

Linear Algebra Homework

```
In [1]: 1 import numpy as np
        2 import scipy.linalg as la
```

Problem 1: Condition Number, Accuracy, and Iterative Updating

```
In [2]: 1 # Defining the arrays
        2
        3 A = np.array([[0.780, 0.563], [0.913, 0.659]])
        4 b = np.array([[0.217], [0.254]])
        5 x = np.array([[1], [-1]])
        6 xalpha = np.array([[0.999], [-1.001]])
        7 xbeta = np.array([[0.341], [-0.087]])
```

Part A

```
In [15]: 1 ralpha = b - A@xalpha
        2 rbeta = b - A@xbeta
        3
        4 print("r_alpha = ",ralpha)
        5 print("r_beta = ",rbeta)
```

```
r_alpha = [[0.001343]
            [0.001572]]
r_beta = [[1.e-06]
          [0.e+00]]
```

The less accurate solution produced the smaller residual.

Part B

```
In [8]: 1 U, s, VT = la.svd(A, full_matrices = True)
2 print("U = ")
3 print(U)
4 print("s = ") # The singular values
5 print(s)
6 print("VT = ")
7 print(VT)
```

```
U =
[[-0.64955581 -0.76031391]
 [-0.76031391  0.64955581]]
s =
[1.48095206e+00 6.75241305e-07]
VT =
[[-0.81084336 -0.58526323]
 [-0.58526323  0.81084336]]
```

```
In [65]: 1 conditionNumber = np.max(s)/np.min(s);
2 print("Condition Number = ", conditionNumber)
3 print("Reciprocal = ", 1/conditionNumber)
```

```
Condition Number = 2193218.9997129813
Reciprocal = 4.559508193804934e-07
```

```
In [72]: 1 print("V^T * (xalpha - x) =")
2 print(VT@(xalpha - x))
3
4 print("\nV^T * (xbeta - x) =")
5 print(VT@(xbeta - x))
```

```
V^T * (xalpha - x) =
[[ 0.00139611]
 [-0.00022558]]
```

```
V^T * (xbeta - x) =
[[4.38606914e-07]
 [1.12598845e+00]]
```

From the above result, we see that \vec{x}_α has most of its error associated with the large singular value, and \vec{x}_β has most of its error associated with the small singular value.

▼ Part C

```
In [39]: 1 x_blackbox = la.solve(A,b)
2 difference = x_blackbox - x;
3 machine = 2.2e-16;
4
5 print("Difference between the black box and exact solutions:")
6 print(difference)
7
8 print("\nDividing that answer by machine accuracy of 2.2 x 10^(-16):")
9 print(difference/machine)
10
11 print("\nWell, I wouldn't exactly say that that is close to machine acc
12
13 print("\nCalculating Ax - b for the two solutions:")
14 print("Exact:\n",A@x - b)
15 print("Black Box:\n",A@x_blackbox - b)
16 print("\nThose answers both seem to satisfy the equation to less than m
17 print("The problem must then be rounding errors in calculating A and b.
```

Difference between the black box and exact solutions:

```
[[-2.30988562e-11]
 [ 3.20018456e-11]]
```

Dividing that answer by machine accuracy of 2.2×10^{-16} :

```
[[-104994.80073246]
 [ 145462.93462688]]
```

Well, I wouldn't exactly say that that is close to machine accuracy...

Calculating $Ax - b$ for the two solutions:

Exact:

```
[[8.32667268e-17]
 [0.00000000e+00]]
```

Black Box:

```
[[-2.77555756e-17]
 [ 0.00000000e+00]]
```

Those answers both seem to satisfy the equation to less than machine accuracy.

The problem must then be rounding errors in calculating A and b.



Part D

```
In [47]: 1 print("Original x-beta:\n",xbeta)
          2
          3 print("\nr_beta:\n",rbeta)
          4
          5 delta_x = la.solve(A,-rbeta)
          6
          7 x_improved = xbeta - delta_x
          8
          9 print("\nImproved x-value:\n",x_improved)
         10
         11 print("This is an improvement over the original x-beta value.")
```

Original x-beta:

```
[[ 0.341]
 [-0.087]]
```

r_beta:

```
[[1.e-06]
 [0.e+00]]
```

Improved x-value:

```
[[ 1.]
 [-1.]]
```

This is an improvement over the original x-beta value.

Now we want to try finding \vec{r}_β analytically, which is shown below:

```
In [50]: 1 rbeta = b - A@xbeta # Exact same definition as before
          2 print("r_beta:\n",rbeta)
```

r_beta:

```
[[1.e-06]
 [0.e+00]]
```

So now we will round to the correct residual values:

```
In [51]: 1 rbeta_exact = np.array([[1.0e-6],[0.0]])
          2 print("r_beta_exact:\n",rbeta_exact)
```

r_beta_exact:

```
[[1.e-06]
 [0.e+00]]
```

Calculating the new $\delta\vec{x}$ value gives us:

```
In [57]: 1 delta_x_exact = la.inv(A)@b
          2
          3 x_improved_exact = xbeta - delta_x_exact
          4
          5 print("Improved x-value:\n",x_improved_exact)
```

Improved x-value:

```
[[ -0.659]
```

```
[ 0.913]]
```

That result is an improvement over the original \vec{x}_β , though not as dramatic of an improvement as the former was.

