

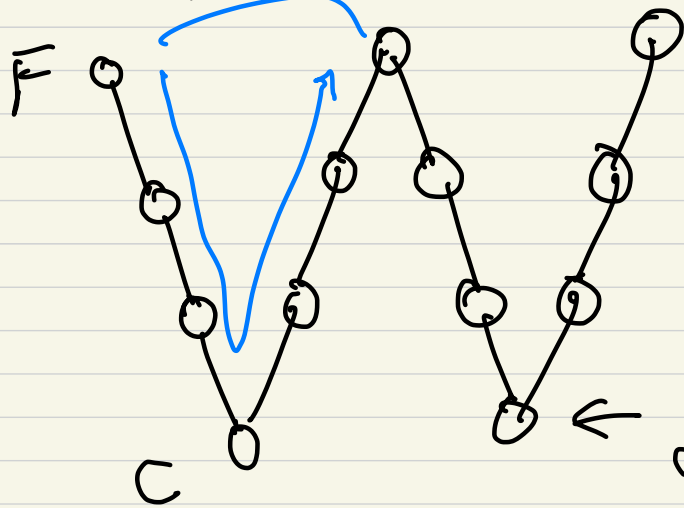
⊙ HW 4 due date Dec. 14 → Dec. 21 (6 pm)

⊙ Final exam: Dec. 14 (Monday) 9:30 – 11:30 am

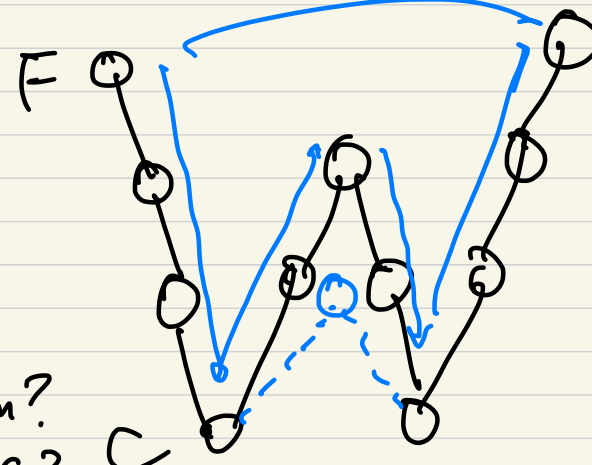
( student id starting w/ 2020 → 301-204  
others → 301 → 105 )

those who have high body temperature before exam should  
tell TA about the situation via e-mail

\* V cycle (cycle iteration)

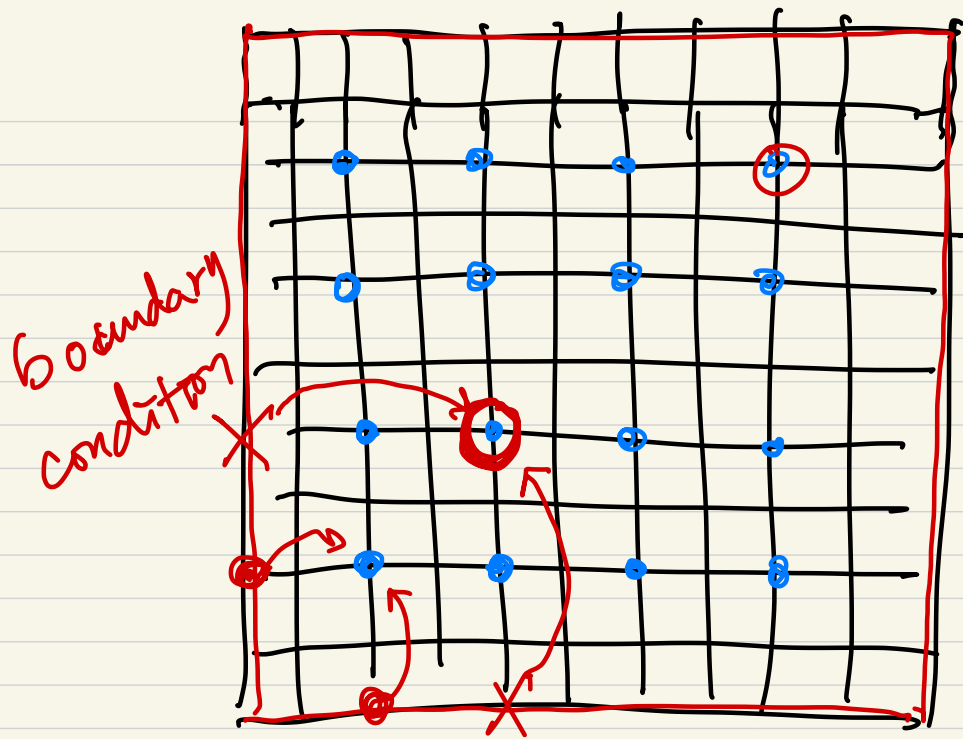


W cycle (cycle iteration)



1 iteration?  
10 " 5?

