

Mathematical Methods in Engineering and Applied Science

This webpage contains all assignments and solutions to the MMEAS course.

Problem Set 1

Problem 1

Some basic problems on matrix/vector multiplication.

(a) Calculate by hand the following matrix/vector products:

(i) $\begin{bmatrix} 2 & 1 \\ 2 & 3 & 2 \\ 2 & 1 \\ 2 & -1 & 0 \end{bmatrix} \begin{bmatrix} 1 & -2 & 1 \\ 2 & 3 & 2 \end{bmatrix}$
 (ii) $\begin{bmatrix} 2 & -1 & 1 \\ 3 & 0 & 4 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 1 & 2 \\ -1 & 0 \end{bmatrix}$

as a combination of columns of the left matrix as well as a combination of rows of the right matrix.

(b) Write down a permutation matrix (P_4) that exchanges row 1 with row 3 and row 2 with row 4. What is the connection of this matrix with the permutation matrices that exchange only row 1 and row 3, and only row 2 and row 4?

Solution

1. a)

i) $\begin{bmatrix} 2 & 1 \\ 2 & 3 & 2 \\ 2 & 1 \\ 2 & -1 & 0 \end{bmatrix} \begin{bmatrix} 1 & -2 & 1 \\ 2 & 3 & 2 \end{bmatrix}$ as rows of right mx

ii) $\begin{bmatrix} 2 & -1 & 1 \\ 3 & 0 & 4 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 1 & 2 \\ -1 & 0 \end{bmatrix}$ as cols of left mx

$$= \begin{bmatrix} 2 & 0 \\ 2 & 3 \end{bmatrix} = \begin{bmatrix} [2 \ 1] \cdot 2 + [-1 \ 0] \cdot 1 + [1 \ 4] \cdot (-1) \\ [3 \ 0] \cdot 2 + [1 \ 4] \cdot 1 + [-1 \ 0] \cdot 1 \end{bmatrix}$$

as rows of right mx

b) Matrix P_4 that changes row 1 with row 3 and row 2 with row 4:

$$P_4 \begin{bmatrix} r_1 \\ r_2 \\ r_3 \\ r_4 \\ \vdots \end{bmatrix} = \begin{bmatrix} r_3 \\ r_4 \\ r_1 \\ r_2 \\ \vdots \end{bmatrix} \quad P_4 = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix} \begin{matrix} (0) \\ (0) \\ (1) \dots (1) \end{matrix}$$

P_4' exchanges only row 1 with row 3: P_4'' exchanges row 2 and row 4:

$$P_4' = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad P_4'' = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

As exchange of rows may be done consecutively ($1 \leftrightarrow 3$, then $2 \leftrightarrow 4$), $P_4 = P_4' P_4''$ or $P_4'' P_4'$.

Problem 2

Given a (3×3) matrix $A = \begin{bmatrix} a_1 & a_2 & a_3 \end{bmatrix}$ with columns (a_i) , find a matrix B that when multiplied with A , either from left or right, performs the following operations with A :

- (a) exchanges row 1 and row 2;
- (b) exchanges columns 1 and 2;
- (c) doubles the first row;
- (d) subtracts twice row 1 from row 2.

Also find the inverse of this matrix. What does the inverse of this B do?

Solution

2. $A = [a_1 \ a_2 \ a_3]$

- a) Exchanges row 1 and row 2:

$$B = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad BA = C$$

- b) Exchanges col 2 and col 1:

Same matrix B , multiplied from right: $AB = C$

- c) Doubles the first row:

$$B = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

- d) Subtracts twice row 1 from row 2:

$$B = \begin{bmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}; \quad B \begin{bmatrix} r_1 \\ r_2 \\ r_3 \end{bmatrix} = \begin{bmatrix} r_1 \\ r_2 - 2r_1 \\ r_3 \end{bmatrix} \Rightarrow \begin{bmatrix} r_1 \\ r_2 \\ r_3 \end{bmatrix} = B^{-1} \begin{bmatrix} r_1 \\ r_2 - 2r_1 \\ r_3 \end{bmatrix}$$



Problem 3

For matrix $A = \begin{bmatrix} 1 & 2 & 3 \\ 3 & 4 & 5 \\ 5 & 6 & 7 \end{bmatrix}$, determine the following:

- (a) rank;
- (b) eigenvalues and eigenvectors;
- (c) nullspace and left nullspace;
- (d) column space and row space;
- (e) write A as a sum of rank-1 matrices in at least two different ways.

