

# **An introduction to Partial Differential Equations**

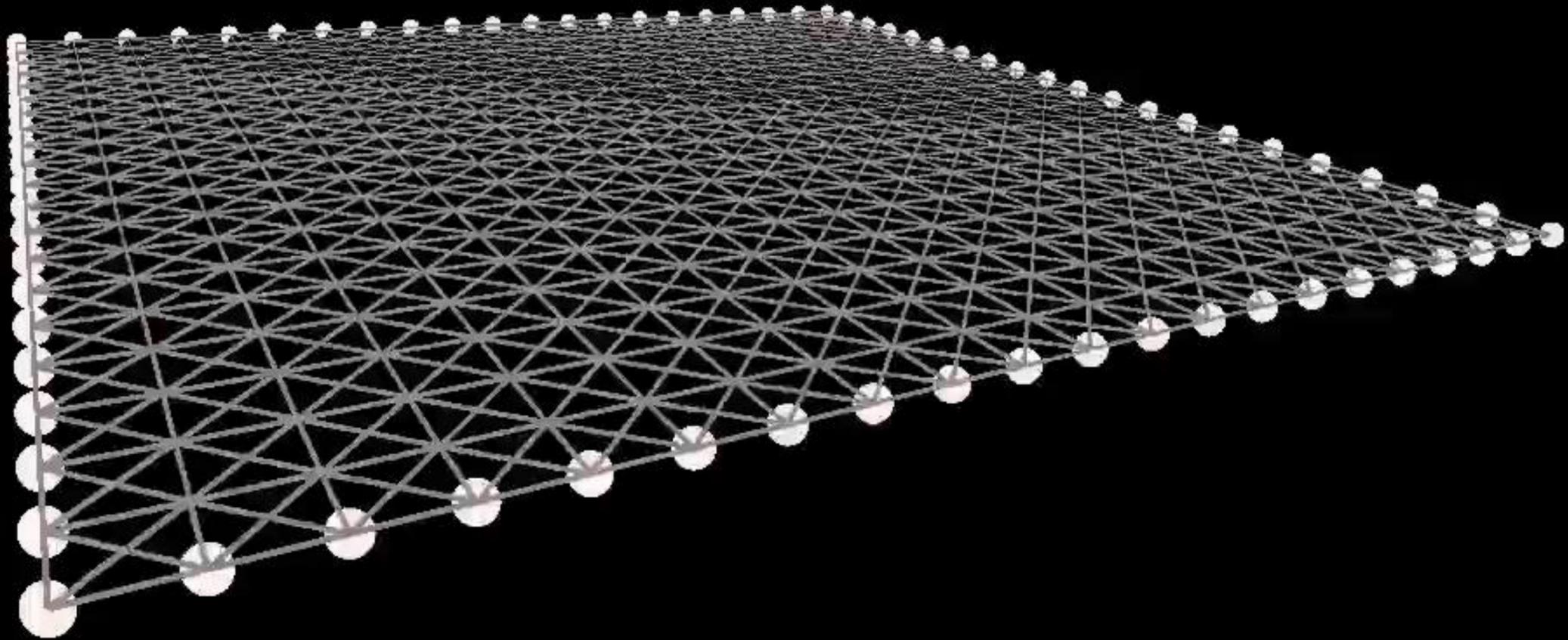
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**Computer Graphics  
CMU 15-462/15-662, Fall 2016**

# Assignments/grading

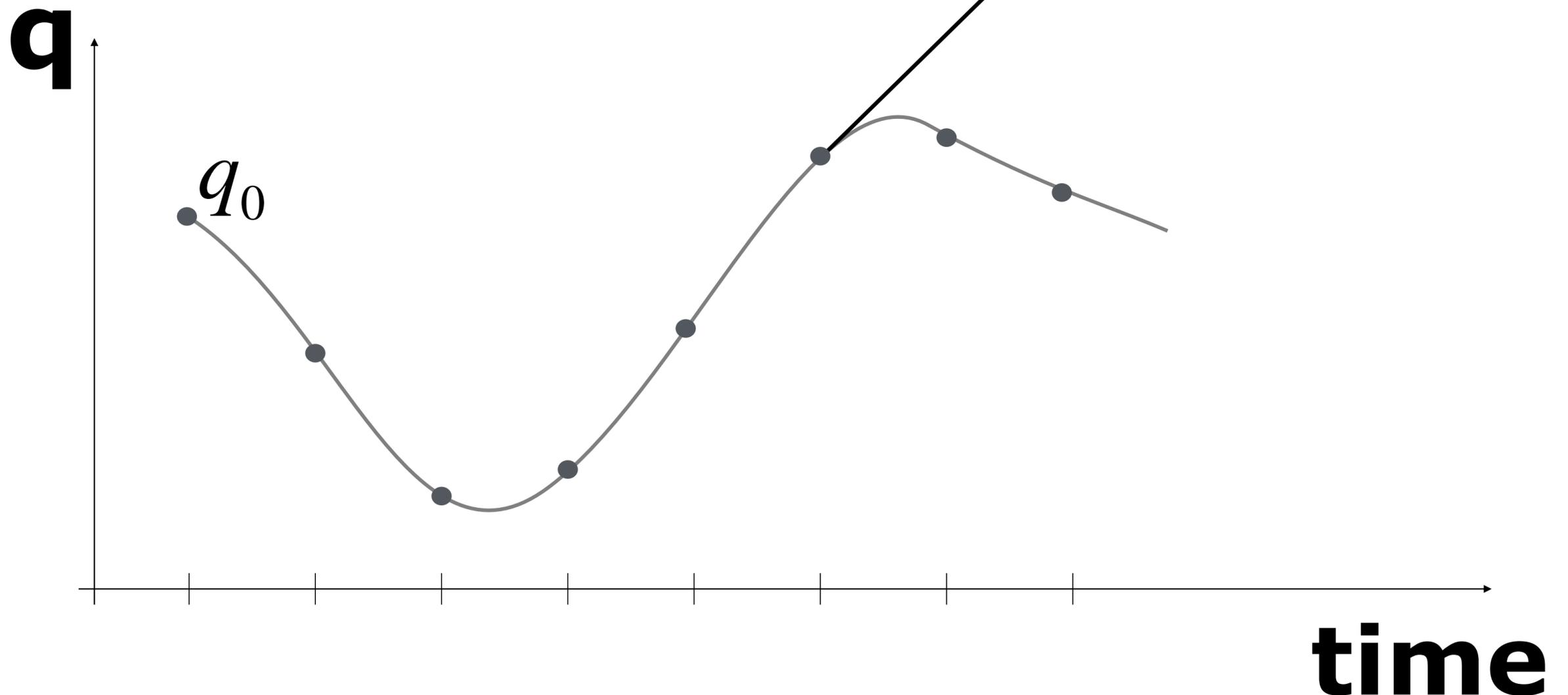
- **(5%) Warm-up Math (P)Review**
    - Written exercises on basic linear algebra and vector calc
  - **(60%) Five programming assignments**
    - Four programming assignments
    - One “go further” final assignment (in pairs)
  - **(7%) Take-home quizzes**
  - **(3%) Class participation**
    - In-class/website comments, other contributions to class
  - ~~**(25%) Midterm / Final**~~
  - **(12.5%) Midterm**
- 
- Final grade : / **87.5**

