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- However, to obtain solutions in the general case, it is necessary to solve the **full nonlinear system**.
- In numerical weather prediction (NWP) the fully nonlinear primitive equations are solved by **numerical means**.
- In the atmosphere, the nonlinear **advection** process is a dominant factor.
- To get some idea of the methods used, we look at the simple problem of formulating time-integration algorithms for the solution of the **simple advection equation**.

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- An *analytical* problem becomes an *algebraic* one.
- A problem with an *infinite* degree of freedom is replaced by one with a *finite* degree of freedom.
- A *continuous* problem goes over to a *discrete* one.

# The Finite Difference Method

We start by looking at the *Taylor expansion* of  $f(x)$ :

$$f(x + \Delta x) = f(x) + f'(x).\Delta x + \frac{1}{2}f''(x)\Delta x^2 + [O(\Delta x^3)] \quad (1)$$

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Keeping only leading terms, we incur **errors of order  $O(\Delta x)$** .

*We can do better than this:* subtracting (2) from (1) yields:

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Adding (1) and (2) gives the corresponding expression for the second derivative:

$$f''(x) = \frac{f(x + \Delta x) - 2f(x) + f(x - \Delta x)}{\Delta x^2} + O(\Delta x^2)$$

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Fourth-order accurate schemes are sometimes used in NWP, but *second order accuracy is more popular*.

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- Demonstrate thus that the **centered difference** is of higher order accuracy.

# Grid Resolution and Accuracy

The size of the gridstep  $\Delta x$  determines the **accuracy** of the numerical scheme.

For the simple sine function the error depended on  $k\Delta x = 2\pi\Delta x/L$ , that is, on the ratio of the grid size  $\Delta x$  to the wavelength  $L$ .

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The **higher the resolution**, that is, the **smaller the grid-size**, the **heavier the computational burden**.

There is a *trade-off between resolution and accuracy*.

# The Leapfrog Method

We consider the equation describing the conservation of a quantity  $Y(x, t)$  following the 1D motion of a fluid flow:

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It is analogous to a factor of the wave equation:

$$\left( \frac{\partial^2}{\partial t^2} - c^2 \frac{\partial^2}{\partial x^2} \right) Y = \left( \frac{\partial}{\partial t} + c \frac{\partial}{\partial x} \right) \left( \frac{\partial}{\partial t} - c \frac{\partial}{\partial x} \right) Y = 0,$$

and its general solution is  $Y = Y(x - ct)$ .

Since the **advection equation is linear**, we can construct a general solution from Fourier components

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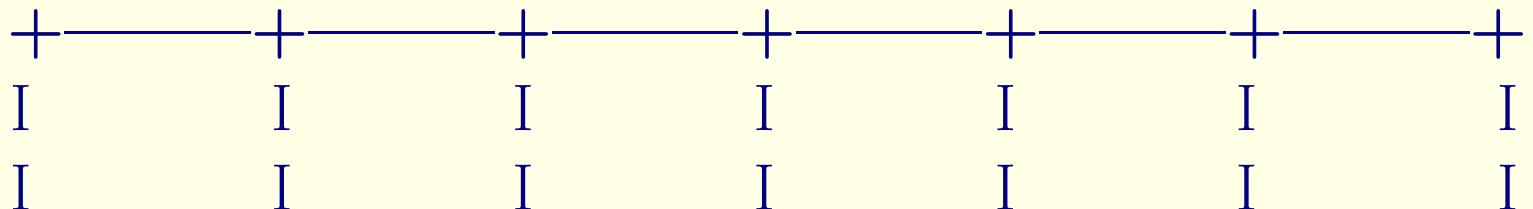
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Let the variables  $x$  and  $t$  be represented by the horizontal and vertical axes. Positive time corresponds to the upper half plane. The initial data occur on the  $x$ -axis.

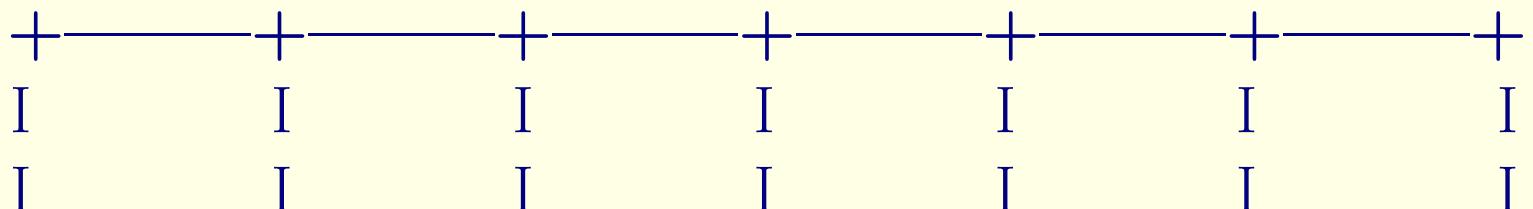
# Space-Time Grid:

