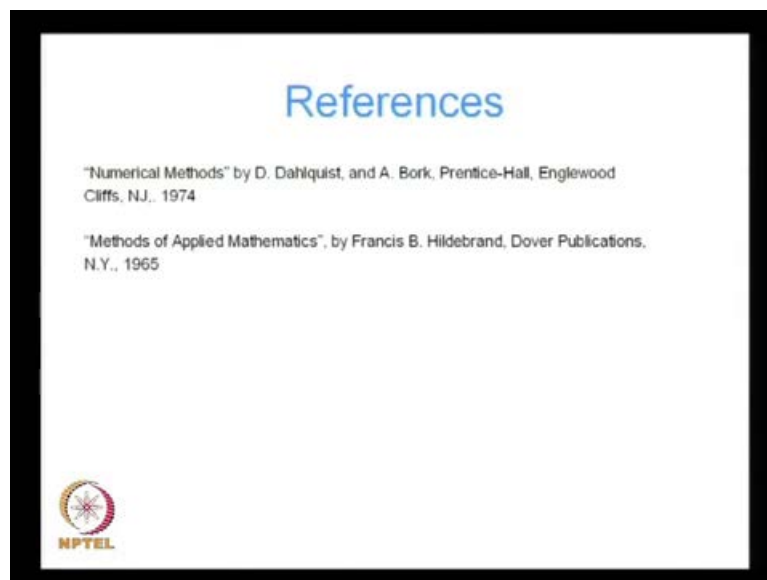


Numerical Methods in Civil Engineering
Prof. Arghya Deb
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Indian Institute of Technology, Kharagpur

Lecture - 1
Introduction to Numerical Methods

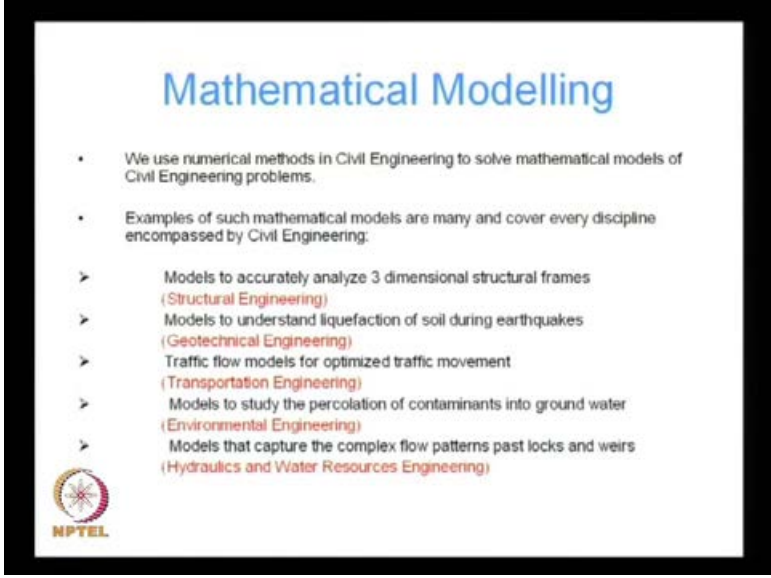
First numerical method in civil engineering, in the first lecture I am going to talk about introduction to numerical methods.

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Before, going into further details, I would like to mention two references, which I am going to follow throughout this course, the first reference is numerical methods by Dahlquist and Birk, the second reference is methods of applied mathematics by Hildebrand.

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Mathematical Modelling

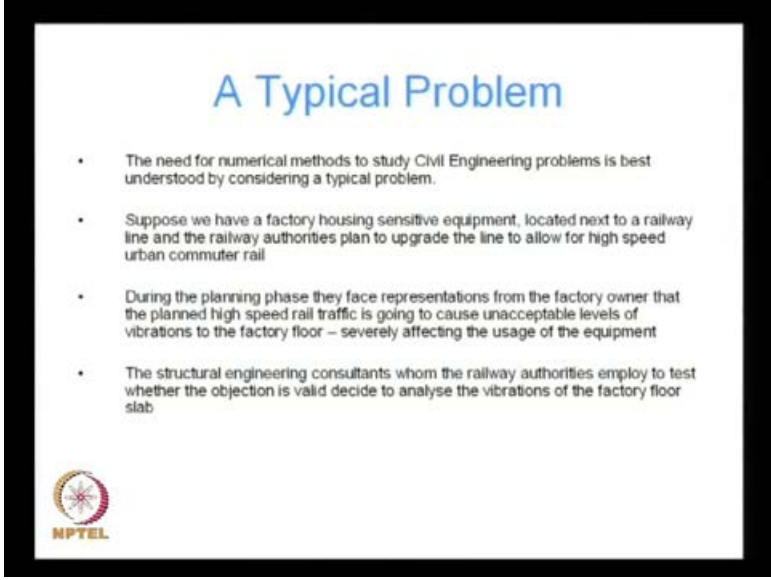
- We use numerical methods in Civil Engineering to solve mathematical models of Civil Engineering problems.
- Examples of such mathematical models are many and cover every discipline encompassed by Civil Engineering:
 - Models to accurately analyze 3 dimensional structural frames
(Structural Engineering)
 - Models to understand liquefaction of soil during earthquakes
(Geotechnical Engineering)
 - Traffic flow models for optimized traffic movement
(Transportation Engineering)
 - Models to study the percolation of contaminants into ground water
(Environmental Engineering)
 - Models that capture the complex flow patterns past locks and weirs
(Hydraulics and Water Resources Engineering)

 NPTEL

First I would like to talk about why it is necessary to do mathematical modeling, we use numerical methods in civil engineering to solve mathematical models of civil engineering problems. Examples of such mathematical models are many and cover every discipline encompassed by civil engineering, for instance in structural engineering, we need models to accurately, analyze dimensional structural frames. In geotechnical engineering, we need models to understand liquefaction of soil during earthquakes transportation station engineering for instance.


We used traffic flow models for optimized traffic movement an environmental engineering, we use models to study, the percolation of contaminants into ground water. And in hydraulics and water resources engineering, we use models that capture the complex flow patterns past locks and weirs.

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A Typical Problem

- The need for numerical methods to study Civil Engineering problems is best understood by considering a typical problem.
- Suppose we have a factory housing sensitive equipment, located next to a railway line and the railway authorities plan to upgrade the line to allow for high speed urban commuter rail
- During the planning phase they face representations from the factory owner that the planned high speed rail traffic is going to cause unacceptable levels of vibrations to the factory floor – severely affecting the usage of the equipment
- The structural engineering consultants whom the railway authorities employ to test whether the objection is valid decide to analyse the vibrations of the factory floor slab

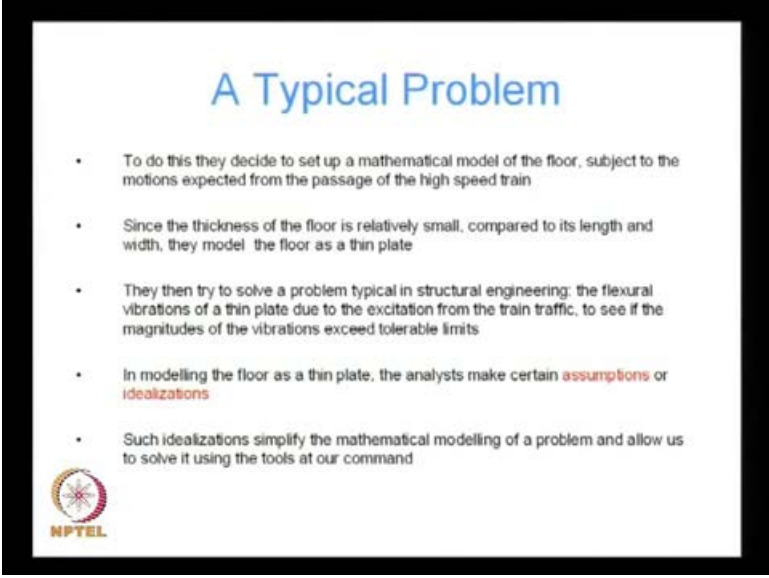


NPTEL

The need for numerical methods to study civil engineering problems is best understood by considering a typical problem, since I am a structural engineer I will choose a typical problem from the field of structural engineering. Suppose we have a factory housing sensitive equipment, located next to a railway line and the railway authorities plan to upgrade the line to allow for high speed urban commuter rail.