# Example: Mass Spring System



# Recap: ODEs

- ODEs: implicitly define a function through its time derivative
- Numerical solve: approximate time-continuous function  $q(t)$  with samples  $q_t$



# Numerical Integration

- How do you compute time-discretized samples?
  - replace *derivatives* with *differences*

$$\frac{d}{dt} q(t) = f(q(t))$$



new configuration  
(unknown—want to solve for this!)

current configuration  
(known)

$$\frac{q_{k+1} - q_k}{\tau} = f(q)$$

“time step,” i.e., interval of time  
between  $q_k$  and  $q_{k+1}$

Wait... where do we  
evaluate the velocity  
function? At the new  
or old configuration?

# Forward Euler

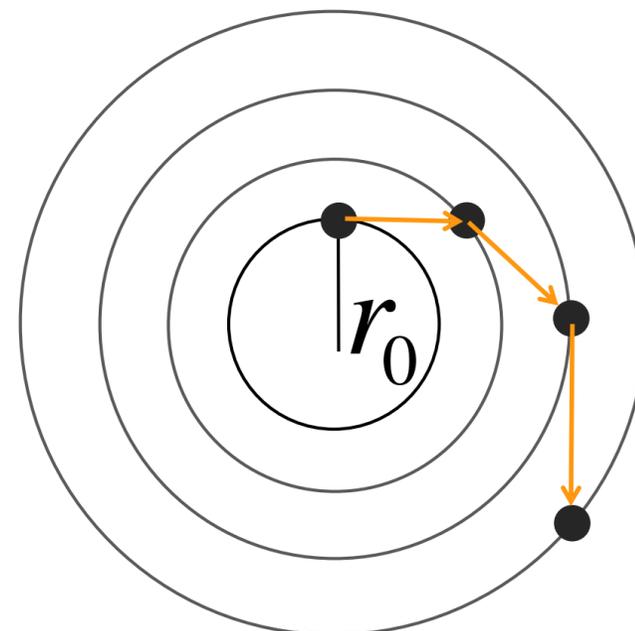
- Simplest scheme: evaluate velocity at current configuration
- New configuration can then be written *explicitly* in terms of known data:

$$q_{k+1} = q_k + \tau f(q_k)$$

new configuration      current configuration      velocity at current time

- Very intuitive: walk a tiny bit in the direction of the velocity
- Unfortunately, not very *stable* ☹️
- Consider the following 2D, first order ODE (what does it do?):

$$\dot{q} = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} q$$



# Forward Euler - Stability Analysis

- Let's consider behavior of forward Euler for simple linear ODE (e.g. temperature of an object):

$$\dot{u} = -au, \quad a > 0$$

- Importantly:  $u$  should *decay* (exact solution is  $u(t)=e^{-at}$ )
- Forward Euler approximation is

$$\begin{aligned} u_{k+1} &= u_k - \tau a u_k \\ &= (1 - \tau a) u_k \end{aligned}$$

- Which means after  $n$  steps, we have

$$u_n = (1 - \tau a)^n u_0$$

- Decays only if  $|1-\tau a| < 1$ , or equivalently, if  $\tau < 2/a$
- In practice: may need *very small* time steps (“stiff ODE”)

# Backward Euler

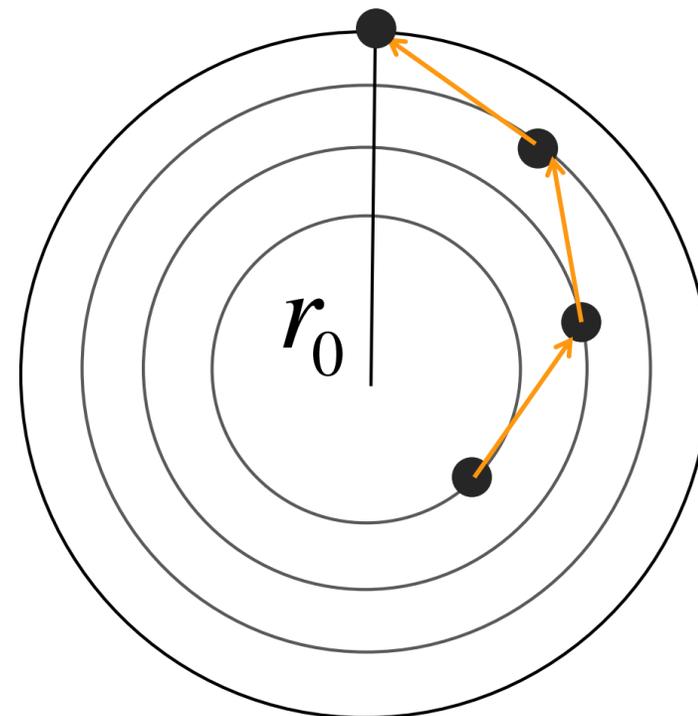
- Let's try something else: evaluate velocity at *next* configuration
- New configuration is then *implicit* - we must solve for it:

new configuration      current configuration      velocity at next time

$$q_{k+1} = q_k + \tau f(q_{k+1})$$

- Much harder to solve, since in general  $f$  can be very nonlinear!