Solution



d) Column space and row space:

- Column space: $\text{span} \left(\begin{bmatrix} 1 \\ 3 \\ 5 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 6 \end{bmatrix}, \begin{bmatrix} 2 \\ 4 \\ 7 \end{bmatrix} \right)$; equals to the row space.

e) write A as a sum of rank-1 matrices in at least two different ways:

Obviously, we can present the matrix A as a sum of single-row or single-column rank-1 matrices (with other rows or columns filled with zeros). Also, we have 3 non-colinear eigenvectors, that can be our matrix basis in the canonical decomposition (diagonalization):

$$A = UDU^{-1} = \sum_{i=1}^3 d_i \lambda_i \lambda_i^T$$

Problem 4

The columns of matrix $C = \begin{bmatrix} 2 & 2 & 1 & 1 & 2 & 2 & 1 & 1 \\ 1 & 2 & 2 & 2 & 1 & 1 & 2 & 2 \\ 1 & 1 & 2 & 2 & 2 & 2 & 2 & 2 \end{bmatrix}$ represent vertices of a cube. Describe transformations of the cube that result from the action on C of the following three matrices:

$A_1 = \begin{bmatrix} 1 & 2 & 2 \\ 0 & 2 & 2 \\ 0 & 0 & 3 \end{bmatrix}$, $A_2 = \begin{bmatrix} 1 & 2 & 2 \\ 0 & 2 & 2 \\ 0 & 0 & 0 \end{bmatrix}$, $A_3 = \begin{bmatrix} 0 & 2 & 2 \\ 0 & 2 & 2 \\ 0 & 0 & 0 \end{bmatrix}$

Relate the results to the ranks of A_k and to the dimensions and bases of the four fundamental subspaces of A_k . Is there a (3×3) matrix A that can transform a cube into a tetrahedron? Explain.

Solution

Firstly, let us see what every transformation does with the cube.

```
# Creating matrices

A1 = np.matrix([
    [1, 2, 2],
    [0, 2, 2],
    [0, 0, 3]
])

A2 = np.matrix([
    [1, 2, 2],
    [0, 2, 2],
    [0, 0, 0]
])

A3 = np.matrix([
    [0, 2, 2],
    [0, 2, 2],
    [0, 0, 0]
])

C = np.matrix([
    [2, 2, 1, 1, 2, 2, 1, 1],
    [1, 2, 2, 1, 1, 2, 2, 1],
    [1, 1, 1, 1, 2, 2, 2, 2]
])

#Applying A matrices to the cube

B1 = A1*C
B2 = A2*C
B3 = A3*C

#Plotting

%config InlineBackend.figure_format = 'svg'
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
ax.scatter(xs = C[0], ys = C[1], zs = C[2])
ax.scatter(xs = B1[0], ys = B1[1], zs = B1[2], color='red', depthshade = True)
ax.scatter(xs = B2[0], ys = B2[1], zs = B2[2], color='green', depthshade = True)
ax.scatter(xs = B3[0], ys = B3[1], zs = B3[2], color='yellow', depthshade = True)
ax.set_xticks(np.arange(0, 11, 2))
ax.set_yticks(np.arange(0, 11, 2))
ax.set_zticks(np.arange(0, 7, 1))
ax.set_xlabel('x')
ax.set_ylabel('y')
ax.set_zlabel('z')

plt.title('Cube Transformations')
plt.legend(['Initial Cube', 'A1', 'A2', 'A3'])
```

<matplotlib.legend.Legend at 0x1a848bc78c8>



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The points on this 3D plot represent the vertices of the initial cube (blue) and resulting shapes. As we see,

- A_1 combines some stretching and rotation;
- A_2 projects the first transformation on the (XY) plane;
- A_3 projects the first (or the second) transformation on a line.

