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#
# This lecture contains
#
# a brief discussion about Taylor Expansion
#
# and then
#
# we move to chapter 6 of the book
# and study SIMULTANEOUS LINEAR EQUATIONS

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# -----
# TAYLOR EXPANSION
# -----

# By using a Taylor expansion we can approximate a given function f(x)
# at a certain point x=a
# by a polynomial.

# The concept of a Taylor series was formulated by the Scottish mathematician
# James Gregory and formally introduced by the English mathematician
# Brook Taylor in 1715. If the Taylor series is centered at zero,
# then that series is also called a Maclaurin series.

# The polynomial that approximates f(x) at x=a is the
# nth degree TAYLOR polynomial:
#  $P(x) = f(a) + f'(a)(x-a) + (f''(a))/2! (x-a)^2 + \dots + (f^{(n)}(a))/n! (x-a)^n$ 

# Example:
# sin(x) close to x=0 is
#  $\sin(x) \sim x - x^3/3! + x^5/5! \dots$ 
# With this expansion, it becomes easy to study the limit  $\sin(x)/x$ 

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# SYMPY
# -----
# In Python, we can use SYMPY to get Taylor expansions.
# Example: Expansion of cos(x) around x=0

import sympy as syp
x = syp.Symbol('x')

# choose n=5 if you want the expansion up to x^4
ff=syp.series(syp.cos(x),x,x0=0,n=5)
print( 'cos(x) ~', ff )

f2 = ff.removeO()
print( 'cos(x) up to x^3: ', f2 )

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print()
# -----
# CAREFUL!! ff and f2 are symbolic expressions
# We cannot use them as functions
# Check what happens with the lines below

# NOT SOLVED!!
print("The function is not solved!")
def func(x):
    return f2
print(func(3))

print()
# WE COULD COPY THE FUNCTION
print('Solved because we copied the function')
x=3
gg = x**4/24 - x**2/2 + 1
print('Taylor of cos up to x^4 with x=3: ', gg)

# WE CAN LAMBDIFY THE EXPRESSION
#
# CAREFUL!! Since above x became the number 3
# Say again that "x" is a SYMBOL
x = symp.Symbol('x')
# To convert a SymPy expression to an expression that can be
# numerically evaluated, use the lambdify function.
print()
print("Now it is solved, because we lambdified the function!")
g2 = symp.lambdify(x,f2)
print(g2(3))

# Now that we have g2 as a FUNCTION of x
# We can get g2 for various values of x
# -----
import numpy as np
x = np.arange(1, 2.1, 0.1)
g2(x)
print()
print("And with numpy we can get all values at once")
print(x)
print(g2(x))

# -----
# Exercise 1
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# Make a plot of sin(x) and
# the first, third, fifth and seventh degree Taylor polynomials
# for x from x=-3.5 to x=3.5 in increments 0.01.
# Label your curves.
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# -----
# After this review of Taylor expansion, we can understand why
# the central difference gives a better approximation to the
# derivative of a function than
# the forward or backward differences
# See Sec.5.10.2 and Sec.5.10.3 of the book.
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print()
# -----
#                               CHAPTER 6 of the book
# -----
# NOTE: chapters beyond chapter 5 are NOT available online!!
# To read them, you can get the book in the library
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# Suppose we want to solve the following four simultaneous equations
# for the variables w, x, y, and z
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#
#  $2w + x + 4y + z = -4$ 
#  $3w + 4x - y - z = 3$ 
#  $w - 4x + y + 5z = 9$ 
#  $2w - 2x + y + 3z = 7$ 
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# which can be written in a matrix form as
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#  $Ax = v$ 
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# where
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import numpy as np
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A = np.array([[2, 1, 4, 1],
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        [3, 4, -1, -1],
        [1, -4, 1, 5],
        [2, -2, 1, 3]], float)
v = np.array([-4, 3, 9, 7], float)
```

```
print("Using 'solve' from numpy.linalg")
# -----
# LINALG and SOLVE
# -----
# This can be done with the
# module LINALG of the
# NUMPY package
# with the function SOLVE
import numpy.linalg as npa
x = npa.solve(A,v)
print('w, x, y, z = ',x)
```