$$\dot{q} = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} q$$



# Backward Euler - Stability Analysis

- Again consider a simple linear ODE:

$$\dot{u} = -au, \quad a > 0$$

- Remember:  $u$  should *decay* (exact solution is  $u(t) = e^{-at}$ )
- Backward Euler approximation is

$$(u_{k+1} - u_k) / \tau = -au_{k+1}$$

$$\iff u_{k+1} = \frac{1}{1 + \tau a} u_k$$

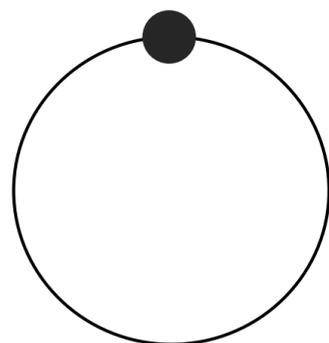
- Which means after  $n$  steps, we have

$$u_n = \left( \frac{1}{1 + \tau a} \right)^n u_0$$

- Decays if  $|1 + \tau a| > 1$ , which is always true!
- $\Rightarrow$  Backward Euler is *unconditionally stable* for linear ODEs

# Symplectic Euler

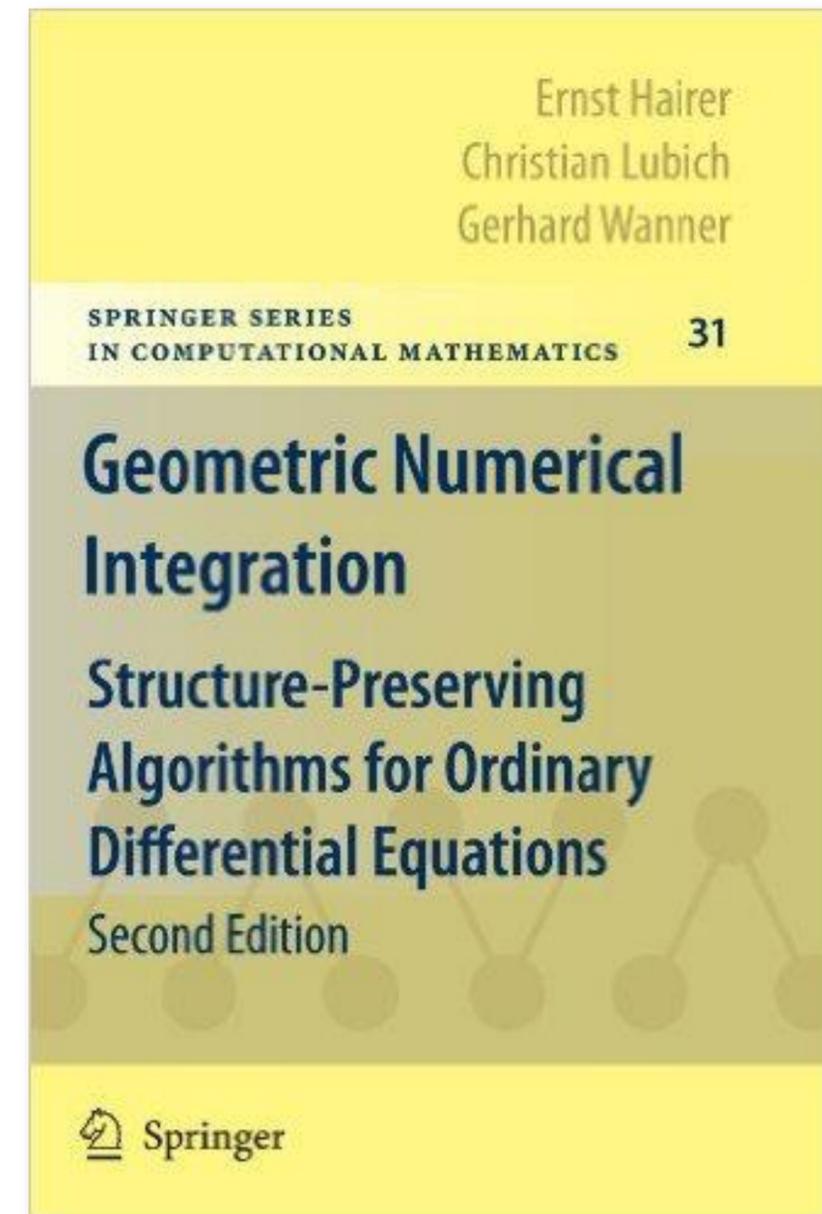
- Backward Euler was stable, but we also saw (empirically) that it exhibits *numerical damping* (damping not found in original eqn.)
- Nice alternative is symplectic Euler (for 2<sup>nd</sup> order ODEs)
  - update velocity using current configuration
  - update configuration using *new* velocity
- Easy to implement; used often in practice (or leapfrog, Verlet, ...)
- Energy is conserved *almost exactly*, forever. Is that desirable?



(Proof? The analysis is not so easy...)

# Numerical Integrators

- Barely scratched the surface
- *Many* different integrators
- Why? Because many notions of “good”:
  - stability
  - accuracy
  - convergence
  - conservation, symmetry, ...
  - computational efficiency (!)
- No one “best” integrator—*pick the right tool for the job!*
- Could do (at least) an entire course on time integration...
- Great book: Hairer, Lubich, Wanner