- single grid transfers the information to an adjacent grid per iteration,  
while multi grid " " " " to all grids per iteration

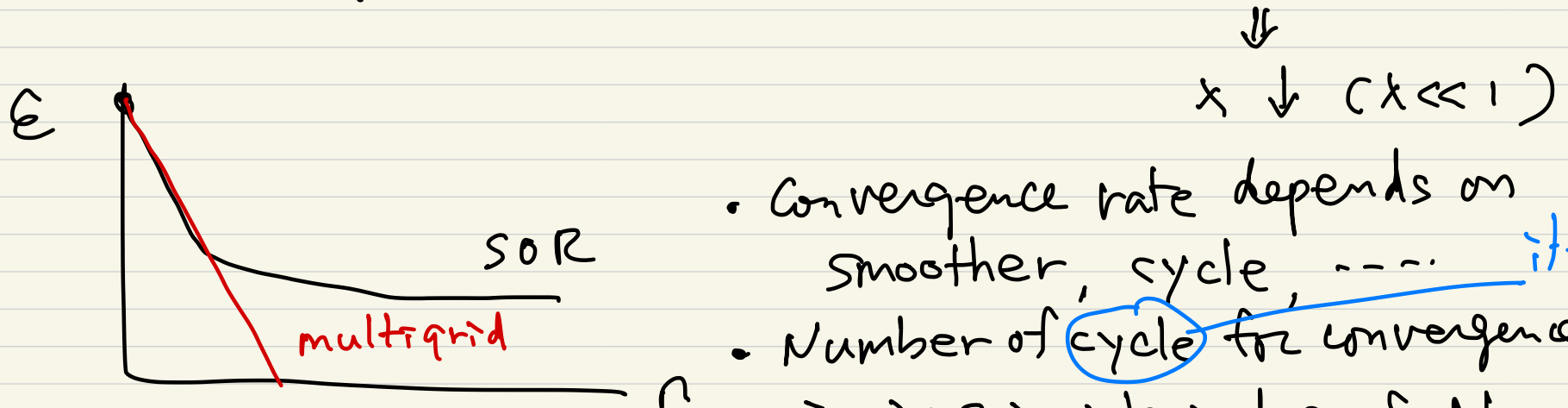


- : fine grid
- : second-level
- : third-level

$$\textcircled{A} \textcircled{\partial} \phi^{n+1} = r^{n+1}$$

As  $N \uparrow$ ,  $\lambda \rightarrow 1 \Rightarrow$  slow convergence.

in multigrid method,  $N \rightarrow N/2 \rightarrow N/4 \rightarrow N/8 \rightarrow N/16 \dots$



- Convergence rate depends on smoother, cycle, ... iteration
- Number of cycle for convergence is in principle indep. of  $N$ .

## ⑥ Hyperbolic PDE

$$a \frac{\partial^2 u}{\partial x^2} + 2b \frac{\partial^2 u}{\partial x \partial y} + c \frac{\partial^2 u}{\partial y^2} = F \quad (cb^2 - ac > 0)$$

$$a, b, c = f(x, y, u, u_x, u_y)$$

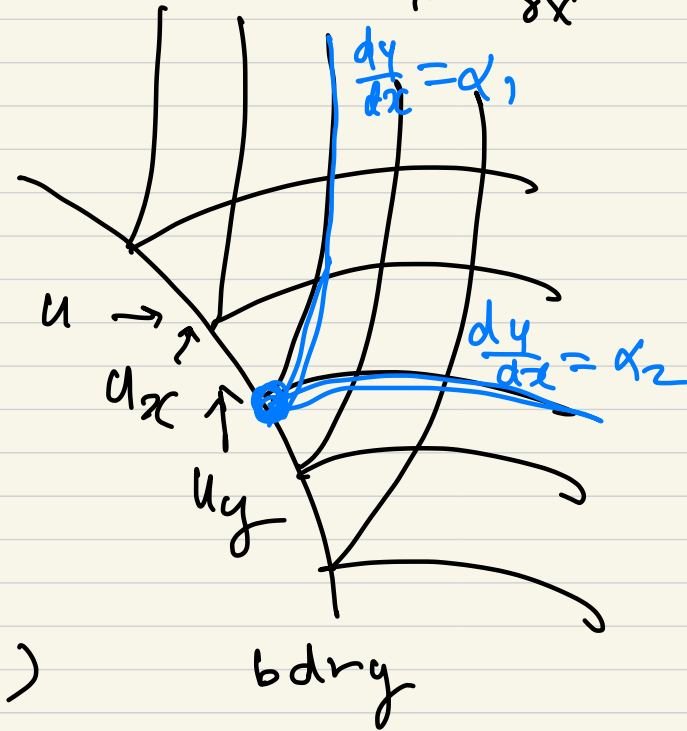
$$u_x = \frac{\partial u}{\partial x}$$

characteristic lines

$$\frac{dy}{dx} = \frac{b \pm \sqrt{b^2 - ac}}{a} = \alpha_1, \alpha_2$$

We need to know locations of char.

lines  $(x, y)$  and variations of  $u_x$  and  $u_y$  on char. lines.



