Numerical Methods for Natural Sciences: Foundation Topics January - April semester, 2024

Raghunathan Ramakrishnan ramakrishnan@tifrh.res.in Tata Institute of Fundamental Research Hyderabad Hyderabad, India

Course material: https://github.com/raghurama123/nm2024



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References

Textbook

 David G. Moursund, Charles S. Duris, "Elementary Theory and Application of Numerical Analysis", Dover Publishers (1988).

General References

- Samuel D. Conte, Carl de Boor, "Elementary Numerical Analysis: An Algorithmic Approach", McGraw-Hill (1981).
- Lars Elden, Linde Wittmeyer-Koch and Hans Bruun Nielsen, "Introduction to Numerical Computing", Overseas Press (2006).
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- Anne Greenbaum, Timothy P. Chartier, "Numerical Methods", Princeton Univerity Press (2012).
- William Bo Rothwell, "Linux for Developers", Pearson (2018). <u>See the chapters about GitHub</u>.
- Numpy and Scipy Documentation, https://docs.scipy.org/doc/

Chapter 1: Solutions of equations by fixed-point iteration

Some definitions

Program, algorithm, elementary operation

- A program is a set of algorithms along with statements for user interaction (i.e. input/output). An algorithm is a set of pre-defined operations to convert an input to an ouput.
- For a given problem, there may not a unique way to write a program, or the algorithms involved, or even the elementary operations involved (that comprise the algorithms).

Types of Numerical Methods: Direct, Iterative, and Heuristic

- Direct methods are predefined recipes (i.e. fixed algorithms with fixed elementary steps) for solving a problem. In this case, the error in the final result is only due to finite computer precision (i.e. rounding-off the numbers involved).
 - The standard formula for finding the root of a quadratic equation is a direct method.
 - It is often the case that for a given problem, a direct method may not exist (either it has not been found, or it may not even exist mathematically). A theorem in algebra says that there is no directmethod for finding a root of a polynomial of degree ≥ 5 .
 - We will later see that Gaussian elimination is a direct method for solving systems of linear equations.
- Iterative methods require an initial guess for the final solution of a problem. This value will be given as an input to an algorithm which will be repeated until its input and output are the same.
 - Newton-Raphson method for finding the solution of non-linear equations is an iterative method.
 - Iterative methods can be shown (using a threom) that a solution (if it exists) can be found as a limit.
- Heuristic methods are methods developed based on experience. These methods are not guarateed to give a solution.
 - Simplex method (Nelder-Mead method) for optimization is a heuristic method.

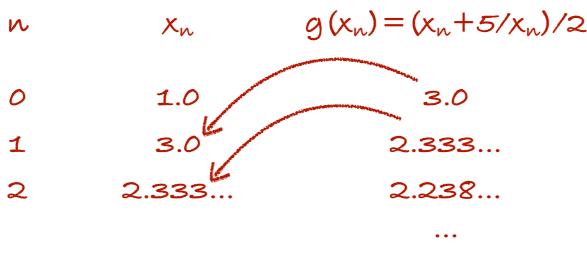
Square root by fixed-point iteration

Square root of a real number

The square root of a number A can be determined using the formula $g(x) = \frac{1}{2}\left(x + \frac{A}{x}\right)$, and using it successively. The procedure involves starting with an initial value x_0 and determining $g(x_0)$ using the formula. Now, one sets $g(x_0)$ as x_1 , and continue the process until $g(x_n)$ (the output to the formula) is the same as x_n (the input).

Example 1

■ Find the square-root of 5 by applying fixed-point iteration. Let's begin with $x_0 = 1$.





2.236068

- You can repeat these steps by a manual calculation with the help of a pocket-calculator, smart phone, or a computer.
- Now, you are ready to try these steps in Python. Try the notebook (*Chapter01_Fixed_Point_Iteration.ipynb*) provided in the course repository¹.

for loop

You can refine the simple steps given in the notebook into a neat program as follows.

