

```
In [1]: %matplotlib notebook
from numpy import *
from matplotlib.pyplot import *
from numpy.linalg import qr
from scipy.linalg import hilbert
from numpy.linalg import eig
```

```
In [2]: def display_mat(msg,A):
        print(msg)
        display(A)
        print("")
```

Homework 10 : Conditioning and stability of linear least squares

The least squares problem

$$A\mathbf{x} = \mathbf{b} \quad (1)$$

where $A \in \mathcal{R}^{m \times n}$, $m \geq n$ has four associated "conditioning" problems, described in the table in Theorem 18.1 of TB (page 131). These are

1. Sensitivity of $\mathbf{y} = A\mathbf{x}$ to right hand side vector \mathbf{b} ,
2. Sensitivity of the solution \mathbf{x} to right hand side vector \mathbf{b} ,
3. Sensitivity of $\mathbf{y} = A\mathbf{x}$ to the coefficient matrix A , and
4. Sensitivity of the solution \mathbf{x} to the coefficient matrix A .

Problem 1

Sensitivity of \mathbf{y} to a perturbation in \mathbf{b} .

In TB Lecture 12, the relative condition number is defined as

$$\kappa = \sup_{\delta x} \left(\frac{\|\delta f\|}{\|f(x)\|} \bigg/ \frac{\|\delta x\|}{\|x\|} \right) \quad (2)$$

Problem 1(a)

Arguing directly from this definition, establish the condition number of \mathbf{y} with respect to perturbations in \mathbf{b} given by TB Lecture 18

$$\kappa = \frac{1}{\cos \theta} \quad (3)$$

Hint: The input " x " in this problem is \mathbf{b} and the output (or model) " f " is \mathbf{y} . Show geometrically that the supremum is attained with $P\delta\mathbf{b} = \delta\mathbf{y}$.

Solution

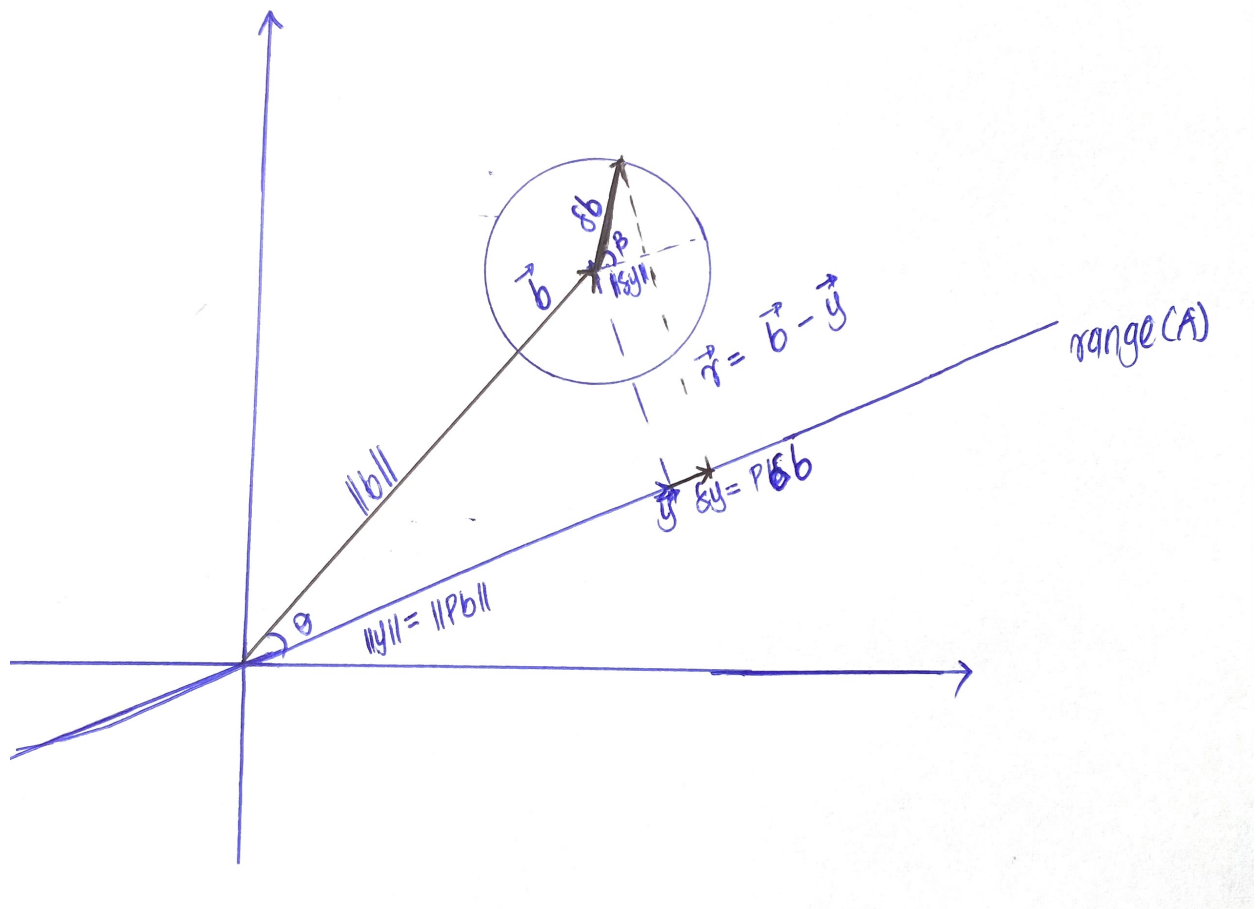
Since the relative condition number is defined as ;