```
print()
print("Using 'inv' from numpy.linalg")
# -----
# LINALG and INV
# -----
# We can also find the inverse of A
# and use  $A^{-1}.A.x = x = A^{-1}.v$ 
# to find v.
# The inverse is also contained in numpy.linalg
# and is called "inv"
Ainv = npa.inv(A)
sol = np.dot(Ainv,v)
print('w, x, y, z = ',sol)
# BUT, calculating the inverse of a matrix is a
# slow process. Unless the inverse is really needed,
# it is better to avoid it.
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###
# WHAT IS BEHIND THE FUNCTION SOLVE?
# Python uses the LU decomposition and backsubstitution.
# To understand what this is, let us start with
# Gaussian elimination and backsubstitution
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# -----
# GAUSSIAN ELIMINATION
# -----
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# Follow the PDF notes called "GaussianElimination"
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# and write a code to find w, x, y, and z for the
# system of linear equations written above.

# The purpose of the Gaussian elimination is to write
# the matrix A as an upper triangular matrix,
# so that w, x, y, z can be obtained by backsubstitution.

import numpy as np

A = np.array([[2, 1, 4, 1],
              [3, 4, -1, -1],
              [1, -4, 1, 5],
              [2, -2, 1, 3]], float)
v = np.array([-4, 3, 9, 7], float)

Ntot = len(v)

# Gaussian Elimination
# -----
for n in range(Ntot):
    # Divide the row by the diagonal element
    # to get the element 1.
    div = A[n,n]
    # NOTE: that we can do the operation on the entire row using ':' as below
    # Alternatively, we could have a loop here.
    A[n,:] = A[n,;]/div
    v[n] = v[n]/div
    # The simplified notation below do the same as above
    # A[n,:] /= div
    # v[m] /= div

    # PRINT to be sure it is doing what we want
    # print()
    # print('n=',n)
    # print('A[n,:]=', A[n,:], ' and v[n]=' , v[n])

# -----
# Now we do (lower row) - (num)*(row just divided by diagonal element)
# to get the element 0.
for k in range(n+1,Ntot):
    mult=A[k,n]
    A[k,:] = A[k,:] - mult*A[n,:]
    v[k] = v[k] - mult*v[n]
    # The simplified notation below do the same as above
    # A[k,:] -= mult*A[n,:]
    # v[m] -= mult*v[n]
    # PRINT to be sure it is doing what we want
    # print('k=',k)
    # print('A[k,:]=', A[k,:], ' and v[k]=' , v[k])

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# BACKSUBSTITUTION
# create an array of zeros, where the solution will be stored
x = np.zeros(Ntot,float)
# n below goes from n=Ntot-1=3 to n=0 (one before the last term -1)
for n in range(Ntot-1,-1,-1):
    x[n] = v[n]
    # k below goes from k=n+1 to k=Ntot-1 (one before the last term Ntot)
    for k in range(n+1,Ntot):
        x[n] = x[n] - A[n,k]*x[k]

print('w, x, y, z =', x)

# -----
# PIVOTING
# -----

# If an element of A is zero, which would lead to a division by zero,
# we swap the row with another one that has the farthest element from zero.
# See the PDF notes called "GaussianElimination".

# -----
# LU DECOMPOSITION
# -----

# Follow the PDF notes called "LUdecomposition"
# to understand what this decomposition is.
# The basic idea is to write the A matrix as a
# product of two matrices
#           A = L U
# where
#           L is a lower triangular matrix
# and
#           U is an upper triangular matrix
#
# In fact, U is the matrix that we obtain after the
# Gaussian elimination
#           U = L3.L2.L1.L0.A
#
# and           L = L0^{-1}.L1^{-1}.L2^{-1}.L3^{-1}

# -----
# TRIDIAGONAL and BANDED matrices
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# When we have tridiagonal matrices or banded matrices,  
# the code for the Gaussian elimination can (and should) be simplified!  
#  
# For a tridiagonal problem, each row only needs to be subtracted  
# from the single row immediately below it!!
```