During the planning phase they face representations from the factory owner, that the planned high speed rail traffic is going to cause unacceptable levels of vibrations to the factory floor, severely affecting the usage of the equipment. The structural engineering consultants whom the railway authorities employ to test, whether the objection is valid decide to analyze the vibrations of the factory floor slab.

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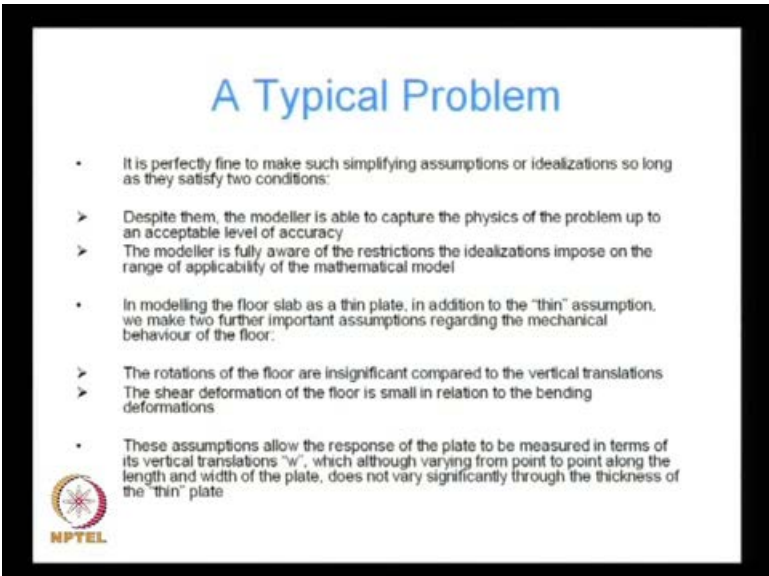
A Typical Problem

- To do this they decide to set up a mathematical model of the floor, subject to the motions expected from the passage of the high speed train
- Since the thickness of the floor is relatively small, compared to its length and width, they model the floor as a thin plate
- They then try to solve a problem typical in structural engineering: the flexural vibrations of a thin plate due to the excitation from the train traffic, to see if the magnitudes of the vibrations exceed tolerable limits
- In modelling the floor as a thin plate, the analysts make certain **assumptions or idealizations**
- Such idealizations simplify the mathematical modelling of a problem and allow us to solve it using the tools at our command




To do this they decide to set up a mathematical model of the floor subject to the motions, expected from the passage of the high speed train, Since the thickness of the floor is relatively small compared to its length. And width they model the floor as a thin plate, then they try to solve a problem, typical in structural engineering the flexural vibrations of a thin plate, due to the excitations from the train traffic, to see if the magnitudes of the vibrations exceed tolerable limits. In modeling the floor as a thin plate the analysts make certain assumptions or idealizations such idealizations, simplify the mathematical modeling of a problem and allow us to solve it using the tools at our command.

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A Typical Problem

- It is perfectly fine to make such simplifying assumptions or idealizations so long as they satisfy two conditions:
 - Despite them, the modeller is able to capture the physics of the problem up to an acceptable level of accuracy
 - The modeller is fully aware of the restrictions the idealizations impose on the range of applicability of the mathematical model
- In modelling the floor slab as a thin plate, in addition to the "thin" assumption, we make two further important assumptions regarding the mechanical behaviour of the floor:
 - The rotations of the floor are insignificant compared to the vertical translations
 - The shear deformation of the floor is small in relation to the bending deformations
- These assumptions allow the response of the plate to be measured in terms of its vertical translations "w", which although varying from point to point along the length and width of the plate, does not vary significantly through the thickness of the "thin" plate



It is perfectly fine to make such simplifying assumptions or idealizations, so long as they satisfy two conditions, first despite them the modeler is able to capture, the physics of the problem up to an acceptable level of accuracy. Two, the modeler is fully aware of the restrictions, the idealizations impose on the range of applicability of the mathematical model.

In modeling the first floor slab as a thin plate, in addition to the thin assumption we make two further important assumptions regarding the mechanical behavior of the floor. First the rotations of the floor are insignificant compared to the vertical translations to the shear deformation of the floor is small in relation to the bending deformations. These assumptions allow the response of the plate to be measured in terms of its vertical translations w , which although varying from point to point along the length and width of the plate does not vary significantly, through the thickness of the thin plate.


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A Typical Problem

- The mathematical model can then be written in terms of the vertical translations w as a function of the planar coordinates x, y , and time, t
- Thus $w = w(x, y, t)$ satisfies the following equation which governs the flexural vibrations of thin plates (see e.g. Meirovitch, "Fundamentals of Vibrations").

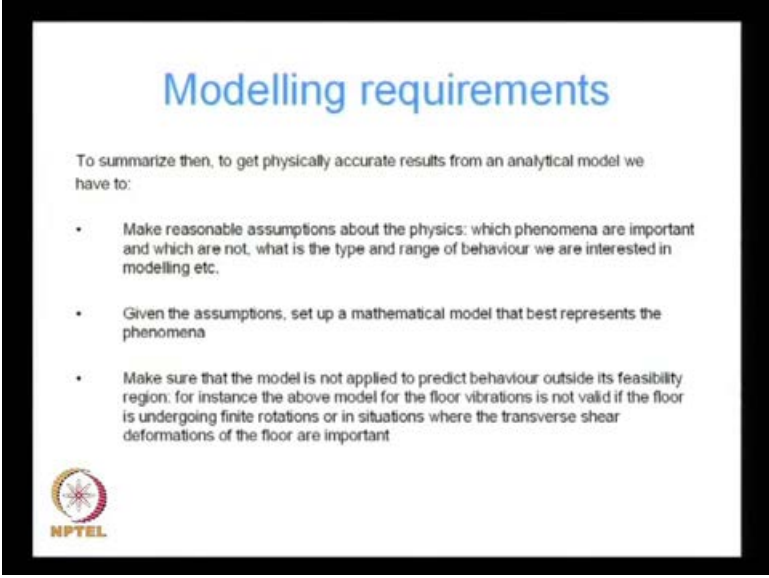
$$-\left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}\right) \left[D(x, y) \left(\frac{\partial^2 w(x, y, t)}{\partial x^2} + \frac{\partial^2 w(x, y, t)}{\partial y^2} \right) \right] + f(x, y, t) = m(x, y) \frac{\partial^2 w(x, y, t)}{\partial t^2}$$

w is the vertical translation, f the applied load
 m the mass of the plate, D the flexural rigidity



The mathematical model can then be written in terms of, the vertical translations w as a function of the planar coordinates x, y and time t , thus w where w is the function of x, y and t . Satisfies the following equation which governs the flexural vibrations of thin plates.