$$\kappa = \sup_{\delta\mathbf{x}} \left(\frac{\|\delta\mathbf{f}\|}{\|\mathbf{f}(\mathbf{x})\|} \bigg/ \frac{\|\delta\mathbf{x}\|}{\|\mathbf{x}\|} \right), \quad (4)$$

then the relative condition number of \mathbf{y} with respect to perturbations in \mathbf{b} is given by;

$$\kappa = \sup_{\delta\mathbf{b}} \left(\frac{\|\delta\mathbf{y}\|}{\|\mathbf{y}\|} \bigg/ \frac{\|\delta\mathbf{b}\|}{\|\mathbf{b}\|} \right) \quad (5)$$

where $\mathbf{y} = A\mathbf{x} = P\mathbf{b}$ is the the projection of \mathbf{b} onto the $\text{range}(A)$, $\delta\mathbf{b}$ is a pertubation in \mathbf{b} with a correponding pertubation $\delta\mathbf{y}$ in \mathbf{y} (which is the projection of $\delta\mathbf{b}$ onto the $\text{range}(A)$) . All this is illustrated geometrically in the image below;



From the above image we notice that $\cos(\theta) = \frac{\|y\|}{\|b\|}$ where θ is the angle between \mathbf{b} and the $\text{range}(A)$.

The relative condition number of \mathbf{y} with respect to perturbations in \mathbf{b} then becomes;

$$\begin{aligned}\kappa &= \sup_{\delta \mathbf{b}} \left(\frac{1}{\cos(\theta)} \times \frac{\|\delta \mathbf{y}\|}{\|\delta \mathbf{b}\|} \right) \\ &= \sup_{\delta \mathbf{b}} \left(\frac{1}{\cos(\theta)} \times \frac{\|P\delta \mathbf{b}\|}{\|\delta \mathbf{b}\|} \right) \\ &= \frac{1}{\cos(\theta)} \times \sup_{\delta \mathbf{b}} \left(\frac{\|P\delta \mathbf{b}\|}{\|\delta \mathbf{b}\|} \right)\end{aligned}$$

But to find the $\sup_{\delta \mathbf{b}} \left(\frac{\|P\delta \mathbf{b}\|}{\|\delta \mathbf{b}\|} \right)$, we must maximize the ratio $\frac{\|P\delta \mathbf{b}\|}{\|\delta \mathbf{b}\|}$.

From the diagram above we see that; for $0 < \beta < \pi/2$, $\|\delta \mathbf{b}\|$ will always be greater than $\|P\delta \mathbf{b}\|$ and therefore to maximize $\frac{\|P\delta \mathbf{b}\|}{\|\delta \mathbf{b}\|}$, β must be equal to zero and $\|\delta \mathbf{b}\| = \|P\delta \mathbf{b}\|$.

This means that we obtain $\sup_{\delta \mathbf{b}} \left(\frac{\|P\delta \mathbf{b}\|}{\|\delta \mathbf{b}\|} \right)$ when $\|\delta \mathbf{b}\| = \|P\delta \mathbf{b}\|$ and therefore the condition number of \mathbf{y} with respect to perturbations in \mathbf{b} becomes;

$$\kappa = \frac{1}{\cos \theta} \quad (6)$$

Problem 1(b)

For $\theta = \pi/2$, the condition number is ∞ . Illustrate what this means by considering the least squares problem

$$\begin{bmatrix} 2 \\ 1 \end{bmatrix} [x] = \begin{bmatrix} -1 \\ 2 \end{bmatrix} \quad (7)$$

Use the results in TB 11.11 and 11.12 (page 82) to determine the projection operator P for this problem. Then compute $\mathbf{y} = P\mathbf{b}$ and show that $P\mathbf{b} = 0$. Find a perturbation $\delta \mathbf{b}$ so that $P\delta \mathbf{b} = \delta \mathbf{b} = \delta \mathbf{y} \neq 0$. Explain what a condition number $\kappa = \infty$ might mean here. Illustrate your argument graphically.

Solution

From the above system we have that;

$$A = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \text{ and } \mathbf{b} = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$$

To find the the projection operator for this problem, we use $P = AA^\dagger$, but

$$\begin{aligned}
A^\dagger &= (A^T A) A^T \\
&= \left(\begin{bmatrix} 2 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right)^{-1} \begin{bmatrix} 2 & 1 \end{bmatrix} \\
&= \frac{1}{5} \begin{bmatrix} 2 & 1 \end{bmatrix} \\
\Rightarrow P &= \frac{1}{5} \begin{bmatrix} 2 \\ 1 \end{bmatrix} \begin{bmatrix} 2 & 1 \end{bmatrix} \\
&= \begin{bmatrix} \frac{4}{5} & \frac{2}{5} \\ \frac{2}{5} & \frac{1}{5} \end{bmatrix} \\
\Rightarrow \mathbf{y} = P\mathbf{b} &= \begin{bmatrix} \frac{4}{5} & \frac{2}{5} \\ \frac{2}{5} & \frac{1}{5} \end{bmatrix} \begin{bmatrix} -1 \\ 2 \end{bmatrix} \\
&= \begin{bmatrix} \frac{-4}{5} + \frac{4}{5} \\ \frac{-2}{5} + \frac{2}{5} \end{bmatrix} \\
\therefore P\mathbf{b} &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \mathbf{0}
\end{aligned}$$