Along any diff'l line element  $(dx, dy)$

$$d\left(\frac{\partial u}{\partial x}\right) = du_x = \frac{\partial^2 u}{\partial x^2} dx + \frac{\partial^2 u}{\partial x \partial y} dy \quad - (1)$$

$$d\left(\frac{\partial u}{\partial y}\right) = du_y = \frac{\partial^2 u}{\partial x \partial y} dx + \frac{\partial^2 u}{\partial y^2} dy \quad - (2)$$

$$\begin{aligned}
 GE: & \quad a u_{xx} + 2b u_{xy} + c u_{yy} = F \\
 (1): & \quad dx u_{xx} + dy u_{xy} = du_x \\
 (2): & \quad dx u_{xy} + dy u_{yy} = du_y
 \end{aligned}$$

$$\begin{vmatrix} a & 2b & c \\ dx & dy & 0 \\ 0 & dx & dy \end{vmatrix} = 0 \rightarrow \frac{dy}{dx} = \frac{b \pm \sqrt{b^2 - ac}}{a} = \alpha_1, \alpha_2$$

eg. for char. lines

For the existence of  $u_{xx}$ ,  $u_{xy}$  &  $u_{yy}$ ,  $\begin{vmatrix} a & F & c \\ dx & du_x & 0 \\ 0 & du_y & dy \end{vmatrix} = 0$ .

$$\rightarrow dy (a du_x - F dx) - du_y (-c dx) = 0$$

$$\rightarrow \frac{dy}{dx} a du_x + c du_y - F dy = 0$$

Char. lines  $\frac{dy}{dx} = \alpha_1, \alpha_2$  — 2 eqs.

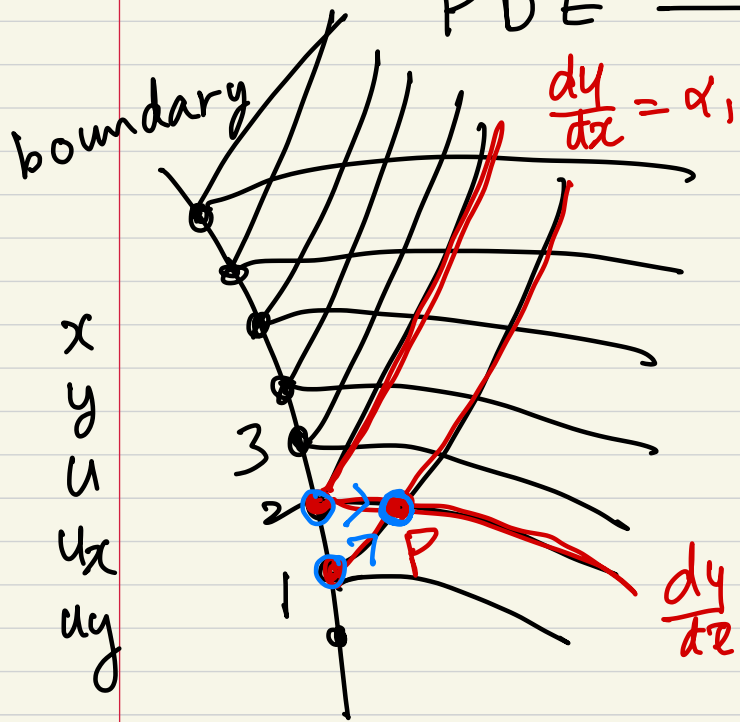
$$\alpha_1 a du_x + c du_y - F dy = 0 \text{ for } \frac{dy}{dx} = \alpha_1 \text{ — 1 eq.}$$

$$\alpha_2 a du_x + c du_y - F dy = 0 \text{ for } \frac{dy}{dx} = \alpha_2 \text{ — 1 eq.}$$

from chain rule,  $du = u_x dx + u_y dy$  — 1 eq.

$\Rightarrow$  5 eqs. for 5 unknowns ( $x, y, u, u_x, u_y$ )  
 $\hookrightarrow$  char. lines

PDE  $\rightarrow$  ODEs : method of characteristics (MOC)



$$\frac{dy}{dx} = \alpha_1 : \frac{y(P) - y(C_1)}{x(P) - x(C_1)} = \frac{1}{2} [\alpha_1(P) + \alpha_1(C_1)]$$

$$\frac{dy}{dx} = \alpha_2 : \frac{y(P) - y(C_2)}{x(P) - x(C_2)} = \frac{1}{2} [\alpha_2(P) + \alpha_2(C_2)]$$

