Test 2 Josh Boehm

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1 Libraries/Imports

```
[]: import numpy as np
  import scipy as sp
  from numpy.linalg import solve
  from numpy.linalg import qr
  from numpy.linalg import svd
  from scipy.linalg import diagsvd
  from scipy.linalg import pinv
  from scipy.optimize import minimize
  from statistics import mean
  import matplotlib.pyplot as plt
```

2 Question 1

Given the data points

derive the equation of the least-squares line

$$y = mx + b$$

that best fits the given data points. Solve the system using the QR factorization, the SVD, and the Normal Equations.

```
[]: A = np.matrix([[2,1],[5,1],[7,1],[8,1]])
b = np.matrix([1,2,3,3]).T
```

2.1 QR Factorization

The matrix created from the data points:

$$\begin{bmatrix} 2,1\\5,1\\7,1\\8,1 \end{bmatrix} \begin{bmatrix} m\\b \end{bmatrix} = \begin{bmatrix} 1\\2\\3\\3 \end{bmatrix}$$

To solve using QR factorization, we first factor A as QR. Next, we pre-multiply with Q^T , giving $Rx = Q^Tb$ (Q^TQ is the identity matrix) Now, we can call solve() with R and Q^Tb

[[0.35714286] [0.28571429]]

2.1.1 Solution

$$x = \begin{bmatrix} 0.35714286 \\ 0.28571429 \end{bmatrix} = \begin{bmatrix} \frac{5}{14} \\ \frac{2}{7} \end{bmatrix}$$

2.2 SVD Factorization

To solve using SVD factorization, we first factor A as SVD.

Now, we create the pseudo-inverse by taking the transpose of the parts in reverse order, except with Σ , we take the take the reciprocals before transposing.

Last, we can call pre-multiply b with A^{\dagger} , as $A^{\dagger}A$ is the identity matrix

$$Ax = bU\Sigma V^T x = bA^{\dagger} = V\Sigma^{\dagger}U^T A^T A = IIx = A^{\dagger}bx = A^{\dagger}bor V\Sigma^{\dagger}U^T b$$

```
[]: U, sigma, VT = svd(A)
Sigma = diagsvd(sigma, len(A), len(A.T))
PseudoA = (VT).T @ pinv(Sigma) @ U.T

x = PseudoA @ b
print(x)
```

[[0.35714286] [0.28571429]]

2.2.1 Solution

$$x = \begin{bmatrix} 0.35714286 \\ 0.28571429 \end{bmatrix} = \begin{bmatrix} \frac{5}{14} \\ \frac{2}{7} \end{bmatrix}$$

2.3 Normal Equations

The normal equation is that which minimizes the sum of the square differences between the left and right sides:

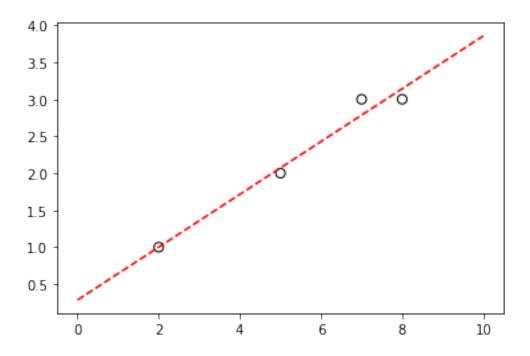
$$A^T A x = A^T b$$

In this case, I would just use solve (A.T @ A, A.T @ b) and see. You could still utilize the previous factorizations, if desired.

2.3.1 Solution

```
[]: solvex = solve(A.T @ A, A.T @ b)
      solveqr = solve(R.T @ Q.T @ Q @ R, R.T @ Q.T @ b)
      \verb|solvesvd| = \verb|solve|(VT.T @ Sigma.T @ U.T @ U @ Sigma @ VT, VT.T @ Sigma.T @ U.T @_{\sqcup}|
       هb)
      print(f"{solvex}\n\n{solveqr}\n\n{solvesvd}")
     [[0.35714286]
      [0.28571429]]
     [[0.35714286]
      [0.28571429]]
     [[0.35714286]
      [0.28571429]]
                                           x = \begin{bmatrix} 0.35714286 \\ 0.28571429 \end{bmatrix} = \begin{bmatrix} \frac{5}{14} \\ \frac{2}{7} \end{bmatrix}
[]: X1 = np.array(A[:,0])
      Y1 = np.array(b)
      x = np.linspace(0,10,50)
      y = (5/14)*x+(2/7)
      plt.scatter(X1,Y1, edgecolor='k',c='none',s=50)
      plt.plot(x,y, "r--")
```