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Modelling requirements

To summarize then, to get physically accurate results from an analytical model we have to:

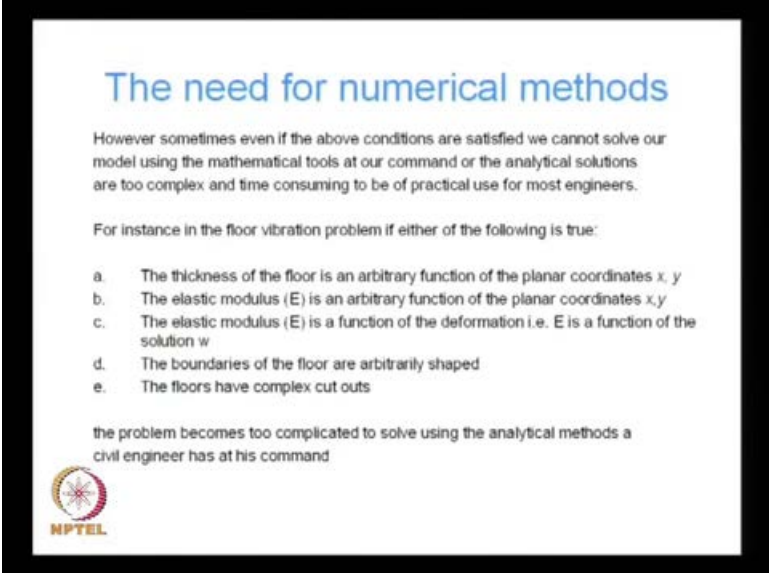
- Make reasonable assumptions about the physics: which phenomena are important and which are not, what is the type and range of behaviour we are interested in modelling etc.
- Given the assumptions, set up a mathematical model that best represents the phenomena
- Make sure that the model is not applied to predict behaviour outside its feasibility region: for instance the above model for the floor vibrations is not valid if the floor is undergoing finite rotations or in situations where the transverse shear deformations of the floor are important

 NPTEL

To summarize then to get physically accurate results from an analytical model, we have to one make reasonable assumptions about, the physics which phenomena are important. And which are not, what is the type and range of behavior, we are interested in modeling etcetera given the assumptions, set up a mathematical model that best represents the phenomena.

Finally, make sure that the model is not applied to predict behavior outside its feasibility region, for instance the above model for the floor vibrations is not valid, if the floor is undergoing finite rotations or in situations where the transverse shear deformations of the floor are important.

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The need for numerical methods

However sometimes even if the above conditions are satisfied we cannot solve our model using the mathematical tools at our command or the analytical solutions are too complex and time consuming to be of practical use for most engineers.

For instance in the floor vibration problem if either of the following is true:

- a. The thickness of the floor is an arbitrary function of the planar coordinates x, y
- b. The elastic modulus (E) is an arbitrary function of the planar coordinates x, y
- c. The elastic modulus (E) is a function of the deformation i.e. E is a function of the solution w
- d. The boundaries of the floor are arbitrarily shaped
- e. The floors have complex cut outs

the problem becomes too complicated to solve using the analytical methods a civil engineer has at his command



However sometimes even if the above conditions are satisfied, we cannot solve our model using the mathematical tools, at our command or the analytical solutions are too complex. And time consuming to be a practical use for most engineers, for instance in the floor vibration problem, if either of the following is true, either the thickness of the floor is an arbitrary function of the planar coordinates x and y .

The elastic modulus is an arbitrary function of the planar coordinates x and y , the elastic modulus is a function of the deformation, that is e is a function of the solution w the boundaries, of the floor are arbitrarily shaped or the floors have complex cut outs the problem, becomes too complicated to solve using the analytical methods a civil engineer has at his command.

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The need for numerical methods


In such situations the problem can only be solved through the use of numerical methods

The complications enumerated above are instances of :

- Complex geometry
- Geometrical and material nonlinearities

two typical scenarios where numerical methods find application in solving otherwise intractable analytical models of civil engineering problems.

For instance for the floor vibration problem, the consultants will probably use either the finite element or finite difference method, two popular numerical techniques for solving partial differential equations, to solve their problem.



In such situations the problem can only be solved through the use of numerical methods, the complications enumerated above are instances of a, complex geometry geometrical and material nonlinearities, two typical scenarios where numerical methods. Find application in solving otherwise intractable analytical models of civil engineering problems, for instance for the floor vibration problem, the consultants will probably use either the finite element or finite difference method, two popular numerical techniques for solving partial differential equations to solve their problem.

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Choosing a numerical method

Before starting to talk in any detail about numerical methods in particular it is appropriate at this stage to make a distinction between a numerical method and a numerical algorithm.

Given the mathematical description of a problem, a numerical method lays down the broad approach to be adopted to solve the problem numerically.

For instance for the floor vibration problem, if we wish to use the finite difference method we would begin by writing the finite difference form (an approximation) of the derivatives appearing in the governing differential equation

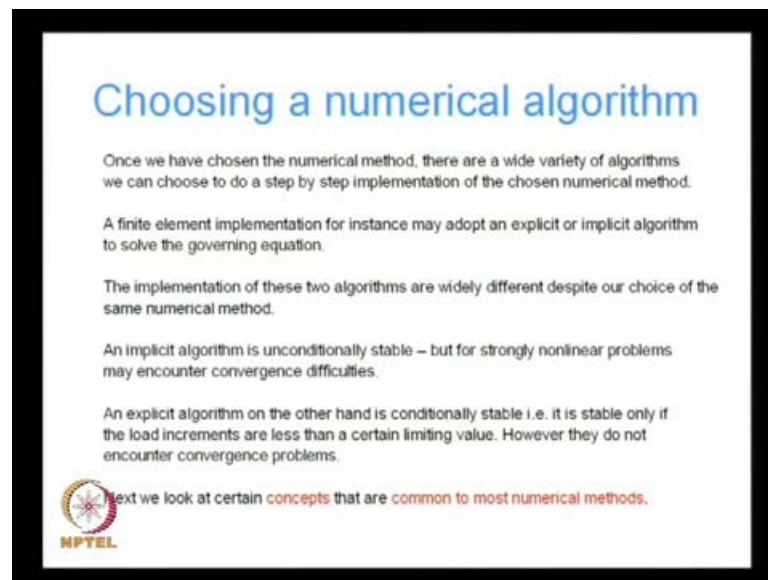
On the other hand, if we wish to use the finite element method, we would start with trying to construct finite dimensional trial and test functions to approximate the exact solution w of the above problem



Before starting to talk in any detail about numerical methods in particular, it is appropriate at this, stage to make a distinction between a numerical method and a numerical algorithm. Given the mathematical description of a problem a numerical method lays down, the broad approach to be adopted to solve the problem numerically, for instance for the floor vibration problem.

If we wish to use the finite difference method, we would begin by writing the finite difference from which is an approximation of the derivatives appearing in the governing differential equation. On the other hand, if we wish to use the finite element method, we would start with trying to construct finite dimensional trial and test functions to approximate, the exact solution w of the above problem.