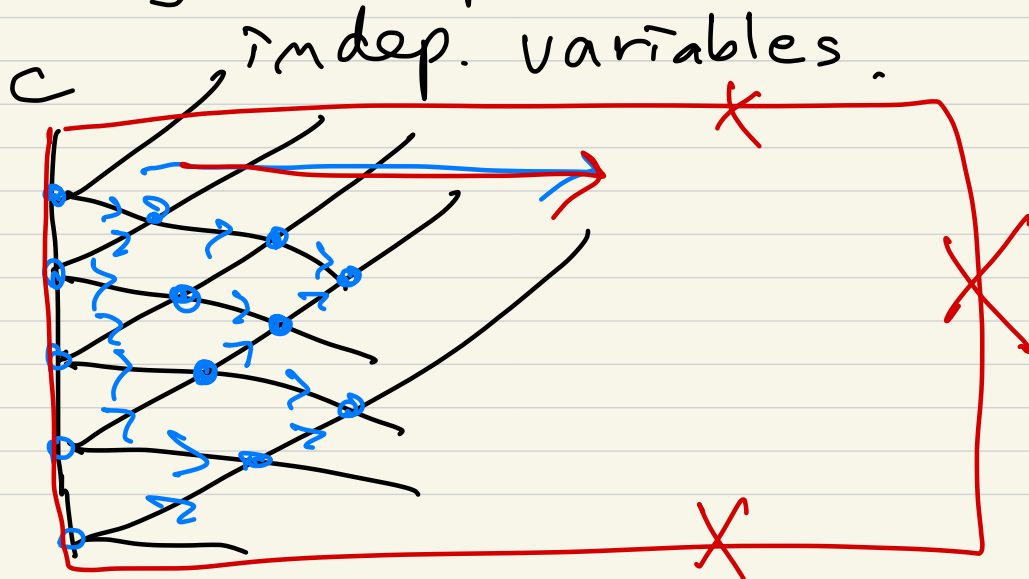
$$\begin{aligned} & \cdot \frac{1}{2} [\alpha_1(P) a(P) + \alpha_1(C_1) a(C_1)] (u_x(P) - u_x(C_1)) \\ & + \frac{1}{2} [c(P) + c(C_1)] (u_y(P) - u_y(C_1)) - \frac{1}{2} [F(P) + F(C_1)] (y(P) - y(C_1)) \\ & \cdot \frac{1}{2} [\alpha_2(P) a(P) + \alpha_2(C_2) a(C_2)] (u_x(P) - u_x(C_2)) \\ & + \frac{1}{2} [c(P) + c(C_2)] (u_y(P) - u_y(C_2)) - \frac{1}{2} (F(P) + F(C_2)) (y(P) - y(C_2)) = 0 \end{aligned}$$

$$\bullet \quad u(x, y) - u(x_1, y_1) = \frac{1}{2} [u_x(x, y) + u_x(x_1, y_1)] (x(x, y) - x(x_1, y_1)) \\ + \frac{1}{2} [u_y(x, y) + u_y(x_1, y_1)] (y(x, y) - y(x_1, y_1))$$

⇒ In general, these are nonlinear → iterative method.

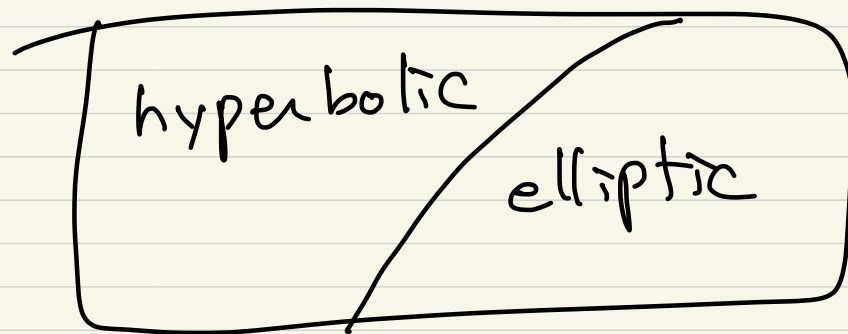
### \* Advantages of MOC

- important properties of exact sol. are preserved in numerical sol.
- method is easily adapted to the computation of problems that contain discontinuities.
- ability to compute the sol. over a long span of indep. variables.



## \* Disadvantages of MOC

- difficulties of keeping track of the locations of the char. lines and the values of variables in 3D.
- difficulties in handling mixed-type PDE (e.g. hyperbolic in one area and elliptic in other area)



## ⑥ Explicit methods for hyperbolic eqs.

Convection eq.  $\frac{\partial \phi}{\partial t} + c \frac{\partial \phi}{\partial x} = 0$   $x - ct = \text{const.}$

wave eq.  $\frac{\partial^2 \phi}{\partial t^2} = c^2 \frac{\partial^2 \phi}{\partial x^2}$   $\rightarrow$   $x - ct = \text{const}$   $\left( \frac{dx}{dt} = \pm c \right)$   
 $x + ct = \text{const}$

$\hookrightarrow u = \phi$   
 $w = u'$   $\rightarrow$   $\frac{\partial u}{\partial t} = c \frac{\partial w}{\partial x}$  &  $\frac{\partial w}{\partial t} = c \frac{\partial u}{\partial x}$

For  $\frac{\partial \phi}{\partial t} + c \frac{\partial \phi}{\partial x} = 0, (c > 0)$

EE + CD2: ~~unstable~~

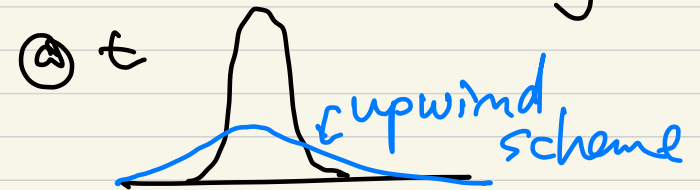
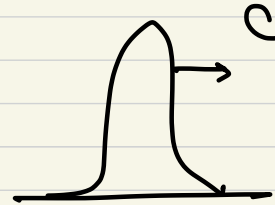
leapfrog: stable, no amp. error, spurious root.  
(CFL < 1)

EE + upwind scheme:  $\frac{\phi_j^{n+1} - \phi_j^n}{\Delta t} + c \frac{\phi_j^n - \phi_{j-1}^n}{\Delta x} = 0$