[]: [<matplotlib.lines.Line2D at 0x17cce7430>]



Question 2 3

Let

$$f(x,y) = 3 + x + \frac{1}{2}y - xy + \frac{1}{2}x^2 + y^2$$

1. Find the Gradiant and the Hessian of this function.
2. Starting at $\begin{bmatrix} x^0 \\ y^0 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ apply **one-step** of Newtown apply **one-step** of Newtown's Method to find $\begin{bmatrix} x^1 \\ y^1 \end{bmatrix}$ and $f(x^1, y^1)$.

3. Use any two methods from SCIPY. OPTIMIZE to minimize this function.

3.0.1 Gradient

In order to derive the gradient, let's first define it:

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \\ \vdots \end{bmatrix}$$

First with regards to x:

$$\frac{\partial f}{\partial x}\left(3 + x + \frac{1}{2}y - xy + \frac{1}{2}x^2 + y^2\right) = x - y + 1$$

Next with regards to y:

$$\frac{\partial f}{\partial y} \left(3 + x + \frac{1}{2}y - xy + \frac{1}{2}x^2 + y^2 \right) = -x + 2y + \frac{1}{2}x^2 + y^2$$

Thus:

$$\nabla f = \begin{bmatrix} x - y + 1 \\ -x + 2y + \frac{1}{2} \end{bmatrix}$$

3.0.2 Hessian

Again, to derive the Hessian, it might help to define it.

$$\mathbf{H_f} = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial y \partial x} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix}$$

So our second partials are as follows:

$$\frac{\partial^2 f}{\partial x^2} = 1$$
$$\frac{\partial^2 f}{\partial y \partial x} = -1$$
$$\frac{\partial^2 f}{\partial y \partial x} = -1$$
$$\frac{\partial^2 f}{\partial y^2} = 2$$

This makes the Hessian:

$$\mathbf{H_f} = \begin{bmatrix} 1 & -1 \\ -1 & 2 \end{bmatrix}$$

3.0.3 Definitions

Apply one step of Newton's Method:

```
[]:
```

[]: array([0.79591837, 0.90816327])

3.1 Use any two methods from SCIPY.OPTIMIZE to minimize this function.

3.1.1 Method 1: Nelder-Mead

```
for x in enumerate(starting_points):
    result = minimize(q2, x[1], method = 'Nelder-Mead', tol = 1.e-7)

print(section_break)
    print('Test Run', x[0] + 1, ':')
    print(section_break)

print("Starting Value Used: ', x[1])
    print("The Minimum Occurs at (x, y) = ", result.x)
    print("The Minimum Value = ", q2(result.x).round(3))

print("Other Statistics:")
    print(result)
    print(section_break)
    print(section_break)
    print('\n')
```

```
Test Run 1 :
______
Starting Value Used: [[-15 4]]
The Minimum Occurs at (x, y) = [-2.5 	 -1.50000002]
The Minimum Value = 1.375
Other Statistics:
final_simplex: (array([[-2.5
                               , -1.50000002],
      [-2.50000009, -1.50000007],
      [-2.50000003, -1.49999994]]), array([1.375, 1.375, 1.375]))
         fun: 1.37500000000000009
     message: 'Optimization terminated successfully.'
        nfev: 145
         nit: 75
       status: 0
      success: True
           x: array([-2.5
                           , -1.50000002])
```

