82
12	5.2	-1.27
13	5.7	-0.92
14	5.8	-0.92
15	6.0	-1.04
16	6.4	-0.79
17	6.9	-0.06
18	7.6	1.00
19	8.0	0.00

This is an overdetermined system. To solve this exercise, I'll first find the coefficient matrix A and then use QR decomposition to solve the system. I'll also calculate the l_2-norm of the residual, and the condition number of the coefficient matrix. Finally, I'll plot the data points with the graph of the function $\phi(x)$.

2   Tools

The following programming language and libraries have been used in this exercise:

- C
- GSL (GNU Scientific Library)
- C Math Library
- Python (for plotting)
- SciPy (for plotting)

The following double-precision GSL data types have been used in the exercise:

- `gsl_matrix`
- `gsl_vector`

The following GSL methods have been used in the exercise:

- `gsl_matrix_alloc(size1, size2)`
- `gsl_matrix_set(matrix, row, column, value)`
- `gsl_matrix_get(matrix, row, column)`
- `gsl_vector_alloc(size)`
- `gsl_vector_set(vector, index, value)`
- `gsl_vector_set_zero(vector)`
- `gsl_vector_get(vector, index)`
- `gsl_matrix_memcpy(destinationMatrix, matrixToCopyFrom)`
- `gsl_linalg_SV_decomp(A, V, S, workspaceVector)`
- `gsl_vector_minmax(vector, minInVector, maxInVector)`
- `gsl_sf_fact(number)` to calculate the factorial
- `gsl_sf_pow_int(base, exponent)`
- `gsl_blas_dnrm2(vector)` to calculate the Euclidean norm
- `gsl_matrix_free(matrixToDeallocate)`
- `gsl_vector_free(vectorToDeallocate)`

In order to decompose the coefficient matrix into its QR decomposition, and then solve the square system $A\vec{x} = \vec{b}$, I've used the following methods:

- `gsl_linalg_QR_decomp(matrixQR, vectorTau)`
- `gsl_linalg_QR_lssolve(matrixQR, vectorTau, vectorB, vectorX, vectorResidual)`

- `gsl_permutation_alloc(size)`

The following method from the C Math library was used in this exercise to calculate the absolute value of a number:

- `fabs(x)`

3 Computation

First off, I compute the coefficients A of the linear system by using the linearly independent basis function. This is what A looks like:

$$
\begin{bmatrix}
1.000000000000000\,e+00 & 0.000000000000000\,e+00 & 0.000000000000000\,e+00 & 0.000000000000000\,e+00 \\
6.400000000000002\,e-02 & 2.880000000000000\,e-01 & 4.320000000000001\,e-01 & 2.160000000000000\,e-01 \\
-1.250000000000000\,e-01 & 1.125000000000000\,e+00 & -3.375000000000000\,e+00 & 3.375000000000000\,e+00 \\
-3.429999999999999\,e-01 & 2.499000000000000\,e+00 & -6.068999999999998\,e+00 & 4.912999999999999\,e+00 \\
-7.289999999999998\,e-01 & 4.616999999999998\,e+00 & -9.747000000000000\,e+00 & 6.858999999999999\,e+00 \\
-1.331000000000000\,e+00 & 7.623000000000002\,e+00 & -1.455300000000000\,e+01 & 9.261000000000001\,e+00 \\
-2.196999999999999\,e+00 & 1.166100000000000\,e+01 & -2.063099999999999\,e+01 & 1.216700000000000\,e+01 \\
-4.096000000000001\,e+00 & 1.996800000000001\,e+01 & -3.244800000000000\,e+01 & 1.757600000000000\,e+01 \\
-5.831999999999998\,e+00 & 2.721599999999999\,e+01 & -4.233599999999999\,e+01 & 2.195199999999999\,e+01 \\
-8.000000000000000\,e+00 & 3.600000000000000\,e+01 & -5.400000000000000\,e+01 & 2.700000000000000\,e+01 \\
-1.757600000000000\,e+01 & 7.300800000000001\,e+01 & -1.010880000000000\,e+02 & 4.665600000000001\,e+01 \\
-5.065300000000001\,e+01 & 1.930290000000000\,e+02 & -2.451990000000000\,e+02 & 1.038230000000000\,e+02 \\
-7.408800000000001\,e+01 & 2.751840000000000\,e+02 & -3.407040000000000\,e+02 & 1.406080000000000\,e+02 \\
-1.038230000000000\,e+02 & 3.777390000000001\,e+02 & -4.581090000000000\,e+02 & 1.851930000000000\,e+02 \\
-1.105920000000000\,e+02 & 4.008960000000000\,e+02 & -4.844160000000000\,e+02 & 1.951120000000000\,e+02 \\
-1.250000000000000\,e+02 & 4.500000000000000\,e+02 & -5.400000000000000\,e+02 & 2.160000000000000\,e+02 \\
-1.574640000000000\,e+02 & 5.598720000000002\,e+02 & -6.635520000000001\,e+02 & 2.621440000000001\,e+02 \\
-2.053790000000000\,e+02 & 7.205670000000001\,e+02 & -8.426970000000001\,e+02 & 3.285090000000001\,e+02 \\
-2.874960000000000\,e+02 & 9.931679999999998\,e+02 & -1.143648000000000\,e+03 & 4.389759999999999\,e+02 \\
-3.430000000000000\,e+02 & 1.176000000000000\,e+03 & -1.344000000000000\,e+03 & 5.120000000000000\,e+02
\end{bmatrix}
$$