To find $\delta\mathbf{b}$, will let $\delta\mathbf{b} = \mathbf{b} + \mathbf{u}$ where $\mathbf{b} = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$ and $\mathbf{u} = \begin{bmatrix} x \\ y \end{bmatrix}$ such that $P\delta\mathbf{b} = \delta\mathbf{b}$ that is;

$$\begin{aligned}
&\Rightarrow P(\mathbf{b} + \mathbf{u}) = (\mathbf{b} + \mathbf{u}) \\
\Rightarrow \frac{1}{5} \begin{bmatrix} 4 & 2 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} -1 + x \\ 2 + y \end{bmatrix} &= \begin{bmatrix} -1 + x \\ 2 + y \end{bmatrix} \\
\Rightarrow \begin{bmatrix} 4x + 2y \\ 2x + y \end{bmatrix} &= \begin{bmatrix} -5 + 5x \\ 10 + 5y \end{bmatrix}
\end{aligned}$$

Equating elements in the two vectors we obtain;

$$x = 2y + 5 \quad (8)$$

$$-4y = 10 - 2x \quad (9)$$

Substituting for x in equation (26), we obtain;

$$-4y = 10 - 2(2y + 5) \quad (10)$$

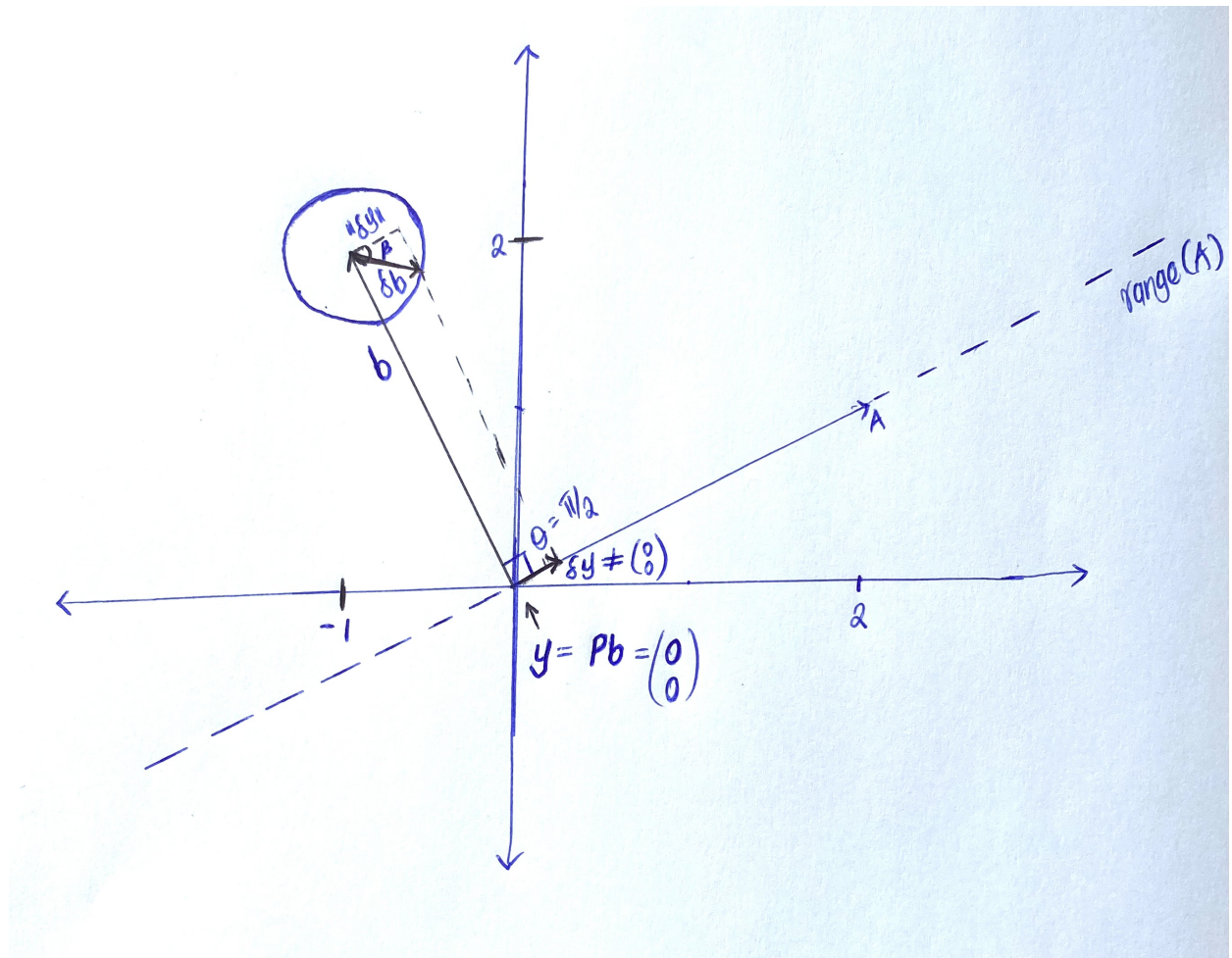
$$\Rightarrow 0 = 0 \quad (11)$$

This means that y can take on any real number ie. $y = t \in \mathbb{R}$.