Test Run 2:

```
Starting Value Used: [[-2 12]]
The Minimum Occurs at (x, y) = [-2.49999995 -1.49999996]
The Minimum Value = 1.375
Other Statistics:
final_simplex: (array([[-2.49999995, -1.49999996],
                , -1.50000003],
      [-2.50000004, -1.50000002]]), array([1.375, 1.375, 1.375]))
         fun: 1.37500000000000009
      message: 'Optimization terminated successfully.'
        nfev: 121
         nit: 63
       status: 0
      success: True
           x: array([-2.49999995, -1.49999996])
______
Test Run 3:
_____
Starting Value Used: [[ 5 -15]]
The Minimum Occurs at (x, y) = [-2.50000001 -1.49999999]
The Minimum Value = 1.375
Other Statistics:
final_simplex: (array([[-2.50000001, -1.49999999],
      [-2.5000001, -1.50000007],
      [-2.49999995, -1.50000005]]), array([1.375, 1.375, 1.375]))
      message: 'Optimization terminated successfully.'
        nfev: 139
         nit: 71
       status: 0
      success: True
           x: array([-2.50000001, -1.49999999])
3.1.2 Method 2: Powell
```

```
[]: for x in enumerate(starting_points):
    result = minimize(q2, x[1], method = 'Powell', tol = 1.e-7)
    print(section_break)
```

```
print('Test Run', x[0] + 1, ':')
   print(section_break)
   print('Starting Value Used: ', x[1])
   print("The Minimum Occurs at (x, y) = ", result.x)
   print("The Minimum Value = ", q2(result.x).round(3))
   print("Other Statistics:")
   print(result)
   print(section_break)
   print(section_break)
   print('\n')
______
Test Run 1:
Starting Value Used: [[-15 4]]
The Minimum Occurs at (x, y) = [-2.5 -1.5]
The Minimum Value = 1.375
Other Statistics:
  direc: array([[ 0. , 1. ],
     [-2.75, -1.375]
    fun: 1.374999999999996
message: 'Optimization terminated successfully.'
   nfev: 89
    nit: 3
 status: 0
success: True
     x: array([-2.5, -1.5])
_____
Test Run 2:
_____
Starting Value Used: [[-2 12]]
The Minimum Occurs at (x, y) = [-2.5 	 -1.49999998]
The Minimum Value = 1.375
Other Statistics:
  direc: array([[ 0. , 1. ],
     [-6.75 , -3.375]])
    fun: 1.375
message: 'Optimization terminated successfully.'
   nfev: 100
```

nit: 3

```
status: 0
success: True
x: array([-2.5 , -1.49999998])
```

```
Test Run 3:
```

```
Starting Value Used: [[ 5 -15]]
The Minimum Occurs at (x, y) = [-2.49999999 -1.50000001]
The Minimum Value = 1.375
Other Statistics:
    direc: array([[0. , 1. ],
        [6.75 , 3.375]])
    fun: 1.375
message: 'Optimization terminated successfully.'
    nfev: 131
    nit: 3
    status: 0
success: True
    x: array([-2.49999999, -1.50000001])
```

4 Question 3

Let

$$f(x,y) = 7 + 5x + 6y + 4xy + 3(x^2 + y^2)^2$$

- 1. Find the Gradiant and the Hessian of this function.
- 2. Use any two optimization methods from SCIPY.OPTIMIZE to minimize this function.

4.0.1 Gradient

As before, the Gradient definition is:

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \\ \vdots \end{bmatrix}$$

First with regards to x:

$$\frac{\partial f}{\partial x} \left(7 + 5x + 6y + 4xy + 3(x^2 + y^2)^2 \right) = 12x(x^2 + y^2) + 4y + 5$$

Next with regards to y:

$$\frac{\partial f}{\partial y} \left(7 + 5x + 6y + 4xy + 3(x^2 + y^2)^2 \right) = 4x + 12y(x^2 + y^2) + 6$$

Thus:

$$\nabla f = \begin{bmatrix} 12x(x^2 + y^2) + 4y + 5\\ 4x + 12y(x^2 + y^2) + 6 \end{bmatrix}$$

4.0.2 Hessian

Again, to derive the Hessian, it might help to define it.

$$\mathbf{H_f} = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial y \partial x} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix}$$

So our second partials are as follows:

$$\frac{\partial^2 f}{\partial x^2} = 36x^2 + 12y^2$$
$$\frac{\partial^2 f}{\partial y \partial x} = 24xy + 4$$
$$\frac{\partial^2 f}{\partial y \partial x} = 24xy + 4$$
$$\frac{\partial^2 f}{\partial y^2} = 12x^2 + 36y^2$$

This makes the Hessian:

$$\mathbf{H_f} = \begin{bmatrix} 36x^2 + 12y^2 & 24xy + 4\\ 24xy + 4 & 12x^2 + 36y^2 \end{bmatrix}$$

