

Math340: Programming in Mathematics

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Lecture #12a:

Symbolic Mathematics in Python (SymPy) for Computational Algebra

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Spring 2025

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San Diego State University,
Spring 2025

an example for ill-conditioning systems

Ill-Conditioning: An Example

An Ill-Conditioned System

condition #: 2.0001E4
(20,001)

You may verify that the system

$$0.9999x - 1.0001y = 1$$

$$x - y = 1$$

The solution is:

$$(x, y) = (0.5, -0.5)$$

has the solution $x = 0.5, y = -0.5$, whereas the system

$$0.9999x - 1.0001y = 1$$

$$x - y = 1 + \epsilon$$

has the solution $x = 0.5 + 5000.5\epsilon, y = -0.5 + 4999.5\epsilon$. This shows that the system is ill-conditioned

The solution is:

$$(x, y) = (0.5, -0.5) + (5000.5\epsilon, 4999.5\epsilon)$$

$\epsilon = 1e-4$ can change the answer significantly.

(Kreyszig, 2011)

Basic Python Functions for Linear Algebra

Basic Linear Algebra

NumPy contains the **linalg** module for:

- Solving linear systems
 - Computing the determinant of a matrix
 - Computing the inverse of a matrix
 - Computing eigenvalues and eigenvectors of a matrix
 - Solving least-squares problems
 - Computing the singular value decomposition of a matrix
 - Computing the Cholesky decomposition of a matrix
-

Consider the following system, which is ill-conditioned:

$$0.9999x - 1.0001y = 1,$$

$$x - y = 1.$$

Express the above system in a matrix form:

$$A = \begin{bmatrix} 0.9999 & -1.0001 \\ 1 & 1 \end{bmatrix}; \quad b = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$A\vec{x} = b; \quad \vec{x} = \begin{bmatrix} x \\ y \end{bmatrix}$$

Solving the above yields the following:

$$\vec{x} = A^{-1}b$$

$$\vec{x} = (x, y) = (0.5, -0.5)$$

Linear Algebra (LA) in numpy and sympy

`np.linalg.solve`

`sympy.solve_linear_system`

```
In [1]: import numpy as np
A = np.array([[0.9999, -1.0001], [1, -1]])
b = np.array([1, 1])
x = np.linalg.solve(A, b)
print(x)
```

```
[ 0.5 -0.5]
```

What does the condition number tell us?

- A large condition number indicates that the matrix is **ill-conditioned**, meaning small changes in the input can lead to large changes in the output. This can cause problems in numerical computations, such as solving linear systems or inverting matrices.
- A small condition number indicates that the matrix is well-conditioned, meaning it is more stable for numerical operations.

Ill-conditioning, Sensitivities, & Hallucination

- A large condition number indicates ill-conditioning, which implies (numerical) sensitivity.
- The condition number $\kappa(C)$ is defined in terms of norm of the matrix C :

$$\kappa(C) = \|C\| \|C^{-1}\|$$

here $\|C\|$ represents the matrix norm of C . It can be written as follows:

$$\kappa(C) = \left| \frac{\lambda_{max}}{\lambda_{min}} \right| \quad \lambda: \text{eigenvalue}$$

- Based on the analysis of condition numbers, Shen et al. (2022a) showed that the Lorenz 1969 multiscale system is ill-conditioning. Such a feature is referred to as the 3rd kind of butterfly effect.
- Since the condition number is defined as the ratio of the largest to the smallest eigenvalue, systems with very large matrices (such as the attention matrix) may have a wide range of eigenvalues, leading to ill-conditioning.
- We hypothesize that **ill-conditioning** may occur in large language models, potentially contributing to **hallucinations**.

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```
In [2]: #import numpy.linalg as LA
eigen=np.linalg.eig(A)
eigen_val=eigen[0]
print(eigen_val)
print(np.linalg.cond(A))
```

```
[-5.e-05+0.01414205j -5.e-05-0.01414205j]
20000.000049995837
```

```
In [3]: U, S, Vh = np.linalg.svd(A)
print(S)
print(S[0]/S[1]) #largest singular value/smallest singular value
```

```
[2.00000000e+00 9.99999999e-05]
20000.000049995837
```

```
In [4]: from sympy import Matrix, Symbol, solve_linear_system
x = Symbol('x')
y = Symbol('y')
```

```
system = Matrix ([[0.9999, -1.0001, 1.0],\
                  [ 1.0, -1.0, 1.0]])\
```

```
sol=solve_linear_system(system, x, y)
```

```
print (sol)
```

```
{x: 0.5000000000000000, y: -0.5000000000000000}
```

Now, we consider the following system with a tiny perturbation

$$0.9999x - 1.0001y = 1$$

$$x - y = 1 + \epsilon$$

Once again, we express the above system in a matrix form

$$A = \begin{bmatrix} 0.9999 & -1.0001 \\ 1 & 1 \end{bmatrix}; \quad b = \begin{bmatrix} 1 \\ 1 + \epsilon \end{bmatrix}$$

$$A\vec{x} = b; \quad \vec{x} = \begin{bmatrix} x \\ y \end{bmatrix}$$

Solving the above yields the following:

$$\vec{x} = A^{-1}b$$

$$\vec{x} = (x, y) = (5000.5\epsilon + 0.5, 4999.5\epsilon - 0.5)$$