Choosing $y = t = 0$, this gives $x = 5$ and $\mathbf{u} = \begin{bmatrix} 5 \\ 0 \end{bmatrix}$

$$\begin{aligned}\Rightarrow \delta \mathbf{b} &= \begin{bmatrix} -1 + 5 \\ 2 + 0 \end{bmatrix} \\ &= \begin{bmatrix} 4 \\ 2 \end{bmatrix} \\ \therefore \delta \mathbf{y} &= P \delta \mathbf{b} = \frac{1}{5} \begin{bmatrix} 4 & 2 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 4 \\ 2 \end{bmatrix} = \begin{bmatrix} 4 \\ 2 \end{bmatrix} = \delta \mathbf{b}\end{aligned}$$

This can be geometrically illustrated as shown in the image below;



From the graph above, we see that the projection of \mathbf{b} onto the $\text{range}(A)$ is a zero vector, that is $\mathbf{y} = P\mathbf{b} = \mathbf{0}$. Surprisingly, a small change in \mathbf{b} say $\delta \mathbf{b}$ results into non-zero perturbation $\delta \mathbf{y}$ in the projection. This means that the residual $\mathbf{r} = \mathbf{b} - A\mathbf{x} = \mathbf{b}$ and that the change in solution is very very large.

With reference to the above ideas, we conclude that when $\theta = \pi/2$, the condition number blows up i.e. $\kappa = \infty$.

The same conclusion can be reached by using the definition of the condition number of \mathbf{y} with respect to perturbations in \mathbf{b} ;

$$\kappa = \frac{1}{\cos(\theta)} = \frac{1}{\cos(\pi/2)} = \infty$$

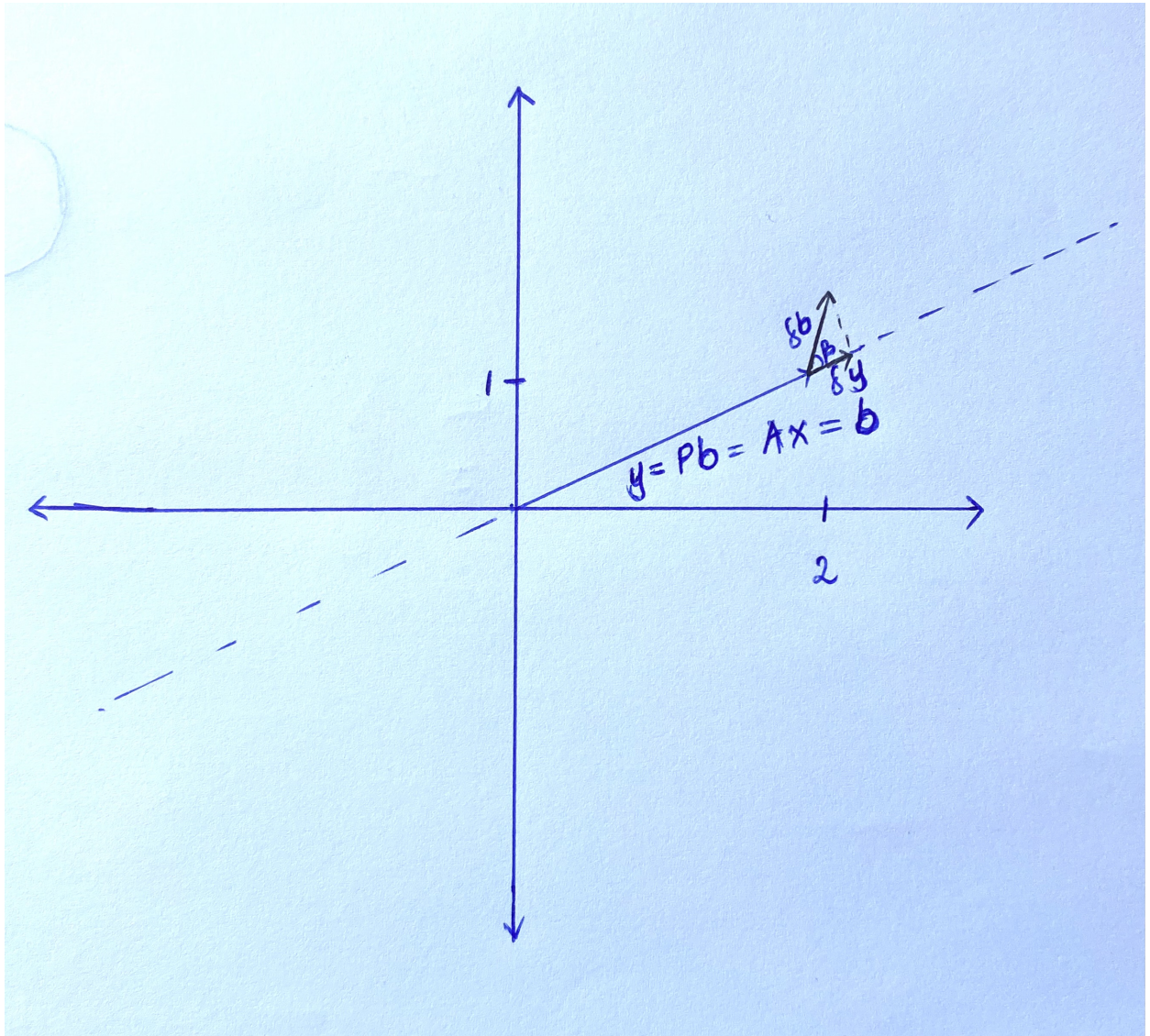
Problem 1(c)