Exercise 1

- Learn about Python's built-in function **range**, and **for** loops in Python.
- Learn what a Python module is. In the following, we are calling a procedure (sqrt) from a module (numpy). Learn about how to use an alias for a module or a procedure while importing in your code.

```
import numpy
print(numpy.sqrt(5))
```

2.23606797749979

Pretty print

You should always use formatted strings to display any output.

```
# Number, whose square root we want to find
A=5
# Maximum number of steps
MaxIter=4
# Start with a guess
xold=1
# Iterate
for n in range(MaxIter):
    xnew=q(xold,A)
    fstr = "{:5d} {:15.8f} {:15.8f}".format(n, xold, xnew)
    print(fstr)
    xold=xnew
           1.00000000
                            3.00000000
    0
    1
           3.00000000
                            2.33333333
           2.33333333
                            2.23809524
           2.23809524
                            2.23606890
```

- How does this code differ from the one given in the previous page?
- You may also try the following two lines to print the output in the same format.

```
output = "{val1:5d} {val2:15.8f} {val3:15.8f}"
print(output.format(val1=n, val2=xold, val3=xnew))
```

■ In this code, we have limited the number of iterations to a fixed number. Suppose we do not know how many iterations. we will require. How will you modify this code by introducing a **while** loop?

Fixed-point iteration: Statement, Algorithm, and Theorem

Statement of the method

The solution of f(x) = 0; where f(x) is single-valued, can be determined by rewriting the equation in the form x = g(x) and starting with an initial value x_0 . Then, under certain conditions, the sequence $x_1 = g(x_0), x_2 = g(x_1), \ldots$ will converge to one of the solutions of x = g(x), denoted as $x^* = \lim_{n \to \infty} x_n$.

Algorithm

- 1. Define the function g(x).
- 2. Initialize x to a real number, let's call it x_0 .
- 3. Generate the sequentially improved estimates for the root through the formula $x_{n+1} = g(x_n)$.
- 4. Stop when $|x_{n+1} x_n|$ is below a threshold and return x_n as the solution x^* .

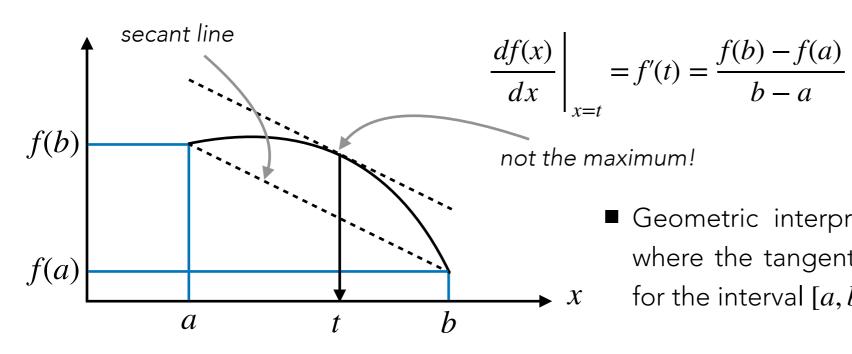
Theorems

- **Theorem 1:** The equation x = g(x) has a solution for some value of x, which we call $x^* \in [a, b]$, provided $g(x) \in C([a, b])$ has its range contained in the same closed interval [a, b].
 - The theorem does not tell us if we will have one solution (a unique solution) or the equation has multiple solutions.
- Theorem 2 (Uniqueness): If the same g(x) (obeying conditions stated above) further satisfies $|g^{(1)}(x)| \le k$ for a constant $0 \le k < 1$ in the open interval (a, b), then x = g(x) has exactly one root in [a, b].
 - The previous theorem stated that the domain of g(x) is [a,b] (and its range is also contained in this interval). Hence, if $x_0 \in [a,b]$, then $g[x_0] \in [a,b]$, and by induction $x_1, x_2, ..., x^* \in [a,b]$.
 - In both the theorems, instead of the closed interval [a,b], we can consider a symmetric interval $[x^* \delta, x^* + \delta]$, where x^* is a solution of the x = g(x), and $\delta > 0$.

Proof of the uniqueness theorem

Mean-value theorem

■ If $f(x) \in C([a,b])$, and if f(x) is differentiable in (a,b), then there is a point $t \in (a,b)$ such that



■ Geometric interpretation: There is a point $t \in (a, b)$ where the tangent of f(x) is parallel to its secant line for the interval [a, b].

Proof-by-contradiction for the uniqueness theorem

- Suppose g(x) defined in Theorem 2 has two roots p and q in [a,b]. At the roots, we have g(p) = p, and g(q) = q.
- Hence, according to the mean-value theorem there must be a point $t \in [p,q]$ such that $g'(t) = \frac{g(q) g(p)}{q p} = \frac{q p}{q p} = 1$.
- This violates our assumption that $|g^{(1)}(x)| \le k$ for some constant $0 \le k < 1$ in the open interval (p,q).