```
In [5]: from sympy import Matrix, Symbol, solve_linear_system
x = Symbol('x')
y = Symbol('y')
e = Symbol('e')

system = Matrix ([[0.9999, -1.0001, 1.0],\
                  [ 1.0,   -1.0,   1.0+e]])\

sol=solve_linear_system(system, x, y)
```

```
print (sol)
```

```
{x: 5000.500000000055*e + 0.5, y: 4999.500000000055*e - 0.5}
```

Solve a Boundary Value Problem (see Details in Lecture #11)

Consider the following 2nd-order ODE with two boundary conditions:

$$\frac{d^2y}{dt^2} = 4y; \quad y(0) = 1.1752; \quad y(1) = 10.0179$$

Applying a finite difference method, we obtain the following system in a matrix form:

$$Ax = b,$$

$$A = \begin{bmatrix} -2.25 & 1.0 & 0 \\ 1.0 & -2.25 & 1 \\ 0 & 1.0 & -2.25 \end{bmatrix};$$

$$b = \begin{bmatrix} -1.1752 \\ 0 \\ -10.0179 \end{bmatrix}$$

$$\text{or } b^T = (-1.1752, 0, 10.0179).$$

Below, we illustrate how to apply `solve_linear_system` to compute the solution to the above system.

```

from sympy import Matrix, Symbol, solve_linear_system
x = Symbol('x')
y = Symbol('y')
z = Symbol('z')

system = Matrix ([[ -2.25, 1.0, 0.0, -1.1752],
                  [ 1.0, -2.25, 1.0, 0.],
                  [ 0.0, 1.0, -2.25, -10.0179]])

#print (system)

sol=solve_linear_system(system, x, y, z)

print (sol)

```

A
 b
 $Ay = b$

```

In [4]: from sympy import Matrix, Symbol, solve_linear_system
x = Symbol('x')
y = Symbol('y')
z = Symbol('z')

system = Matrix ([[ -2.25, 1.0, 0.0, -1.1752],\
                  [ 1.0, -2.25, 1.0, 0.],\
                  [ 0.0, 1.0, -2.25, -10.0179]])

sol=solve_linear_system(system, x, y, z)

print (sol)

```

{x: 2.14670657596372, y: 3.65488979591837, z: 6.07679546485261}

Numerical Results for the Example

$$\frac{d^2y}{dt^2} = 4y \quad y(0) = 1.1752 \quad y(1) = 10.0179$$

	t	x	numerical	analytical	error
	0	1.0	(1.1752)	1.1752	n/a
X	0.25	1.5	2.1467	2.1293	-0.0174
Y	0.50	2.0	3.6549	3.6269	-0.0280
Z	0.75	2.5	6.0768	6.0502	-0.0266
	1.0	3.0	(10.0179)	10.0179	n/a

Below, we illustrate the advantage of symbolic computing by adding a tiny perturbation into the boundary condition as follows:

$$\frac{d^2y}{dt^2} = 4y; \quad y(0) = 1.1752 + \epsilon; \quad y(1) = 10.0179$$

Applying a finite difference method, we obtain the following

$$Ax = b$$

$$A = \begin{bmatrix} -2.25 & 1.0 & 0 \\ 1.0 & -2.25 & 1 \\ 0 & 1.0 & -2.25 \end{bmatrix}; \quad b = \begin{bmatrix} -1.1752 + \epsilon \\ 0 \\ 10.0179 \end{bmatrix}$$

Below, we solve the above system using `solve_linear_system` again.

```

from sympy import Matrix, Symbol, solve_linear_system
x = Symbol('x')
y = Symbol('y')
z = Symbol('z')
e = Symbol('e')

system = Matrix ([[ -2.25, 1.0, 0.0, -1.1752-e],
                  [ 1.0, -2.25, 1.0, 0.],
                  [ 0.0, 1.0, -2.25, -10.0179]])

#print (system)

sol=solve_linear_system(system, x, y, z)

print (sol)

```

A
b
Ay = b

```

In [5]: from sympy import Matrix, Symbol, solve_linear_system
x = Symbol('x')
y = Symbol('y')
z = Symbol('z')

```

```
e = Symbol('e')
system = Matrix ([[ -2.25, 1.0, 0.0, -1.1752-e ],\
[ 1.0, -2.25, 1.0, 0. ],\
[ 0.0, 1.0, -2.25, -10.0179 ]])
sol=solve_linear_system(system, x, y, z)
print (sol)
```

```
{x: 0.589569160997732*e + 2.14670657596372, y: 0.326530612244898*e + 3.65488
979591837, z: 0.145124716553288*e + 6.07679546485261}
```

$$\frac{\partial^2 u}{\partial x^2} = f(x)$$

$$f(x_i) = f_i$$

$$\frac{\partial^2 u}{\partial x^2} \approx \frac{u_{i+1} - 2u_i + u_{i-1}}{(\Delta x)^2}$$

$$\frac{u_{i+1} - 2u_i + u_{i-1}}{(\Delta x)^2} = f_i$$

backup

```
In [3]: from sympy import Matrix, Symbol, solve_linear_system
x = Symbol('x')
y = Symbol('y')
e = Symbol('e')

system = Matrix ([[ 0.9999, -1.0001, 0.0 ],\
[ 1.0, -1.0, 0.0+e ]])

sol=solve_linear_system(system, x, y)

print (sol)
```

```
{x: 5000.50000000055*e, y: 4999.50000000055*e}
```

```
In [ ]:
```