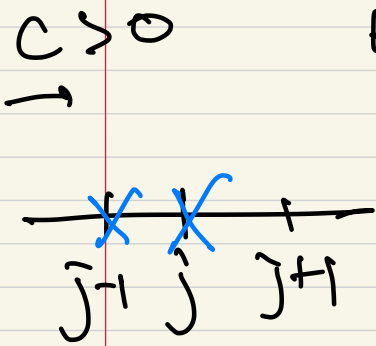
complex eigenvalue

Von Neumann stability analysis  $\rightarrow \frac{c \Delta t}{\Delta x} < 1$  (CFL < 1)  
for stability

too dissipative



$c < 0, \frac{\partial \phi}{\partial x} = \frac{\phi_{j+1} - \phi_j}{\Delta x}$





For wave eq., two char. lines  $x-ct = \text{const}$   $\rightarrow$   
 $x+ct = \text{const}$   $\leftarrow$

$\Rightarrow$  no upwind scheme!

CD scheme + EE  $\Rightarrow$  unstable

+ leapfrog  $\Rightarrow$  stable for CFL < 1  
 spurious root

+ RK4  $\rightarrow$  conditionally stable.

\* Lax - Wendroff scheme

$$\frac{\partial \phi}{\partial t} + c \frac{\partial \phi}{\partial x} = 0$$

$$\phi(x, t+\Delta t) = \phi(x, t) + \Delta t \frac{\partial \phi}{\partial t}(x, t) + \frac{1}{2} \Delta t^2 \frac{\partial^2 \phi}{\partial t^2}(x, t) + \frac{1}{6} \Delta t^3 \frac{\partial^3 \phi}{\partial t^3} + \dots$$

$$-c \frac{\partial \phi}{\partial x}$$

$$\frac{\partial}{\partial t} \left( \frac{\partial \phi}{\partial t} \right) = \frac{\partial}{\partial t} \left( -c \frac{\partial \phi}{\partial x} \right)$$

$$= -c \frac{\partial}{\partial x} \frac{\partial \phi}{\partial t} = c^2 \frac{\partial^2 \phi}{\partial x^2}$$

$$CD2: \phi_j^{n+1} = \phi_j^n - c \Delta t \frac{\phi_{j+1}^n - \phi_{j-1}^n}{2\Delta x} + \frac{1}{2} c^2 \Delta t^2 \frac{\phi_{j+1}^n - 2\phi_j^n + \phi_{j-1}^n}{\Delta x^2} + O(\Delta t^3)$$

Lax-Wendroff scheme

explicit

stable for CFL < 1

2nd-order accurate in space & time.

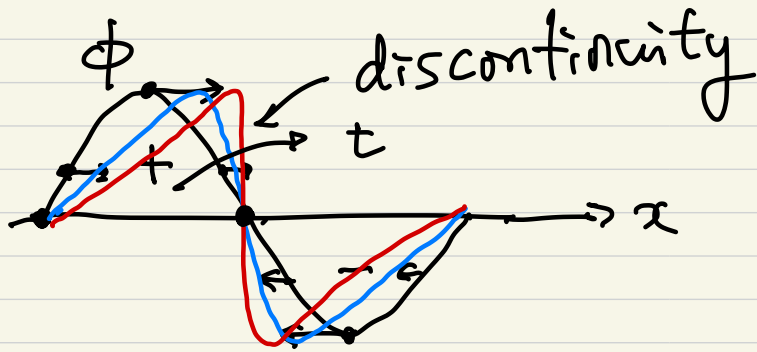
dispersive error  
 $\Delta t^3 \frac{\partial^3 \phi}{\partial x^3}$

disadvantage:  $c$  is not constant  $\sqrt{f(\phi)}$   
 nonlinear,  $c = c(\phi)$   
 higher dimension  $\rightarrow$  difficulty

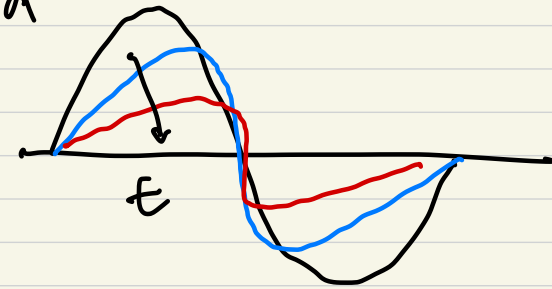
this method can be applied to

$$\frac{\partial^2 \phi}{\partial t^2} = c^2 \frac{\partial^2 \phi}{\partial x^2} \rightarrow \begin{cases} \frac{\partial u}{\partial t} = c \frac{\partial w}{\partial x} \\ \frac{\partial w}{\partial t} = c \frac{\partial u}{\partial x} \end{cases}$$