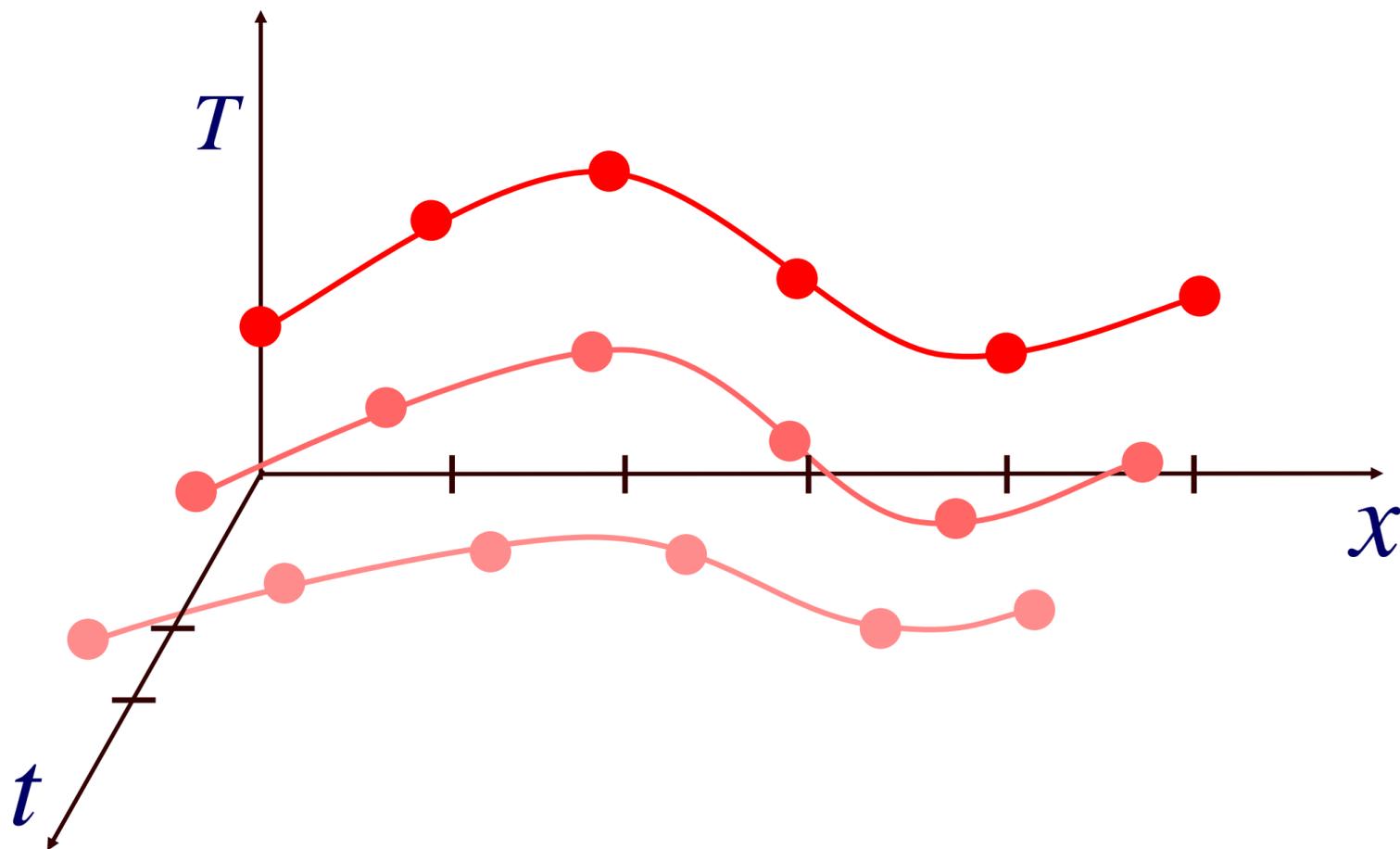


**Let's look at an example...**



# Partial Differential Equations (PDEs)

- ODE: Implicitly describe function in terms of its time derivatives
- Like any implicit description, have to solve for actual function
- PDE: Also include spatial derivatives in description
- An example: temperature of a particle
  - on a wire



$$\frac{\partial T}{\partial t} = \alpha \frac{\partial^2 T}{\partial x^2}$$

# To make a long story short...

- Solving ODE looks like *“add a little velocity each time”*

$$q_{k+1} = q_k + \tau f(q)$$

- Solving a PDE looks like *“use neighbor information to get velocity (...and then add a little velocity each time)”*

	1	
1	-4	1
	1	

$f(q)$

$$q_{k+1} = q_k + \tau f(q)$$

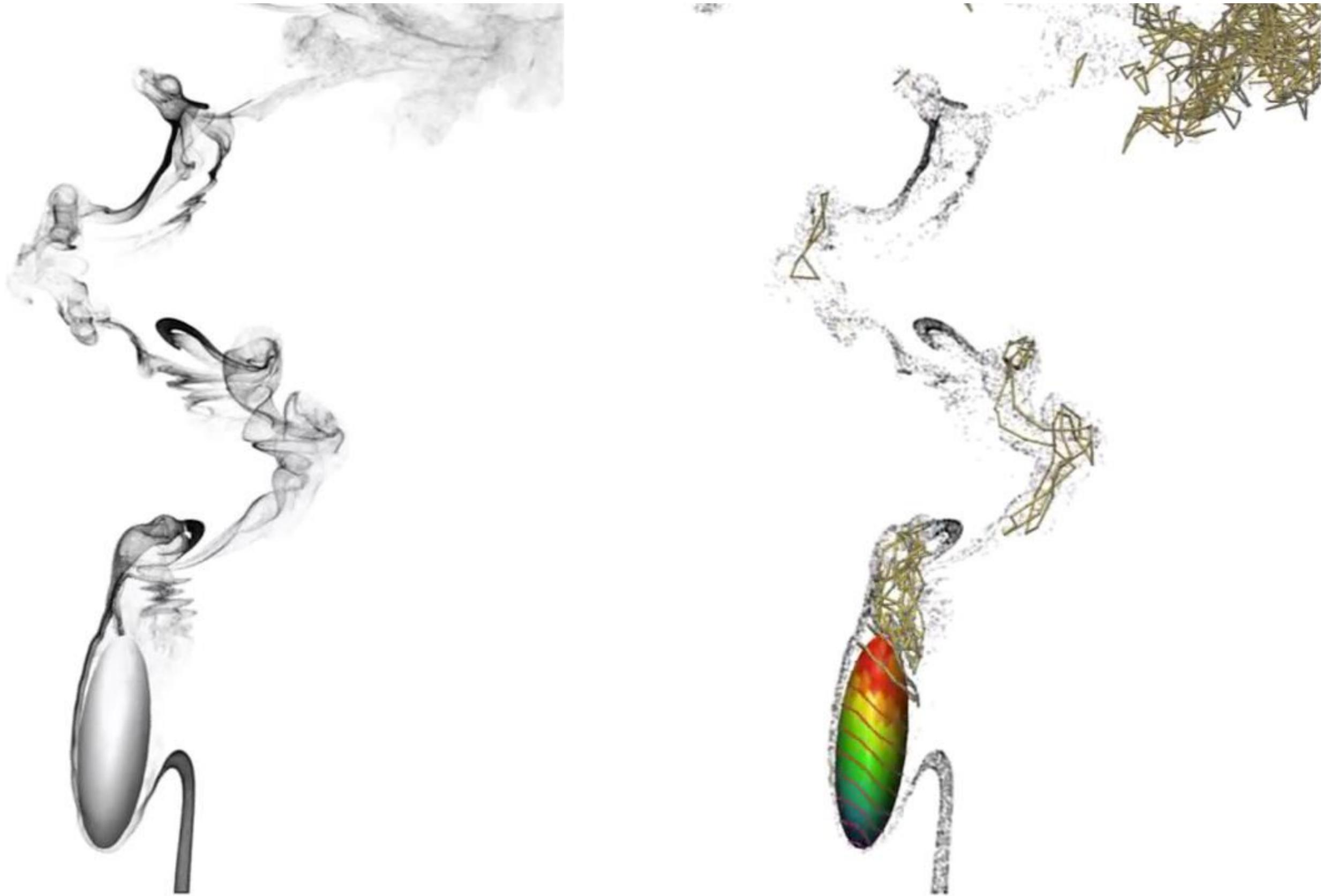
**...obviously there is a *lot* more to say here!**

