

# Finite Difference Method



# Simple Finite Difference Approximation to a Derivative

Truncating (1) after the first derivative term gives,

$$U(x_0 + h) = U(x_0) + hU_x(x_0) + O(h^2)$$

Rearranging gives,

$$U_x(x_0) = \frac{U(x_0 + h) - U(x_0)}{h} - \frac{O(h^2)}{h}$$

**Neglecting** the  $O(h)$  term gives,

$$U_x(x_0) \approx \frac{U(x_0 + h) - U(x_0)}{h}$$

The last Eq. is called **a first order FD approximation** to  $U_x(x_0)$  since the approximation **error =  $O(h)$**  which depends on the first power of  $h$ .

This approximation is called a **forward FD approximation** since we start at  $x_0$  and step forwards to the point  $x_0 + h$ .  $h$  is called the **step size** ( $h > 0$ ).

# Simple Finite Difference Approximation to a Derivative

As an example we choose a simple function for  $U$ . Let

$$U(x) = x^3$$

We will find the first order forward FD approximation to  $U_x(1)$  using step size  $h = 0.1$

Since

$$U_x(x_0) \approx \frac{U(x_0 + h) - U(x_0)}{h}$$

Substituting for  $U$  gives

$$U_x(x_0) \approx \frac{(x_0 + h)^3 - x_0^3}{h}$$

Replacing  $x_0$  by 1 and  $h$  by 0.1 gives,

$$U_x(1) \approx \frac{(1 + 0.1)^3 - 1^3}{0.1} = 1.10333$$

*What if  $h=0.05$ ?*

*Lets do it by hand*

# Finite Difference Approximations

For simplicity we suppose that  $U$  is a function of **only two variables**,  $t$  and  $x$ .

We will approximate the partial derivatives of  $U$  with respect to  $x$ .

As  $t$  is held constant  $U$  is effectively a function of the single variable  $x$  so we can use Taylor's formula (1) where the ordinary derivative terms are now partial derivatives and the arguments are  $(t, x)$  instead of  $x$ .

Finally we will replace the step size  $h$  by  $\Delta x$  (to indicate a change in  $x$ ) so that (1) becomes,

$$U(t, x_0 + \Delta x) = U(t, x_0) + \Delta x U_x(t, x_0) + \frac{\Delta x^2}{2!} U_{xx}(t, x_0) + \dots + \frac{\Delta x^{n-1}}{(n-1)!} U_{n-1}(t, x_0) + O(\Delta x^n) \quad (2)$$

Truncating it to  $O(\Delta x^2)$  gives,

$$U(t, x_0 + \Delta x) = U(t, x_0) + \Delta x U_x(t, x_0) + O(\Delta x^2)$$

Now we derive some FD approximations to partial derivatives. Rearranging it gives,

$$U_x(t, x_0) = \frac{U(t, x_0 + \Delta x) - U(t, x_0)}{\Delta x} - O(\Delta x)$$

# Finite Difference Approximations

In numerical schemes for solving PDEs we are restricted to a **grid of discrete**  $x$  values,  $x_1, x_2, \dots, x_N$ , and **discrete**  $t$  levels  $t_0, t_1, \dots$ .

We will assume a **constant** grid spacing,  $\Delta x$ , in  $x$ , so that  $x_{i+1} = x_i + \Delta x$ .

Evaluating the last equation for a point,  $(t_n, x_i)$ , on the grid gives,

$$U_x(t_n, x_i) = \frac{U(t_n, x_{i+1}) - U(t_n, x_i)}{\Delta x} - O(\Delta x)$$

We will use the common **subscript/superscript** notation

$$U_i^n = U(t_n, x_i)$$

so that dropping the  $O(\Delta x)$  error term,

$$U_x(t_n, x_i) \approx \frac{U_{i+1}^n - U_i^n}{\Delta x}$$

# Finite Difference Approximations

We now derive another FD approximation to  $U_x(t_n, x_i)$ . Replacing  $\Delta x$  by  $-\Delta x$

$$U(t, x_0 - \Delta x) = U(t, x_0) - \Delta x U_x(t, x_0) + O(\Delta x^2)$$

Evaluating it at  $(t_n, x_i)$  and rearranging as previously gives,

$$U_x(t_n, x_i) \approx \frac{U_i^n - U_{i-1}^n}{\Delta x}$$

And it is the first order **backward** difference approximation to  $U_x(t_n, x_i)$ .

Our first two FD approximations are first order in  $x$  but we can increase the order (and so make the approximation more **accurate**) by taking more terms in the Taylor series as follows.

