

Next assignment...

$$\frac{\partial^2 U}{\partial t^2} + \tau \frac{\partial U}{\partial t} = c^2 \nabla^2 U$$

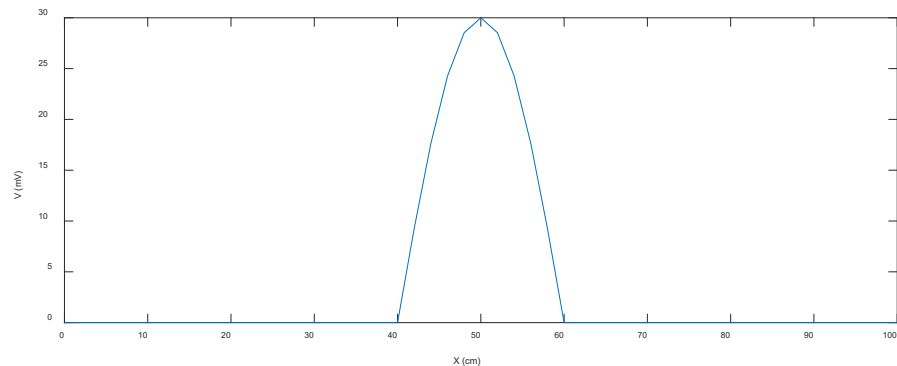
$$U = \theta \left(\frac{U^{l+1} + U^{l-1}}{2} \right) + (1 - \theta) U^l$$

BCs

$$\frac{\partial U}{\partial t} - c \frac{\partial U}{\partial x} + \frac{\tau U}{2} = 0 \quad \text{for } x = 0$$

$$\frac{\partial U}{\partial t} + c \frac{\partial U}{\partial x} + \frac{\tau U}{2} = 0 \quad \text{for } x = L_x$$

$$U(x, t = 0) = 30 \cos\left(\frac{\pi r}{2r_o}\right) \text{ for } r \leq r_o, \text{ and } U(x, t = 0) = 0 \text{ for } r \geq r_o$$



Let's consider...

$$\frac{\partial^2 U}{\partial t^2} + \tau \frac{\partial U}{\partial t} = c^2 \nabla^2 U$$

$$U = \theta \left(\frac{U^{l+1} + U^{l-1}}{2} \right) + (1 - \theta) U^l$$

What is the approach?

Now what?

$$\frac{\partial U}{\partial t} = \frac{U_i^{l+1} - U_i^{l-1}}{2\Delta t}$$

$$c^2 \nabla^2 U$$

$$\frac{\partial^2 U}{\partial t^2} = \frac{U_i^{l+1} - 2U_i^l + U_i^{l-1}}{\Delta t^2}$$

$$\theta \left(\frac{c^2 \nabla^2 U^{l+1} + c^2 \nabla^2 U^{l-1}}{2} \right) + (1 - \theta) (c^2 \nabla^2 U^l)$$

Continuing...

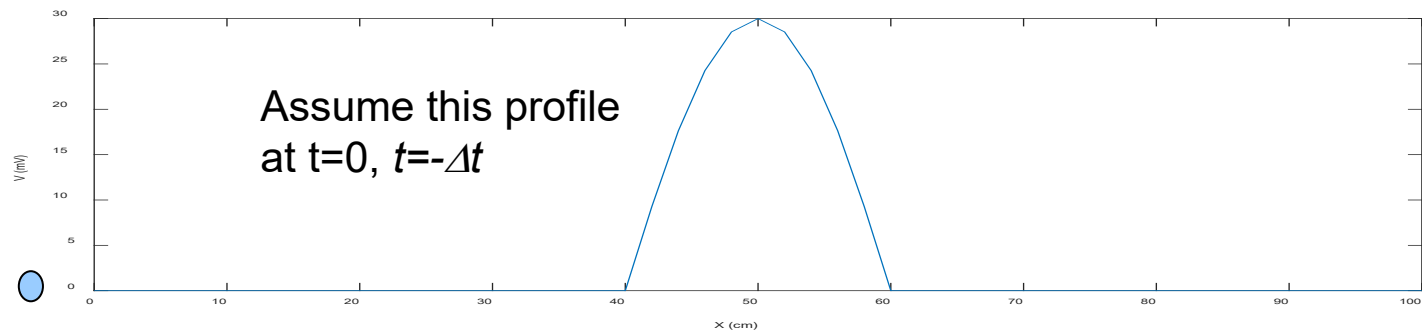
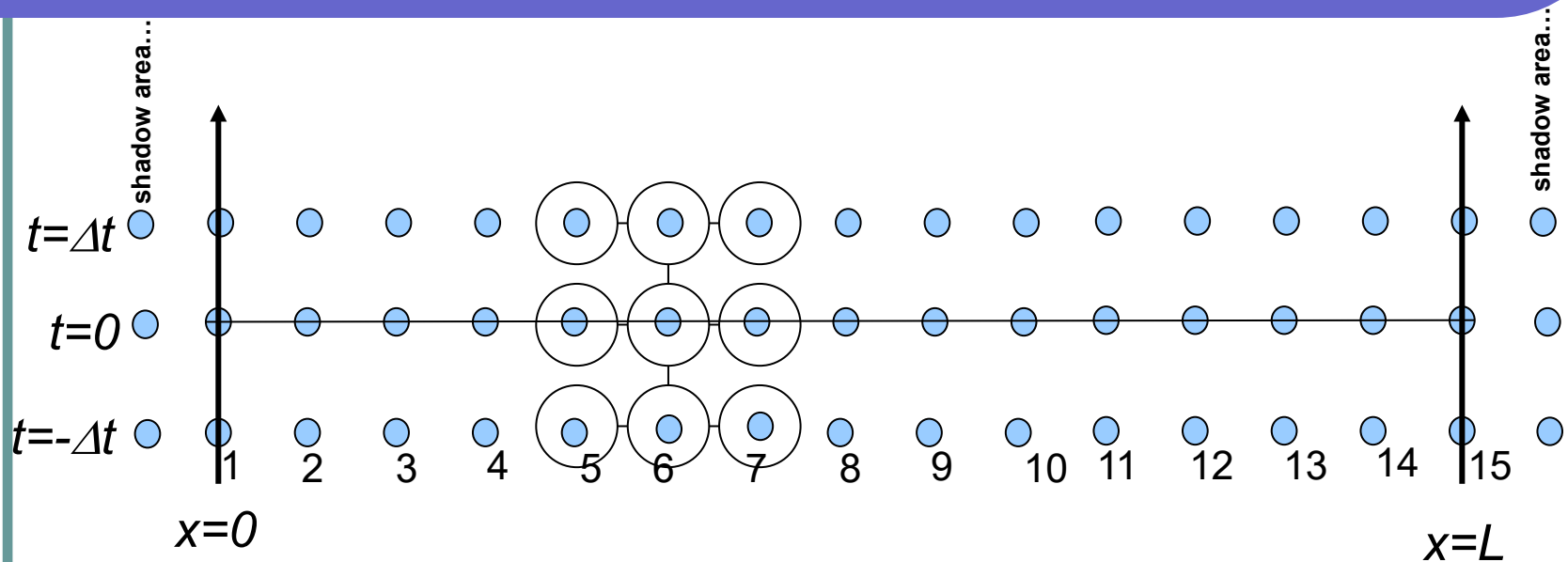
$$U_i^{l+1} - 2U_i^l + U_i^{l-1} + \frac{\tau\Delta t}{2}(U_i^{l+1} - U_i^{l-1}) - k \left(\theta \left(\frac{U_{i+1}^{l+1} - 2U_i^{l+1} + U_{i-1}^{l+1} + U_{i+1}^{l-1} - 2U_i^{l-1} + U_{i-1}^{l-1}}{2} \right) + (1-\theta)(U_{i+1}^l - 2U_i^l + U_{i-1}^l) \right) = 0$$

$$(u_i^{l+1} - 2u_i^l + u_i^{l-1}) + \frac{\tau\Delta t}{2}(u_i^{l+1} - u_i^{l-1}) - k\delta_x^2 \left[\theta \left(\frac{u_{i+1}^{l+1} + u_{i-1}^{l+1}}{2} \right) + (1-\theta)u_i^l \right]$$

$$k = c^2 \Delta t^2 / h^2$$

$$\begin{array}{ccccc} \left(\frac{-k\theta}{2} \right) & \text{---} & \left(1 + \frac{\tau\Delta t}{2} + k\theta \right) & \text{---} & \left(\frac{-k\theta}{2} \right) \\ & & \downarrow & & \\ \left(-k(1-\theta) \right) & \text{---} & \left(-2 + 2k(1-\theta) \right) & \text{---} & \left(-k(1-\theta) \right) \\ & & \downarrow & & \\ \left(\frac{-k\theta}{2} \right) & \text{---} & \left(-1 - \frac{\tau\Delta t}{2} + k\theta \right) & \text{---} & \left(\frac{-k\theta}{2} \right) \end{array} = 0$$

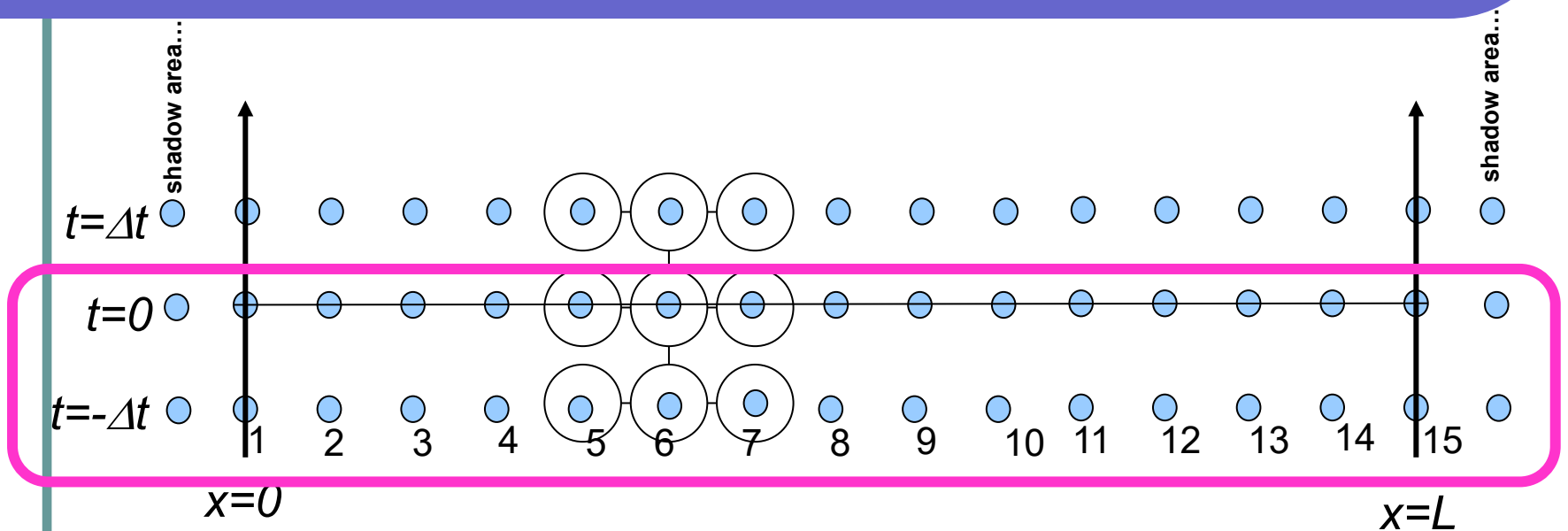
Continuing ...



$x=-2$
 $U=0$ here too...

$x=102$
 $U=0$ here too...