Now consider the problem

$$\begin{bmatrix} 2 \\ 1 \end{bmatrix} [x] = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \quad (12)$$

For this problem, show that $\kappa = 1$. What is qualitatively different about this problem than the problem in which $\kappa = \infty$?

Solution



Since in 1(a) we proved that $\kappa = \frac{1}{\cos(\theta)}$ and the angle between \mathbf{b} and the $\text{range}(A)$ is zero, the condition number for this case is then given as;

$$\kappa = \frac{1}{\cos(\theta)} = \frac{1}{\cos(0)} = 1$$

For this problem, we see that the projection of \mathbf{b} onto the column space of A is \mathbf{b} itself, that is $\mathbf{y} = P\mathbf{b} = \mathbf{b}$. This means that \mathbf{b} is in the $\text{range}(A)$, the residual $\mathbf{r} = \mathbf{b} - A\mathbf{x} = \mathbf{0}$ and that

the change in the solution is very very small which isn't the case when $\kappa = \infty$.

Problem 2

Problem 18.1 in TB (page 136)

2(a)

In [3]:

```
A=array([[1,1],[1,1.0001],[1,1.0001]])
b=array([[2],[0.0001],[4.0001]])
A_inv = linalg.pinv(A)
#A_inv = linalg.inv(A.T@A)@A.T
P=A@A_inv
display_mat(" A = ",A)
display_mat("Pseudo inverse of matrix A = ",A_inv)
display_mat("P = ",P)

A =
array([[1.      , 1.      ],
       [1.      , 1.0001],
       [1.      , 1.0001]])
Pseudo inverse of matrix A =
array([[10000.999999998, -4999.999999999, -4999.999999999],
       [-9999.999999998,  4999.999999999,  4999.999999999]])
P =
array([[1.000000000e+00,  9.09494702e-13,  9.09494702e-13],
       [0.000000000e+00,  5.000000000e-01,  5.000000000e-01],
       [0.000000000e+00,  5.000000000e-01,  5.000000000e-01]])
```

2(b)

In [4]:

```
#x1 = linalg.lstsq(A,b)
#display_mat(" x = ",x1[0])
x = A_inv@b
y = P@b

display_mat(" x = ",x)
display_mat(" y = ",y)
```

```
x =
array([[1.],
       [1.]])
y =
array([[2.      ],
       [2.0001],
       [2.0001]])
```

2(c)

In [5]:

```
k =linalg.cond(A)
K = linalg.norm(A)*linalg.norm(A_inv)
theta = arccos(linalg.norm(y)/linalg.norm(b))
eta = (linalg.norm(A)*linalg.norm(x))/linalg.norm(y)
```

```
display_mat(" K(A) = ",k)
display_mat(" theta = ",theta)
display_mat(" eta = ",eta)
```

```
K(A) =
42429.235416083044
theta =
0.684702873261185
eta =
1.000000000833278
```

2(d)

In [20]:

```
##d
K_by = 1/cos(theta)
K_bx = k/(eta*cos(theta))
K_Ay = k/(cos(theta))
K_Ax = k+ (((k**2) *tan(theta))/eta)
display_mat(" K_by = ",K_by)
display_mat(" K_bx = ",K_bx)
display_mat(" K_Ay < or = ",K_Ay)
display_mat(" K_Ax < or = ",K_Ax)
```

```
K_by =
1.290977236078942
K_bx =
54775.1770207547
K_Ay < or =
54775.17706639765
K_Ax < or =
1469883252.449082
```

2(e)

(i)

The first condition number K_{by} is attained when $\|\delta \mathbf{b}\| = \|P\delta \mathbf{b}\|$ and this occurs when $\delta \mathbf{b}$ is equal to zero except in the first $n = 2$ entries (n is the number of columns of A),

I therefore used $\delta \mathbf{b}$ as $\begin{bmatrix} 0.0001 \\ 0.0001 \\ 0 \end{bmatrix}$ and this gave $K_{by} = 1.29108$

(ii)

The condition number K_{bx} is attained when $\|A^\dagger \delta \mathbf{b}\|_2 = \|A^\dagger\|_2 \|\delta \mathbf{b}\|_2$ and this occurs when $\delta \mathbf{b}$ is equal to zero except in the 2^{nd} entry.