Now, let's derive the properties of each matrix A_i .

$$\text{rg}(A_1) = 3; \text{rg}(A_2) = 2; \text{rg}(A_3) = 1$$

It follows from the Main theorem of Linear Algebra that

$$\text{rg}(\ker(A_1)) = 0; \text{rg}(\ker(A_2)) = 1; \text{rg}(\ker(A_3)) = 2$$

That means,

- A_1 maps \mathbb{R}^3 to \mathbb{R}^3
- A_2 maps \mathbb{R}^3 to \mathbb{R}^2
- A_3 maps \mathbb{R}^3 to \mathbb{R}^1

That corresponds to our findings in the previous section.

Let us find the four fundamental subspaces for each A_i operator:

- A_1 is a full-rank matrix, that means nullspace is empty.

The same applies to A_1^T . A_1 column space is $\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$, $\begin{bmatrix} 0 \\ 2 \\ 0 \end{bmatrix}$, $\begin{bmatrix} 0 \\ 0 \\ 3 \end{bmatrix}$, as well as for A_1^T (row space of A_1).

- for A_2 we solve a simple set of linear equations and receive the following result:

$$\text{Null}(A_2) = \text{span} \left(\begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix} \right); \text{Null}(A_2^T) = \text{span} \left(\begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix} \right).$$

The column space of A_2 is $\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$, $\begin{bmatrix} 0 \\ 2 \\ 0 \end{bmatrix}$, the row space is the same.

- for A_3 , we have two-dimensional null space: $\text{Null}(A_3) = \text{span} \left(\begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} \right)$. It coincides with the nullspace of A_3^T .

The column space of A_3 is $\text{span} \left(\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \right)$, as well as the row space. This result is easily observed on the visualisation: the result of the 3rd transformation lies on the $(y = x)$ line on the (XY) plane.

```
def print_eig(A, number):
    val, vec = np.linalg.eig(A)
    print("Eigenvalues and eigenvectors for matrix A{}:".format(number))
    print(val)
    print(vec)
    print()

#print_eig(A1, 1)
#print_eig(A2, 2)
#print_eig(A3, 3)
```

On transforming a cube into a tetrahedron: Linear transformation implies that we can describe it only acting on basis vectors. That means, I suppose there is no such 3×3 matrix to perform this operation.

Problem 5

For matrix $A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$ determine which unit vector x_M is stretched the most and which x_m the least and by how much. That is, find x such that $y = Ax$ has the largest (or smallest) possible Euclidian length. You can do this by calculus methods, e.g. using Lagrange multipliers. Relate your findings to eigenvalues and eigenvectors of A .

Solution

Firstly, we SVD the matrix A :

```
U:
[[-0.70710678 -0.70710678]
 [-0.70710678  0.70710678]]
E: [3.  1.]
V*:
[[-0.70710678 -0.70710678]
 [-0.70710678  0.70710678]]
```

We see that the matrices U and V^* may be rewritten as a combination of the following matrices:

$$U = V^* = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$$

$\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 0 \end{bmatrix} \times \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} = cR \times M$, where $c = \frac{\sqrt{2}}{2}$, cR is a rotation matrix with $\varphi = \frac{1}{4}\pi$, M is a mirror operator that mirrors about X axis.

The matrix Σ has diagonal elements $\begin{bmatrix} 3 & 1 \end{bmatrix}$ and represents stretching times 3 along X axis.

```
M = np.matrix([
    [-1, 0],
    [0, 1]
])
c = np.sqrt(2)/2
R = np.matrix([
    [1, -1],
    [1, 1]
])

#c*R*M

#c*R
```

After the stretch has been completed, the matrix U does the reverse transformation: mirrors the X axis and rotates $\frac{1}{4}\pi$ counterclockwise.

Now we can say that the most stretched vector x_M will be the $\frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ (or it's mirrored counterpart) unit vector, which during the transformations is aligned along the direction of the stretch operation and it's Euclidian length will be $\sqrt{3}$, and the least stretched vector x_m is the $\frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$ (or it's mirrored counterpart), which lies perpendicular to the axis of the stretch operation. It's Euclidian length remains 1 .