Space axis horizontal  
Time axis vertical

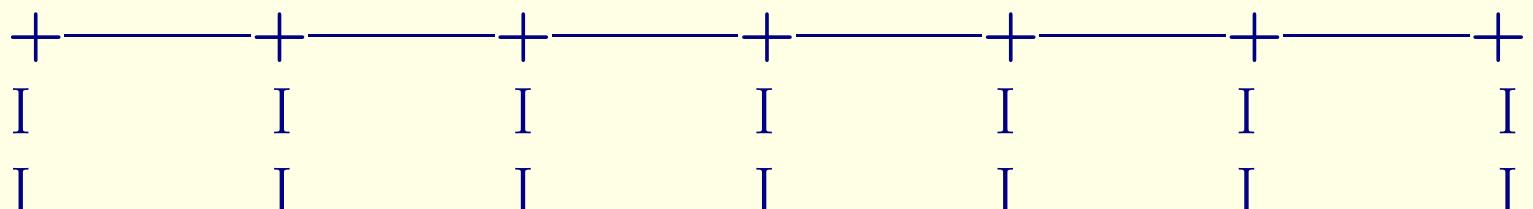
$n = 5$



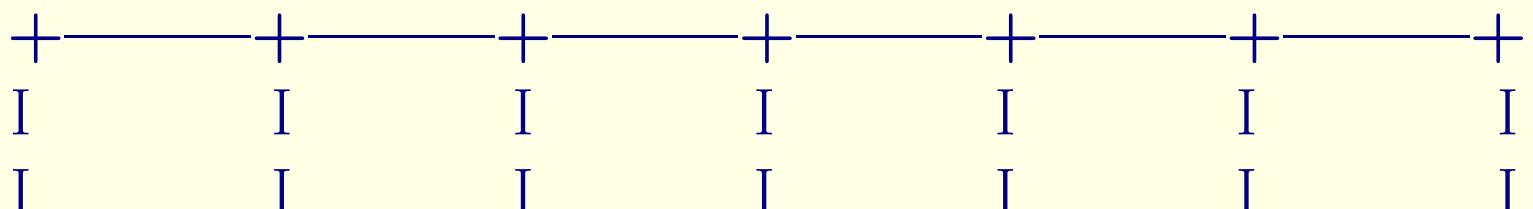
$n = 4$



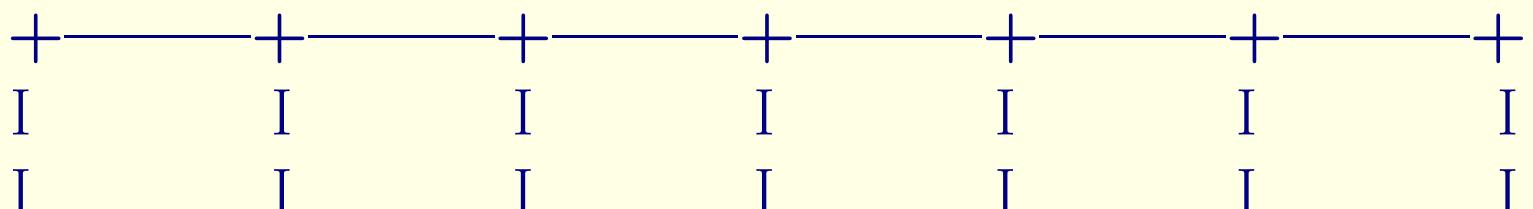
$n = 3$



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m=-3 m=-2 m=-1 m=0 m=1 m=2 m=3

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Then the **(CTCS)** finite difference approximation to the differential equation may be written as follows:

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Solving for the value at time  $(n + 1)\Delta t$  gives