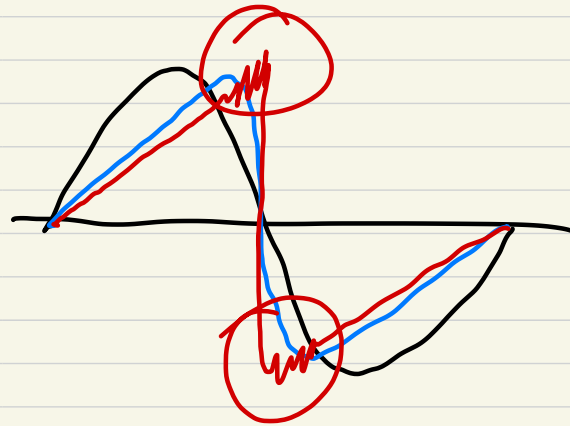
$$\frac{\partial \phi}{\partial t} + \phi \frac{\partial \phi}{\partial x} = 0 \quad (c = \phi) \quad \text{nonlinear}$$



upwind



CD2



TVD Schemes  
ENO

⊙ Implicit method for hyperbolic eqs.

$$\frac{\partial \phi}{\partial t} + c \frac{\partial \phi}{\partial x} = 0$$

$$\text{CD2 + CN: } \frac{\phi_j^{n+1} - \phi_j^n}{\Delta t} + c \cdot \frac{1}{2} \left[ \frac{\phi_{j+1/2}^n - \phi_{j-1/2}^n}{\Delta x} + \frac{\phi_{j+1/2}^n - \phi_{j-1/2}^n}{\Delta x} \right] = 0$$

no amplitude error (no dissipation)

dispersive error  
stable

$$\frac{\partial^2 \phi}{\partial t^2} = c^2 \frac{\partial^2 \phi}{\partial x^2}$$

① splitting into two eqs, u & w  
and applying CN to two eqs.

② applying CN directly to wave eq.

$$\frac{\phi_j^{n+1} - 2\phi_j^n + \phi_j^{n-1}}{\Delta t^2} = \frac{1}{2}c^2 \left[ \frac{\phi_{j+1}^{n+1} - 2\phi_j^{n+1} + \phi_{j-1}^{n+1}}{\Delta x^2} + \frac{\phi_{j+1}^n - 2\phi_j^n + \phi_{j-1}^n}{\Delta x^2} \right]$$

stable  
a little more accurate than the method  
applied to two splitted eqs.  
spurious root

• higher dimension (2D/3D) → ADI

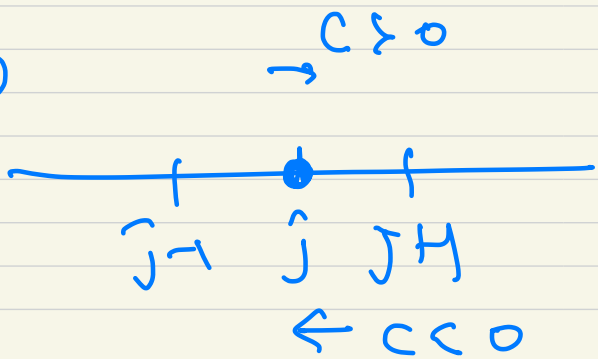
• nonlinear eq  $\frac{\partial \phi}{\partial t} + \phi \frac{\partial \phi}{\partial x} = 0$  → iterative method for  
implicit scheme.

- MacCormack scheme - very popular  $\rightarrow$  EE + downwind

$$\frac{\partial \phi}{\partial t} + c \frac{\partial \phi}{\partial x} = 0 \quad \left( \begin{array}{l} \phi_j^* = \phi_j^n - \frac{c \Delta t}{\Delta x} (\phi_{j+1}^n - \phi_j^n) \text{ predictor} \\ \phi_j^{n+1} = \frac{1}{2} (\phi_j^n + \phi_j^*) - \frac{c \Delta t}{\Delta x} (\phi_j^* - \phi_{j-1}^*) \text{ corrector} \end{array} \right)$$

explicit  
 equivalent to Lax-Wendroff scheme  $\left( \begin{array}{l} \text{upwind} \\ \text{for linear prob.} \\ \hookrightarrow O(\Delta x^2) \text{ \& } O(\Delta t^2) \end{array} \right)$   
 stable for CFL < 1  
 readily extended to 2D & 3D  
 accurate and easier to program  
 desirable nonlinear properties

$$\frac{\partial \phi}{\partial t} + c \frac{\partial \phi}{\partial x} = 0$$



$$\left. \frac{\partial \phi}{\partial x} \right|_j = \frac{\phi_j - \phi_{j-1}}{\Delta x} \quad (c > 0) \text{ upwind}$$

$$= \frac{\phi_{j+1} - \phi_j}{\Delta x} \quad (c < 0) \text{ downwind}$$

# Ch. 6. Discrete Transform methods : spectral method

## 6.1 Fourier series

$$f(x) = \sum_{k=-\infty}^{\infty} \hat{f}_k e^{ikx} \quad k: \text{wavenumber}$$

↑ continuous ft      ↘ Fourier coeff.

$$f'(x) = \sum_{k=-\infty}^{\infty} \hat{f}_k i k e^{ikx} = \sum_{k=-\infty}^{\infty} i k \hat{f}_k e^{ikx}$$

↘ Fourier coeff. of  $f'$

$$f(x) \xrightarrow{\text{FT}} \hat{f}_k \rightarrow i k \hat{f}_k \xrightarrow{\text{IFT}} f'(x)$$