For this I used $\delta \mathbf{b} = \begin{bmatrix} 0 \\ 10^{-8} \\ 0 \end{bmatrix}$ this gave $K_{by} = 54775.17695228298$

(iii)

The condition number K_{Ay} is attained when $\delta A = \delta p v_2^T$ where δp is the vector orthogonal to the $\text{range}(A)$ and v_2 is the second column of the right singular matrix v .

for this I used $\delta p = (I - AA^\dagger) \begin{bmatrix} 10^{-7} \\ 10^{-7} \\ 0 \end{bmatrix}$, $v_2^T = [-0.70713035 \quad -0.70708321]$ and obtained $\delta A = 54775.16415665296$

Problem 3

Show that if (λ, \mathbf{v}) is an eigenvalue/eigenvector pair for matrix A , then $((\lambda - \mu)^{-1}, \mathbf{v})$ is an eigenvalue/eigenvector pair for the matrix $(A - \mu I)^{-1}$.

Why is this observation useful when using the power iteration to find an eigenvalue close to μ ?

Solution

If λ is an eigenvalue of matrix A with a corresponding eigenvector \mathbf{v} , then we have that;

$$A\mathbf{v} = \lambda\mathbf{v} \quad (13)$$

Subtracting $\mu\mathbf{v}$ from equation() above we obtain;

$$A\mathbf{v} - \mu\mathbf{v} = \lambda\mathbf{v} - \mu\mathbf{v} \quad (14)$$

$$(A - \mu I)\mathbf{v} = (\lambda - \mu)\mathbf{v} \quad (15)$$

Since $\mu \in \mathbb{R}$ is not an eigenvalue of A , then $A - \mu I$ is invertible and therefore multiplying the above equation with $(A - \mu I)^{-1}$, we get;

$$(A - \mu I)^{-1}(A - \mu I)\mathbf{v} = (\lambda - \mu)(A - \mu I)^{-1}\mathbf{v} \quad (16)$$

$$(17)$$

$$\Rightarrow \mathbf{v} = (\lambda - \mu)(A - \mu I)^{-1}\mathbf{v} \quad (18)$$

$$(19)$$

$$\Rightarrow (A - \mu I)^{-1}\mathbf{v} = (\lambda - \mu)^{-1}\mathbf{v} \quad (20)$$

Therefore from the above equation, we can conclude that $((\lambda - \mu)^{-1}, \mathbf{v})$ is an eigenvalue/eigenvector pair for the matrix $(A - \mu I)^{-1}$.

Why is this observation useful when using the power iteration to find an eigenvalue close to μ ?

This observation is useful when using the power iteration to find an eigenvalue (λ_j) close to μ because the dominant eigenvalue of $(A - \mu I)^{-1}$ will be $(\lambda_j - \mu)^{-1}$ from which we can easily obtain λ_j .

Problem 4

Exercise 29.1 (Lecture 29, TB page 223). This is a five part problem that asks you to code an eigenvalue solver for a real, symmetric matrix using the shifted QR algorithm. Do your code in Python, using the Numpy `qr` algorithm where needed.

The basic steps are :

1. Reduce your matrix A to tridiagonal form. You may use the hessenberg code we wrote in class.
2. Implement the unshifted QR code (also done in class). Use the Numpy routine `qr`. Your iteration should stop when the off diagonal elements are smaller (in absolute value) than $\tau \approx 10^{-12}$.
3. Find all eigenvalues of a matrix A using the "deflation" idea described in Algorithm 28.2.
4. Introduce the Wilkinson shift, described in Lecture 29.

Notes

- Your code should work for a real, symmetric matrix
- Your code does not have to be efficient in the sense of optimizing the cost of matrix/vector multiplies and so on.
- Apply your algorithm to the Hilbert matrix `scipy.linalg.hilbert`. The entries of the $m \times m$ Hilbert matrix are given by

$$H_{ij} = \frac{1}{i+j-1}, \quad i, j = 1, 2, \dots, m \quad (21)$$

```
In [7]: def display_mat(msg,A):
        print(msg)
        fstr = {'float' : ":{>10.8f}".format}
        with printoptions(formatter=fstr):
            display(A)
        print("")
```

```
In [8]: def hessenberg(A):
        m,n = A.shape
        assert m == n, "A must be square"

        H = A.copy()
        Qt = eye(m)
        for j in range(m-1):
            x = H[j+1:,j:j+1]
            I = eye(m-j-1)
            s = 1 if x[0] > 0 else -1 # sign function, with sign(0) = 1
            v = s*linalg.norm(x,2)*I[:,0:1] + x

            vn = linalg.norm(v,2)
            if vn!=0:
                v = v/vn
```

```

F = I - 2*(v@v.T)
H[j+1:,j:] = F@H[j+1:,j:]
H[0:,j+1:] = H[0:,j+1:]@F    # Apply F to the right side of H.
break

return H