Now let's look at the Eigenvalues and Eigenvectors of the matrix (the values and the vectors can be easily calculated by hand):

```
Eigenvalues: [3. 1.]
Eigenvectors:
[[ 0.70710678 -0.70710678]
 [ 0.70710678  0.70710678]]
```

The result coincides with the result derived from SV decomposition: the $\frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ vector is stretched 3 times, the $\frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$ vector remains the same.

Problem 6

Find eigenvalues and eigenvectors of the following matrices:

(a) $A_1 = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$. If x is any real vector, how is $y = A_1 x$ related to x geometrically?

(b) $A_2 = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}$. What is the rank of A_2 ? How many eigenvectors are there?

Solution

The calculation of eigenvalues and eigenvectors may be performed by hand easily, as well as with *NumPy* package.

We start with matrix A_1 :

```
Eigenvalues and eigenvectors for matrix A1:
[0.+1.j 0.-1.j]
[[0.70710678+0.j      0.70710678-0.j      ]
 [0.      +0.70710678j 0.      -0.70710678j]]
```

Instantly from one glance at the matrix (A_1) , as well as by seeing the result of `eigen_operations`, we derive that the matrix conducts a rotation. There are no real eigenvectors, obviously, as there are no vectors (x) that would be collinearly translated into another vectors (y) .

Now, let's analyze the matrix (A_2) . It is obvious, that $(\text{rg}(A_2) = 1)$, because we can perform simple row operations $(r_2 = r_2 - r_3; r_1 = r_1 - (r_2 - r_3))$ to get the resulting matrix $(\begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix})$.

```
Eigenvalues and eigenvectors for matrix A2:
[1. 1. 1.]
[[ 1.00000000e+00 -1.00000000e+00  1.00000000e+00]
 [ 0.00000000e+00  2.22044605e-16 -2.22044605e-16]
 [ 0.00000000e+00  0.00000000e+00  4.93038066e-32]]
```

There is one eigenvalue $(\lambda = 1)$ of multiplicity 3, and only one eigenvector $(h = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix})$. This matrix is a linear operator that projects on (YZ) plane.

Problem Set 2

Problem 1

Consider linear system

$$\begin{aligned} 2x_1 + x_2 &= 1 \\ x_1 + 2x_2 + x_3 &= 2 \\ x_2 + 2x_3 &= 3 \end{aligned}$$

(a) Find the (LU) factorization of the coefficient matrix (A) . Show that $(U = DL^T)$ with (D) diagonal and thus $(A = LDL^T)$. Find the exact solution using the (LU) factorization.

(b) Solve the system using Jacobi and Gauss-Seidel iterations. How many iterations are needed to reduce the relative error of the solution to (10^{-8}) ?

(c) Plot in semilog scales the relative errors by both methods as a function of the number of iterations.

(d) Explain the convergence rate. Which of the methods is better and why?

Solution

Let us perform the (LU) factorization by hand:

$$\begin{aligned} \begin{bmatrix} 2 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix} &\rightarrow \begin{bmatrix} 2 & 1 & 0 \\ 2 & 1 & 0 \\ 0 & 1 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 2 & 1 & 0 \\ 0 & 0 & \frac{3}{2} \\ 0 & 1 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 2 & 1 & 0 \\ 0 & 1 & 2 \\ 0 & 0 & \frac{3}{2} \end{bmatrix} = U; \quad L = \begin{bmatrix} 1 & 0 & 0 \\ \frac{1}{2} & 1 & 0 \\ 0 & \frac{2}{3} & 1 \end{bmatrix} \end{aligned}$$

And check it via *numpy*.

```

import numpy as np
from fractions import Fraction
from scipy import linalg as lin
import sympy as sp
from sympy import abc

A = np.matrix([
    [2, 1, 0],
    [1, 2, 1],
    [0, 1, 2]
])

def bmatrix(a):
    """Returns a LaTeX bmatrix

    :a: numpy array
    :returns: LaTeX bmatrix as a string
    """
    if len(a.shape) > 2:
        raise ValueError('bmatrix can at most display two dimensions')
    lines = str(a).replace('[', '').replace(']', '').splitlines()
    rv = [r'\begin{bmatrix}']
    rv += [' ' + ' & '.join(l.split()) + r'\\' for l in lines]
    rv += [r'\end{bmatrix}']
    return '\n'.join(rv)

E, L, U = lin.lu(A, permute_1 = False)
L = np.matrix(L)
U = np.matrix(U)
print("L:")
print(L)
print("\nU:")
print(U)