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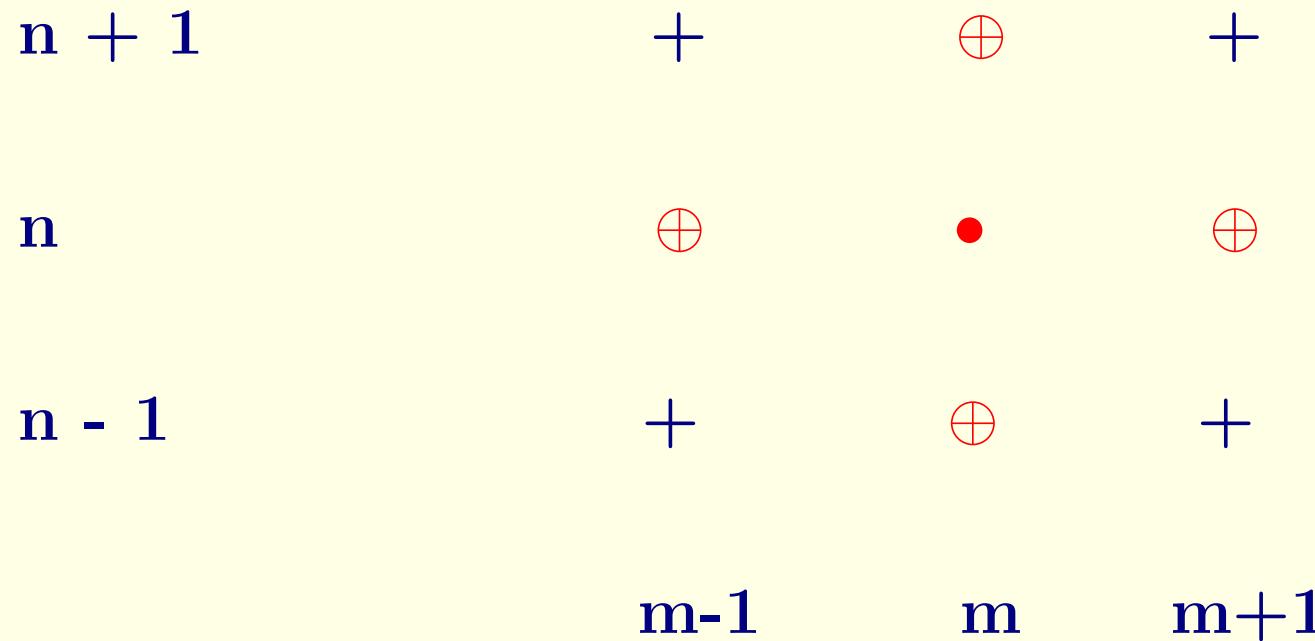
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The ratio  $\mu \equiv \frac{c\Delta t}{\Delta x}$  will be found to be crucial.

# Inter-dependency of Points



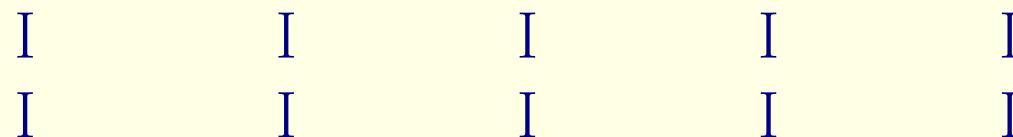
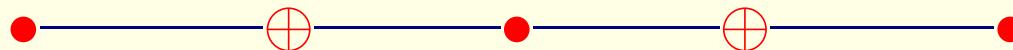
The evaluation of the equation at point  $\bullet$  involves values of the variable at points  $\oplus$ . Solving for  $Y_m^{n+1}$  thus requires

$$Y_m^{n-1}, \quad Y_{m-1}^n \quad \text{and} \quad Y_{m+1}^n.$$

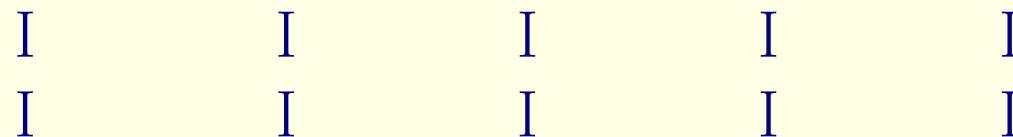
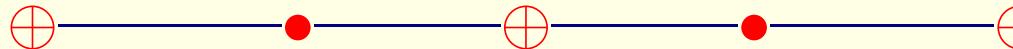
The leapfrog scheme *splits the grid* into two independent sub-grids.