▼ Problem 2: The Sherman-Morrison Formula

First, we will define the matrices T and C:

```
In [92]: 1 T = np.mat('[2 1 0 0 0; 1 2 1 0 0; 0 1 2 1 0; 0 0 1 2 1; 0 0 0 1 2]')
          2 C = np.mat('[2 1 0 0 1; 1 2 1 0 0; 0 1 2 1 0; 0 0 1 2 1; 1 0 0 1 2]')
          3
          4 print("T = \n",T)
          5 print("C = \n",C)
```

T =

```
[[2 1 0 0 0]
```

```
[1 2 1 0 0]
```

```
[0 1 2 1 0]
```

```
[0 0 1 2 1]
```

```
[0 0 0 1 2]]
```

C =

```
[[2 1 0 0 1]
```

```
[1 2 1 0 0]
```

```
[0 1 2 1 0]
```

```
[0 0 1 2 1]
```

```
[1 0 0 1 2]]
```

Now we will compute their inverses:

```
In [89]: 1 Tinv = la.inv(T)
2 Cinv = la.inv(C)
3
4 print("Tinv = \n",Tinv)
5 print("Cinv = \n",Cinv)

Tinv =
[[ 0.83333333 -0.66666667  0.5          -0.33333333  0.16666667]
 [-0.66666667  1.33333333 -1.          0.66666667 -0.33333333]
 [ 0.5         -1.          1.5         -1.          0.5         ]
 [-0.33333333  0.66666667 -1.          1.33333333 -0.66666667]
 [ 0.16666667 -0.33333333  0.5         -0.66666667  0.83333333]]

Cinv =
[[ 1.25 -0.75  0.25  0.25 -0.75]
 [-0.75  1.25 -0.75  0.25  0.25]
 [ 0.25 -0.75  1.25 -0.75  0.25]
 [ 0.25  0.25 -0.75  1.25 -0.75]
 [-0.75  0.25  0.25 -0.75  1.25]]
```

And now we will compute the difference between the two

```
In [90]: 1 delta = Tinv - Cinv
2 print("Difference = \n",delta)

Difference =
[[-0.41666667  0.08333333  0.25          -0.58333333  0.91666667]
 [ 0.08333333  0.08333333 -0.25          0.41666667 -0.58333333]
 [ 0.25         -0.25          0.25         -0.25          0.25         ]
 [-0.58333333  0.41666667 -0.25          0.08333333  0.08333333]
 [ 0.91666667 -0.58333333  0.25          0.08333333 -0.41666667]]
```

Checking this with the Sherman-Morris formula, where the difference should be

$$\Delta = \frac{\vec{z} \otimes \vec{w}}{1 + \lambda} \quad (1)$$

where

$$\vec{z} = A^{-1} \cdot \vec{u} \quad (2)$$

$$\vec{w} = \vec{v} \cdot A^{-1} \quad (3)$$

$$\lambda = \vec{v} \cdot \vec{z} \quad (4)$$

And vectors \vec{u} and \vec{v} are defined such that

$$C = T + \vec{u} \otimes \vec{v} \quad (5)$$

where the \otimes symbol denotes a tensor product.

```
In [143]: 1 u = np.mat('[1; 0; 0; 0; 1]')
          2 v = np.mat('[1 0 0 0 1]')
          3
          4 print("u = \n",u)
          5
          6 print("\nv = \n",v)
          7
          8 print("\nkron(u,v) = \n",la.kron(u,v))
          9
         10 print("\nT + kron(u,v) = \n",T + la.kron(u,v))
```

u =

```
[[1]
 [0]
 [0]
 [0]
 [1]]
```

v =

```
[[1 0 0 0 1]]
```

kron(u,v) =

```
[[1 0 0 0 1]
 [0 0 0 0 0]
 [0 0 0 0 0]
 [0 0 0 0 0]
 [1 0 0 0 1]]
```

T + kron(u,v) =

```
[[3 1 0 0 1]
 [1 2 1 0 0]
 [0 1 2 1 0]
 [0 0 1 2 1]
 [1 0 0 1 3]]
```

```
In [153]: 1 z = la.inv(T)@u
          2 w = v@la.inv(T)
          3 lam = v@z
          4
          5 delta_sherman = la.kron(z,w) / (1 + lam)
          6
          7 print("Difference = \n",delta_sherman)
          8
          9 print(Tinv - delta_sherman)
```

```
Difference =
[[ 0.33333333 -0.33333333  0.33333333 -0.33333333  0.33333333]
 [-0.33333333  0.33333333 -0.33333333  0.33333333 -0.33333333]
 [ 0.33333333 -0.33333333  0.33333333 -0.33333333  0.33333333]
 [-0.33333333  0.33333333 -0.33333333  0.33333333 -0.33333333]
 [ 0.33333333 -0.33333333  0.33333333 -0.33333333  0.33333333]]
[[ 5.00000000e-01 -3.33333333e-01  1.66666667e-01  5.55111512e-17
 -1.66666667e-01]
 [-3.33333333e-01  1.00000000e+00 -6.66666667e-01  3.33333333e-01
  0.00000000e+00]
 [ 1.66666667e-01 -6.66666667e-01  1.16666667e+00 -6.66666667e-01
  1.66666667e-01]
 [ 0.00000000e+00  3.33333333e-01 -6.66666667e-01  1.00000000e+00
 -3.33333333e-01]
 [-1.66666667e-01 -5.55111512e-17  1.66666667e-01 -3.33333333e-01
  5.00000000e-01]]
```