Convergence of fixed point iteration

Upper bound for the error in each iteration

- In the Textbook, Theorem1-5-3 and its corollary are proved using the mean-value theorem. This theorem states that at the n-th iteration, the upper bound for the error in the root is given by, $|x_n x^*| \le k^n(b a)$.
- So, for a given problem, if we select the domain [a,b] appropriately, and find k, we can estimate the maximum error that one can expect in each iteration.
- With the known information, $|g^{(1)}(x)| \le k$ and $0 \le k < 1$, we can find an approximate value of k. To do this, we can use (x_0, g_0) , and (x_1, g_1) and estimate k as the finite derivative $(g_1 g_0)/(x_1 x_0)$.

Example 2

Let's find the error bound for finding the square-root of 5. Let's begin with $x_0 = 1$, and assume the domain to be [1,3]. The following results are obtain using the notebook (Chapter01_Fixed_Point_Iteration.ipynb) provided in the course repository.

actual error

			in ea	in each iteration	
n	x_n	x_(n+1)	x_n-x^*	upper-bound	
0	1.00000000	3.00000000	1.23606798		
1	3.00000000	2.33333333	0.76393202		
2	2.33333333	2.23809524	0.09726536	0.11111111	
3	2.23809524	2.23606890	0.00202726	0.03703704	
4	2.23606890	2.23606798	0.00000092	0.01234568	
5	2.23606798	2.23606798	0.00000000	0.00411523	
6	2.23606798	2.23606798	0.00000000	0.00137174	
7	2.23606798	2.23606798	0.00000000	0.00045725	
8	2.23606798	2.23606798	0.00000000	0.00015242	
9	2.23606798	2.23606798	0.00000000	0.00005081	

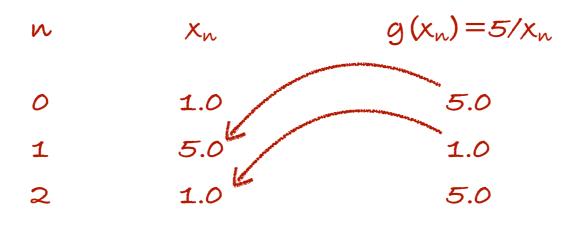
Error bound estimated using k = 0.3333

Choice of g(x) and initial guess

- To find the square root of a number, the equation we want to solve is $x = \sqrt{A} \rightarrow x^2 = A \rightarrow x^2 A = 0$. This equation is of the known form f(x) = 0. To apply fixed-point iteration (see p.9), we have to rewrite the equation in the form x = g(x). Let's look at some choices of g(x).
- Choice-1: $x^2 A = 0 \rightarrow x^2 = A \rightarrow x = A/x$. Now, $g_1(x) = A/x$.
- Choice-1: $x^2 A = 0 \rightarrow x^2 = A \rightarrow x = A/x \rightarrow 2x = x + A/x \rightarrow x = (x + A/x)/2$. Now, $g_2(x) = (x + A/x)/2$.

Example 3

■ Let's find the square-root of 5 using $x_0 = 1$ and $g_1(x)$.





Exercise 2

- To prevent the code from running indefinetly, one can estimate k and decide whether the loop should run beyond iteration, n = 1. For $g_1(x) = A/x$, we can see that k = 1 violating our assumption about g(x).
- Include such a condition in your code.
- The equation $e^{-x} + x/5 1 = 0$ is encountered in the derivation of Wien's displacement law. Write this equation in the form x = g(x) and apply fixed-point iteration. Analyse how the choice of initial value affects the convergence to a desired value of x^* for $g_1(x) = 5(1 e^{-x})$ and $g_2(x) = -\log(1 x/5)$.

Bisection method

Statement of the method

■ The equation f(x) = 0; $x \in [a, b]$ has a solution, $x^* \in [a, b]$ if f(a)f(b) < 0.

Algorithm

- 1. Determine f(a) and f(b), verify $\operatorname{sign} f(a) \neq \operatorname{sign} f(b)$. If $\operatorname{sign} f(a) = \operatorname{sign} f(b)$, exit.
- 2. Determine c = (a + b)/2.
- 3. If |a b| < threshold, $x^* = c$; else continue.
- 4. Determine f(c) and f(a)f(b).
- 5. If sign f(c) = sign f(a), set a = c, else if sign f(c) = sign f(b), set b = c.
- 6. Repeat 2, then the sequence $c_0, c_1, \dots, c_n \in [a, b]$ will converge to x^* .