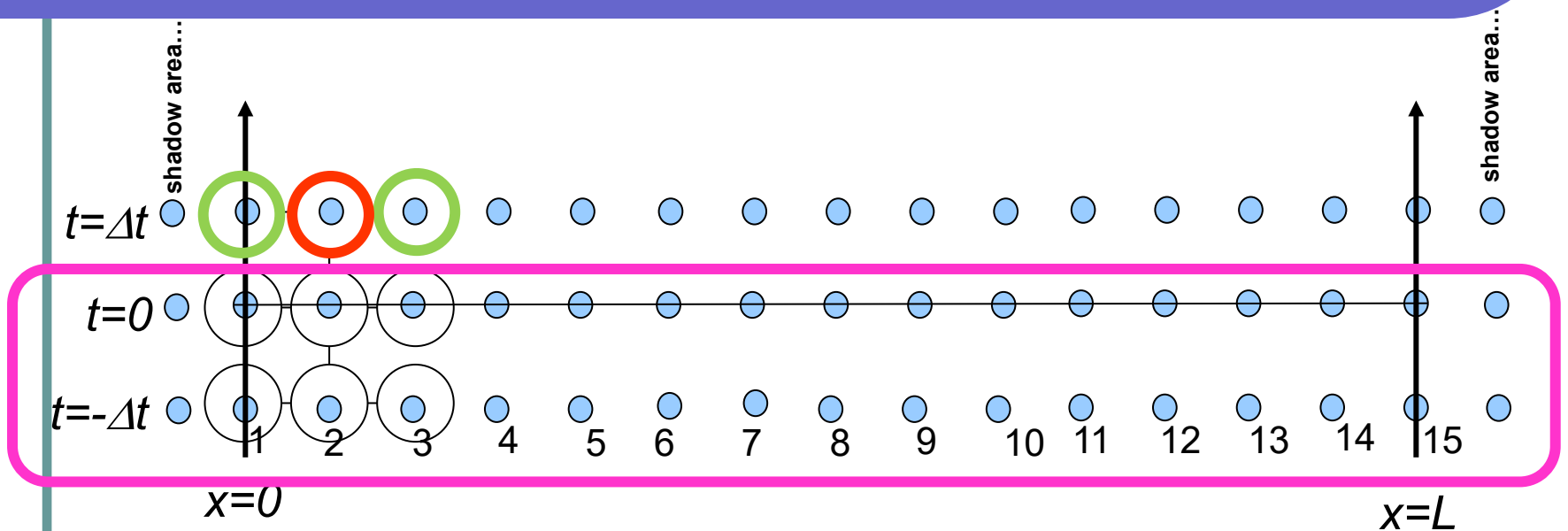
Continuing ...



I know every u -value here at the start including the shadow nodes

My task is to solve for u -values at $t = \Delta t$, the $l+1$ level...

Continuing ...



Let's assume Jacobi's method.... What am I doing?

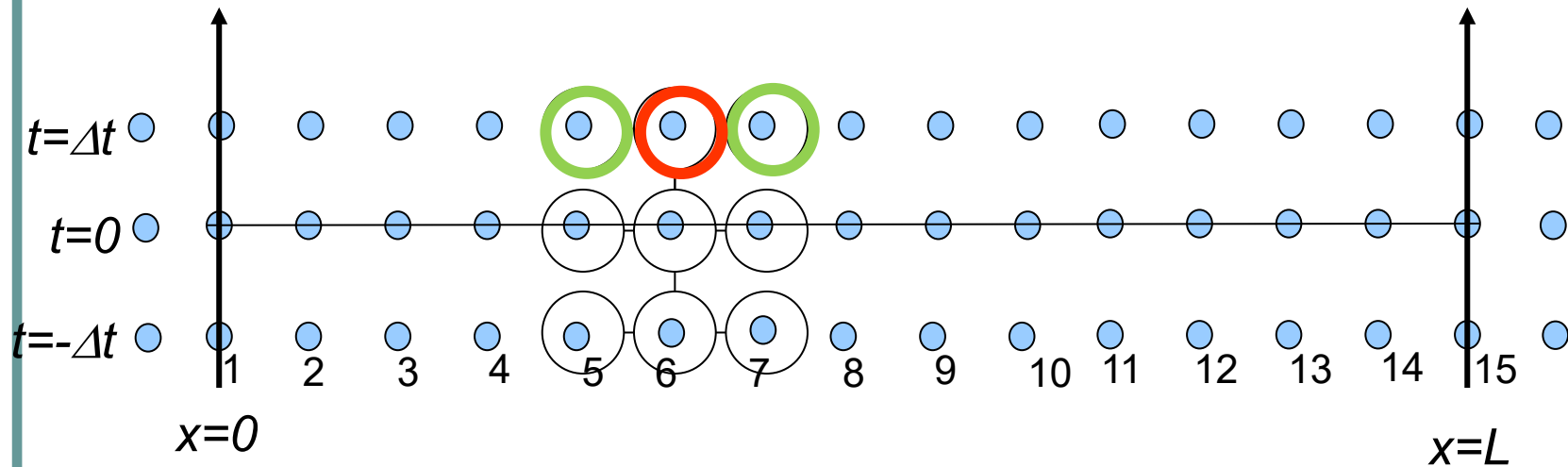
Assume a solution at $u(t=\Delta t)$, call it u_{old} .

Magenta is all known from previous values

Green – use values from u_{old}

Solve for the Red Node Only

Step-by-Step Tick-Tock



$$U_6^{l+1} - 2U_6^l + U_6^{l-1} + \frac{\tau\Delta t}{2}(U_6^{l+1} - U_6^{l-1}) - k \left(\theta \left(\frac{U_7^{l+1} - 2U_6^{l+1} + U_5^{l+1}}{2} + \frac{U_7^{l-1} - 2U_6^{l-1} + U_5^{l-1}}{2} \right) + (1-\theta)(U_7^l - 2U_6^l + U_5^l) \right) = 0$$

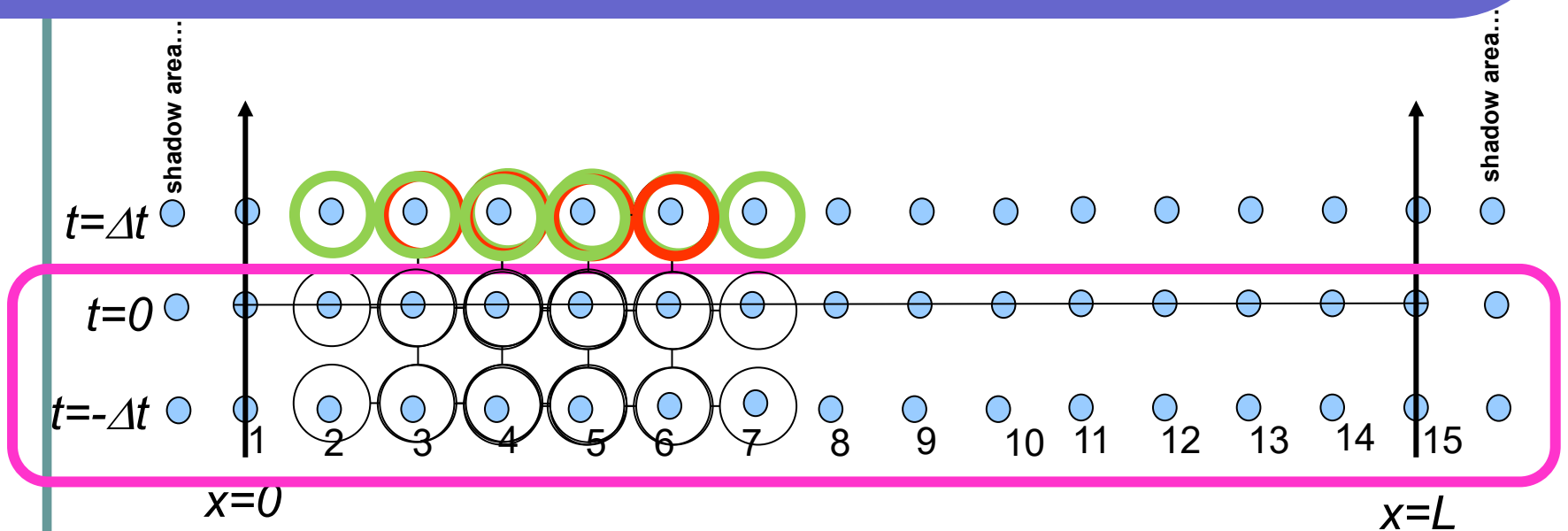
Have to group these right? ☐

Have to use solution at previous iterate? ☐

This is explicit info already known from previous time steps? ☐

$$U_i^{l+1} - 2U_i^l + U_i^{l-1} + \frac{\tau\Delta t}{2}(U_i^{l+1} - U_i^{l-1}) - k \left(\theta \left(\frac{U_{i+1}^{l+1} - 2U_i^{l+1} + U_{i-1}^{l+1}}{2} + \frac{U_{i+1}^{l-1} - 2U_i^{l-1} + U_{i-1}^{l-1}}{2} \right) + (1-\theta)(U_{i+1}^l - 2U_i^l + U_{i-1}^l) \right) = 0 \quad k = \frac{c^2\Delta t^2}{h^2}$$

Continuing ...



Let's assume Jacobi's method.... What am I doing?

Assume a solution at $u(t=\Delta t)$, call it u_{old} .

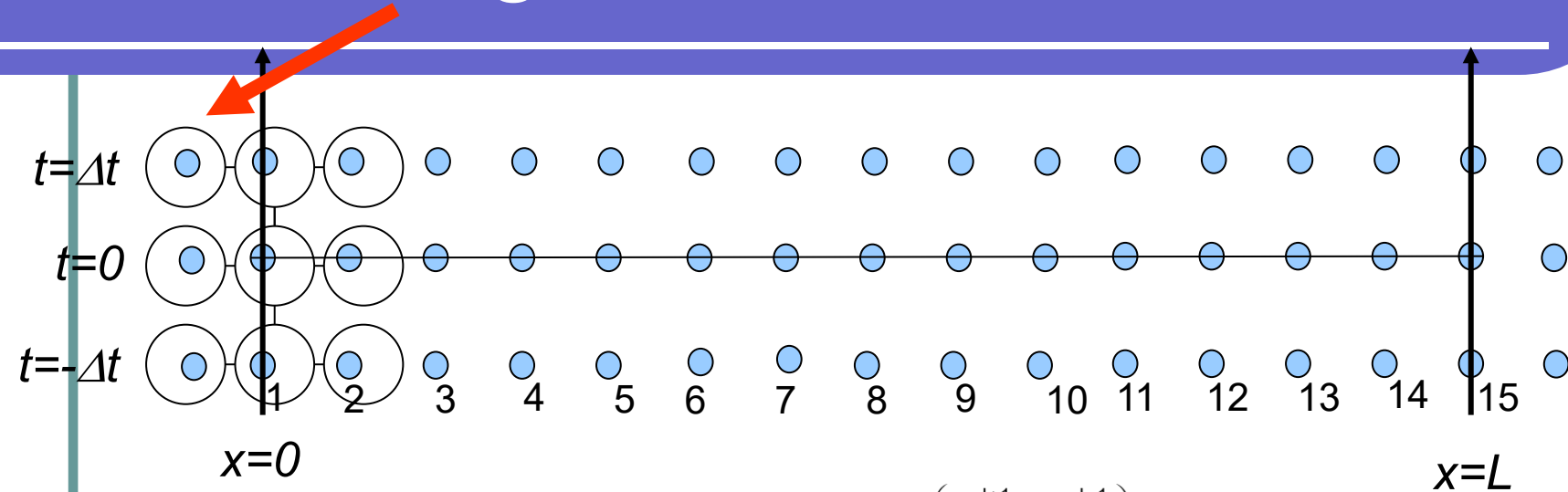
Magenta is all known from previous values

Green – use values from u_{old}

Solve for the Red Node Only

Move to the next internal node ...

Continuing ...



$$\frac{\partial U}{\partial t} - c \frac{\partial U}{\partial x} + \frac{\tau U}{2} = 0 \quad \text{for } x = 0$$

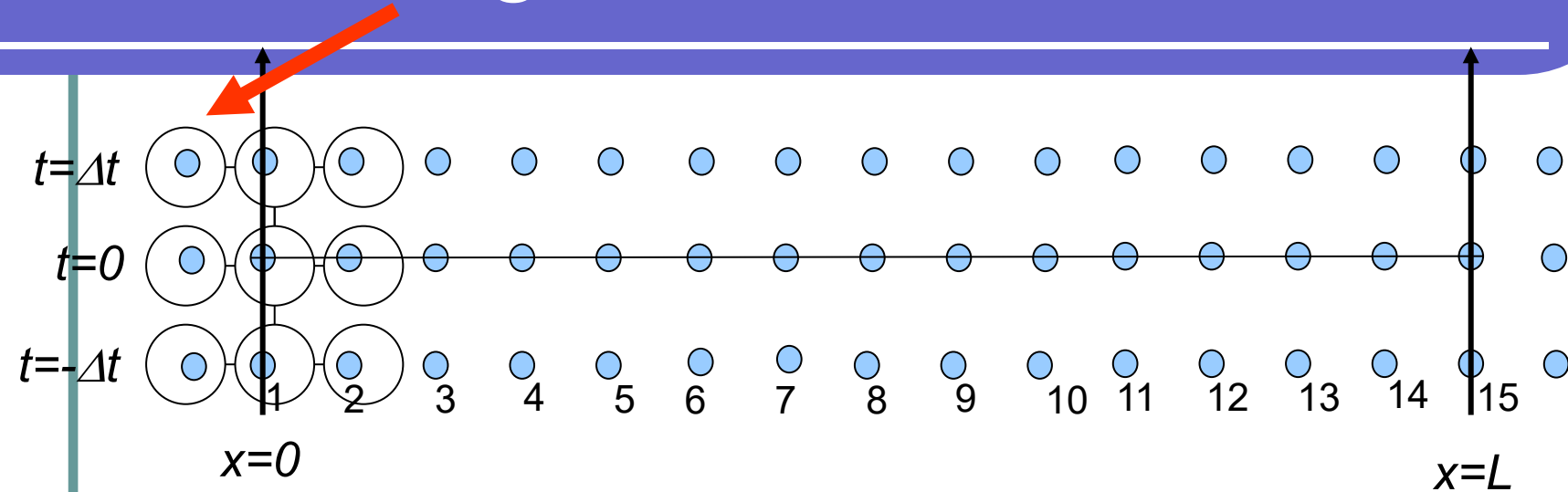
$$U = \theta \left(\frac{U^{l+1} + U^{l-1}}{2} \right) + (1 - \theta) U^l$$

$$\frac{U_i^{l+1} - U_i^{l-1}}{2\Delta t} - c \left[\theta \left(\frac{U_{i+1}^{l+1} - U_{i-1}^{l+1}}{2h} + \frac{U_{i+1}^{l-1} - U_{i-1}^{l-1}}{2h} \right) + (1 - \theta) \left(\frac{U_{i+1}^l - U_{i-1}^l}{2h} \right) \right] + \frac{\tau}{2} \left[\theta \left(\frac{U_i^{l+1} + U_i^{l-1}}{2} \right) + (1 - \theta) (U_i^l) \right] = 0$$

Solve for the shadow node...