```

In [9]:

```

def eigenvalue_QR_solver(A,kmax,method=''):
    H = hessenberg(A)
    Ak = H.copy()
    mu = 0
    e = zeros((kmax,1))
    lam = zeros((size(H,0),1))
    for k in range(kmax):
        m = size(Ak,0)
        mu = 0
        Q,R = qr(Ak - mu*eye(m))
        Ak = R@Q + mu*eye(m)
        if method == 'unshifted':
            mu=mu
            if abs(Ak[-1,-2]) < 1e-12:
                print ("number of iterations required=",k+1)
                lam[0:m] = array([diag(Ak)]).T
                break
        elif method == 'Rayleigh shift':
            mu = Ak[-1,-1]
            if m==1:
                e[0] = abs(Ak[-1,-1])
                lam[0] = Ak[-1,-1]
                print ("number of iterations required to find the eigenvalue")
                print("eigenvalue = {:12.4e} \n".format(Ak[-1,-1]))
                break
            else:
                e[1:k] = abs(Ak[-1,-2])
                if abs(Ak[-1,-2]) < 1e-12:
                    print ("number of iterations required to find the eigenv")
                    print("eigenvalue = {:12.4e} \n".format(Ak[-1,-1]))
                    lam[1:m]= Ak[-1,-1]
                    Ak = Ak[0:m-1,0:m-1]
        elif method=='Wilkinson shift':
            if m==1:
                print ("number of iterations required to find the eigenvalue")
                print("eigenvalue = {:12.4e} \n".format(Ak[-1,-1]))
                lam[0]=Ak[0,0]
                break
            else:
                sigma = (Ak[-2,-2]-Ak[-1,-1])/2
                if sigma !=0:
                    sn = sign(sigma)
                else:
                    sn = -1
                mu = Ak[m-1,m-1] - (sn*Ak[m-2,m-1]**2/(abs(sigma) + sqrt(sig
                if abs(Ak[-1,-2]) < 1e-12:
                    print ("number of iterations required to find the eigenv")
                    print("eigenvalue = {:12.4e} \n".format(Ak[-1,-1]))
                    lam[1:m]= Ak[-1,-1]
                    Ak = Ak[0:m-1,0:m-1]

```

```
return e,sort(lam)[::-1]
```

```
In [10]: H = hilbert(4)
```

```
In [11]: # TRUE EIGENVALUES
eval_true1, vec_true = eig(H)
eval_true1 = sort(array(eval_true1).reshape(size(H,0),1),axis=0)
eval_true1 = sort(eval_true1)
eval_true1
```

```
Out[11]: array([[9.67023040e-05],
               [6.73827361e-03],
               [1.69141220e-01],
               [1.50021428e+00]])
```

```
In [12]: # USING UNSHIFTED QR
e1,lam1= eigenvalue_QR_solver(H,kmax= 20,method='unshifted')
#lam1 = sort(lam1)[::-1]
display_mat("Eigenvalues = ",lam1)
display_mat("Error = ",linalg.norm(eval_true1 - lam1))
```

number of iterations required= 6

Eigenvalues =

```
array([[0.00009670],
       [0.00673827],
       [0.16914122],
       [1.50021428]])
```

Error =

```
4.282800079194783e-12
```

```
In [13]: #USING RAYLEIGH SHIFT
e2,lam2= eigenvalue_QR_solver(H,kmax= 20,method='Rayleigh shift')
#lam2 = sort(lam2)[::-1]
display_mat("Eigenvalues = ",lam2)
display_mat("Error = ",linalg.norm(eval_true1 - lam2))
```

number of iterations required to find the eigenvalue below= 6

eigenvalue = 9.6702e-05

number of iterations required to find the eigenvalue below= 8

eigenvalue = 6.7383e-03

number of iterations required to find the eigenvalue below= 13

eigenvalue = 1.6914e-01

number of iterations required to find the eigenvalue below= 14

eigenvalue = 1.5002e+00

Eigenvalues =

```
array([[0.00009670],
       [0.00673827],
       [0.16914122],
       [1.50021428]])
```

Error =

2.2303812898233666e-16

In [14]:

```
# USING WILKINSON SHIFT

e3,lam3= eigenvalue_QR_solver(H,kmax= 20,method='Wilkinson shift')
#lam3 = sort(lam3)[::-1]
display_mat("Eigenvalues = ",lam3)
display_mat("Error = ",linalg.norm(eval_true1 - lam3))
```

```
number of iterations required to find the eigenvalue below= 6
eigenvalue = 9.6702e-05
```

```
number of iterations required to find the eigenvalue below= 8
eigenvalue = 6.7383e-03
```

```
number of iterations required to find the eigenvalue below= 13
eigenvalue = 1.6914e-01
```

```
number of iterations required to find the eigenvalue below= 14
eigenvalue = 1.5002e+00
```

```
Eigenvalues =
array([[0.00009670],
       [0.00673827],
       [0.16914122],
       [1.50021428]])
Error =
2.2303812898233666e-16
```

Part (e)

In [15]:

```
a = arange(15,0,-1)
A = diag(a) + ones((15,15))
```

In [16]:

```
# TRUE EIGENVALUES
eval_true,eval_true = eig(A)
eval_true = sort(array(eval_true).reshape(size(A,0),1),axis=0)
eval_true = sort(eval_true)
eval_true
```

Out[16]:

```
array([[ 1.21465537],
       [ 2.25695098],
       [ 3.28777559],
       [ 4.31431185],
       [ 5.33895988],
       [ 6.36294449],
       [ 7.38709275],
       [ 8.41211207],
       [ 9.43874576],
       [10.46792166],
       [11.50098302],
       [12.54018637],
       [13.59013196],
       [14.664097 ],
       [24.22313127]])
```