Upper bound for the error in each iteration

- The upper bound for the error in the root is given by, $|x_n x^*| \le (b a)/2^n$.
- Bisection method is guaranteed to find x^* how ever with a slower convergence compared to other iterative methods. Often bisection method is used to find an initial guess for a solution in an interval.

Exercise 3

■ Write a Python program to find the square-root of 5 by solving the equation $x^2 - 5 = 0$ using the bisection method in the interval [1,3]. How many iterations does it take to reach |a - b| < 0.001 and compare with the number of iterations taken in fixed-point-iteration method to reach $|x_{n+1} - x_n| < 0.001$.

Newton-Raphson method

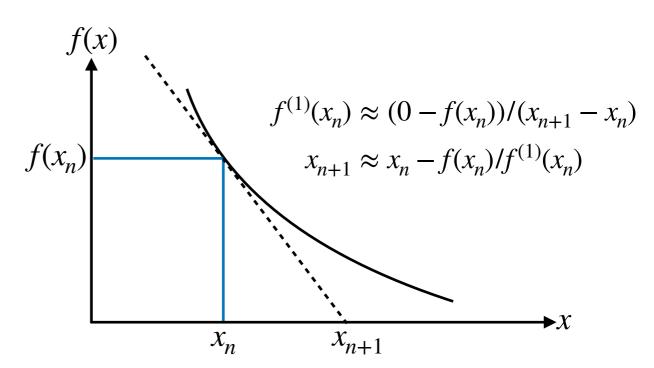
Statement of the method

- Newton-Raphson method is a variant of the fixed-point iteration method for solving f(x) = 0, in the form x = g(x) and starting with an initial value x_0 , where $g(x) = x f(x)/f^{(1)}(x)$.
- The iteration predicts x_{n+1} where the function is estimated to vanish.

Algorithm

- 1. If $f^{(1)}(x_n)$ < threshold, stop with warning.
- 2. If $|f(x_n)| < \text{threshold}$, $x^* = x_n$; else continue.

$$3. x_{n+1} = g(x_n) \Rightarrow x_{n+1} = x_n - f(x_n) / f^{(1)}(x_n).$$

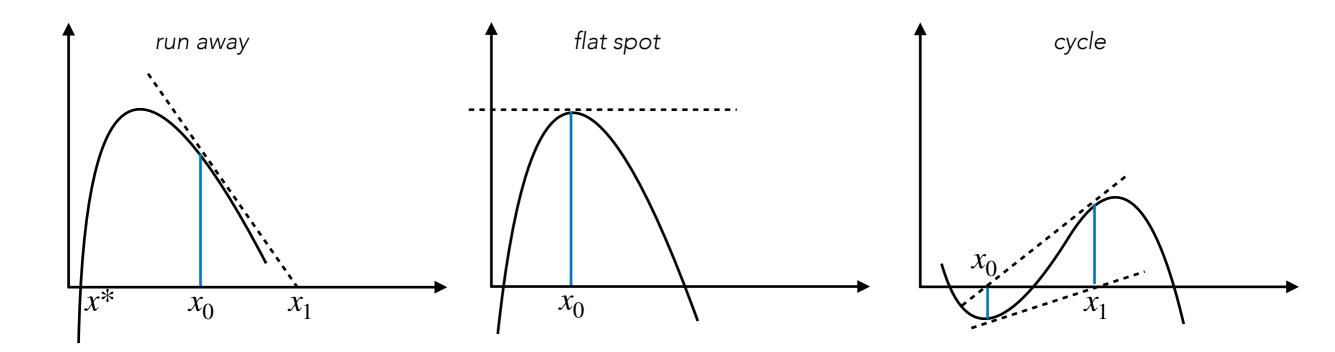


Exercise 4

- In general for the fixed point iteration method, show that $|x^* x_{n+1}| = |g^{(1)}(t)| |x^* x_n|$, where $t \in (x_n, x^*)$. Show that for the Newton-Raphson method, $|x^* x_{n+1}| = (g^{(2)}(t)/2) |x^* x_n|^2$ (i.e., the error converges quadratically).
- Write a Python program to find the square-root of 5 by solving the equation $x^2 5 = 0$ using the Newton-Raphson method starting with $x_0 = 1$. How many iterations does it take to reach $|x_{n+1} x_n| < 0.001$.
- Multiple roots: If f(x) has more than one root at $x = x^*$ (for example, $f(x) = (x x^*)^M$), then show that Newton-Raphson iteration fails to converge. Show that in this case, the modified Newton-Raphson iteration given below works

$$x_{n+1} = x_n - \frac{f(x_n)f^{(1)}(x_n)}{\left[f^{(1)}(x_n)\right]^2 - f(x_n)f^{(2)}(x_n)}$$