Truncating to  $O(\Delta x^3)$ , then replacing  $\Delta x$  by  $-\Delta x$  and subtracting this new expression from (2) and evaluating at  $(t_n, x_i)$  gives, after some algebra,

$$U_x(t_n, x_i) \approx \frac{U_{i+1}^n - U_{i-1}^n}{2 \Delta x}$$

And is called the **second order central difference** FD approximation to  $U_x(t_n, x_i)$ .

# Finite Difference Approximations

Many PDEs of interest contain **second order** (and higher) partial derivatives so we need to derive approximations to them.

We will restrict our attention to second order **unmixed** partial derivatives i.e.  $U_{xx}$ .  
Truncating (2) to  $O(\Delta x^4)$  gives

$$U(t, x_0 + \Delta x) = U(t, x_0) + \Delta x U_x(t, x_0) + \frac{\Delta x^2}{2!} U_{xx}(t, x_0) + \frac{\Delta x^3}{3!} U_{xxx}(t, x_0) + O(\Delta x^4) \quad (3)$$

Replacing  $\Delta x$  by  $-\Delta x$  gives

$$U(t, x_0 - \Delta x) = U(t, x_0) - \Delta x U_x(t, x_0) + \frac{\Delta x^2}{2!} U_{xx}(t, x_0) - \frac{\Delta x^3}{3!} U_{xxx}(t, x_0) + O(\Delta x^4) \quad (4)$$

Adding (3) and (4) gives

$$U(t, x_0 + \Delta x) + U(t, x_0 - \Delta x) = 2U(t, x_0) + \Delta x^2 U_{xx}(t, x_0) + O(\Delta x^4)$$

Evaluating at  $(t_n, x_i)$

$$U_{i+1}^n + U_{i-1}^n = 2U_i^n + \Delta x^2 U_{xx}(t_n, x_i) + O(\Delta x^4)$$

# Finite Difference Approximations

Rearranging it and dropping the  $O(\Delta x^2)$  error term gives

$$U_{xx}(t_n, x_i) \approx \frac{U_{i+1}^n - 2U_i^n + U_{i-1}^n}{\Delta x^2} \quad (5)$$

And it is the **second order symmetric difference FD approximation** to  $U_{xx}(t_n, x_i)$

partial derivative	finite difference approximation	type	order
$\frac{\partial U}{\partial x} = U_x$	$\frac{U_{i+1}^n - U_i^n}{\Delta x}$	forward	first in x
$\frac{\partial U}{\partial x} = U_x$	$\frac{U_i^n - U_{i-1}^n}{\Delta x}$	backward	first in x
$\frac{\partial U}{\partial x} = U_x$	$\frac{U_{i+1}^n - U_{i-1}^n}{2\Delta x}$	central	second in x
$\frac{\partial^2 U}{\partial x^2} = U_{xx}$	$\frac{U_{i+1}^n - 2U_i^n + U_{i-1}^n}{\Delta x^2}$	symmetric	second in x



# Finite Difference Approximations

Approximations to partial derivatives with respect to  $t$  are derived in a similar manner

partial derivative	finite difference approximation	type	order
$\frac{\partial U}{\partial t} = U_t$	$\frac{U_i^{n+1} - U_i^n}{\Delta t}$	forward	first in $t$
$\frac{\partial U}{\partial t} = U_t$	$\frac{U_i^n - U_i^{n-1}}{\Delta t}$	backward	first in $t$
$\frac{\partial U}{\partial t} = U_t$	$\frac{U_i^{n+1} - U_i^{n-1}}{2\Delta t}$	central	second in $t$
$\frac{\partial^2 U}{\partial t^2} = U_{tt}$	$\frac{U_i^{n+1} - 2U_i^n + U_i^{n-1}}{\Delta t^2}$	symmetric	second in $t$

# Example

The 1D linear advection equation is

$$U_t + vU_x = 0$$

where the independent variables are  $t$  (time) and  $x$  (space).  $x$  is restricted to the finite interval  $[p, q]$  which is called the **computational domain**.

$v$  is a constant and the dependent variable,  $U = U(t, x)$ .

Let the initial conditions be,

$$U(0, x) = f(x) \quad \text{Known!} \quad p \leq x \leq q$$

A solution is a function  $U = U(t, x)$  which satisfies the PDE at **all** points  $x$  in the computational domain and **all** times  $t$  and the initial conditions.