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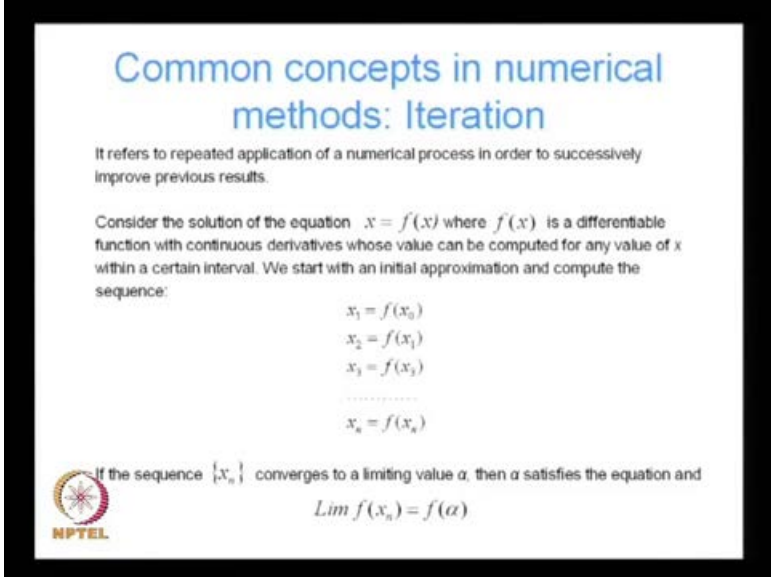


Once we have chosen a numerical method there are a wide variety of algorithms, we can choose to do a step by step implementation of the chosen numerical method. A finite element implementation for instance may adopt an explicit or implicit algorithm, to solve the governing equation. The implementation of these two algorithms are widely different, despite our choice of the same numerical method, that is the finite element method an implicit algorithm is unconditionally stable.

But, for strongly non-linear problems, may encounter convergence difficulties an explicit algorithm, on the other hand is conditionally stable, that is it is stable only if the load increments are less than a certain limiting value, however, they do not encounter

convergence problems next we would look like, we would like to look at certain concepts that are common to most numerical methods.

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Common concepts in numerical methods: Iteration


It refers to repeated application of a numerical process in order to successively improve previous results.

Consider the solution of the equation $x = f(x)$ where $f(x)$ is a differentiable function with continuous derivatives whose value can be computed for any value of x within a certain interval. We start with an initial approximation and compute the sequence:

$$\begin{aligned}x_1 &= f(x_0) \\x_2 &= f(x_1) \\x_3 &= f(x_2) \\&\dots\dots\dots \\x_n &= f(x_{n-1})\end{aligned}$$

If the sequence $\{x_n\}$ converges to a limiting value α , then α satisfies the equation and

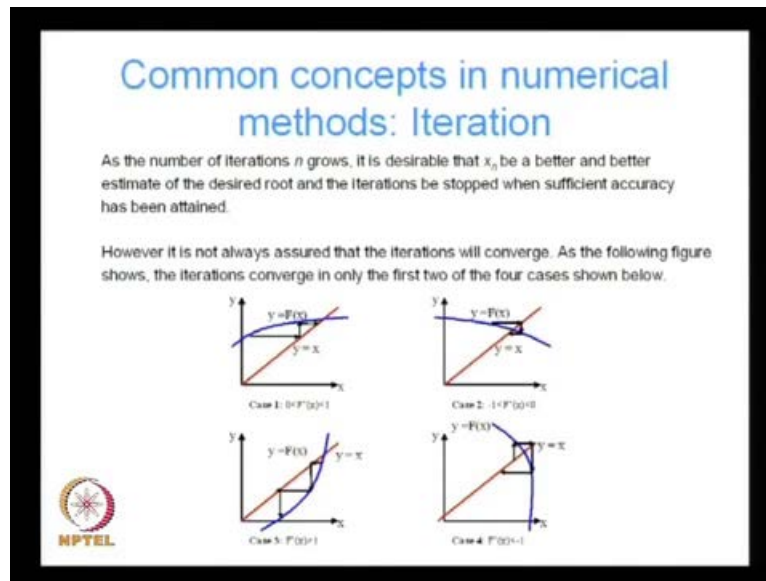
$$\lim_{n \rightarrow \infty} f(x_n) = f(\alpha)$$

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The first concept, that we wish to examine is the idea of iteration, it refers to repeated application of numerical process in order to successively improve previous results. Consider the solution of the equation x is equal to f of x , where f of x is a differentiable function with continuous derivatives, whose value can be computed for any value of x within a certain interval. We start with an initial approximation and compute the sequence, we start with the initial approximation x_0 and substituting x_0 , in the and expression for f of x we compute the value x_1 .

We use the new value x_1 , again in the equation for f of x to come up with the next iterate x_2 and so on, and so forth, until we get f of x_{n-1} , which is equal to x_n , if the sequence x_n converges to a limiting value α then α satisfies, the equation and limit limiting value of f of x_n is equal to f of α . So, α is the root of this equation.

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As the number of iterations n grows, it is desirable that x_n be a better and better estimate of the desired root and the iterations be such stopped, when sufficient accuracy has been attained. However, it is not always assured that the iterations will converge as the following figure shows, the iterations converge in only the first two of the four cases shown below.

We start with an initial assumption and in case 1 and case 2, we converge to the true solution which is where the blue curve intersects, the red curve. In case 3 and 4, we can see that even, if we start near these two solutions are iteration process, takes us away from the root of the true solution.

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Common concepts in numerical methods: Iteration

In Case 1 and Case 2, the solution becomes closer and closer to the root as n increases while in Cases 3 and 4 the solution moves farther and farther away from the root as n increases.

The reason for this is clear from the following. From the iteration algorithm:

$$x_{n+1} - x_n = F(x_n) - F(x_{n-1})$$

Dividing both sides by $x_n - x_{n-1}$ we get:

$$\frac{x_{n+1} - x_n}{x_n - x_{n-1}} = \frac{F(x_n) - F(x_{n-1})}{x_n - x_{n-1}}$$

But using the Mean Value Theorem,

$$F(x_n) - F(x_{n-1}) = (x_n - x_{n-1})F'(\xi), \quad \xi \in [x_{n-1}, x_n]$$

Thus convergence is faster i.e. $|F(x_n) - F(x_{n-1})|$ is smaller the smaller $|F'(\xi)|$ in the neighbourhood of the root.

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In case 1 and case 2, the solution becomes closer and closer to the root as n increases, while in cases 3 and 4 the solution moves farther and farther away from the root as n increases. The reason for this is clear from the following from the iteration algorithm, we can write $x_{n+1} - x_n$ is equal to $f(x_n) - f(x_{n-1})$, we called that according to algorithm x_{n+1} is equal to $f(x_n)$ and x_n is equal to $f(x_{n-1})$, dividing both sides by $x_n - x_{n-1}$, we get the following.

But, using the mean value theorem, we can write $f(x_n) - f(x_{n-1})$ is equal to $(x_n - x_{n-1})$ times the derivative of f evaluated at a value ξ , where ξ lies in the interval x_{n-1} and x_n . Thus looking at the last equation it is clear, that convergence is faster that is the modulus of $f(x_n) - f(x_{n-1})$ is smaller, the smaller $f'(\xi)$ is in the neighborhood of the root, $f(x_n)$ will be closer to $f(x_{n-1})$, that is the iterates are going to convert faster the smaller is the value of the derivative $f'(\xi)$.