```

```

L:
[[1.      0.      0.      ]
 [0.5     1.      0.      ]
 [0.      0.66666667 1.     ]]

U:
[[2.      1.      0.      ]
 [0.      1.5     1.      ]
 [0.      0.      1.33333333]]

```

Let us show, that $(U = DL^T)$:

$$\begin{pmatrix} L^T = \begin{bmatrix} 1 & \frac{1}{2} & 0 \\ 0 & 1 & \frac{2}{3} \\ 0 & 0 & 1 \end{bmatrix} D = \begin{bmatrix} 2 & 0 & 0 \\ 0 & \frac{3}{2} & 0 \\ 0 & 0 & 1 \end{bmatrix} U = DL^T \end{pmatrix}$$

That means, $(A = LU = LDL^T)$.

Now, let us solve the system using (LU) factorization:

$$\begin{aligned} Ax &= b \quad \Rightarrow \quad LUx = b; \quad \begin{cases} Ux = y; \\ Ly = b \end{cases} \\ \begin{pmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{2} & 1 \\ 0 & \frac{2}{3} & 1 \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} &= \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix} \Rightarrow \begin{cases} y_1 = 1 \\ y_2 = \frac{3}{2} \\ y_3 = 2 \end{cases} \\ \begin{pmatrix} 2 & 1 & 0 \\ 0 & \frac{3}{2} & 1 \\ 0 & 0 & \frac{4}{3} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} &= \begin{pmatrix} 1 \\ \frac{3}{2} \\ 2 \end{pmatrix} \Rightarrow \begin{cases} x_1 = \frac{1}{2} \\ x_2 = 0 \\ x_3 = \frac{3}{2} \end{cases} \end{aligned}$$

Next we solve the system using Jacobi and Gauss-Seidel methods:

```

import matplotlib.pyplot as plt
import copy

```

```

D = np.matrix(np.diag(np.diag(A)))
U = np.matrix(np.triu(A-D))
L = np.matrix(np.tril(A-D))

x_exact = np.matrix([1/2, 0, 3/2]).T
tol = 1e-8
err = 1
x_init = np.matrix([1, 1, 1]).T #initial x
b = np.matrix([1, 2, 3]).T

def Jacobi(L, D, U, x_init, b, err, tol):

    x = copy.deepcopy(x_init)

    max_iters = 500

    err_iter = np.array([])
    err_exact_iter = np.array([])

    iters = 0
    while ((err > tol) and (iters <= max_iters)) :
        iters = iters + 1
        bb = b - (U + L)*x
        x_new = np.linalg.solve(D, bb)
        err = np.linalg.norm(x_new - x)/np.linalg.norm(x)
        err_exact = np.linalg.norm(x_new - x_exact)

        err_iter = np.append(err_iter, err)
        err_exact_iter = np.append(err_exact_iter, err_exact)

        x = x_new

    return err_iter, err_exact_iter, x_new, iters

def Gauss_Seidel(L, D, U, x_init, b, err, tol):

    x = copy.deepcopy(x_init)

    max_iters = 250

    err_iter = np.array([])
    err_exact_iter = np.array([])

    iters = 0
    while ((err > tol) and (iters <= max_iters)):
        iters = iters + 1

        bb = b - U*x
        x_new = np.linalg.solve(D+L, bb)
        err = np.linalg.norm(x_new - x)/np.linalg.norm(x)
        err_exact = np.linalg.norm(x_new - x_exact)

        err_iter = np.append(err_iter, err)
        err_exact_iter = np.append(err_exact_iter, err_exact)

        x = x_new

    return err_iter, err_exact_iter, x_new, iters