# Step by Step

# Step 1: Spatial Discretization

The computational domain contains an **infinite** number of  $x$  values so first we must replace them by a **finite set**. This process is called spatial discretization

For simplicity the computational domain is replaced by a grid of  **$N$  equally spaced grid points**. Starting with the first grid point at  $x=p$  and ending with the last grid point at  $x=q$ , the constant grid spacing,  $\Delta x$ , is,

$$\Delta x = \frac{q - p}{N - 1}$$

The values of  $x$  in the discretized computational domain are indexed by subscripts to give,

$$x_1 = p, x_2 = p + \Delta x, \dots, x_i = p + (i - 1) \Delta x, \dots, x_N = p + (N - 1) \Delta x = q$$

So the grid spacing is constant,

$$x_{i+1} = x_i + \Delta x$$

Fixing  $t$  at  $t = t_n$  we approximate the spatial partial derivative,  $U_x$  at each point  $(t_n, x_i)$  using the forward difference formula

$$U_t + v U_x = 0 \quad \longrightarrow \quad U_t + v \frac{U_{i+1}^n - U_i^n}{\Delta x} = 0$$

**semi-discrete** form  
since only the spatial  
derivative has been  
discretized

# Step 2: Time Discretization

Fixing  $x$  at  $x=x_i$ , we approximate the temporal partial derivative,  $U_t$  at each point  $(t_n, x_i)$  using the first order forward difference formula

$$U_t \approx \frac{U_i^{(n+1)} - U_i^n}{\Delta t}$$

and

$$U_t + v \frac{U_{i+1}^n - U_i^n}{\Delta x} = 0 \quad \longrightarrow \quad \frac{U_i^{(n+1)} - U_i^n}{\Delta t} + v \frac{U_{i+1}^n - U_i^n}{\Delta x} = 0$$

which rearranges to give

$$U_i^{(n+1)} = U_i^{(n)} - \frac{v \Delta t}{\Delta x} (U_{i+1}^{(n)} - U_i^{(n)})$$

It is an example of a FDS to approximate the solution of the PDE. Is a so-called **time-marching scheme** which enables  $U$  values at time level  $n+1$  to be approximated from  $U$  values at the previous **time level**  $n$ .

Since all  $U$  values are only known exactly at the initial time level is rewritten as

$$u_i^{(n+1)} = u_i^{(n)} - \frac{v \Delta t}{\Delta x} (u_{i+1}^{(n)} - u_i^{(n)}) \quad : u(t_n, x_i) \text{ is a numerical approximation to } U(t_n, x_i)$$

# Step 2: Time Discretization

## Remarks

- $u(0, x_i) = U(0, x_i)$  but this will **not** be true in general for later times.
- **u** values on the right hand side of are all at time  $t_n$  whereas on the left hand side **u** values are all at the **next** timed level  $t_n + \Delta t = t_{n+1}$
- It is an example of a **time-marching** scheme in that (known) data for each grid point at time  $t_n$  is used to find data at each grid point at the future time  $t_n + \Delta t$ . This is called an **iteration** of the scheme. After an iteration of the scheme all  $u$  values at each grid point are known at time  $t_n + \Delta t$ .
- These new values can be used as known data for another iteration of the scheme to give data for each grid point at the next time level.
- This process can be repeated until the required future time is attained.
- The errors in approximating the spatial and temporal derivatives which are used are  $O(\Delta x)$  and  $O(\Delta t)$  respectively and so it is said to be (formally) first order in space ( $x$ ) and first order in time ( $t$ ).
- The grid spacing,  $\Delta x$ , was determined by choosing the number of grid points,  $N$ . A larger  $N$  gives a smaller  $\Delta x$  and a (**hopefully**) more accurate solution as spatial derivatives are more accurately approximated. However as  $N$  increases **compute time increases** so there is a trade off between **accuracy and speed**.

# Step 2: Time Discretization

## Remarks

- The time step,  $\Delta t$ , is for the moment, chosen **arbitrarily**. However a smaller time step will mean that more iterations are needed to reach a stated future time which will obviously increase the compute time.
- In addition, since the result of each iteration is an approximation to the required solution, more iterations could cause the build up of more error.

$$u_i^{(n+1)} = u_i^{(n)} - \frac{v \Delta t}{\Delta x} (u_{i+1}^{(n)} - u_i^{(n)})$$

is said to be an **explicit method** since the value of  $u$  at the next time level is given by an explicit formula for each grid point.

### MATHEMATICAL WARNING:

It does not work for  $v > 0$ ...

# PEN AND PAPER CALCULATION



# Example

## Board II

# References

D. M. Causon, C. G. Mingham, Introductory Finite Difference Methods for PDEs  
Ventus Publishing ApS, ISBN 978-87-7681-642-1 (2010).