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Common concepts in numerical methods: Iteration

If $|F'(\xi)| < 1$ for all x in the neighbourhood of the starting iterates x_0 and x_1 , and this neighbourhood includes the root, we can be sure of convergence

This is true in Cases 1 and 2 above where $0 < F'(x) < 1$ and $-1 < F'(x) < 0$


On the other hand, if the magnitude of the slope is greater than one near the root $|F'(a)| > 1$, x_n converges to a only in exceptional cases, no matter how close to one chooses the starting point x_0 (x_0 not equal to a)

This can be proved as follows:

$$x_2 = x_1 + (x_1 - x_0)F'(\xi_1) \quad x_0 < \xi_1 < x_1$$

$$x_3 = x_2 + (x_2 - x_1)F'(\xi_2) \quad x_1 < \xi_2 < x_2$$

$$= x_1 + (x_1 - x_0)F'(\xi_1) + (x_1 - x_0)F'(\xi_1)F'(\xi_2)$$



If $|f'(x_i)|$ is less than 1 for all x in the neighborhood of the starting iterates x_0 and x_1 and this neighborhood includes the root, we can therefore, be sure of convergence. This is true in cases 1 and 2 above, where $f'(x)$ is always greater than 0 and less than 1 in case of case 1 and $f'(x)$ is greater than minus 1 and less than 0 in case of case 2, thus we can see that in case 1 and case 2 $|f'(x_i)|$, the mod of $f'(x_i)$ will always be less than 1.

On the other hand, if the magnitude of the slope is greater than 1 near the root, that is $|f'(a)| > 1$, x_n converges to a only in exceptional cases no matter, how close to a one chooses the starting point x_0 , for instance in case 3 and case 4 even though, we have actually started quite close to the root, you can see that we are moving away from the trial solution, this is because the slope at the root is greater than 1.

The absolute value of the slope at the root is greater than 1, thus as we iterate we move further and further away from the trial solution, while in case in case 1 and case 2, as we iterate we move closer and closer to the trial solution. We can come up with a quick mathematical proof for this can be proved as follows, we can write x_2 is equal to x_1

plus x_1 minus x_0 times f' of ξ_1 again according to the mean value theorem provided ξ_1 lies between x_0 and x_1 . Similarly, we can write x_3 is equal to x_2 plus x_2 minus x_1 times f' of ξ_2 , where ξ_2 lies between x_1 and x_2 , using the first equation in the second, we can write x_3 in terms of x_1 x_0 and the derivatives f' at ξ_1 and ξ_2 .

Using the same idea by induction for any iterate, we can write the following for instance x_{n-1} , we can write in terms of x_1 and x_0 , according to this equation to the first equation. Similarly x_n , we can write in terms of x_1 and x_0 , according to the second equation subtracting, the second equate the first equation from the second equation, we get this equation x_n minus x_{n-1} is equal to x_1 minus x_0 times f' of ξ_{n-1} times f' of ξ_{n-2} times up, which is the series extending up to f' of ξ_1 .

Thus we can see that if the magnitude of f' of ξ_i is less than 1 for all i modulus of x_n minus x_{n-1} , becomes smaller and smaller for large values of n and the iteration converges, f' of ξ_{n-1} will be less than f' of ξ_{n-2} times, f' of ξ_{n-3} up to f' of ξ_{n-1} and so on and so forth. As the as we add more and more terms the right hand side, becomes smaller and smaller and the left hand side converges.

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Common concepts in numerical methods: Iteration

Let us consider two implementations of the above iterative scheme for calculating the square root of a positive real number c , i.e. we want to find the roots of the equation:


$$x^2 = c$$

Implementation A
 To do this, we first write $x^2 = c$ in the form $x = f(x)$ e.g. $f(x) = \frac{1}{2}(x + \frac{c}{x})$
 The root is $\alpha = c^{1/2}$. Also,

$$F'(x) = \frac{1}{2} - \frac{c}{2x^2}$$

$$\therefore F'(\alpha) = 0$$

Hence, $|F'| < 1$ in a neighborhood of the root since F' is continuous
 For $c = 2$, and $x_0 = 1.5$, our iterative scheme converges in 2-3 iterations!
 $x_0 = 1.5, x_1 = 1.4167, x_2 = 1.414216 \dots$



Next, let us consider two implementations of the above iterative scheme for calculating the square root of a positive real number c , that is we want to find the roots of the equation $x^2 = c$. We look at the first implementation where we write f of x , as f of x is equal to half x plus c of x , the root obviously is α is equal to c of half, c to the power half, also it is clear that f prime of x the derivative of f of x is half minus c by $2x^2$.

Therefore at the root α f prime of α is equal to 0, hence mod of f prime is less than 1 in a neighborhood of the root actually, it is 1 in a neighborhood of at the root and in at the neighborhood of the root, it has to be they must they must exist a neighborhood of the root, where mod of f prime is less than 1. Since, f prime of x is a continuous function for c is equal to 2 and with us starting case of x_0 is equal to 1 point 5 are iterative scheme converges in 2 to 3 iterations. We start with the x_0 is equal to 1 point 5 and by the time, we reach iteration number 2, we can see we are really close to the true solution which is root 2, 1 point 4 1 4.

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Common concepts in numerical methods: Iteration

Implementation B
 In this case we write $x^2 = c$ in the form $x = f(x)$ with $f(x) = \frac{c}{x}$

For $c = 2$, and $x_0 = 1.5$, our iterative scheme,


$$x_{n+1} = \frac{c}{x_n} \text{ gives :}$$

$$x_0 = 1.5, x_1 = 1.333333, x_2 = 1.5 \dots$$

The sequence does not converge.

If one thinks of successive approximation or iteration as the 'numerical method' adopted to find a numerical solution to the problem $x^2 = 2$, it is obvious that our choice of implementation i.e. the 'algorithm' is crucial for the success of the method!

This is true for numerical methods in general.

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On the other hand, if we consider implementation b in which case we write f of x is equal to c by x for c is equal to 2 and x is equal to 1 point 5 are iterative scheme, which recall is $x_{n+1} = \frac{c}{x_n}$ is equal to f of x_n , which is equal to c by x_n gives x_0 is equal to 1 point 5 x_1 is equal to 1 point 3 point 3 x_2 is equal to 1 point 5. So, it oscillates right the equate the sequence does not converge, If one thinks of successive approximation or

iteration as the numerical method, adopted to find a numerical solution to the problem x^2 equal to 2.

It is obvious that our choice of implementation, that is the algorithm is crucial for the success of the method, the first implementation converged in two iterations by the second implementation is never going to converge, this is true for numerical methods in general.

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The slide features a title in blue text: "Common concepts in numerical methods: Linear Approximation". Below the title, it states: "Another common concept consists of locally approximating a complicated function by its linear approximation". It then poses the problem: "Suppose we wish to find the root of the equation $f(x) = 0$ ". Geometrically, it explains this as finding x where the curve $y=f(x)$ meets the x -axis. A graph shows a red curve $y=f(x)$ and a blue tangent line intersecting the x -axis at x_1 . A vertical dashed line marks x_2 on the x -axis. The NPTEL logo is in the bottom left corner.

Another commonly used technique in numerical methods is linear approximation here, we locally approximate a complicated function by its linear approximation. Suppose, we wish to find the root of the equation $f(x) = 0$, geometrically this means finding x , for which the curve $y = f(x)$ intersects the x axis. So, we start with the starting, case x_0 and then use a numerical method an algorithm to try to reach the solution, which is where the red curve intersects the x axis.

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Common concepts in numerical methods: Linear Approximation


The most well known method for solving this problem, the Newton Raphson method, consists of an iterative scheme where at each successive iteration, we approximate the function $y=f(x)$ by its tangent at that point, and use that to find the next iterate:

$$x_{n+1} = x_n + \frac{f(x_n)}{f'(x_n)}$$

The next iterate x_{n+1} is the point where the linear approximation to the function $y=f(x)$ given by the straight line passing through $(x_n, f(x_n))$ and with slope $f'(x_n)$ intersects the X axis.

The approximation of $y=f(x)$ by its tangent at the point $(x_n, f(x_n))$ is equivalent to replacing the function with the first degree terms in its Taylor series about $x=x_n$.