Problematic initial guesses for Newton-Raphson



Quasi-Newton-Raphson method (Secant method)

- Nearly in all practical applications of root-finding or minimization problems (especially in higher-dimensional problems such as geometry optimization in computational chemistry research), a variant of Newton-Raphson method, called as the quasi-Newton-Raphson method is used. In one-dimension, it is called as the Secant method.
- The word 'quasi' implies that $f^{(1)}(x)$ is estimated through finite derivatives and an explicit formula for it is not requried. This makes the method very useful for problems where the analytic derivative of f(x) is not amenable.
- Along with x_0 , the approach requires a small increment Δx , and x_1 is set as $x_0 + \Delta x$. Then, $f^{(1)}(x_1)$ is estimated as $(f(x_1) f(x_0))/\Delta x$.
- At the *n*-th iteration, $f^{(1)}(x_n)$ is estimated as $(f(x_n) f(x_{n-1}))/(x_n x_{n-1})$.

Python basics

10 things in Python to know

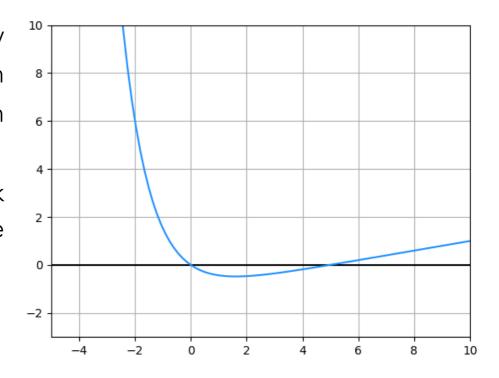
- 1. Basic datatypes in Python (int, float, complex, string)
- 2. String manipulation (splitting, splicing)
- 3. Python list (more commonly encountered datatype during string processing)
- 4. String concatenation and list appending (building larger strings)
- 5. For loop (to iterate over a list)
- 6. While loop (when the number of cycles is unknown a priori)
- 7. Break vs. continue (gracefully exiting a loop)
- 8. Functions (writing custom functions, doc string, help)
- 9. Module (importing modules, math, numpy, numpy arrays.)
- 10. Input/output (Read from/Write in a file, formatted printing)

Exercise 5

- Go through the content in (*Python_Basics.ipynb*) provided in the course repository.
- Go through the content in (*Python_NumpyBasics.ipynb*) provided in the course repository.
- Go through the content in (*Python_Matplotlib.ipynb*) provided in the course repository.

Graphical solution

- Graphically, the solution(s) of an equation can be determined by plotting f(x) = 0, and inspecting where f(x) crosses the x-axis. In fixed point iteration, we solve x = g(x), where we can plot both the L.H.S. and the R.H.S. and inspect the point(s) of intersection.
- The plots shown here were obtained using the notebook (Chapter01_Fixed_Point_Iteration.ipynb) provided in the course repository.

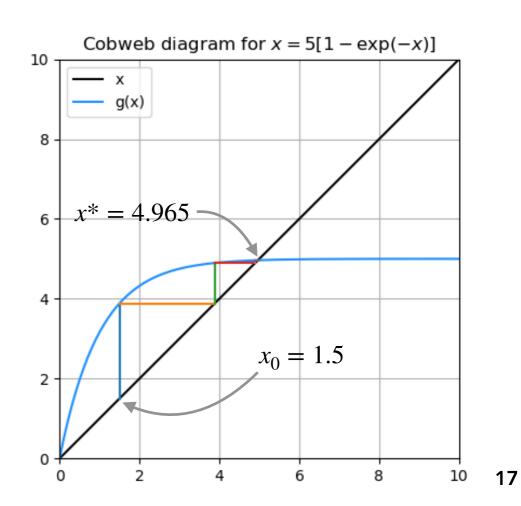


Graphical representation of fixed-point iteration using cobweb diagram

- Mark the point $\{x_0,0\}$; find $g(x_0)$, which is x_1
- Connect $\{x_0, x_0\}$ to $\{x_0, x_1\}$ (vertical line)
- Connect $\{x_0, x_1\}$ to $\{x_1, x_1\}$ (horizontal line)
- Connect $\{x_1, x_1\}$ to $\{x_1, x_2\}$ (vertical line)
- Connect $\{x_1, x_2\}$ to $\{x_2, x_2\}$ (horizontal line)
- Repeat until you Connect $\{x_{n-1}, x_n\}$ to $\{x_n, x_n\}$ (horizontal line)