# Fluid Simulation in Graphics



[Losasso, F., Shinar, T. Selle, A. and Fedkiw, R., "Multiple Interacting Liquids"](#)

# Smoke Simulation in Graphics



**S. Weißmann, U. Pinkall. "Filament-based smoke with vortex shedding and variational reconnection"**

# Cloth Simulation in Graphics



**Zhili Chen, Renguo Feng and Huamin Wang, *"Modeling friction and air effects between cloth and deformable bodies"***

# Fracture in Graphics

## Adaptive Tearing and Cracking of Thin Sheets

Tobias Pfaff  
Rahul Narain  
Juan Miguel de Joya  
James F. O'Brien

UC Berkeley



SIGGRAPH2014



**Tobias Pfaff, Rahul Narain, Juan Miguel de Joya, James F. O'Brien,  
"Adaptive Tearing and Cracking of Thin Sheets"**

# Hair Simulation in Graphics



[Danny M. Kaufman](#), [Rasmus Tamstorf](#), [Breannan Smith](#), [Jean-Marie Aubry](#), [Eitan Grinspun](#), "[Adaptive Nonlinearity for Collisions in Complex Rod Assemblies](#)"

# Definition of a PDE

- Want to solve for a function of time *and* space

$$u(t, x)$$

↑      ↑  
**time space**

- Function given implicitly in terms of derivatives:

$$\dot{u}, \ddot{u}, \frac{d}{dt^3} u, \frac{d}{dt^4} u, \dots$$

**any combination of time derivatives**

$$\frac{\partial u}{\partial x_1}, \frac{\partial u}{\partial x_2}, \frac{\partial^2 u}{\partial x_1 \partial x_2}, \frac{\partial^m + n u}{\partial x_i^m \partial x_j^n}, \dots$$

**plus any combination of space derivatives**

- **Example:**

$$\dot{u} + uu' = au''$$

**(Burgers' equation)**

# Anatomy of a PDE

- Linear vs. nonlinear: how are derivatives combined?

**nonlinear!**

$$\dot{u} + uu' = au'' \quad \text{(Burgers' equation)}$$

$$\dot{u} = au'' \quad \text{(diffusion equation)}$$

- Order: how many derivatives in space & time?

1st order in time

2nd order in space

$$\dot{u} + uu' = au'' \quad \text{(Burgers' equation)}$$

2nd order in time

2nd order in space

$$\ddot{u} = au'' \quad \text{(wave equation)}$$

- Nonlinear / higher order  $\Rightarrow$  HARDER TO SOLVE!

# Model Equations

- Fundamental behavior of many important PDEs is well-captured by three model linear equations:

“Laplacian” (more later!)

LAPLACE EQUATION (“ELLIPTIC”)

“what’s the smoothest function interpolating the given boundary data”

$$\Delta u = 0$$

HEAT EQUATION (“PARABOLIC”)

“how does an initial distribution of heat spread out over time?”

$$\dot{u} = \Delta u$$

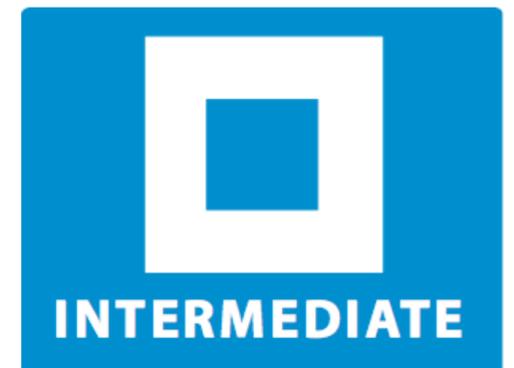
WAVE EQUATION (“HYPERBOLIC”)

“if you throw a rock into a pond, how does the wavefront evolve over time?”

$$\ddot{u} = \Delta u$$

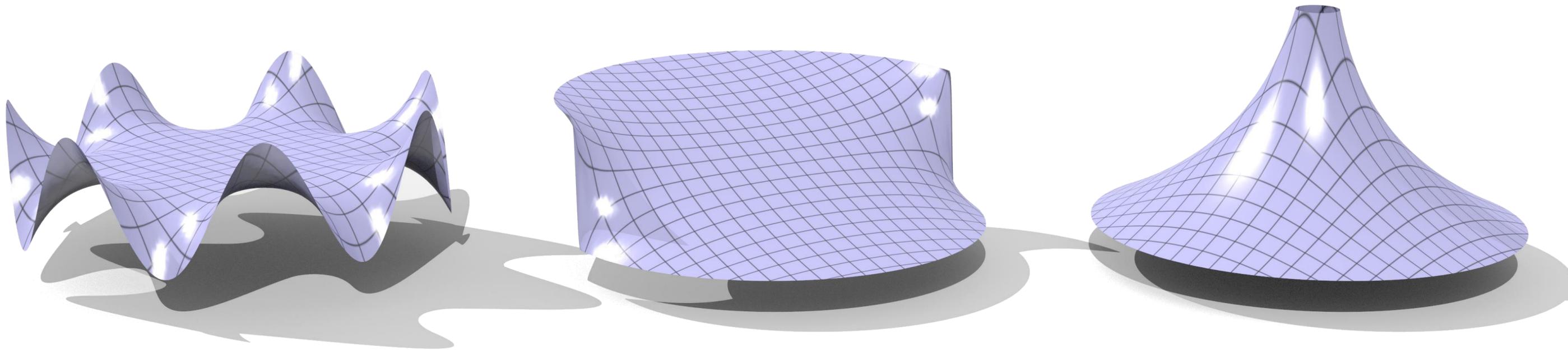
[ NONLINEAR + HYPERBOLIC + HIGH-ORDER ]

Solve numerically?