Remember... U_{i-1}^{l+1} is solved for in terms of other term ...

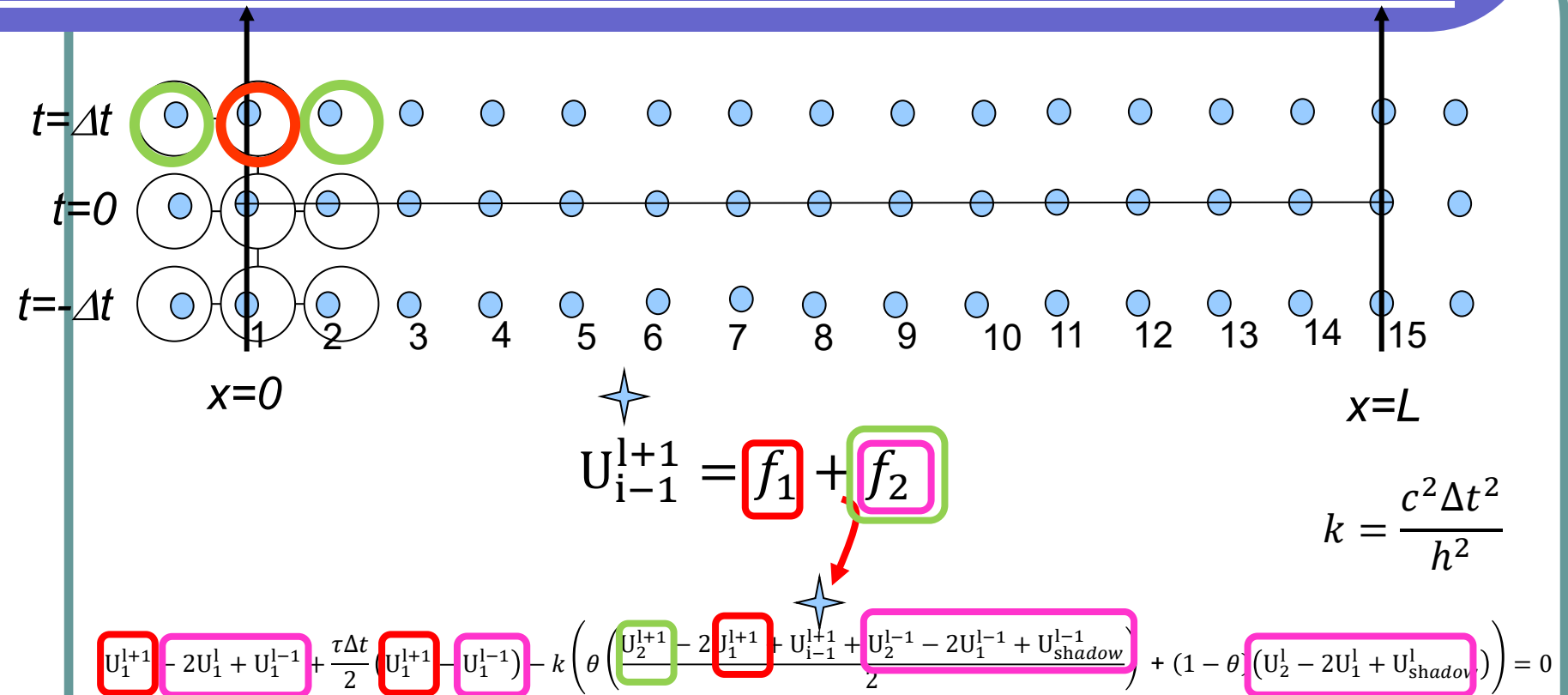
Continuing ...



$$\frac{U_i^{l+1} - U_i^{l-1}}{2\Delta t} - c \left[\theta \left(\frac{U_{i+1}^{l+1} - U_{i-1}^{l+1}}{2h} + \frac{U_{i+1}^{l-1} - U_{i-1}^{l-1}}{2h} \right) + (1 - \theta) \left(\frac{U_{i+1}^l - U_{i-1}^l}{2h} \right) \right] + \frac{\tau}{2} \left[\theta \left(\frac{U_i^{l+1} + U_i^{l-1}}{2} \right) + (1 - \theta)(U_i^l) \right] = 0$$

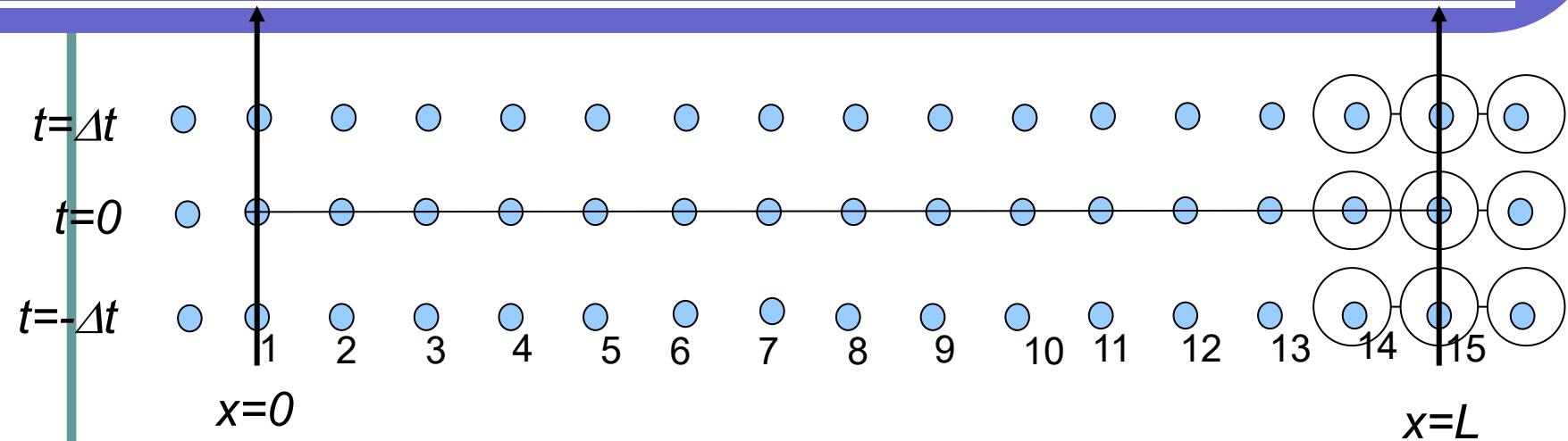
$$U_{i-1}^{l+1} = f_1 + f_2 = fcn(U_i^{l+1}) + fcn(U_{i+1}^{l+1}, U_{i-1}^l, U_i^l, U_{i+1}^l, U_{i-1}^{l-1}, U_i^{l-1}, U_{i+1}^{l-1})$$

Continuing ...



For Jacobi iteration update at node 1, group these right? ☐

Continuing ...



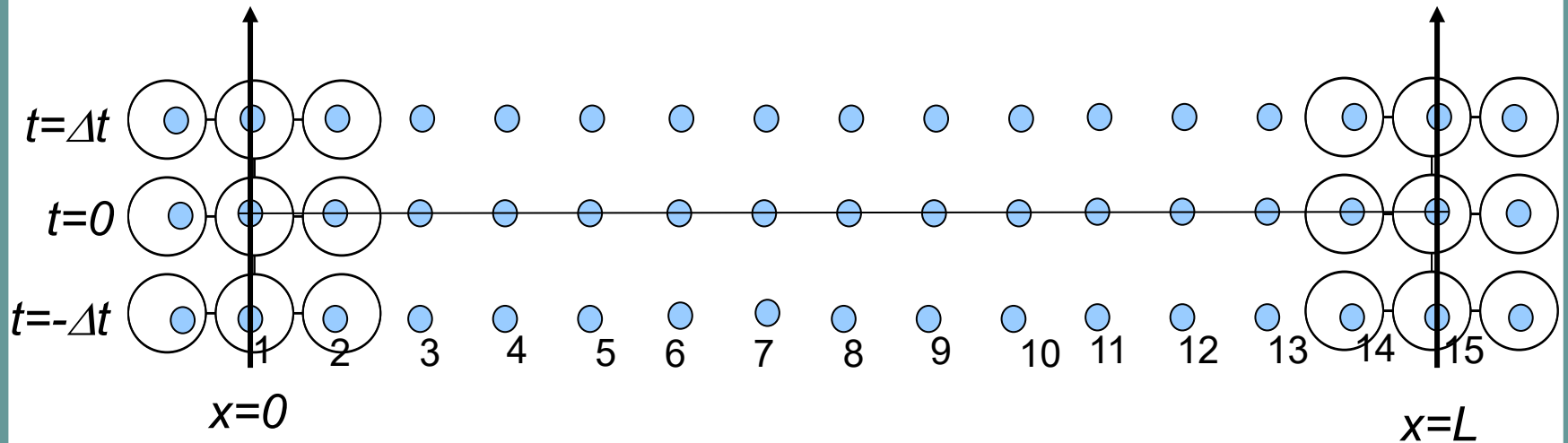
Solve for the shadow node...

$$\frac{\partial U}{\partial t} + c \frac{\partial U}{\partial x} + \frac{\tau U}{2} = 0 \quad \text{for } x = L$$

$$\frac{U_i^{l+1} - U_i^{l-1}}{2\Delta t} + c \left[\theta \left(\frac{\frac{U_{i+1}^{l+1} - U_{i-1}^{l+1}}{2h} + \frac{U_{i+1}^{l-1} - U_{i-1}^{l-1}}{2h}}{2} \right) + (1 - \theta) \left(\frac{U_{i+1}^l - U_{i-1}^l}{2h} \right) \right] + \frac{\tau}{2} \left[\theta \left(\frac{U_i^{l+1} + U_i^{l-1}}{2} \right) + (1 - \theta)(U_i^l) \right]$$

Do the same on this side....

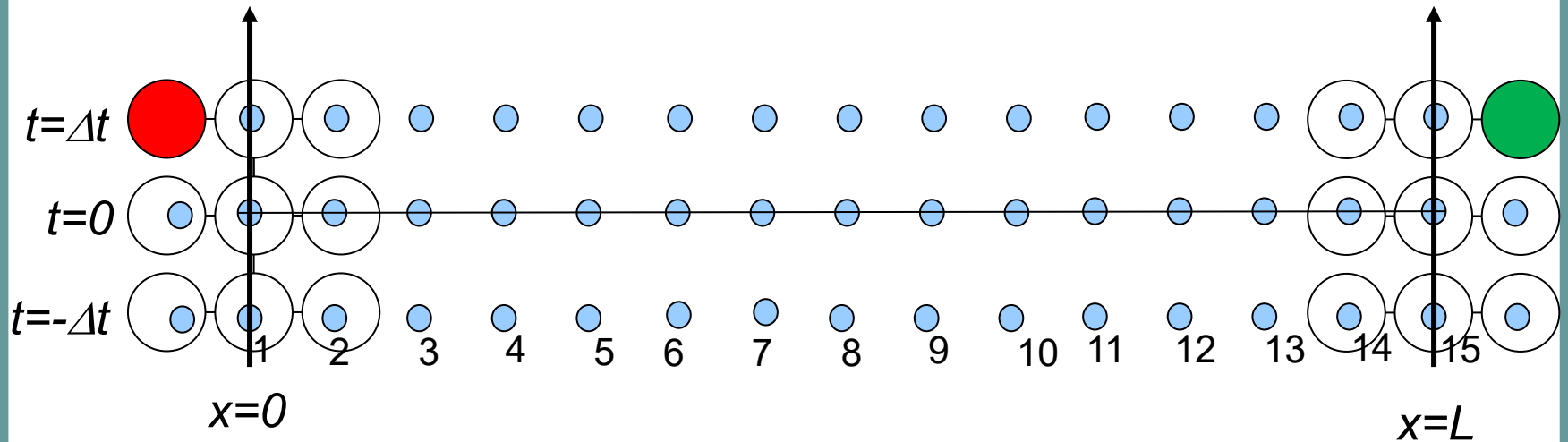
Continuing ...