Then, I calculate the condition number of the matrix A of order n. In GSL there is no direct function that calculates the condition number, but it's possible to use the ratio of the largest singular value of matrix A, $\sigma_n(A)$, to the smallest $\sigma_1(A)$:

$$
\kappa(A) := \frac{\sigma_n(A)}{\sigma_1(A)} = \frac{\|A\|}{\|A^{-1}\|^{-1}}
$$

I proceed to factorize A into its singular value decomposition SVD using the `gsl_linalg_SV_decomp` method, and then use `gsl_vector_minmax` to extract the minimum and maximum singular values out of the vector S that contains the diagonal elements of the singular value matrix. The condition number of the matrix A is equal to $3.741019262503867e+03$.

The column vector $\vec{b}$ is formed by the input y values:

$$\begin{bmatrix} -8.000000000000000e-01 \\ -3.400000000000000e-01 \\ 5.900000000000000e-01 \\ 5.900000000000000e-01 \\ 2.300000000000000e-01 \\ 1.000000000000000e-01 \\ 2.800000000000000e-01 \\ 1.030000000000000e+00 \\ 1.500000000000000e+00 \\ 1.440000000000000e+00 \\ 7.400000000000000e-01 \\ -8.200000000000000e-01 \\ -1.270000000000000e+00 \\ -9.200000000000000e-01 \\ -9.200000000000000e-01 \\ -1.040000000000000e+00 \\ -7.900000000000000e-01 \\ -6.000000000000000e-02 \\ 1.000000000000000e+00 \\ 0.000000000000000e+00 \end{bmatrix}$$

In order to calculate the residual of this system, I first need to calculate the missing solutions vector containing λ. Since this is an overdetermined system, I can use QR decomposition to solve the system. QR decomposition of A:

$$\begin{bmatrix} -5.607137694902810e+02 & 1.956202843752372e+03 & -2.276212763756861e+03 & 8.833928944999552e+02 \\ 1.139370324819986e-04 & -4.671135706796601e+01 & 1.122030535262658e+02 & -6.782418228480103e+01 \\ -2.225332665664034e-04 & 1.460497799957120e-02 & 7.581872706318327e+00 & -8.735870723873337e+00 \\ -6.106312834582108e-04 & 2.762429988027977e-02 & 1.797466673315370e-01 & -2.470454024049311e+00 \\ -1.297814010615264e-03 & 4.400918925292650e-02 & 2.113118885654055e-01 & 1.354991299702775e-01 \\ -2.369534222399064e-03 & 6.326913656703972e-02 & 2.350053228690535e-01 & 9.686987975376644e-02 \\ -3.911244693171105e-03 & 8.491363227214763e-02 & 2.513310790520081e-01 & 6.050043190845661e-02 \\ -7.291970078847909e-03 & 1.207784144212678e-01 & 2.631080548709738e-01 & 1.049772432830278e-02 \\ -1.038251208492211e-02 & 1.462383018205487e-01 & 2.632200917938682e-01 & -1.959354810540480e-02 \\ -1.424212906024982e-02 & 1.723659541841733e-01 & 2.577288314294048e-01 & -4.692208258102275e-02 \\ -3.128995754536886e-02 & 2.498504055563917e-01 & 2.126763547071380e-01 & -1.108942994397425e-01 \\ -9.017582041110428e-02 & 3.520968788593226e-01 & 5.605686650054093e-02 & -1.473630562460556e-01 \\ -1.318963572269736e-01 & 3.635568863958127e-01 & -2.831753402090372e-02 & -1.240982343374392e-01 \\ -1.848325706777897e-01 & 3.424022086740725e-01 & -1.099043818739413e-01 & -7.278910904340619e-02 \\ -1.968831921288935e-01 & 3.335830602668363e-01 & -1.251940955112117e-01 & -5.896438574071358e-02 \\ -2.225332665664034e-01 & 3.108660410390103e-01 & -1.542417580429807e-01 & -2.760834500928011e-02 \\ -2.803278262928973e-01 & 2.434003295032724e-01 & -2.044456433018340e-01 & 5.043304854412397e-02 \\ -3.656292780331310e-01 & 1.127004233192019e-01 & -2.472054281433762e-01 & 1.782091144383195e-01 \\ -5.118193920381977e-01 & -1.705668773785795e-01 & -2.556299463550832e-01 & 4.175378294298211e-01 \\ -6.106312834582110e-01 & -3.921595584433181e-01 & -2.261060282111244e-01 & 5.880648466528077e-01 \end{bmatrix}$$