# Elliptic PDEs / Laplace Equation

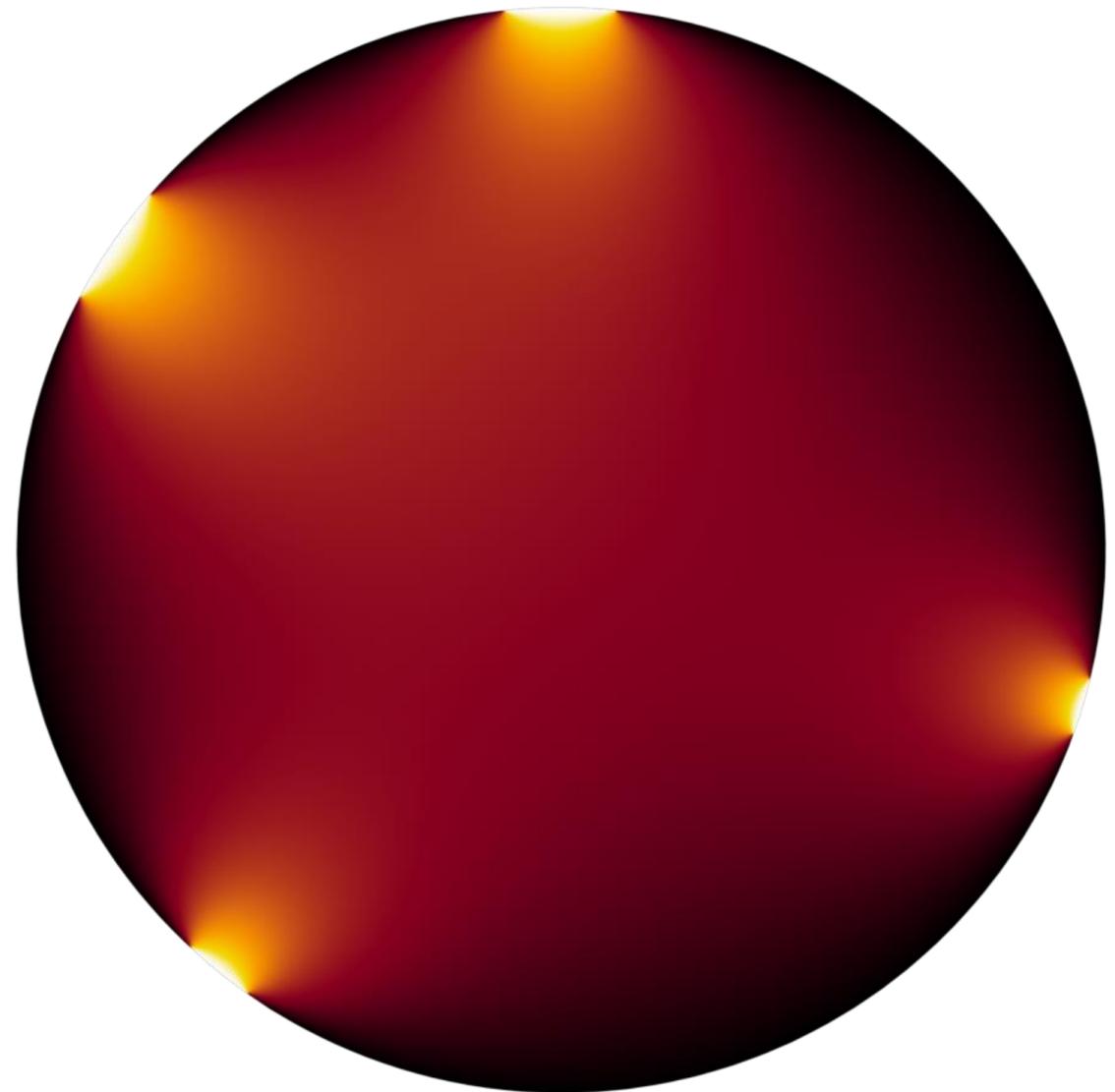
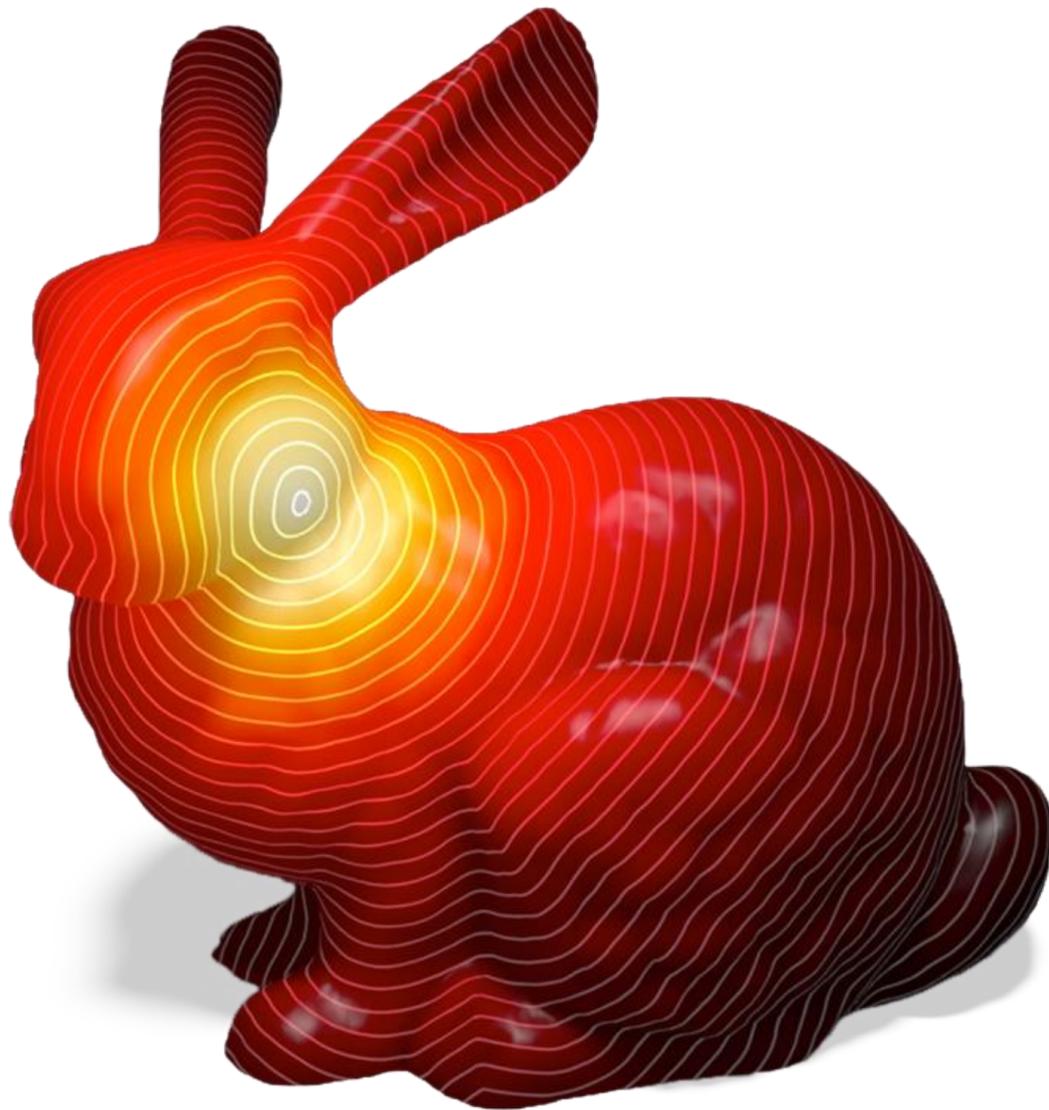
- “What’s the smoothest function interpolating the given boundary data?”