In [17]:

```
# USING UNSHIFTED QR
e11,lam11= eigenvalue_QR_solver(A,kmax=1000,method='unshifted')
#lam1 = sort(lam1)[::-1]
display_mat("Eigenvalues = ",lam11)
display_mat("Error = ",linalg.norm(eval_true - lam11))
```

number of iterations required= 42

Eigenvalues =

```
array([[1.21465537],
       [2.25695098],
       [3.28777559],
       [4.31431185],
       [5.33895991],
       [6.36294484],
       [7.38709463],
       [8.41211890],
       [9.43876514],
       [10.46797027],
       [11.50111645],
       [12.54132790],
       [13.58892879],
       [14.66394811],
       [24.22313127]])
```

Error =

0.0016713681173739802

In [18]:

```
#USING RAYLEIGH SHIFT
e22,lam22= eigenvalue_QR_solver(A,kmax=1000,method='Rayleigh shift')
#lam2 = sort(lam2)[::-1]
display_mat("Eigenvalues = ",lam22)
display_mat("Error = ",linalg.norm(eval_true - lam22))
```

number of iterations required to find the eigenvalue below= 42

eigenvalue = 1.2147e+00

number of iterations required to find the eigenvalue below= 70

eigenvalue = 2.2570e+00

number of iterations required to find the eigenvalue below= 97

eigenvalue = 3.2878e+00

number of iterations required to find the eigenvalue below= 124

eigenvalue = 4.3143e+00

number of iterations required to find the eigenvalue below= 151

eigenvalue = 5.3390e+00

number of iterations required to find the eigenvalue below= 178

eigenvalue = 6.3629e+00

number of iterations required to find the eigenvalue below= 205

eigenvalue = 7.3871e+00

number of iterations required to find the eigenvalue below= 232

eigenvalue = 8.4121e+00

number of iterations required to find the eigenvalue below= 259


```
eigenvalue = 9.4387e+00
```

```
number of iterations required to find the eigenvalue below= 286
eigenvalue = 1.0468e+01
```

```
number of iterations required to find the eigenvalue below= 313
eigenvalue = 1.1501e+01
```

```
number of iterations required to find the eigenvalue below= 345
eigenvalue = 1.2540e+01
```

```
number of iterations required to find the eigenvalue below= 348
eigenvalue = 1.3590e+01
```

```
number of iterations required to find the eigenvalue below= 349
eigenvalue = 1.4664e+01
```

```
number of iterations required to find the eigenvalue below= 350
eigenvalue = 2.4223e+01
```

```
Eigenvalues =
array([[1.21465537],
       [2.25695098],
       [3.28777559],
       [4.31431185],
       [5.33895988],
       [6.36294449],
       [7.38709275],
       [8.41211207],
       [9.43874576],
       [10.46792166],
       [11.50098302],
       [12.54018637],
       [13.59013196],
       [14.66409700],
       [24.22313127]])
```

```
Error =
7.965709004822976e-14
```

In [19]:

```
# USING WILKINSON SHIFT

e33,lam33= eigenvalue_QR_solver(A,kmax=1000,method='Wilkinson shift')
#lam3 = sort(lam3)[::-1]
display_mat("Eigenvalues = ",lam33)
display_mat("Error = ",linalg.norm(eval_true - lam33))
```

```
number of iterations required to find the eigenvalue below= 42
eigenvalue = 1.2147e+00
```

```
number of iterations required to find the eigenvalue below= 70
eigenvalue = 2.2570e+00
```

```
number of iterations required to find the eigenvalue below= 97
eigenvalue = 3.2878e+00
```

```
number of iterations required to find the eigenvalue below= 124
eigenvalue = 4.3143e+00
```

number of iterations required to find the eigenvalue below= 151
eigenvalue = 5.3390e+00

number of iterations required to find the eigenvalue below= 178
eigenvalue = 6.3629e+00

number of iterations required to find the eigenvalue below= 205
eigenvalue = 7.3871e+00

number of iterations required to find the eigenvalue below= 232
eigenvalue = 8.4121e+00

number of iterations required to find the eigenvalue below= 259
eigenvalue = 9.4387e+00

number of iterations required to find the eigenvalue below= 286
eigenvalue = 1.0468e+01

number of iterations required to find the eigenvalue below= 313
eigenvalue = 1.1501e+01

number of iterations required to find the eigenvalue below= 345
eigenvalue = 1.2540e+01

number of iterations required to find the eigenvalue below= 348
eigenvalue = 1.3590e+01

number of iterations required to find the eigenvalue below= 349
eigenvalue = 1.4664e+01

number of iterations required to find the eigenvalue below= 350
eigenvalue = 2.4223e+01

Eigenvalues =
array([[1.21465537],
[2.25695098],
[3.28777559],
[4.31431185],
[5.33895988],
[6.36294449],
[7.38709275],
[8.41211207],
[9.43874576],
[10.46792166],
[11.50098302],
[12.54018637],
[13.59013196],
[14.66409700],
[24.22313127]])

Error =
7.965709004822976e-14