If instead of approximating the function locally by its tangent we approximate it by the secant connecting two neighboring points on the curve, we have what is known as a secant method.



The most well-known method for solving this problem, the Newton rap son method consists of an iterative scheme, where at each successive iteration. We approximate the function y is equal to f of x by its tangent, at that point and use that to find the next iterate, for instance at x_0 , we have approximated the true the curve y is equal to f of x by the blue line, the blue line being the tangent to the function y is equal to f of x I take x_0 , where the blue line meets the x axis that gives me by next iterate x_1 .

So, x_{n+1} I can write as $x_n + f$ of x_n divided by f prime of x_n , the next iterate x_{n+1} being the point, where the linear approximation of the function y is equal to f of x given by the straight line, passing through x_n and f of x_n with slope f prime of x_n intersects, the x axis. The approximation of y is equal to f of x by its tangent at the point x_n, f of x_n is equivalent to replacing, the function with the first degree terms in its Taylor series about x is equal to x_n .

If instead of approximating the function locally by its tangent, we approximate it by the secant connecting two neighboring points on the curve, we have what is known as a secant method, which is another commonly used method for linear approximation of a non-linear function.

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Common concepts in numerical methods: Linear Approximation

In the secant method, given the iterates x_n and x_{n-1} , as well as the function values $f(x_n)$ and $f(x_{n-1})$ we find the next iterate using the following update formula:

$$x_{n+1} = x_n - f(x_n) \frac{x_n - x_{n-1}}{f(x_n) - f(x_{n-1})}$$

At $x = x_{n+1}$, the local linear approximation to the curve $y=f(x)$ intersects the x axis.

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In the secant method given the iterates x_n and x_{n-1} , as well as the function values $f(x_n)$ and $f(x_{n-1})$, we find the next iterate using the following update formula. At $x = x_{n+1}$ the local linear approximation to the curve $y = f(x)$ intersects the x axis. As you can see we have tried to fit a line through the values of the function at iterate x_{n-1} , which is $f(x_{n-1})$ and x_n which is $f(x_n)$. And then where the line meets the x axis, that is going to give me by next iterate x_{n+1} .

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Common concepts in numerical methods: Recursion formula

Suppose we wish to solve numerically the differential equation

$$\frac{dy}{dx} = f(x, y) \text{ with initial condition } y(0) = p$$

According to the above equation the slope of y changes from point to point. The simplest approximate solution to the problem discretizes the problem domain into equal sized increments of size h with function values $y_0, y_1, y_2, \dots, y_n$ corresponding to x values of $h, 2h, 3h, \dots, nh$.

It is also assumed that the slope remains constant between the points and the slope of the curve between $(n-1)h$ and nh is evaluated as: $\frac{y_{n+1} - y_n}{h}$

Substituting this value of the slope in the differential equation, we have:

$$\frac{y_{n+1} - y_n}{h} = f(nh, y_n)$$

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The third common numerical concept that we wish to talk about is the idea of recursion, suppose we wish to solve numerically the differential equation $\frac{dy}{dx} = f(x, y)$

with initial condition y_0 is equal to p . According to the above equation, the slope of y changes from point to point, the simplest approximate solution to the problem discreteness, the problem domain into equal sized increments of size h with function values y_0, y_1, y_2 and y_n , corresponding to x values of $h, 2h, 3h$ and $n h$.

So, at x is equal to 0 , we have y is equal to y_0 at x is equal to h , we have y equal to y_1 , at x is equal to $2 h$, we have y equal to y_2 and so on and so forth. It is also assumed that the slope remains, constant between the points and the slope of the curve, between n minus $1h$ and $n h$ for instance is evaluated as $y_{n+1} - y_n$ divided by h . Substituting this value of the slope in the differential equation, we have $y_{n+1} - y_n$ divided by h is equal to $f(n h, y_n)$, which is the value of x and y_n which is the value of y . (Refer Slide Time 29:33)

Common concepts in numerical methods: Recursion formula

This yields the recursion formula:


$$y_{n+1} = y_n + f(nh, y_n)h, \quad n = 0, 1, 2, \dots$$

During the computation, each y_n occurs first on the left hand side then recurs on the right hand side of the equation. Hence the above relation is called a recursion formula.

Iteration, linear approximation and recursion are methods which are widely used throughout the field of numerical analysis.

Often a numerical method may involve several iterative schemes, linear approximations or recursions.

However the success of these schemes is measured in terms of their ability to come up with **accurate** and **stable** solutions.

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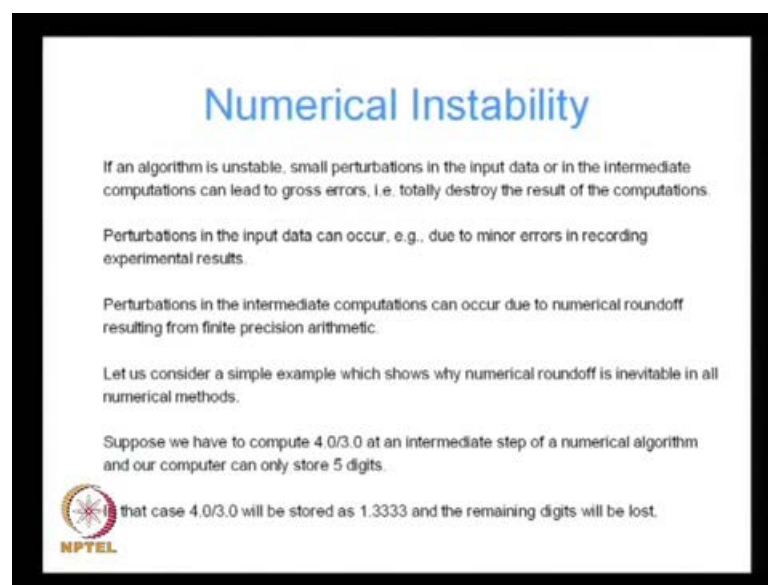
We can rewrite this equation to yield the recursion formula, we can rewrite the previous equation by keeping y_{n+1} , on the left hand side and moving the other terms to the right hand side So, y_{n+1} is equal to $y_n + f(n h, y_n) h$, this is going to be true for all values of n , n is equal to $0, 1, 2$ and so and so forth, from this equation you can see that each y_n occurs first on the left hand side, then recurs on the left hand on the right hand side of the equation, hence the above relation is called a recursion formula.

So, if we know a starting value for y , if we know y_0 for instance using this recursion formula, we can successively calculate y_1, y_2, y_3 up to y_n . And we can continue the recursion process, until my recursion formula converges that is until my value $y_{n+1} - y_n$ is

1, becomes equal to y_n iteration linear approximation and recursion are methods, which are used widely throughout the field of numerical analysis, often a numerical method may involve several iterative schemes linear approximations or recursions.

However the success of these schemes is measured in terms of their ability to come up, with accurate and stable solutions accuracy and stability are two prerequisites of any successful, numerical algorithm in the following we are going to talk about each of these concepts in greater detail. We will start with talking about the notion of stability, following which we will talk in greater detail about accuracy.

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Numerical Instability

If an algorithm is unstable, small perturbations in the input data or in the intermediate computations can lead to gross errors, i.e. totally destroy the result of the computations.


Perturbations in the input data can occur, e.g., due to minor errors in recording experimental results.

Perturbations in the intermediate computations can occur due to numerical roundoff resulting from finite precision arithmetic.

Let us consider a simple example which shows why numerical roundoff is inevitable in all numerical methods.

Suppose we have to compute $4.0/3.0$ at an intermediate step of a numerical algorithm and our computer can only store 5 digits.