- **Conceptually: each value is at the average of its “neighbors”**
- **Roughly speaking, why is it easier to solve?**
- **Very robust to errors: just keep averaging with neighbors!**

# Parabolic PDEs / Heat Equation

- “How does an initial distribution of heat spread out over time?”



- After a long time, solution is same as Laplace equation!
- Models damping / viscosity in many physical systems

# Hyperbolic PDEs / Wave Equation

- “If you throw a rock into a pond, how does the wavefront evolve over time?”



- No steady state solution. Errors made at the beginning will persist for a long time! (hard)

**How can we do that?**

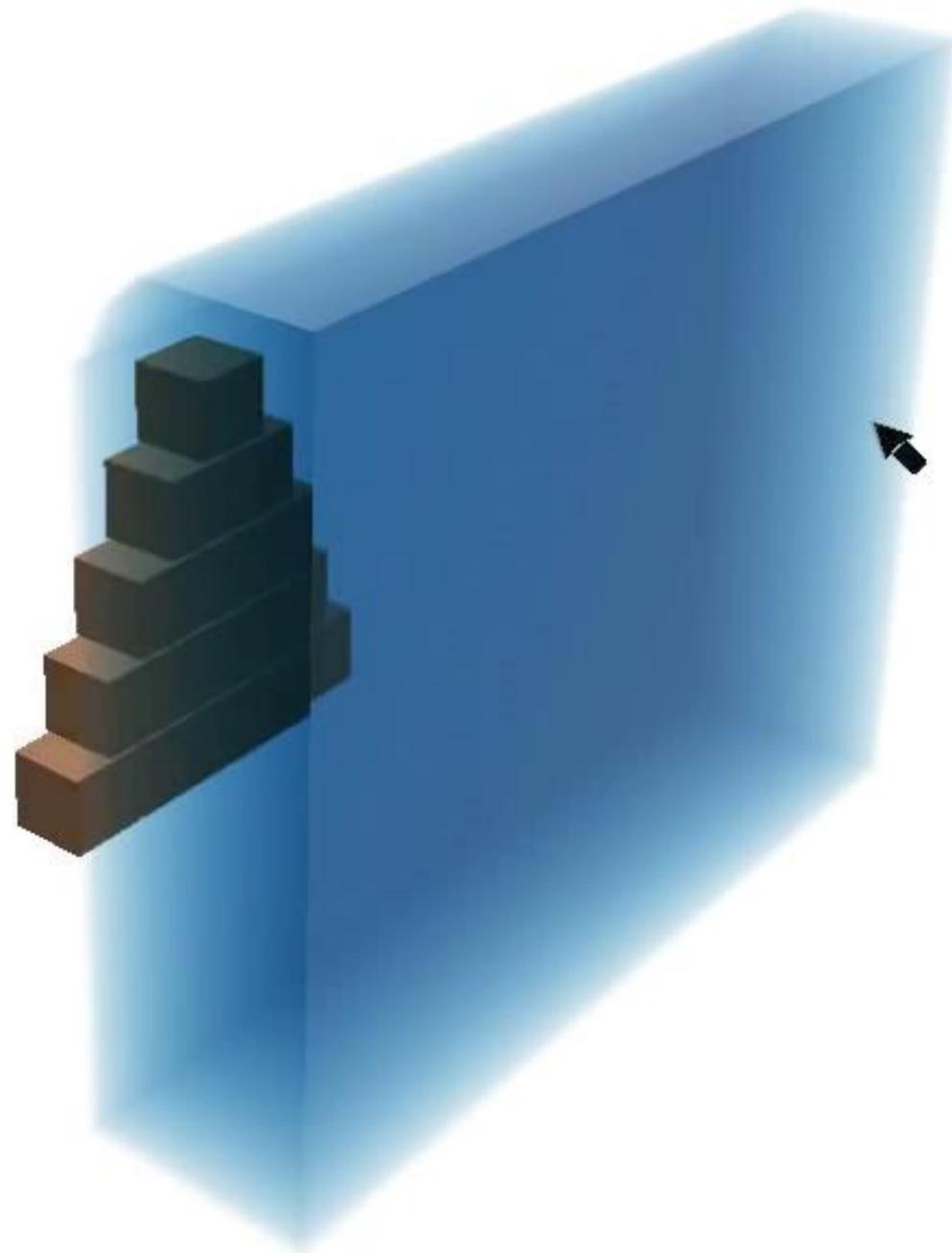
# Numerical Solution of PDEs—Overview

- Like ODEs, many interesting PDEs are difficult or impossible to solve analytically
- Must instead use numerical integration
- Basic strategy:
  - pick a spatial discretization (TODAY)
  - pick a time discretization (forward Euler, backward Euler...)
  - as with ODEs, run a time-stepping algorithm
- Historically, very expensive—only for “hero shots” in movies
- Computers are ever faster...
- More & more use of PDEs in games, interactive tools, ...