The following are the λ found:

$$\begin{bmatrix} -1.118262027055321e+00 \\ -4.515724133992401e-01 \\ 2.972563550105292e-03 \\ 2.972882574075207e-01 \end{bmatrix}$$
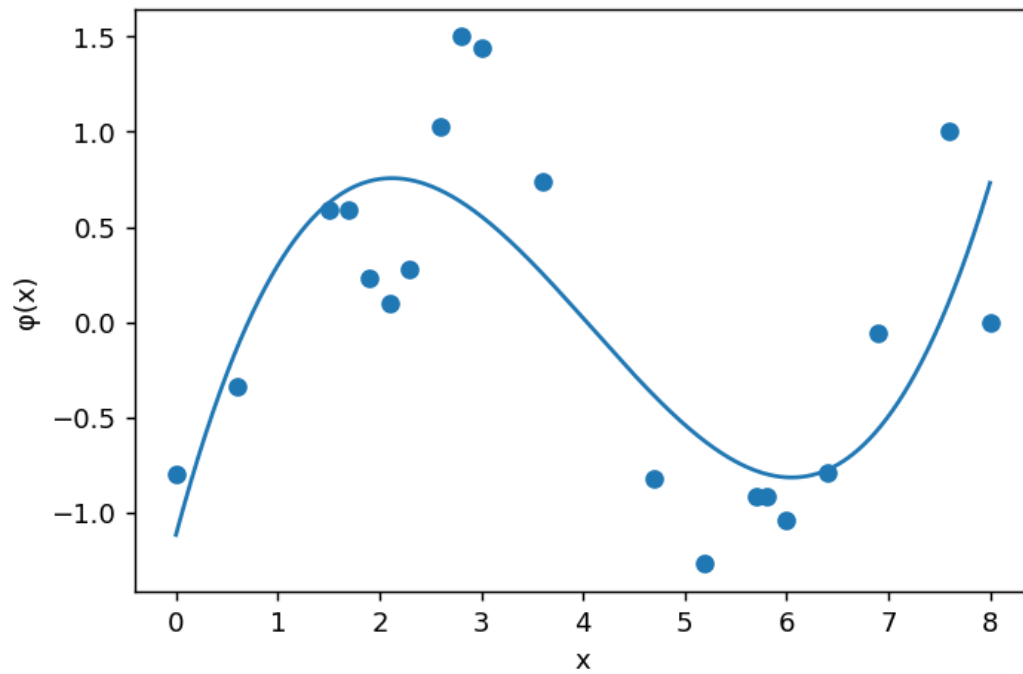
The residual vector $\vec{r}$ is directly given by the `gsl_linalg_QR_lssolve` method.

$$\begin{bmatrix} 3.182620270553753e - 01 \\ -2.038767862631474e - 01 \\ -3.507925507654632e - 02 \\ -1.076211346528342e - 01 \\ -5.104297656943454e - 01 \\ -6.559970851745927e - 01 \\ -4.668150300670836e - 01 \\ 3.379120178166642e - 01 \\ 8.680652851344475e - 01 \\ 8.842461476326978e - 01 \\ 4.840349364751467e - 01 \\ -4.332442092900336e - 01 \\ -6.426370573997744e - 01 \\ -1.387527086448619e - 01 \\ -1.218089886087358e - 01 \\ -2.242466352247385e - 01 \\ -1.314405461740510e - 02 \\ 5.037445845512266e - 01 \\ 8.885672158267567e - 01 \\ -7.311795037780225e - 01 \end{bmatrix}$$

The Euclidean norm of the residual vector is $2.282876480420795e + 00$.

4 Plot

I will plot the computed function together with the data points.

5 Observations