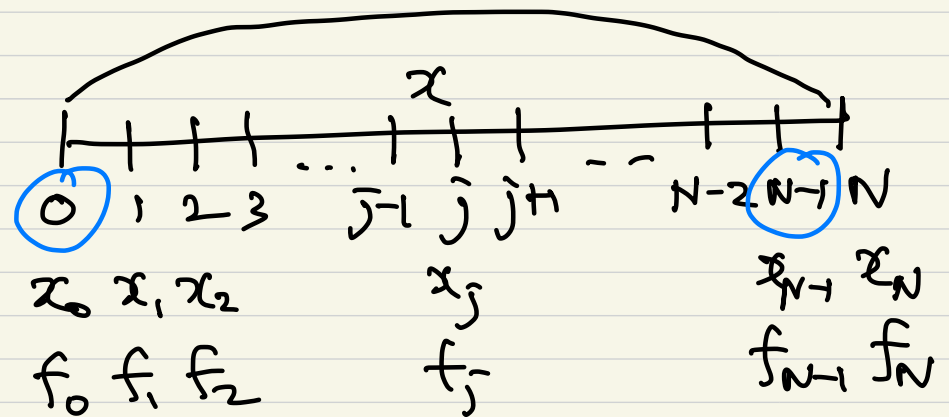
## 6.1.1 Discrete Fourier series

$f$  : periodic ft.

$$f_0 = f_N$$

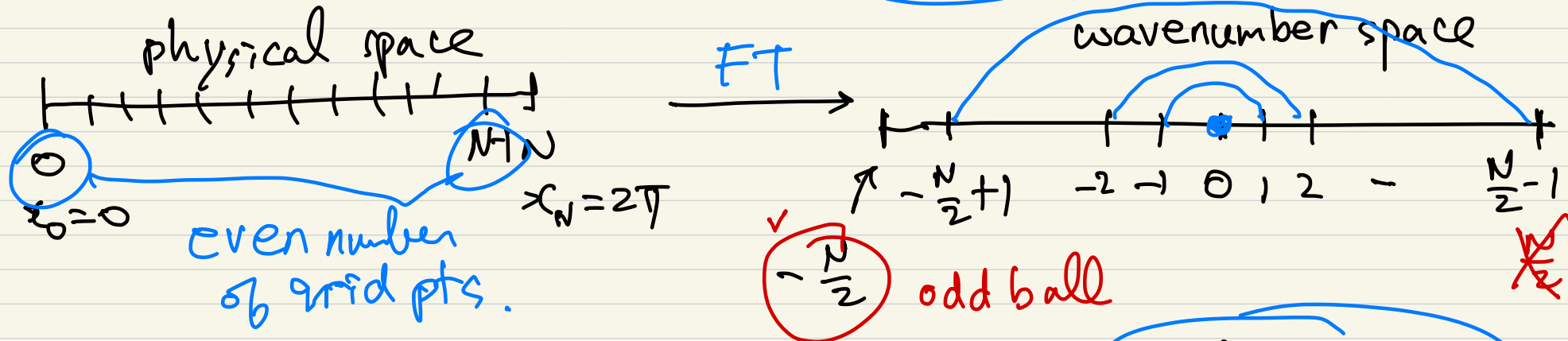
$N$  grid pts.

$N$  : even number



Let us take  $N$  to be even number and period of  $f$  to be  $2\pi$

$$e^{ikx} : \Delta k \cdot 2\pi = 2\pi \Rightarrow \Delta k = 1$$



$$x_j = jh, \quad h = \frac{2\pi}{N} \text{ (grid spacing)} \quad \text{uniform grids}$$

### Discrete Fourier transformation (DFT)

$$f_{\hat{j}} = \sum_{k=-N/2}^{N/2-1} f_k e^{ikx_j}, \quad \hat{j} = 0, 1, 2, \dots, N-1$$

$f_k$  discrete Fourier coeff. of  $f_j$

$O(N^2)$  operations

(If a period of  $f$  is  $L$ ,  $\Delta k \cdot L = 2\pi \rightarrow \Delta k = 2\pi/L$ )

$$f_j \xrightarrow{\text{DFT}} \hat{f}_k \Rightarrow \underset{\substack{\uparrow \\ \text{full matrix } X}}{A} \hat{f}_k = f_j$$

to get  $\hat{f}_k$ ,  
 $O(N^3)$  operations.  
 too expensive!

so, use orthogonality.

$$I = \sum_{j=0}^{N-1} e^{ikx_j} e^{-ik'x_j} = \sum_{j=0}^{N-1} e^{i(k-k')x_j} = \begin{cases} N & \text{if } k=k' \\ & +mN \\ 0 & \text{otherwise} \end{cases}$$

$m=0, \pm 1, \pm 2, \dots$

$$f_j = \sum_{k=-N/2}^{N/2-1} \hat{f}_k e^{ikx_j}$$

$$\sum_{j=0}^{N-1} f_j e^{-ik'x_j} = \sum_{j=0}^{N-1} \sum_{k=-N/2}^{N/2-1} \hat{f}_k e^{ikx_j} e^{-ik'x_j}$$

$$= \sum_{k=-N/2}^{N/2-1} \sum_{j=0}^{N-1} \hat{f}_k e^{i(k-k')x_j} = N \hat{f}_k$$

$$\hat{f}_k = \frac{1}{N} \sum_{j=0}^{N-1} f_j e^{-ikx_j}$$

$$k = -\frac{N}{2}, -\frac{N}{2}+1, \dots, 0, \dots, \frac{N}{2}-1$$

$O(N^2)$  operations.