You can now update the solution at each node for one Jacobi iteration... keep doing it until you converge.

Point iterative method

Continuing ...

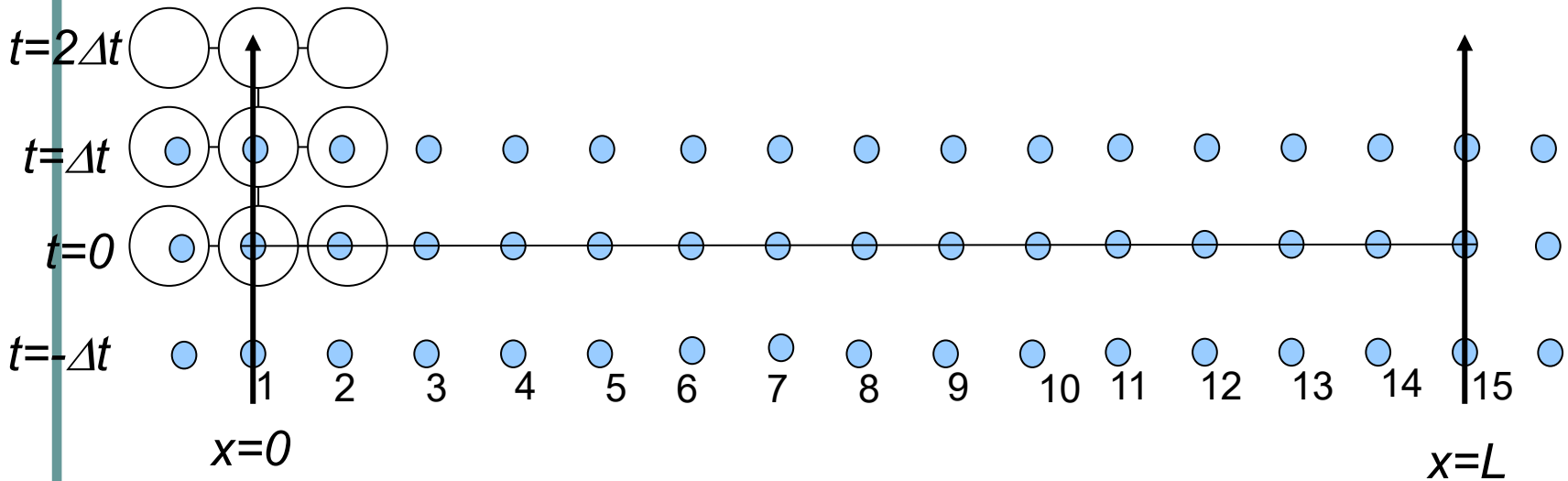


Once you converged.... Take your solution and calculate the shadow nodes at $t = \Delta t$

$$U_{i-1}^{l+1} = f_1 + f_2 = fcn(U_i^{l+1}, U_{i+1}^{l+1}, U_{i-1}^l, U_i^l, U_{i+1}^l, U_{i-1}^{l-1}, U_i^{l-1}, U_{i+1}^{l-1})$$

$$U_{i+1}^{l+1} = f_1 + f_2 = fcn(U_i^{l+1}, U_{i-1}^{l+1}, U_{i-1}^l, U_i^l, U_{i+1}^l, U_{i-1}^{l-1}, U_i^{l-1}, U_{i+1}^{l-1})$$

Continuing ...



Moving forward? ...

With shadow nodes known at $t=\Delta t$, the process for solving $t=2\Delta t$ is identical...



Review

$$(a.) \quad P_N = \frac{1}{3} P_{N-1} \quad \text{EXACT}$$

$$\hat{P}_N = \frac{1}{3} \hat{P}_{N-1} \quad \text{COMPUTER}$$

$$P_N - \hat{P}_N = \frac{1}{3} (P_{N-1} - \hat{P}_{N-1})$$

$$E_N = \frac{1}{3} E_{N-1}$$

$$P_N = \frac{10}{3} P_{N-1} - P_{N-2} \quad w/ \quad P_0 = 1, P_1 = \frac{1}{3}$$

$$\text{then } E_N = \frac{10}{3} E_{N-1} - E_{N-2} \Rightarrow \text{difference eqn. with constant coefficients}$$

$$E_N = C_1 \left(\frac{1}{3}\right)^N + C_2 (3)^N$$

HW 1

$$w_{i+1} = w_i + \frac{\Delta t}{2} (-2k * w_i + k^2 \Delta t * w_i) \quad (3)$$

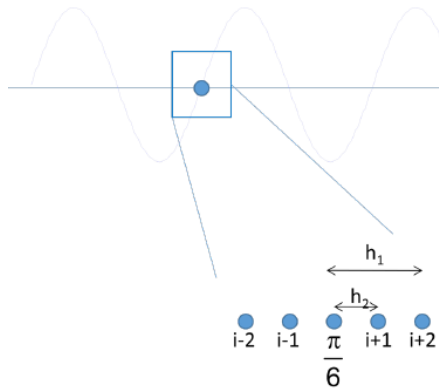
$$w_N = \left(1 - \Delta t k + \frac{\Delta t^2 k^2}{2}\right)^N$$

$$\text{Center Difference Expression: } \frac{du}{dt} = \frac{u_{i-2} - 8u_{i-1} + 8u_{i+1} - u_{i+2}}{12h} \quad \text{Order } (h^4)$$

$$\text{Backward Difference Expression: } \frac{du}{dt} = \frac{u_{i-2} - 4u_{i-1} + 3u_i}{2h} \quad \text{Order } (h^2)$$

$$\text{Forward Difference Expression: } \frac{du}{dt} = \frac{u_{i+1} - u_i}{h} \quad \text{Order } (h)$$

$$u'_i = \frac{du_i}{dx} = \frac{u_{i+1} - u_i}{h} - \frac{h}{2!} u''_i + \dots$$

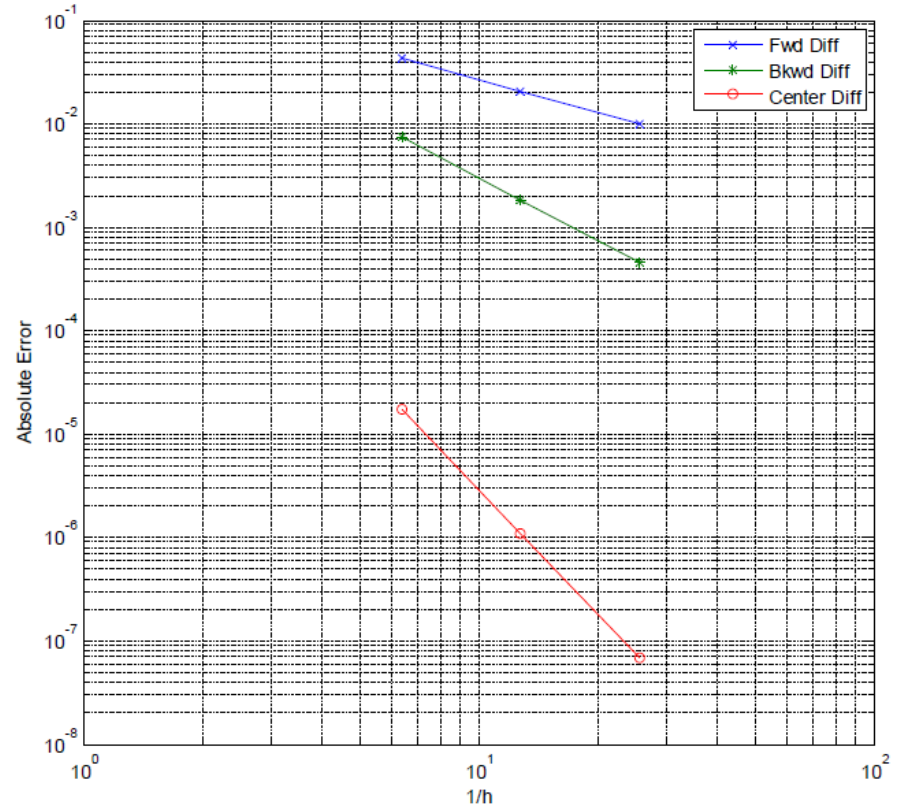


Half-h error cuts -1/2, 1/4, 1/16

$$m = \frac{\log(6.864e-8) - \log(1.7523e-5)}{\log(80/\pi) - \log(20/\pi)}$$

$m = -4$

Slope of the order



Expr.	$\cos(\pi/6)$	h_1 val.	h_2 val.	h_3 val.	Error for h_1	Error for h_2	Error for h_3
Cntr	0.866025403784	0.866007880594	0.866024306169	0.866025335145717	1.75231895e-05	1.09761485e-06	6.8638721706371e-08
Back	0.866025403784	0.873569309894	0.867862752074	0.866477904830691	0.007543906109	0.001837348290	4.5250104625227e-04
Fwd	0.866025403784	0.823279179126	0.845510468697	0.855986618817722	0.042746224658	0.020514935086	0.010038784966716

$$\begin{aligned}
 &= \sum_{j=1}^N \left[\frac{h}{2} (f_j + f_{j-1}) - \frac{h^3}{12} f''(\xi_j) \right] \quad \xi_j \in [x_{j-1}, x_j] \\
 &= \frac{h}{2} \left[f_0 + f_N + 2 \sum_{j=1}^{N-1} f_j \right] - \frac{h^3}{12} \underbrace{\sum_{j=1}^N f''(\xi_j)}_{N \overline{f''(\xi_j)} \leftarrow \text{average value}}
 \end{aligned}$$

So

$$I(b) = \underbrace{\frac{h}{2} \left[f_a + f_b + 2 \sum_{j=1}^{N-1} f_j \right]}_{\text{Composite Trap Rule } b} - \underbrace{\left(\frac{b-a}{12} \right) h^2 \overline{f''(\xi_j)}}_{\substack{\text{Error term} \\ \text{one order lower} \\ \text{in } h \text{ relative to} \\ \text{single application}}}$$

$Nh = b-a$

Also talked in the context of integration and quadrature

Better (easier) to use concepts of a basis function

$$\text{i.e. } P_N(x) = \sum_{j=0}^N \alpha_j b_j(x)$$

$$\text{Since you have seen that } \int_{\ell} (\vec{J} \cdot \hat{n}) d\ell = J_{n1} \int \phi_1 d\ell + J_{n2} \int \phi_2 d\ell$$

$$\int_1^2 (\vec{J} \cdot \vec{n}) \phi_1 d\ell = J_{n1} \int \phi_1 \phi_1 d\ell + J_{n2} \int \phi_2 \phi_1 d\ell$$

$$\int \phi_n \phi_n = L/3 \quad \text{and} \quad \int \phi_m \phi_n = L/6$$

HW 2

then for the first scenario we obtain

$$J_{n1}(L/3) + J_{n2}(L/6)$$

Likewise,

$$\int_1^2 (\vec{J} \cdot \vec{n}) \phi_2 d\ell \quad \text{evaluates to}$$

$$J_{n1}(L/6) + J_{n2}(L/3)$$

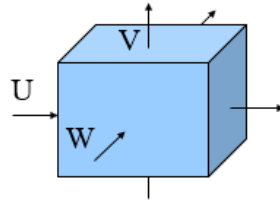
HW 2

$$\frac{\partial}{\partial \mathbf{x}}(\rho \mathbf{U}) + \frac{\partial}{\partial \mathbf{y}}(\rho \mathbf{V}) + \frac{\partial}{\partial \mathbf{z}}(\rho \mathbf{W}) = 0$$

$$\nabla \cdot (\rho \vec{\mathbf{V}}) = 0$$

If density is constant ...

$$\nabla \cdot \vec{\mathbf{V}} = \frac{\partial V_x}{\partial x} + \frac{\partial V_y}{\partial y} + \frac{\partial V_z}{\partial z} = 0$$

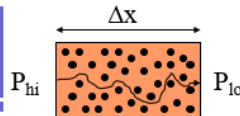


- Operates on vector/tensor and is principally used in *conservation* statements within physics

Divergence op (+) , gradient op (no +, just deriv of vector)

(conservation of mass)

Porous-Media Example



$$\nabla \cdot \vec{\mathbf{V}} = \nabla \cdot (-k \nabla p) = 0$$

$$\frac{\partial}{\partial x} \left(-k \frac{\partial p}{\partial x} \right) + \frac{\partial}{\partial y} \left(-k \frac{\partial p}{\partial y} \right) + \frac{\partial}{\partial z} \left(-k \frac{\partial p}{\partial z} \right) = 0$$

Assume homogeneous constant hydraulic conductivity...

$$\frac{\partial}{\partial x} \left(\frac{\partial p}{\partial x} \right) + \frac{\partial}{\partial y} \left(\frac{\partial p}{\partial y} \right) + \frac{\partial}{\partial z} \left(\frac{\partial p}{\partial z} \right) = 0$$

$$\frac{\partial^2 p}{\partial x^2} + \frac{\partial^2 p}{\partial y^2} + \frac{\partial^2 p}{\partial z^2} = 0$$

Laplacian Operator

$$\nabla^2 p = 0$$

Laplace's Equation

What am I assuming?

$$\iint_S \mathbf{F} \cdot \hat{\mathbf{n}} dS = \iiint_V \nabla \cdot \mathbf{F} dV$$

Gradient Operator

What if ???