In that case $4.0/3.0$ will be stored as 1.3333 and the remaining digits will be lost.

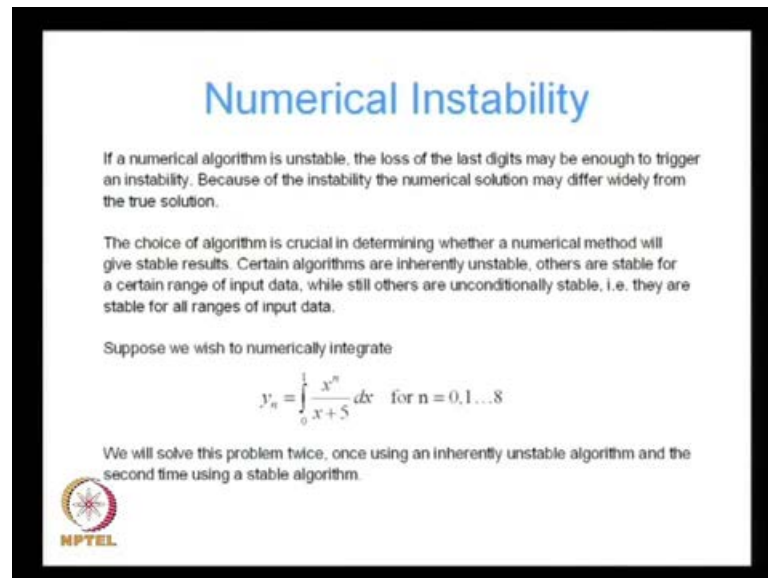
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What do we mean by numerical instability, if a numerical algorithm is unstable small perturbations in the input data or in the intermediate computations can lead to gross errors, that is they totally destroy the result of the computations. Perturbations on the input data in the input data can occur for instance, due to minor errors in recording experimental results.

If the input data to a numerical algorithm is experimental data and there are minor errors in the experiment which are always present, then if it is an unstable algorithm those minor perturbations can give me totally erroneous results. Perturbations in the intermediate computations, can occur due to numerical round off resulting from finite precision arithmetic.

Any computer; however, sophisticated only deals with that many numbers, so any number can be if a computer has accuracy up to t digits, it can only approximate a number using t digits for instance. Suppose we have to compute 4 by 3 at an intermediate, step of a numerical algorithm and our computer can only store 5 digits in that case 4 by 3 will be stored as 1 point 3333 and the remaining digits will be lost.

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Numerical Instability


If a numerical algorithm is unstable, the loss of the last digits may be enough to trigger an instability. Because of the instability the numerical solution may differ widely from the true solution.

The choice of algorithm is crucial in determining whether a numerical method will give stable results. Certain algorithms are inherently unstable, others are stable for a certain range of input data, while still others are unconditionally stable, i.e. they are stable for all ranges of input data.

Suppose we wish to numerically integrate

$$y_n = \int_0^1 \frac{x^n}{x+5} dx \quad \text{for } n = 0, 1 \dots 8$$

We will solve this problem twice, once using an inherently unstable algorithm and the second time using a stable algorithm.



If the numerical algorithm is unstable the loss of the last digits, may be enough to trigger an instability, because of the instability the numerical solution may differ widely from the true solution. The choice of algorithm is crucial in determining, whether a numerical method will give stable results, certain algorithms are inherently unstable, others are stable for a certain range of input data, while still others are unconditionally stable, that is they are stable for all ranges of input data.

Suppose, we wish to numerically integrate, the following integral y_n equal to integral of x to the power n , divided by x plus 5 and we wish to integrate within the limits 0 and 1 for values of n equal to 0 1 through 8. We will solve this problem twice, once using an inherently unstable algorithm and the second time using a stable algorithm.

(Refer Slide Time 35:25)

Numerical Instability


First algorithm
We can write:

$$y_n + 5y_{n-1} = \int_0^1 \frac{x^n + 5x^{n-1}}{x+5} dx = \int_0^1 \frac{x^{n-1}(x+5)}{(x+5)} dx$$
$$= \int_0^1 x^{n-1} dx = \frac{1}{n}$$

Thus we get the recursion formula :

$$y_n + 5y_{n-1} = \frac{1}{n}$$

Using 3 decimals the following are the results of the iteration:

$$y_0 = \int_0^1 \frac{dx}{x+5} = .182$$


For the first algorithm, we write $y_n + 5y_{n-1}$ is equal to integral of $x^n + 5x^{n-1}$ divided by $x + 5$. Recall that this is our integrand, so $y_n + 5y_{n-1}$ is equal to integral from 0 to 1, $x^n + 5x^{n-1}$ divided by $x + 5$. So, we can write this and doing certain simplifications, we can reduce it to $\frac{1}{n}$, if we perform this integration it comes out as $\frac{1}{n}$, thus we get the recursion formula $y_n + 5y_{n-1} = \frac{1}{n}$ using three decimals the following are the results of a iteration.

We start with y_0 , which we calculate accurately up to three decimal places from which we get y_0 is approximately equal to 1 point 8 2, then using y_0 in our recursion formula, we get y_1 is equal to 1 minus five times y_0 .

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Numerical Instability

$$y_1 = 1 - 5y_0 \approx 182$$
$$y_2 = \frac{1}{2} - 5y_1 \approx .050$$
$$y_3 = \frac{1}{3} - 5y_2 \approx .083$$
$$y_4 = \frac{1}{4} - 5y_3 \approx .165$$

The answers are all over the map and are obviously wrong. The reason is as follows:

The round off error ϵ in y_0 is of the order 10^{-4} . This gets multiplied by -5 in the calculation of y_1 , which thus has an error of -5ϵ . Similarly the error in y_1 is 25ϵ .

Thus the error gets scaled by a factor of 5 every iteration. The error in y_4 is as large as $625 \cdot 5 \cdot 10^{-4} = 0.3125$. This is just the error propagating from the first iteration. Additional errors accumulate due to additional round off errors in each iteration.



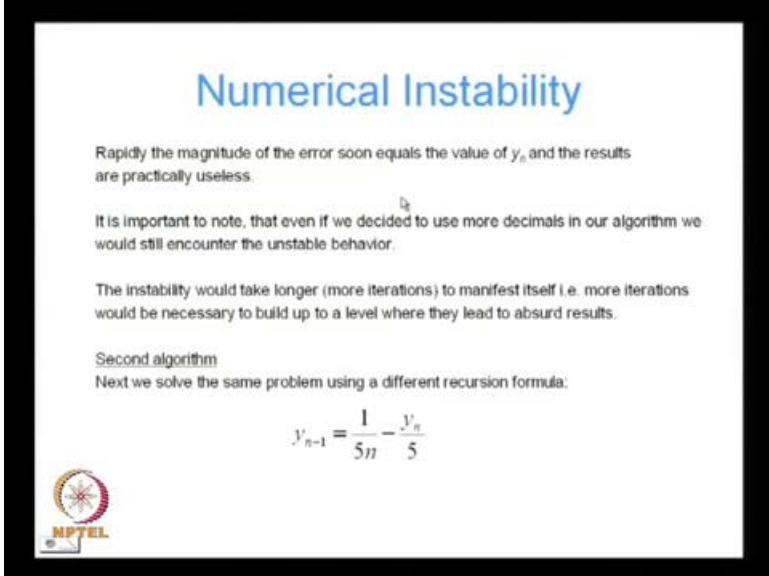
Which comes out as point 1 8 2 y_2 can be written as half 1 by 2 minus five times y_1 , again according to our recursion formula, which gives me point 0 5 0, y_3 gives me 1 by 3 minus 5 times y_2 which is point 0 8 3 all being computed accurately up to three decimal places and y_4 gives me point 1 6 5. As you can see the answers are varying widely, they are all over the map and are obviously wrong, the reason is as follows.