FFT  $\rightarrow O(N \log_2 N)$  operations  
 (fast FT) see 'Numerical Recipes' for this routine.

DFT: 
$$\begin{cases} \hat{f}_j = \sum_{k=-N/2}^{N/2-1} \hat{f}_k e^{ikx_j}, & j = 0, 1, 2, \dots, N-1 \quad \textcircled{1} \\ \hat{f}_k = \frac{1}{N} \sum_{j=0}^{N-1} f_j e^{-ikx_j}, & k = -\frac{N}{2}, \dots, 0, \dots, \frac{N}{2}-1 \quad \textcircled{2} \end{cases}$$

$\downarrow$  complex number  $a+ib$

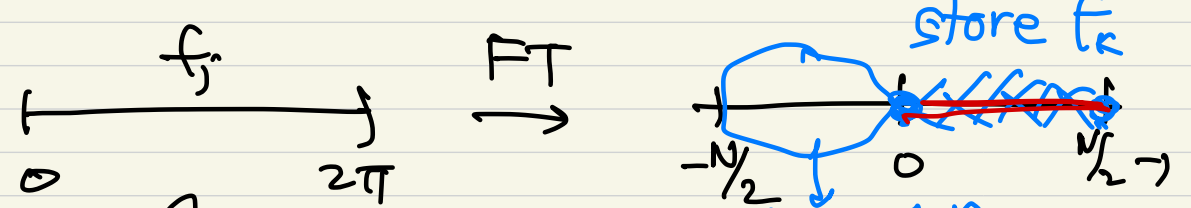
$N$   $\times$   $2N$

• FT of a real ft.

$f$ : real ft  $\xrightarrow{FT}$   $\hat{f}_k$ : complex

$$\left( \hat{f}_k = \frac{1}{N} \sum_j f_j e^{-ikx_j} \right)^* \rightarrow \hat{f}_k^* = \frac{1}{N} \sum_j f_j e^{ikx_j} = \hat{f}_{-k}$$

$$\Rightarrow \boxed{\hat{f}_{-k} = \hat{f}_k^*}$$



No need to store  $\hat{f}_{-k}$  when  $f$  is real.

Higher dimensions

$f(x, y)$ : doubly periodic in  $x$  &  $y$  directions

$$f(x_m, y_l) = \sum_{k_1 = -\frac{N_1}{2}}^{\frac{N_1}{2}-1} \sum_{k_2 = -\frac{N_2}{2}}^{\frac{N_2}{2}-1} \hat{f}_{k_1, k_2} e^{ik_1 x_m} e^{ik_2 y_l} \quad \begin{matrix} m=0, 1, \dots, N_1-1 \\ l=0, 1, \dots, N_2-1 \end{matrix}$$

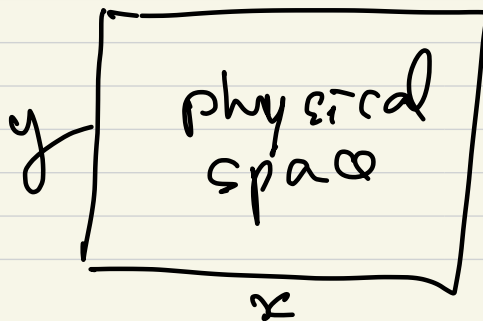
use orthogonality

$$\hat{f}_{k_1, k_2} = \frac{1}{N_1} \frac{1}{N_2} \sum_{m=0}^{N_1-1} \sum_{l=0}^{N_2-1} f_{m, l} e^{-ik_1 x_m} e^{-ik_2 y_l}$$

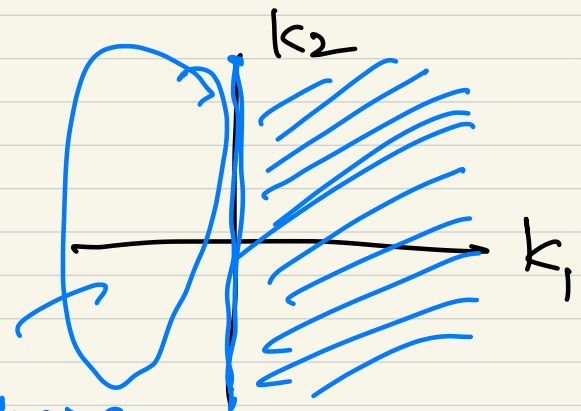
$$k_1 = -\frac{N_1}{2}, \dots, 0, \dots, \frac{N_1}{2}-1$$

$$k_2 = -\frac{N_2}{2}, \dots, 0, \dots, \frac{N_2}{2}-1$$

If  $f$  is real,  $\hat{f}_{-k_1, -k_2} = \hat{f}_{k_1, k_2}^*$



FT  
 $\longrightarrow$   
 no need to store data here



$$\underbrace{H(x)} = \underbrace{f(x)} \underbrace{g(x)}$$

$$\underbrace{\hat{H}} = ?$$

[ aliasing error  
" control ]