$P_{hi} \rightarrow P_{lo} \rightarrow V_x = -k \frac{dp}{dx} \rightarrow p = f(x, y, z)$

Velocity a vector, right !!

$$\begin{cases} V_x = -k \frac{\partial p}{\partial x} \\ V_y = -k \frac{\partial p}{\partial y} \\ V_z = -k \frac{\partial p}{\partial z} \end{cases} \rightarrow \vec{V} = -k \nabla p$$

What if I dotted this into the unit vector normal to a surface, i.e. perpendicular to the surface?

(conservation of volume) = laplacian of pressure

curl = limit of circulation of a path

HW 2

$$\nabla \cdot (-\partial \nabla V) = 0$$

expand

$$\nabla \cdot \left(-\partial \begin{bmatrix} \frac{\partial V}{\partial x} \hat{i} \\ \frac{\partial V}{\partial y} \hat{j} \end{bmatrix} \right) = 0$$

$$\frac{\partial}{\partial x} \underbrace{\left(-\partial \frac{\partial V}{\partial x} \right)}_{\text{let} = F} + \frac{\partial}{\partial y} \underbrace{\left(-\partial \frac{\partial V}{\partial y} \right)}_{\text{let} = G} = 0$$

$$\frac{\partial}{\partial x} \underbrace{\left(-\partial \frac{\partial V}{\partial x} \right)}_{\text{let} = F} + \frac{\partial}{\partial y} \underbrace{\left(-\partial \frac{\partial V}{\partial y} \right)}_{\text{let} = G} = 0$$

expand using FD technique @ half-grid point

$$\frac{F_{i+1/2} - F_{i-1/2}}{h} + \frac{G_{j+1/2} - G_{j-1/2}}{k} = 0$$

$$\frac{\left(-\partial \frac{\partial V}{\partial x} \Big|_{i+1/2} \right) - \left(-\partial \frac{\partial V}{\partial x} \Big|_{i-1/2} \right)}{h} + \frac{\left(-\partial \frac{\partial V}{\partial y} \Big|_{j+1/2} \right) - \left(-\partial \frac{\partial V}{\partial y} \Big|_{j-1/2} \right)}{k} = 0$$

HW 2

$$\frac{\left(-\theta_{i+1/2,j} \left(\frac{V_{i+1,j} - V_{i,j}}{h}\right)\right) - \left(-\theta_{i-1/2,j} \left(\frac{V_{i,j} - V_{i-1,j}}{h}\right)\right)}{h} + \frac{\left(-\theta_{i,j+1/2} \left(\frac{V_{i,j+1} - V_{i,j}}{k}\right)\right) - \left(-\theta_{i,j-1/2} \left(\frac{V_{i,j} - V_{i,j-1}}{k}\right)\right)}{k} = 0$$

simplify

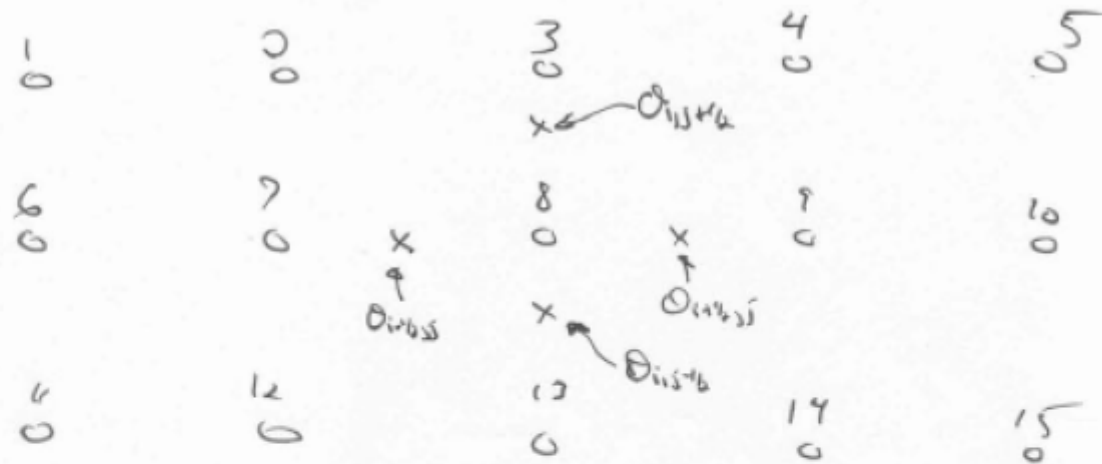
$$\frac{-\theta_{i+1/2,j} V_{i+1,j} + (\theta_{i+1/2,j} + \theta_{i-1/2,j}) V_{i,j} - \theta_{i-1/2,j} V_{i-1,j}}{h^2} + \frac{-\theta_{i,j+1/2} V_{i,j+1} + (\theta_{i,j+1/2} + \theta_{i,j-1/2}) V_{i,j} - \theta_{i,j-1/2} V_{i,j-1}}{k^2} = 0$$

on equal grid, $h=k$, multiply through by spatial step size..

$$-\theta_{i+1/2,j} V_{i+1,j} - \theta_{i-1/2,j} V_{i-1,j} - \theta_{i,j+1/2} V_{i,j+1} - \theta_{i,j-1/2} V_{i,j-1} + (\theta_{i+1/2,j} + \theta_{i-1/2,j} + \theta_{i,j+1/2} + \theta_{i,j-1/2}) V_{i,j} = 0$$

HW 2

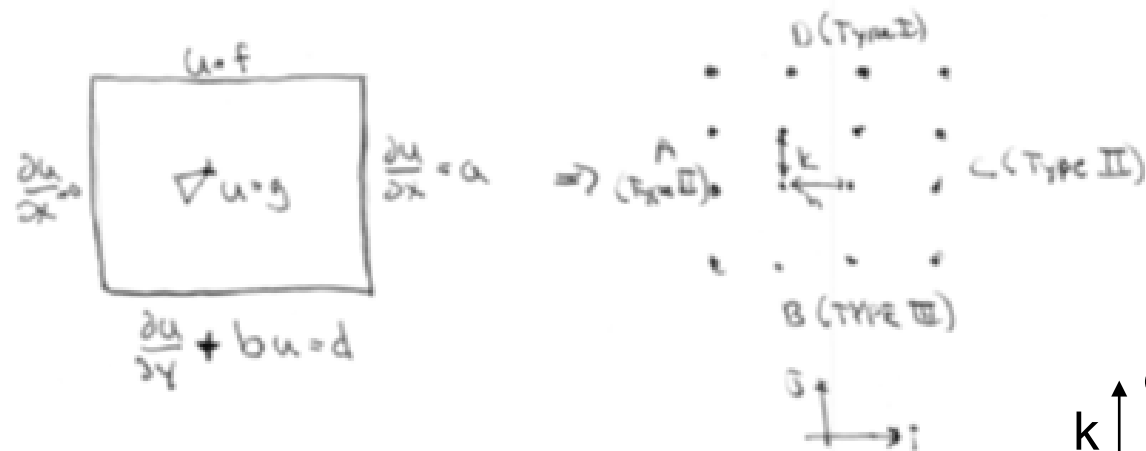
GRID



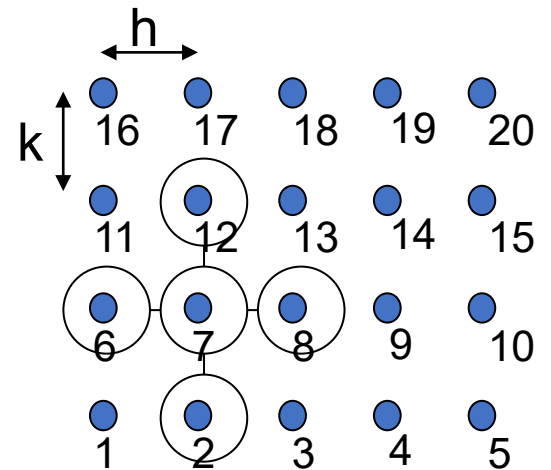
so for equation (8)

$$\begin{aligned}
 & -\partial_{i+\frac{1}{2},j} V_9 - \partial_{i-\frac{1}{2},j} V_7 - \partial_{i,j+\frac{1}{2}} V_3 - \partial_{i,j-\frac{1}{2}} V_{13} \\
 & \quad + \\
 & (\partial_{i+\frac{1}{2},j} + \partial_{i-\frac{1}{2},j} + \partial_{i,j+\frac{1}{2}} + \partial_{i,j-\frac{1}{2}}) V_8 = 0
 \end{aligned}$$

Ex. Consider :



PDE : $\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} = g$

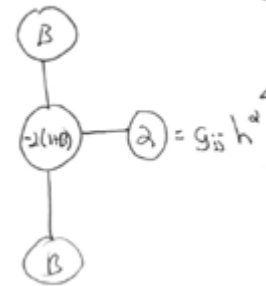
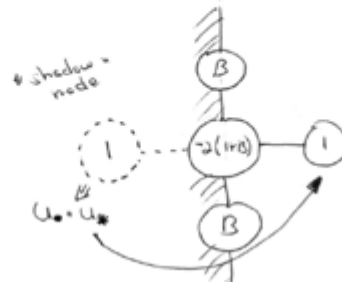


$$\Rightarrow \frac{\delta_x^2 u_{i,j}}{h^2} + \frac{\delta_y^2 u_{i,j}}{k^2} = g_{i,j}$$

$$\frac{u_8 - 2u_7 + u_6}{h^2} + \frac{u_{12} - 2u_7 + u_2}{k^2} = g_7$$

$$\frac{u_{i+2,j} - 2u_{i,j} + u_{i-2,j}}{h^2} + \frac{u_{i,j+2} - 2u_{i,j} + u_{i,j-2}}{k^2} = g_{i,j}$$

\Rightarrow for nodes on Boundary A, the molecule becomes:



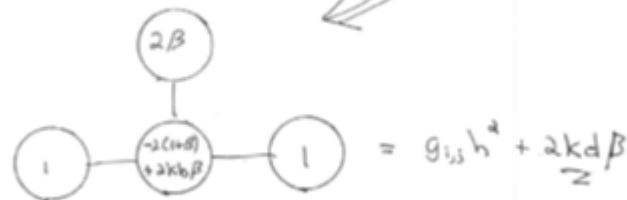
Boundary B:

$$\left. \frac{\partial u}{\partial \nu} \right|_{j=0} + bu = d \quad \Rightarrow \quad \frac{u_0 - u_*}{2k} + bu_{ij} = d$$

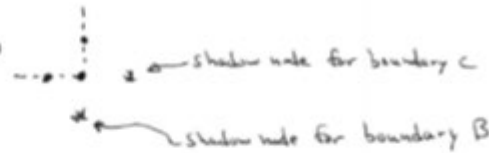
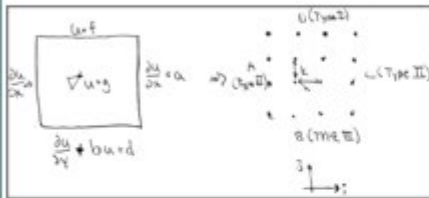
solve for u_*

$$\hookrightarrow u_* = 2kb u_{ij} - 2kd + u_0$$

becomes:

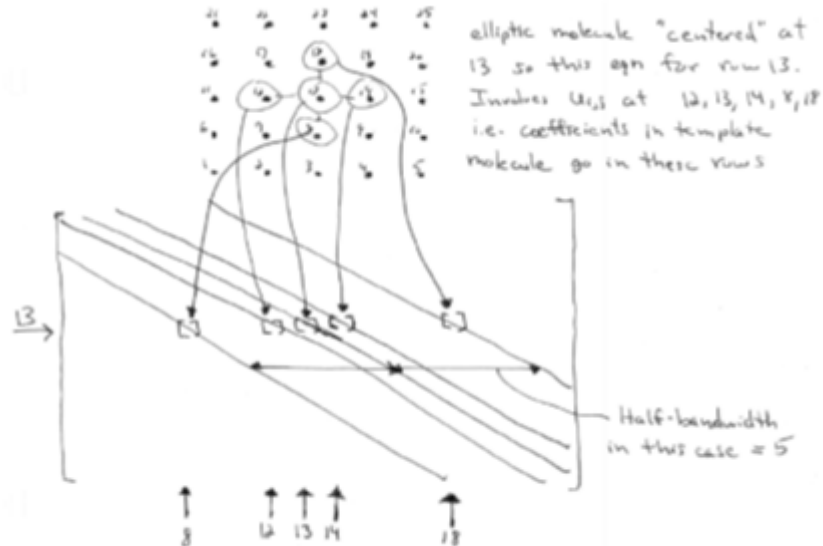


Corners: e.g.



$$2 \quad \begin{matrix} 2B \\ 2(111) + 2k\beta\beta \end{matrix} = g_{i,j}h^2 - 2ah + 2k\beta d$$

- Basic Rule:
- Type I BC do not use PDE (i.e. let type 1 override)
 - Type II, III, use PDE PLUS BC together (i.e. use BC to eliminate shadow nodes)



Typical to store as banded matrix...

Classical Point Iteration Methods (For Solving System $Au=b$)

- Need stopping criterion

Typical : $\|u^{l+1} - u^l\| < \epsilon$

Better : $\frac{\|u^{l+1} - u^l\|}{\|u^{l+1}\|} < \epsilon$

Absolute

Relative

• **Jacobi**

$$u_{i,j}^{l+1} = \frac{1}{\beta_0} [\beta_1 u_{i+1,j}^l + \beta_2 u_{i-1,j}^l + \beta_3 u_{i,j+1}^l + \beta_4 u_{i,j-1}^l - h^2 g_{i,j}]$$

$l \equiv$ iteration # j $u_{i,j}^0$ "initial guess"

• **SOR**

$$u_{i,j}^{l+1} = \frac{\omega}{\beta_0} [\beta_1 u_{i+1,j}^l + \beta_2 u_{i-1,j}^{l+1} + \beta_3 u_{i,j+1}^l + \beta_4 u_{i,j-1}^{l+1} - h^2 g_{i,j}] + (1-\omega) u_{i,j}^l$$

- Determining $\rho(A)$ in practice

• can compute w/ Power Method requires ω to actually construct G_1 \rightarrow (see B+F, Appendix)

• estimate during iteration

$$\rho \approx \frac{\|\delta^l\|}{\|\delta^{l-1}\|} \quad \text{where } \delta^l = u^l - u^{l-1}$$

↳ so for error reduction by factor K

$$\|e\|^{l+m} = \rho^m \|e\|^l, \quad K = \rho^m \Rightarrow m > \frac{\log K}{\log(\rho)}$$

ω = relaxation parameter ($\omega=1$ is Gauss Seidel)

Summary

$$\left(1 + \frac{1}{2}P_e h\right) \quad -2 \quad \left(1 - \frac{1}{2}P_e h\right) = 0$$

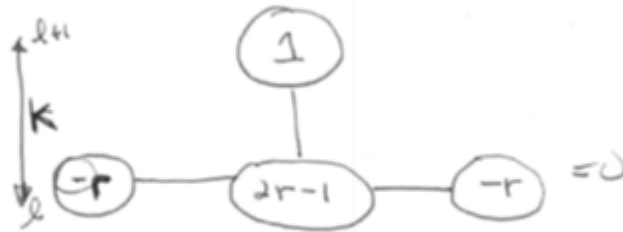
$$\left(1 + P_e h\right) \quad -2 - P_e h \quad 1 = 0$$

$$1 \quad -2 + P_e h \quad 1 - P_e h = 0$$

Figure 3.8: Centered, Upstream, and Downstream difference approximations to the Advection-Diffusion equation.

$$u_i^{l+1} - u_i^l - \frac{Dk}{h^2} (u_{i-1}^l - 2u_i^l + u_{i+1}^l) = 0$$

let $r = \frac{Dk}{h^2}$



- "Explicit"

- pointwise propagation

- $O(k+h^2)$

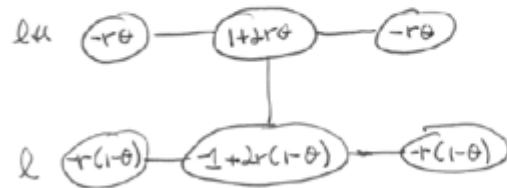
- Forward Difference in t

↳ Euler integration

- conditional stability

2. SEMI-IMPLICIT MOLECULE

Generalization: $u_i^{l+1} - u_i^l = r \underbrace{\theta \delta_x^2 u_i^{l+1} + (1-\theta) \delta_x^2 u_i^l}_{\substack{\text{averaging of } u_i^l + u_i^{l+1} \\ \text{weighted by } \theta}}$



$\theta = 1$ fully implicit
 $\theta = 0$ explicit

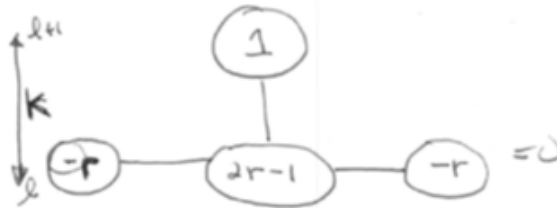
$\theta = 0.5$ "Crank-Nicolson"

(molecule centered a $l+\frac{1}{2}$
 $O(k+h^2)$)

$\theta \geq 0.5$ unconditional stability
 $\theta < 0.5$ conditional stability

$$u_i^{l+1} - u_i^l - \frac{Dk}{h^2} (u_{i-1}^l - 2u_i^l + u_{i+1}^l) = 0$$

let $r = \frac{Dk}{h^2}$



- "Explicit"

- pointwise propagation

- $O(k+h^2)$

- Forward Difference in t

→ Euler integration

- Conditional stability

1) Convergence: $u_i^l \rightarrow U(x_i, t_l)$ as $h, k \rightarrow 0$

Exact solution
to FD eqns

Exact solution to PDE

- requires Discretization error $\rightarrow 0$ as mesh lengths $\rightarrow 0$

2) Consistency: $L_i \rightarrow L$ as $h, k \rightarrow 0$

FD molecule

PDE operator

- weaker than convergence, but easier to show

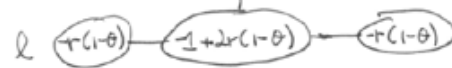
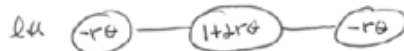
- requires Truncation error $\rightarrow 0$ as mesh lengths $\rightarrow 0$

3) Stability: u_i^l bounded for bounded BCs, ICs and forcing

2. SEMI-IMPLICIT MOLECULE

Generalization: $u_i^{l+1} - u_i^l = r\theta \Delta_x^2 u_i^{l+1} + r(1-\theta) \Delta_x^2 u_i^l$

averaging of $u_i^l + u_i^{l+1}$
weighted by θ



= 0

$\theta = 1$ fully implicit

$\theta = 0$ explicit

$\theta = 0.5$ "Crank-Nicolson"

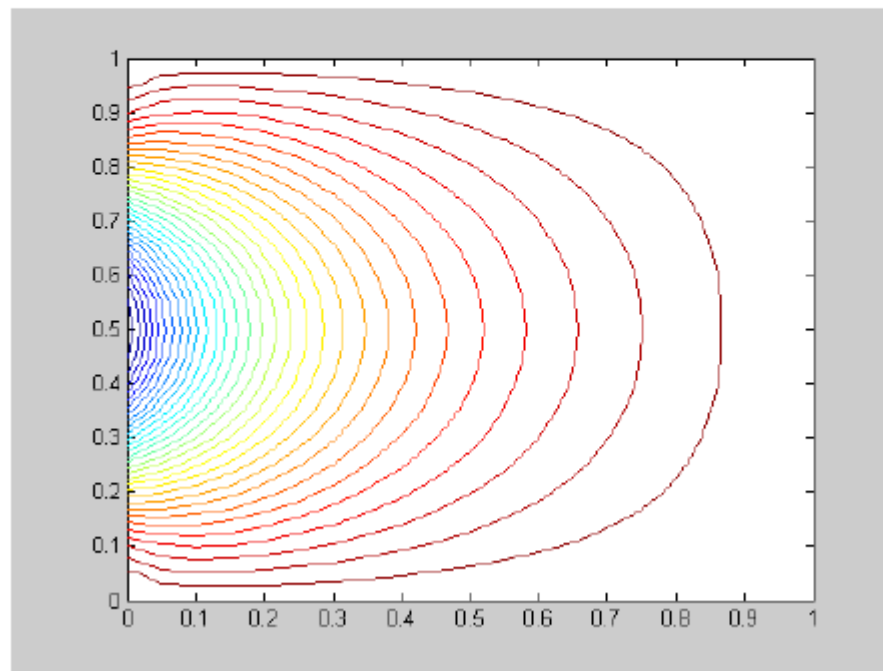
(molecule centered at $l+\frac{1}{2}$
 $O(k^2+h^2)$)

$\theta \geq 0.5$ unconditional stability
 $\theta < 0.5$ conditional stability

Jacobi # of iterations: 582
 Spectral radius estimate: 0.9877
 Analytic spectral radius: $1-\pi^2 h^2/2=0.98766$
 $\Phi(0.7,0.7)=0.86971$

Gauss-Seidel # of iterations: 322
 Spectral radius estimate: 0.97553
 Analytic spectral radius: $(\rho_{\text{jacobi}})^2=0.97547$
 $\Phi(0.7,0.7)=0.869996$

$\omega_{\text{opt}}=2/(1-\sqrt{1-\rho_{\text{Gauss-Seidel}}})=1.7293$
 $\rho_{\text{SOR}}=1.7293-1=0.7293$
 $\rho_{\text{estimate}}=0.8339$
 SOR # of iterations = 49
 $\Phi(0.7,0.7)=0.870227$



Gauss-Seidel converges approximately twice as fast as Jacobi according to theory. Here we see that the reduction of iterations is approximately 2 with Jacobi taking 582 iterations versus 322 for Gauss-Seidel

In reducing our tolerance from 10^{-5} to 10^{-6} we expect the following number of additional iterations:

$$N_{\text{Jacobi}} @ 10^{-6} = N_{\text{Jacobi}} @ 10^{-5} + \log(0.1)/\log(\rho_{\text{Jacobi}}) = 582 + \log(0.1)/\log(0.9877) = 768$$

$$N_{\text{Gauss-Seidel}} @ 10^{-6} = N_{\text{Gauss-Seidel}} @ 10^{-5} + \log(0.1)/\log(\rho_{\text{Gauss-Seidel}}) = 322 + \log(0.1)/\log(0.97553) = 415$$

$$\text{so for error reduction by factor } K \\ \|e\|^{l+m} = f^m \|e\|^l, \quad K = f^m \Rightarrow m > \frac{\log K}{\log(f)}$$

In reducing our tolerance from 10^{-5} to 10^{-6} we expect the following number of additional iterations:

$$N_{\text{Jacobi}} @ 10^{-6} = N_{\text{Jacobi}} @ 10^{-5} + \log(0.1)/\log(\rho_{\text{Jacobi}}) = 582 + \log(0.1)/\log(0.9877) = 768$$