Exercise 6

■ Find example equations to show using fixed-point iteration: (i) monotonous convergence, (ii) monotonous divergence, (iii) oscillatory convergence, (iv) oscillatory divergence. Present your results in the form of cobweb diagrams.





System of linear equations

Finding simultaneous solution of N equations

- We have discussed methods for solving an equation of the form f(x) = 0. Here x is a scalar variable and the function f(x) is also scalar-valued.
- Suppose we have an equation containing two variables: f(x,y) = 0, then it is possible that we may not be able to find the solution (x^*, y^*) using information contained in one equation. It may however be possible to find the solution if we have two equations in the same variables: $f_1(x,y) = 0$ and $f_2(x,y) = 0$. We call these two equations as a system of two equations in two unknowns. We can write these equations in many ways as follows:

$$f_1(x, y) = 0$$

$$f_2(x, y) = 0$$

$$\mathbf{f}(\mathbf{x}) = 0$$

Here $\mathbf{x} = [x, y]^{\mathrm{T}}$ and $\mathbf{f} = [f_1(x, y), f_2(x, y)]^{\mathrm{T}}$, where T indicates a transpose because we normally denote these vector valued variables and functions as column vectors. For simplicity, the RHS is not written in bold face, 0 indicates a 0-vector.

Finding simultaneous solution of N linear equations

If the functions involve only the first power (or lower, which is a constant) of the independent variables, we have a linear equation. For example, f(x,y) = ax + by + c. Suppose we have $f_1(x,y) = a_{11}x + a_{12}y + b_1 = 0$ and $f_1(x,y) = a_{21}x + a_{22}y + b_2 = 0$, we can write the equations in the matrix form as follows

$$f_1(x, y) = b_1$$

$$f_2(x, y) = b_2$$

$$\begin{vmatrix} a_{11} & a_{12} \\ a_{11} & a_{12} \end{vmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{vmatrix} b_1 \\ b_2 \end{vmatrix}$$

$$\mathbf{A}\mathbf{x} = \mathbf{b}$$

■ In Ch. 2, we will discuss methods to solve systems of linear equations and in Ch.3, we will discuss methods for non-linear equations.

- The formula to calculate the matrix-vector multiplication, $\mathbf{A}\mathbf{x} = \mathbf{b}$, is $b_i = \sum_j A_{i,j} x_j$. In the matrix notation, we can define b_i as $\mathbf{A}_{i,} \cdot \mathbf{x}$, where $\mathbf{A}_{i,}$ is the i-th row of \mathbf{A} and \mathbf{x} is the column vector, which we can calculate using the np.dot function. This is usually the convention we will follow.
- One can also think of $\mathbf{A}\mathbf{x}$ as a linear combination of columns of \mathbf{A} with the elements of \mathbf{x} as the linear expansion coefficient, $b_i = \mathbf{x}^T \cdot \mathbf{A}_{,j}$
- For mutliplying two matrices A and B, we will use the np.dot function as C=np.dot (A, B)

Exercise 6

- Go through the content in *Chapter02_Matrix_Computations.ipynb* provided in the course repository.
- Write a Python function for reading a matrix from a file if the elements are listed sequentially, one below another. Use reshape function to convert a 1D array into a 2D array (matrix).

Exercise 7

- As you have seen in the example code, the computational complexity of addition of two matrices is $\mathcal{O}(N^2)$, and for multiplication it is $\mathcal{O}(N^3)$. Write Python functions to
 - (1) add two circulant matrices with a computational complexity of $\mathcal{O}(N)$, i.e., a linear scaling procedure.
 - (2) multiply two circulant matrices with a computational complexity of $\mathcal{O}(N^2)$, i.e., a quadratically scaling procedure.

You can figure out the definition of a circulant matrix by printing a square Toeplitz matrix using the scipy.linalg.toeplitz function and passing the first row of the matrix as the argument.

 $[4, 3, 2, 1]])_{20}$