Suppose the round off error in the computation of y_0 epsilon is of the order 10 to the power minus 4, which is the reasonable, because we are using three significant digits in our computations. So, the error in y_0 is of the order of ten to the power minus 4 in our second recursion relationship, this gets multiplied by minus 5 in the calculation of y_1 . Because, you can see there is 5 times y_0 , so whatever error there is in y_0 gets multiplied by factor of 5, therefore y_1 has an error of minus 5 epsilon.

Similarly, y_2 will have an error of 25 epsilon, because again we are multiplied y_1 by a factor of 5, thus the error gets scaled by a factor of 5 in every iteration, the error in y_4 is as large as 625 times 5 times 10 to the power minus 4, which you recall was an initial error the error in y_4 is actually point 3125. So, you can see that the error has increased by at least three orders of magnitude, this is however note is just the error propagating from the first iteration.

Epsilon was the error in the first iteration, additional errors accumulate due to additional round off errors in each iteration, because in each iteration we are doing computations up to only three decimal places.

(Refer Slide Time 39:48)



Numerical Instability


Rapidly the magnitude of the error soon equals the value of y_n and the results are practically useless.

It is important to note, that even if we decided to use more decimals in our algorithm we would still encounter the unstable behavior.

The instability would take longer (more iterations) to manifest itself i.e. more iterations would be necessary to build up to a level where they lead to absurd results.

Second algorithm
Next we solve the same problem using a different recursion formula:

$$y_{n-1} = \frac{1}{5n} - \frac{y_n}{5}$$



Rapidly the magnitude of the error soon equals the value of y_n and the results are practically useless, it is important to note that even if, we decided to use more decimals in our algorithm for instance, instead of using numbers with three decimals. If we use numbers to 5 or 6 decimals, we would still encounter the unstable behavior the only difference would be that the instability would take longer more iterations to manifest itself, that is more iterations would be necessary to build up to a level where they lead to absurd results.

So, this is not a problem of performing computations with too few, too little precision, it is the problem is the algorithm we have chosen is inherently unstable. The second algorithm we use is slightly different in this case, we use a variation of initial recursion formula, which you recall was this instead of using this recursion formula. We use the following recursion formula, where you can see the only difference is that we have divided both sides, by we have brought the five down to the denominator in the right hand side, but those two equations are identical it is just that a recursion formula is different.

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Numerical Instability

Using this formula, the error will be reduced by 5 in each step. However we need a starting value of y_n .

If we assume that the iteration very nearly converges after a certain number of increments, we can use the recursion formula to calculate the converged value.

Assuming in this case, that convergence has occurred after 10 iterations, we get:

$y_5 = \frac{1}{50} \approx 0.02$

Similarly

$y_3 \approx 0.19$

$y_2 \approx 0.28$

$y_2 \approx 0.58, y_1 \approx 0.88, y_0 \approx 1.82$ (exact)

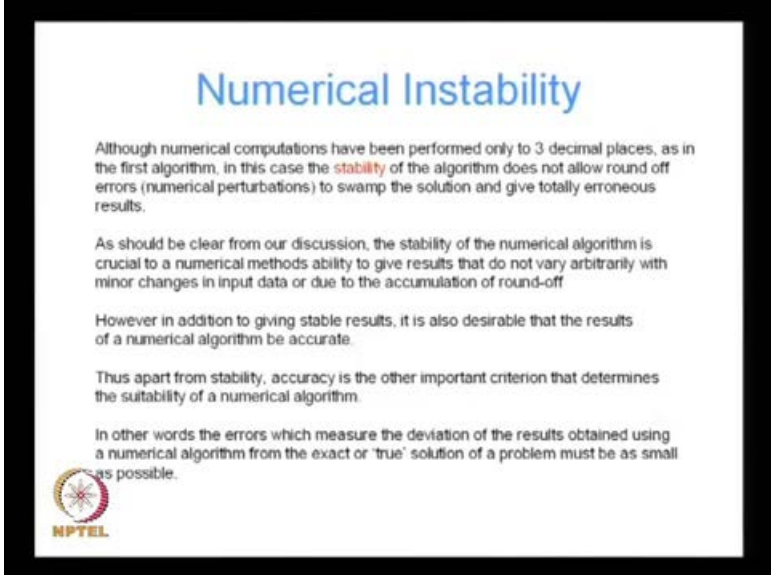
The slide also features a screenshot of a calculator showing the calculation of $1/50 = 0.02$ and a list of menu options including 'New', 'Clipboard', 'Settings', 'Storage', 'Printer Options', 'Screen', 'Date', and 'End Show'. The NPTEL logo is visible in the bottom left corner.

If we use this algorithm the error will be reduced by 5, in each step however, we need a starting value y_n if we assume that the iteration very nearly converges after a certain number of increments. We can use the recursion formula to calculate the converged value, assuming in this case that convergence has occurred after 10 iterations, so let us go back to our previous slide.

So, we are assuming that the iteration has converged in 10 iterations, so y_{10} , y_9 is equal to 1 by 5 times, 10 minus y_{10} by 5 . Since, we have assumed that the iteration as converged in 10 iterations on the right hand side, we can replace by 10 by y_9 , the assumption being that y_{10} is almost exactly equal to y_9 , since the iteration has converged in 10 iteration.

So, we can write y_9 is equal to 1 by 5 times 10 , which is 1 by 50 minus y_9 by 5 , which gives me y_9 is approximately equal to point 0.17 , again notice, that we are do performing our computations only for up to three decimal places. We are we have not increased the accuracy of our computations, similarly doing the same using the same recursion formula, we get y_8 is approximately equal to point 0.19 , y_7 is approximately equal to point 0.21 , y_6 is point 0.25 , eventually at y_0 , we get point 1.82 , which is the exact solution for this problem.

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Numerical Instability


Although numerical computations have been performed only to 3 decimal places, as in the first algorithm, in this case the **stability** of the algorithm does not allow round off errors (numerical perturbations) to swamp the solution and give totally erroneous results.

As should be clear from our discussion, the stability of the numerical algorithm is crucial to a numerical methods ability to give results that do not vary arbitrarily with minor changes in input data or due to the accumulation of round-off

However in addition to giving stable results, it is also desirable that the results of a numerical algorithm be accurate.

Thus apart from stability, accuracy is the other important criterion that determines the suitability of a numerical algorithm.

In other words the errors which measure the deviation of the results obtained using a numerical algorithm from the exact or 'true' solution of a problem must be as small as possible.



Although the numerical computations have been performed up to three decimal places as in the first algorithm, in this case the stability of the algorithm does not allow round off errors, that is numerical perturbations to swamp the solution. And give totally erroneous results. As should be clear from our discussion, the stability of numerical algorithm is crucial to a numerical methods, ability to give results that do not vary arbitrarily with minor changes in input data or due to the accumulation of round off.

However, in addition to giving stable results it is also desirable the results of a numerical algorithm be accurate, thus apart from stability accuracy is the other important criteria, that determines the suitability of a numerical algorithm. In other words the errors, which measure the deviation of the results obtained using a numerical algorithm from the exact or true solution of a problem must be as small as possible. This can be analyzed through what is known as error analysis, if the next lecture in the series, we are going to talk up in greater detail about error analysis. Since error and stability are the two criteria, which determine the effectiveness of a numerical algorithm.

Thank you.