```

```

%config InlineBackend.figure_format='svg'

fig = plt.figure()
ax = plt.gca()

errs_j, ex_errs_j, x_j, i_j = Jacobi(L, D, U, x_init, b, err, tol)
plt.plot(errs_j)

errs_g, ex_errs_g, x_g, i_g = Gauss_Seidel(L, D, U, x_init, b, err, tol)
plt.plot(errs_g)

ax.set_yscale('log')

ax.legend(['Jacobi', 'Gauss_Seidel'])
ax.set_xlabel('Iterations')
ax.set_ylabel('Relative error')
ax.set_yticks([1e-7, 1e-5, 1e-3, 1e-1])
ax.tick_params(axis='y', which='minor')
ax.grid(which='both')

```



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As we see, it took 26 iterations for Gauss-Seidel method to reach the target tolerance of (10^{-8}) , while Jacobi method required 54 iterations.

This can be explained by the following: in Gauss-Seidel, as soon as we acquire a new iteration of a vector (x) component $x_i^{(k+1)}$, we instantly utilize this updated value in the computation of the following components: $x_{i+1}^{(k+1)} = f(x_1^{(k+1)}, \dots, x_{i-1}^{(k+1)}, x_i^{(k+1)}, \dots, x_n^{(k)})$. In Jacobi, we calculate the new vector $x^{(k+1)}$ relying solely on the result of the previous iteration: $x_i^{(k+1)} = f(x_j^{(k)}, j \neq i)$.

Problem 2

Factor these two matrices (A) into $(S\Lambda S^{-1})$:

$A1 = \begin{bmatrix} 1 & 2 \\ 0 & 3 \end{bmatrix}$, $A2 = \begin{bmatrix} 1 & 2 \\ 0 & 3 \end{bmatrix}$

Using that factorization, find for both: (a) (A^3) ; (b) (A^{-1}) .

Solution

Firstly, we find the eigenvalues and eigenvectors:

$\begin{bmatrix} 1-\lambda & 2 \\ 0 & 3-\lambda \end{bmatrix} = 0$

By performing simple calculations by hand, we obtain:

$\begin{bmatrix} \lambda_1 = 1 \\ \lambda_2 = \frac{\sqrt{2}}{2} \end{bmatrix}$

$\begin{bmatrix} \lambda_1 = 1 \\ \lambda_2 = 3 \end{bmatrix}$

Note

We normalized the eigenvectors

Now let's perform a check with *numpy*:

```
A1 = np.matrix([
    [1, 2],
    [0, 3]
])

val1, vec1 = np.linalg.eig(A1)
print("E_values A1:")
print(val1)
print("E_vectors A1:")
print(vec1)
```

```
E_values A1:
[1.  3.]
E_vectors A1:
[[1.      0.70710678]
 [0.      0.70710678]]
```

As we have our vectors and values, we can construct (Λ) and (S, S^{-1}) matrices:

```
Lambda = np.matrix(np.diag(val1))
S = vec1
Si = np.linalg.inv(S)

print("S:")
print(S)
print("Lambda:")
print(Lambda)
print("S_inverse:")
print(Si)
```

```
S:
[[1.      0.70710678]
 [0.      0.70710678]]
Lambda:
[[1.  0.]
 [0.  3.]]
S_inverse:
[[ 1.      -1.      ]
 [ 0.      1.41421356]]
```

$S = \begin{bmatrix} 1 & \frac{\sqrt{2}}{2} \\ 0 & \frac{\sqrt{2}}{2} \end{bmatrix}$, $\Lambda = \begin{bmatrix} 1 & 0 \\ 0 & 3 \end{bmatrix}$, $S^{-1} = \begin{bmatrix} 1 & -1 \\ 0 & 2/\sqrt{2} \end{bmatrix}$

From now, we can find the (A^3) powered matrix by simply multiplying the decomposition:

$$\begin{pmatrix} A^3 = S \Lambda S^{-1} S \Lambda S^{-1} S \Lambda S^{-1} = S \Lambda^3 S^{-1} \end{pmatrix}$$

$$\end{pmatrix}$$

And for (Λ) it is easy to power because it is a diagonal matrix.

$$\begin{pmatrix} \Lambda^3 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 9 & 0 \\ 0 & 0 & 8 \end{pmatrix}, S \Lambda^3 S^{-1} = \begin{pmatrix} 1 & 8 \\ 0 & 9 \end{pmatrix} \end{pmatrix}$$