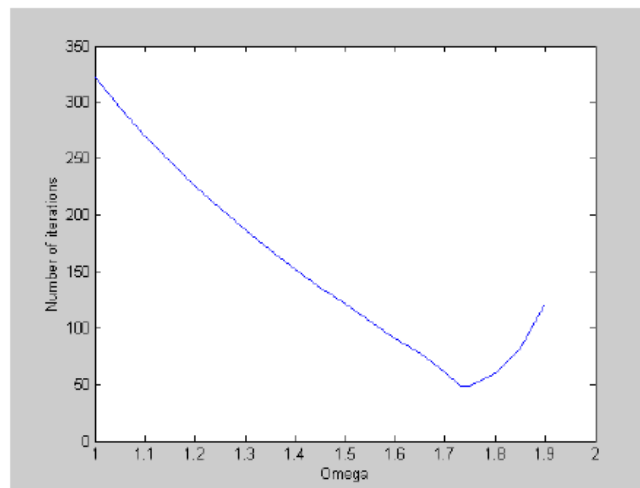
$$N_{\text{Gauss-Seidel}} @ 10^{-6} = N_{\text{Gauss-Seidel}} @ 10^{-5} + \log(0.1)/\log(\rho_{\text{Gauss-Seidel}}) = 322 + \log(0.1)/\log(0.97553) = 415$$

Rerunning the simulations at a tolerance of 10^{-6} , produced the following:

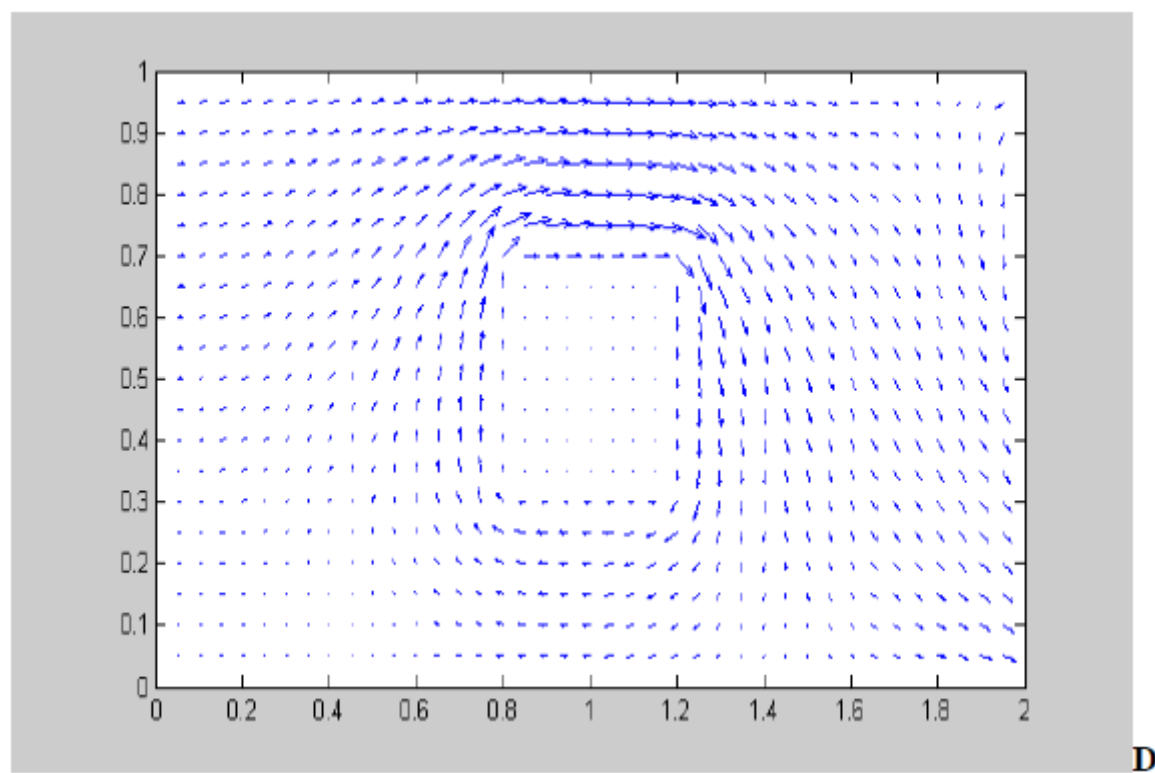
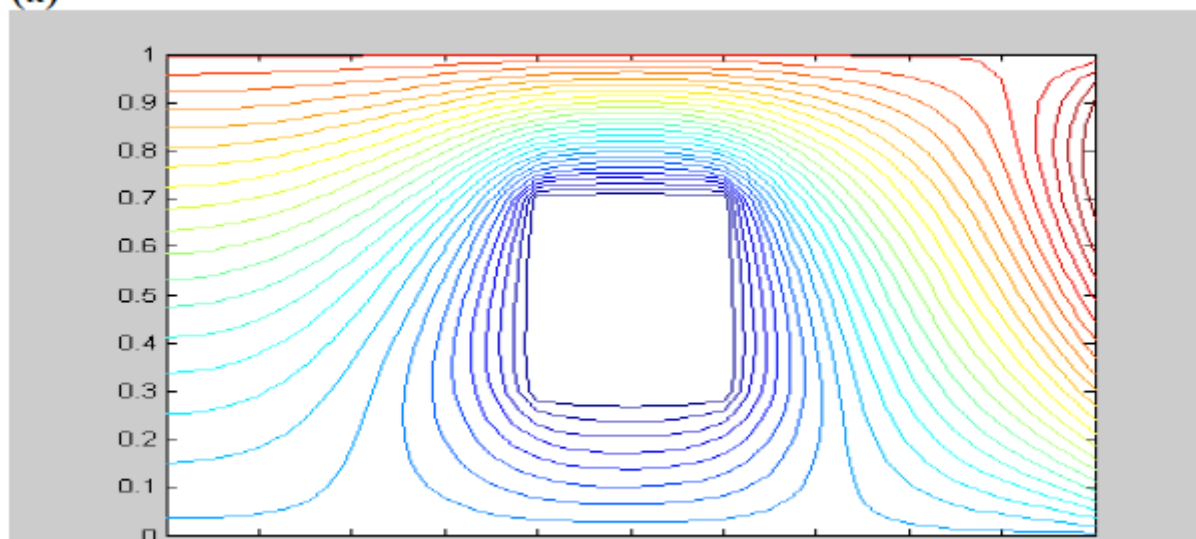
$$N_{\text{Jacobi}} @ 10^{-6} = 768$$

$$N_{\text{Gauss-Seidel}} @ 10^{-6} = 415$$

The estimated increase in the number of iterations for the new tolerance is the same as the numerical output.



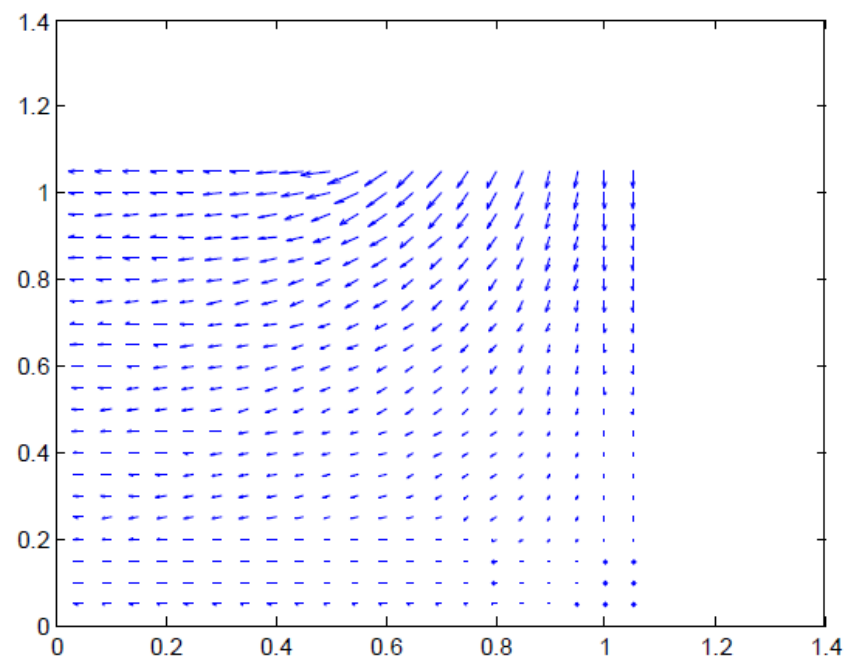
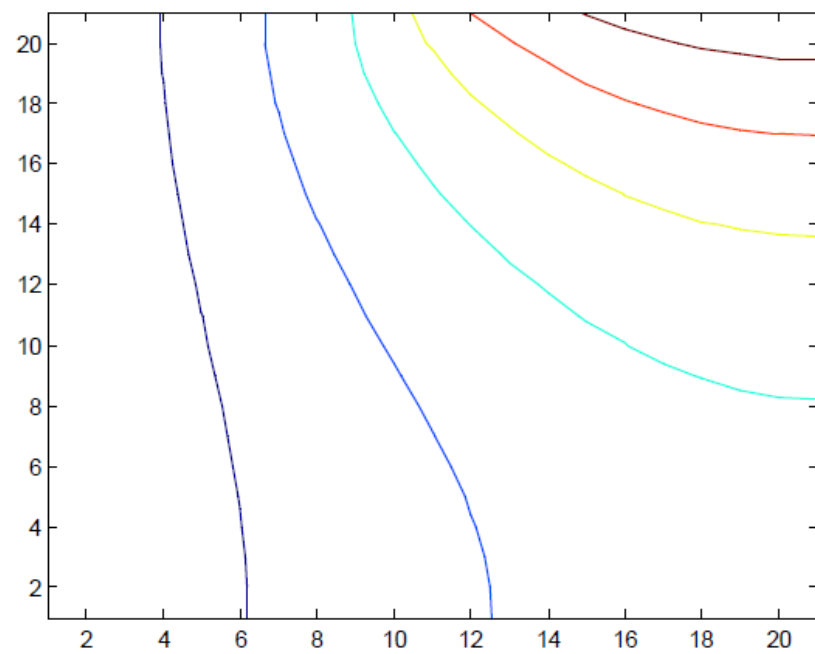
(a)

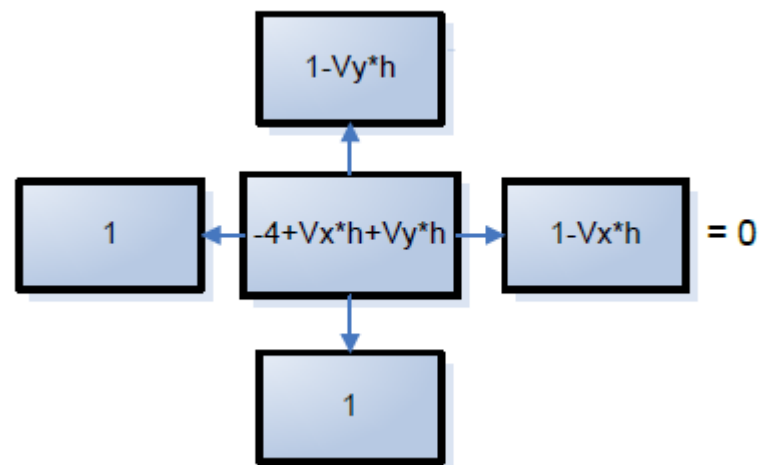
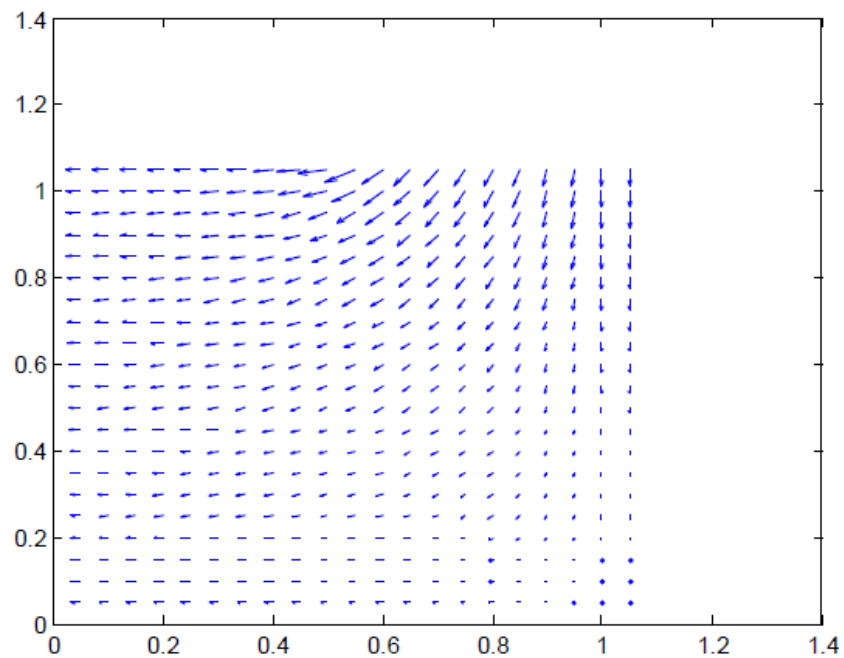
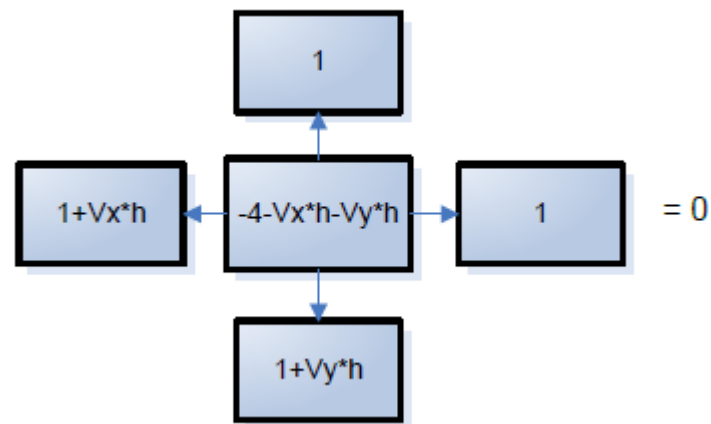
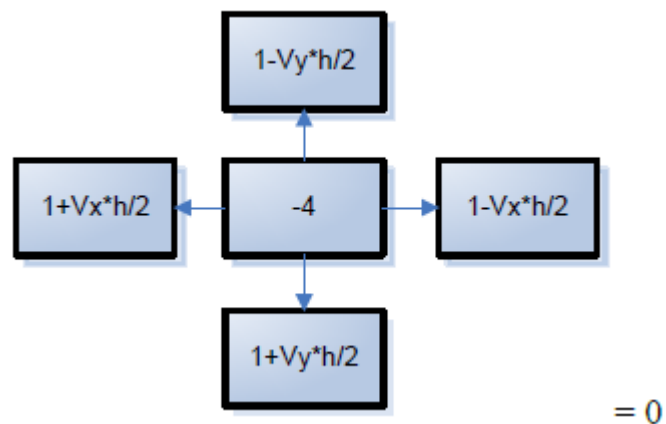