# Grid Splitting

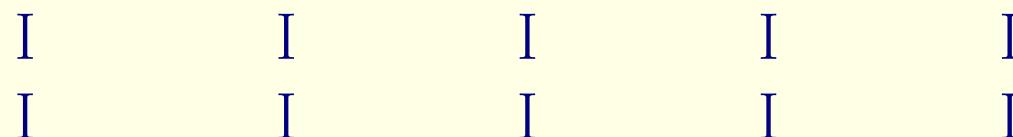
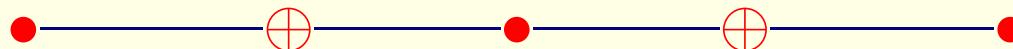
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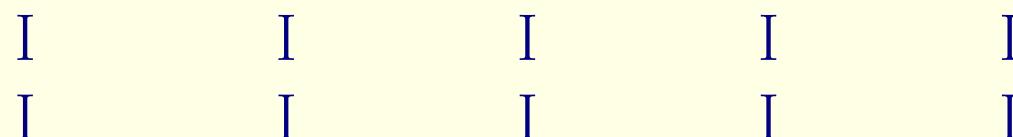
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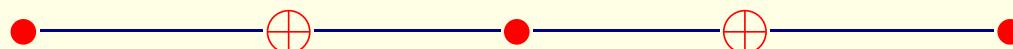
$n = 2$



$n = 1$



$n = 0$



$m = -2 \quad m = -1 \quad m = 0 \quad m = 1 \quad m = 2$

The finite difference grid splits into two sub-grids.

Steps must be taken to avoid divergence of the two solutions.

Recall the (CTCS) finite difference approximation:

$$\left( \frac{Y_m^{n+1} - Y_m^{n-1}}{2\Delta t} \right) + c \left( \frac{Y_{m+1}^n - Y_{m-1}^n}{2\Delta x} \right) = 0.$$

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Solving for the value at time  $(n + 1)\Delta t$  gives

$$Y_m^{n+1} = Y_m^{n-1} - \left( \frac{c\Delta t}{\Delta x} \right) (Y_{m+1}^n - Y_{m-1}^n)$$

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Then the whole procedure can be repeated to advance the solution to  $(n + 2)\Delta t$ , and so on.

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We write

$$A_{\pm} = -i\sigma \pm \sqrt{1 - \sigma^2} \quad \text{where} \quad \sigma \equiv \mu \sin k \Delta x$$

We consider in turn the two cases.

# Case I: $|\mu| \leq 1$

The quantity under the square-root sign is positive, so the modulus of  $A$  is given by

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Note that

$$\begin{array}{ll} \Re\{A_+\} = +\sqrt{1 - \sigma^2} & \Im\{A_+\} = -\sigma \\ \Re\{A_-\} = -\sqrt{1 - \sigma^2} & \Im\{A_-\} = -\sigma \end{array}$$

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The two values of the phase are

$$\psi_1 = -\arcsin \sigma$$

and

$$\psi_2 = \pi - \psi_1.$$

The solution of the equation may now be written

$$Y_m^n = \left[ D \exp(i\psi_1 n) + E \exp[i(-\psi_1 + \pi)n] \right] \exp(ikm\Delta x)$$

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$$Y_m^n = \underbrace{(a - E) \exp[ik(m\Delta x + \psi_1 n/k)]}_{\text{Physical Mode}} + \underbrace{(-1)^n E \exp[ik(m\Delta x - \psi_1 n/k)]}_{\text{Computational Mode}}$$

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**Exercise:**

Check in detail the algebra leading to this solution.

Once again, the solution is

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If the ratio  $\mu$  is small, the **physical mode solution** is given approximately by

$$Y \approx a \exp[ik(m\Delta x - cn\Delta t)]$$

which is just the **analytical solution**.

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In this simple case, we can **eliminate the computational mode**. In general, it is much more difficult.

# Case II: $|\mu| > 1$

Recall that the roots of the quadratic are

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This phenomenon is called computational instability.

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We thus require that  $|\mu| \leq 1$ . This condition for stability is known as the CFL Criterion:

$$\frac{c\Delta t}{\Delta x} \leq 1$$

after Courant, Friedichs and Lewy (1928), who first published the result.

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Thus, **halving** the grid size in a two dimensional domain results in an **eightfold increase** in computation time.

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It is so formulated that **the numerical domain of dependence always includes the physical domain of dependence**. This necessary condition for stability is satisfied automatically by the scheme.

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It is so formulated that **the numerical domain of dependence always includes the physical domain of dependence**. This necessary condition for stability is satisfied automatically by the scheme.

The semi-Lagrangian algorithm has enabled us to integrate the primitive equations using a **time step of 15 minutes**.

This can be compared to a typical timestep of 2.5 minutes for Eulerian schemes.

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We discuss semi-Lagrangian schemes in a later lecture.

End of §3.2.2