For inverse matrix:

$$[S \Lambda S^{-1} A^{-1} = E, \Rightarrow A^{-1} = S^{-1} \Lambda^{-1} S]$$

We already have (S) and (S^{-1}) , and for diagonal (Λ) the inverse matrix contains the inverse diagonal elements of (Λ) :

$$\begin{pmatrix} \Lambda^{-1} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1/3 & 0 \end{pmatrix} \end{pmatrix}$$

So we easily find (A^{-1}) :

$$\begin{pmatrix} A^{-1} = \begin{pmatrix} 1 & \sqrt{2}/3 \\ 0 & 1/3 \end{pmatrix} \end{pmatrix}$$

Now let's look at the second matrix (A_2) . Instantly we notice it is a rank-1 matrix, thus, (A_2^{-1}) matrix doesn't exist.

$$\begin{pmatrix} h_1 = \begin{pmatrix} 1 \\ -1 \end{pmatrix}, \lambda_1 = 0 \\ h_2 = \begin{pmatrix} 1 \\ 3 \end{pmatrix}, \lambda_2 = 4 \end{pmatrix}$$

It's eigenvectors are non-collinear and form a basis in 2-dimensional space. Thus we can perform the factorization.

$$\begin{pmatrix} S = \begin{pmatrix} 1 & 1 \\ -1 & 3 \end{pmatrix}, \Lambda = \begin{pmatrix} 0 & 0 \\ 0 & 4 \end{pmatrix}, S^{-1} = \begin{pmatrix} 3/4 & -1/4 \\ 1/4 & 1/4 \end{pmatrix} \end{pmatrix}$$

For (A_2^3) :

$$\begin{pmatrix} A_2^3 = \begin{pmatrix} 64 & 64 \\ 192 & 192 \end{pmatrix} \end{pmatrix}$$

Problem 3

Given a system $(Ax = b)$ with

$$\begin{pmatrix} A = \begin{pmatrix} 1 & -1 & -3 \\ 2 & 3 & 4 \\ -2 & 1 & 4 \end{pmatrix}, b = \begin{pmatrix} 3 \\ a \\ -1 \end{pmatrix} \end{pmatrix}$$

for which (a) there is a solution? Find the general solution of the system for that (a) .

Solution

Let's check the matrix' rank:

```
a = abc.symbols('a')
A = sp.Matrix([
    [1, -1, -3],
    [2, 3, 4],
    [-2, 1, 4]
])
b = sp.Matrix([
    3, a, -1
])
print('Rank: {}'.format(A.rank()))
A.rref()[0]
```

Rank: 2

$$\begin{pmatrix} \begin{pmatrix} 1 & 0 & -1 \\ 0 & 1 & 2 \\ 0 & 0 & 0 \end{pmatrix} \end{pmatrix}$$

This matrix is a rank-2 matrix. Let's find it's left nullspace, write down the solvability condition and find the appropriate (a) . Starting with the left null-space:

```
y = A.T.nullspace()[0]
y
```

$$\begin{pmatrix} \begin{pmatrix} \frac{8}{5} \\ \frac{1}{5} \end{pmatrix} \end{pmatrix}$$

We want to fulfill the following condition:

$$[y^T b = 0]$$

```
ans = sp.solve(y.T*b, a)
ans
```

{a: -19}

As we see, the system is solvable with $(a = -19)$. Let us perform some check:

```
bs = b.subs(a, -19)
y.T*bs
```

$$\left[\begin{matrix}0\end{matrix}\right]$$

Now as we have our vector (b) with which the system is solvable, we may find the general solution for the system:

```
a, b, c = abc.symbols('a b c')
system = A, bs
sol = sp.linsolve((A, bs), a, b, c); sol
```

$$\left(\left(c - 2, -2c - 5, c\right)\right)$$

With $(c \in \mathbb{R})$ we get our solution:

$$\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} -2 \\ -5 \end{pmatrix} + \begin{pmatrix} 1 \\ -2 \end{pmatrix} c$$

Problem 4

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