4.0.3 Definitions

4.0.4 Method 1: Nelder-Mead

[]: for x in enumerate(starting points):

```
result = minimize(q3, x[1], method = 'Nelder-Mead', tol = 1.e-7)
   print(section_break)
   print('Test Run', x[0] + 1, ':')
   print(section_break)
   print('Starting Value Used: ', x[1])
   print("The Minimum Occurs at (x, y) = ", result.x)
   print("The Minimum Value = ", q3(result.x).round(3))
   print("Other Statistics:")
   print(result)
   print(section break)
   print(section_break)
   print('\n')
Test Run 1:
______
Starting Value Used: [[-15 4]]
The Minimum Occurs at (x, y) = [-2.5 	 -1.50000002]
The Minimum Value = 1.375
Other Statistics:
final_simplex: (array([[-2.5 , -1.50000002],
      [-2.50000009, -1.50000007],
      [-2.50000003, -1.49999994]]), array([1.375, 1.375, 1.375]))
         fun: 1.37500000000000009
     message: 'Optimization terminated successfully.'
        nfev: 145
         nit: 75
      status: 0
     success: True
           x: array([-2.5 , -1.50000002])
______
Test Run 2:
Starting Value Used: [[-2 12]]
The Minimum Occurs at (x, y) = [-2.49999995 -1.49999996]
The Minimum Value = 1.375
Other Statistics:
final_simplex: (array([[-2.49999995, -1.49999996],
```

```
, -1.50000003],
     [-2.5]
     [-2.50000004, -1.50000002]]), array([1.375, 1.375, 1.375]))
        fun: 1.37500000000000009
     message: 'Optimization terminated successfully.'
       nfev: 121
        nit: 63
      status: 0
     success: True
          x: array([-2.49999995, -1.49999996])
______
______
Test Run 3:
______
Starting Value Used: [[ 5 -15]]
The Minimum Occurs at (x, y) = [-2.50000001 -1.49999999]
The Minimum Value = 1.375
Other Statistics:
final_simplex: (array([[-2.50000001, -1.49999999],
     [-2.5000001, -1.50000007],
     [-2.49999995, -1.50000005]]), array([1.375, 1.375, 1.375]))
        fun: 1.375
     message: 'Optimization terminated successfully.'
       nfev: 139
        nit: 71
      status: 0
     success: True
         x: array([-2.50000001, -1.49999999])
------
```

4.0.5 Method 2: Powell

```
for x in enumerate(starting_points):
    result = minimize(q3, x[1], method = 'Powell',tol = 1.e-7)

print(section_break)
    print('Test Run', x[0] + 1, ':')
    print(section_break)

print('Starting Value Used: ', x[1])
    print("The Minimum Occurs at (x, y) = ", result.x)
    print("The Minimum Value = ", q3(result.x).round(3))
```

```
print(result)
   print(section_break)
   print(section_break)
   print('\n')
______
Test Run 1:
______
Starting Value Used: [[-15 4]]
The Minimum Occurs at (x, y) = [-2.5 -1.5]
The Minimum Value = 1.375
Other Statistics:
 direc: array([[ 0. , 1.
    [-2.75, -1.375]
   fun: 1.374999999999996
message: 'Optimization terminated successfully.'
  nfev: 89
   nit: 3
 status: 0
success: True
    x: array([-2.5, -1.5])
______
_____
_____
Test Run 2:
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Starting Value Used: [[-2 12]]
The Minimum Occurs at (x, y) = [-2.5 	 -1.49999998]
The Minimum Value = 1.375
Other Statistics:
 direc: array([[ 0. , 1. ],
    [-6.75, -3.375]])
message: 'Optimization terminated successfully.'
  nfev: 100
   nit: 3
 status: 0
success: True
                , -1.49999998])
    x: array([-2.5
```

print("Other Statistics:")

```
Test Run 3:
Starting Value Used: [[ 5 -15]]
The Minimum Occurs at (x, y) = [-2.49999999 -1.50000001]
The Minimum Value = 1.375
Other Statistics:
  direc: array([[0.
                  , 1.
                         ],
      [6.75, 3.375]
    fun: 1.375
message: 'Optimization terminated successfully.'
   nfev: 131
    nit: 3
 status: 0
success: True
     x: array([-2.49999999, -1.50000001])
______
```

```
[]:
```

/var/folders/90/b16ybj8s2gv__lhxf5ttmvj40000gn/T/ipykernel_34318/1248200888.py:6 : MatplotlibDeprecationWarning: Calling gca() with keyword arguments was deprecated in Matplotlib 3.4. Starting two minor releases later, gca() will take no keyword arguments. The gca() function should only be used to get the current axes, or if no axes exist, create new axes with default keyword arguments. To create a new axes with non-default arguments, use plt.axes() or plt.subplot(). ax = fig.gca(projection='3d')