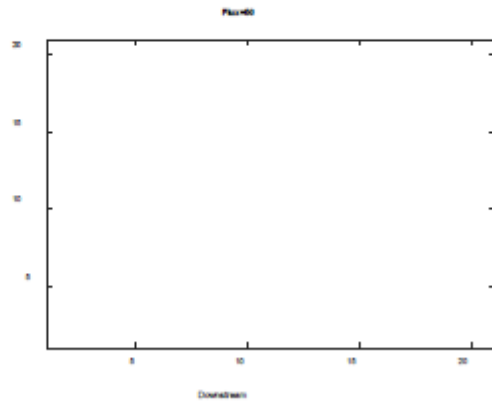
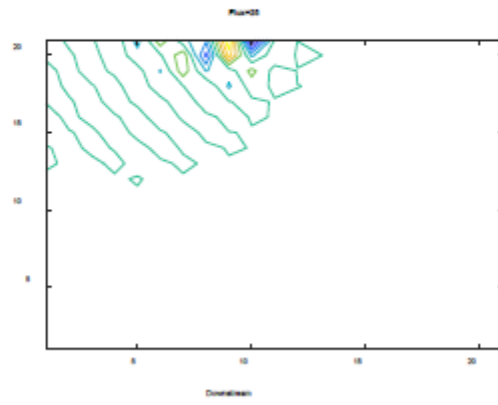
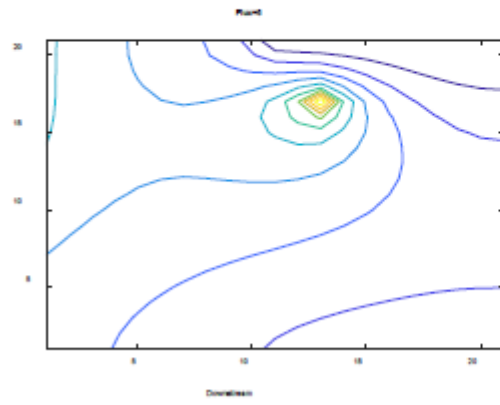
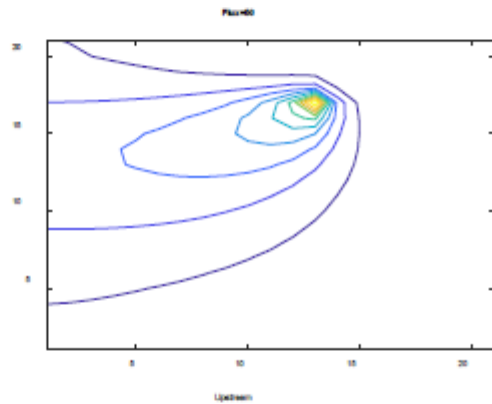
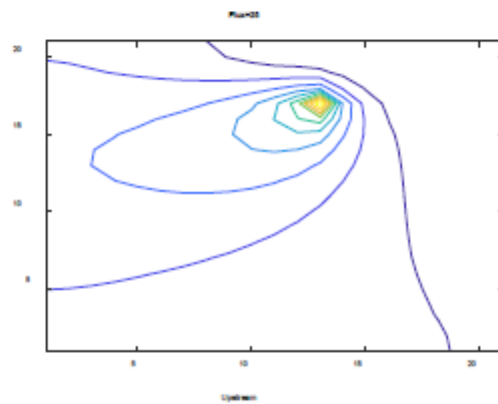
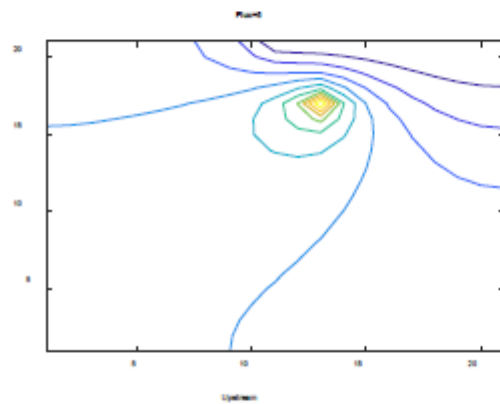
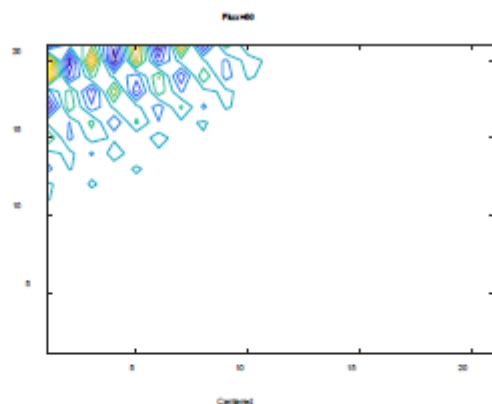
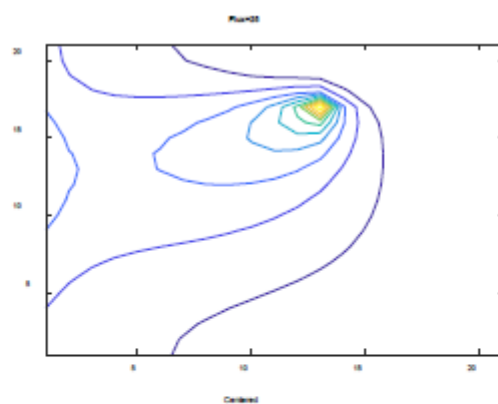
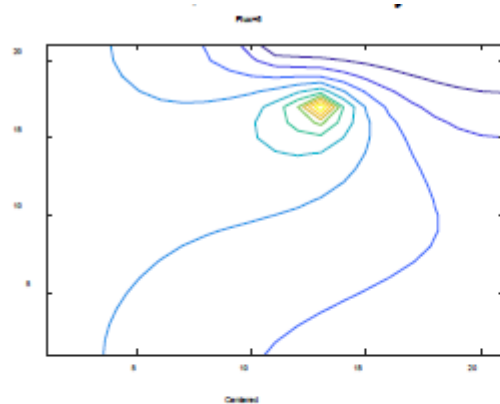
2

The velocity 'potential' isocontours (problem #1 physics) are orthogonal to the streamlines, i.e. if we were to be solving the potential problem of #1 with the boundary conditions of problem #2, the quiver plot shown above would be crossing potential lines orthogonally in the potential solution. As we can see in problem #2 streamlines, the stream function follows the vectors nicely. So streamlines actually indicate flow direction and where streamlines are concentrated such as at the top of the obstruction, this indicates large flow.

More specifically, as opposed to the potential where concentrated contours indicate rapid flow across the contours, concentrated contours in the stream function indicate rapid flow along the contours.

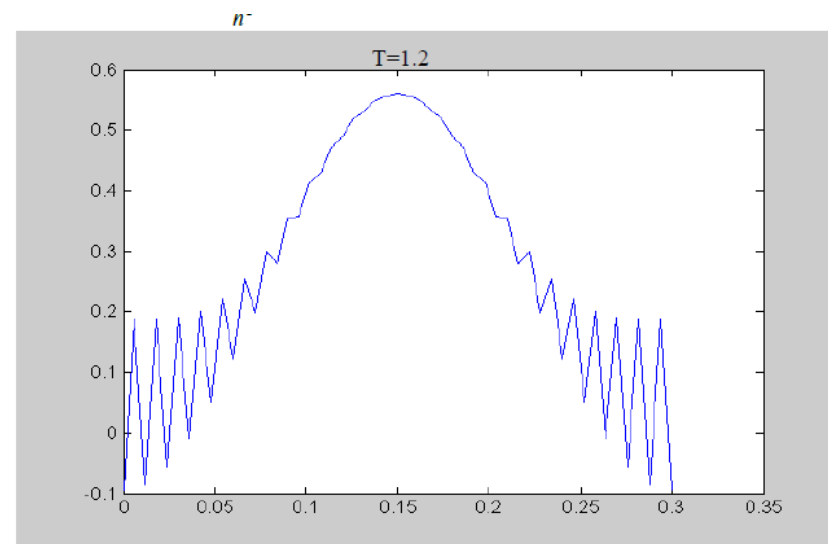
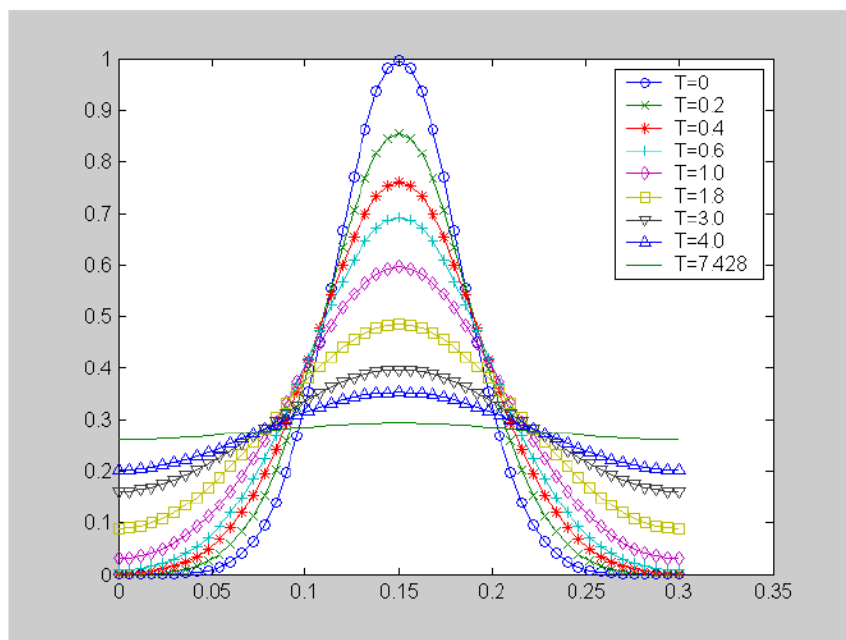






$$\text{LTE \& RHS} = -D \frac{h^2}{12} \frac{\partial^4 C_i(r)}{\partial x^4} \quad r \in [-h, h]$$

$$\text{LTE \& LHS} = -\frac{\Delta t}{2} \frac{\partial^2 C(r)}{\partial x^2} \quad r \in [0, \Delta t]$$



(c) Now, investigate your numerical algorithm from part (b), specifically, does your model go unstable? if so, can you determine a threshold for when instability occurs empirically. Now go back the notes from class, write out the Von Neumann analysis yourself step by step for this model. How do your findings with the Von Neumann analysis compare to your empirical analysis?

According to the Von Neumann analysis in the notes, if the quantity $\frac{D\Delta t}{h^2} < \frac{1}{4}$ we have a stable system. At $\Delta t = 0.0089$, the quantity is 0.2472