# Real Time PDE-Based Simulation (Fire)



# Real Time PDE-Based Simulation (Water)

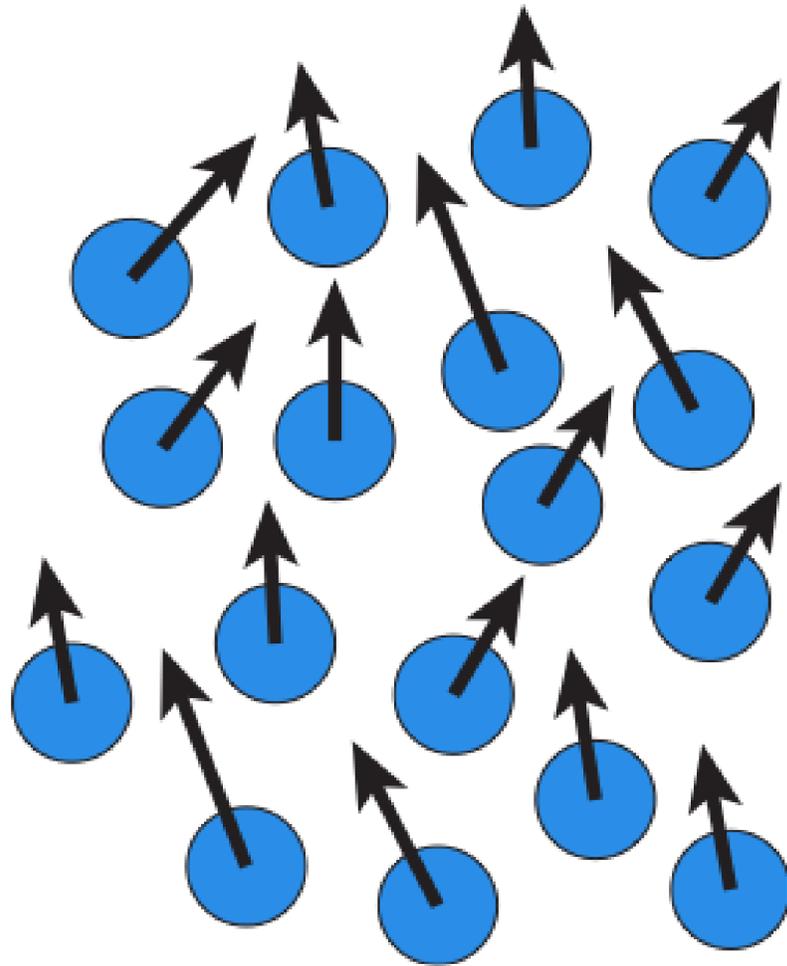


[Nuttapong Chentanez](#), [Matthias Müller](#), *"Real-time Eulerian water simulation using a restricted tall cell grid"*

# Lagrangian vs. Eulerian

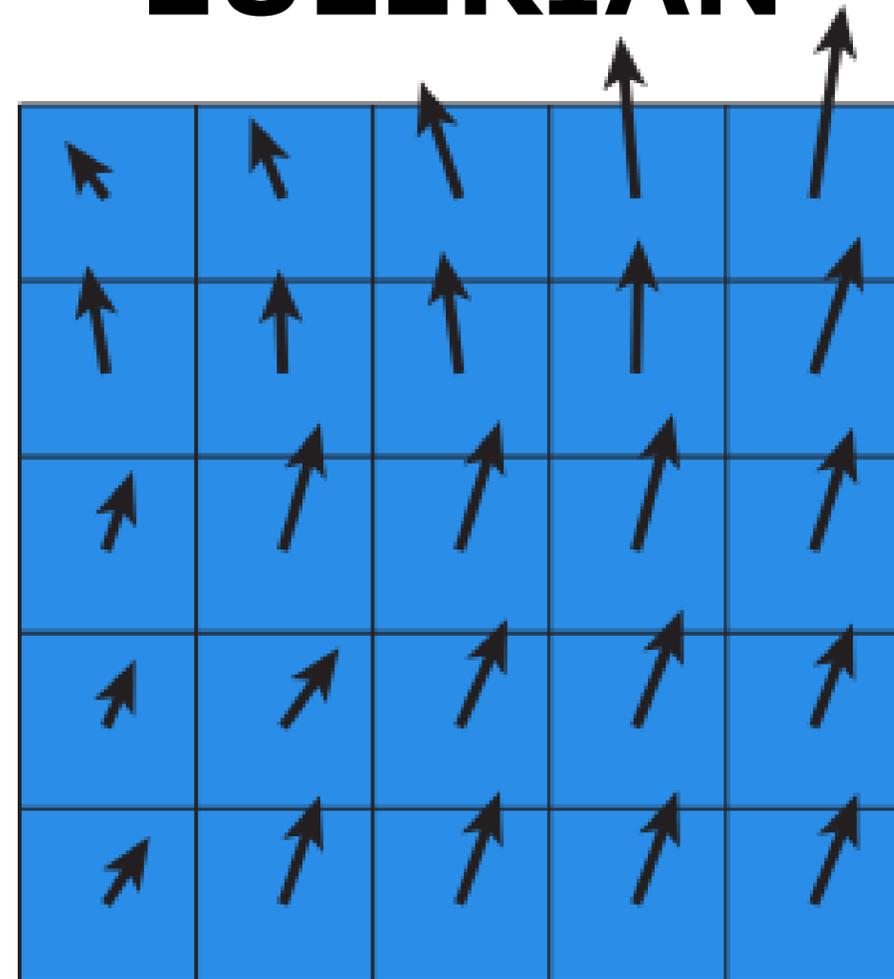
- Two basic ways to discretize space: Lagrangian & Eulerian (particle-based & grid-based)
- Suppose you want to keep track of the weather...

## LAGRANGIAN



track moving particles and read what they are measuring

## EULERIAN

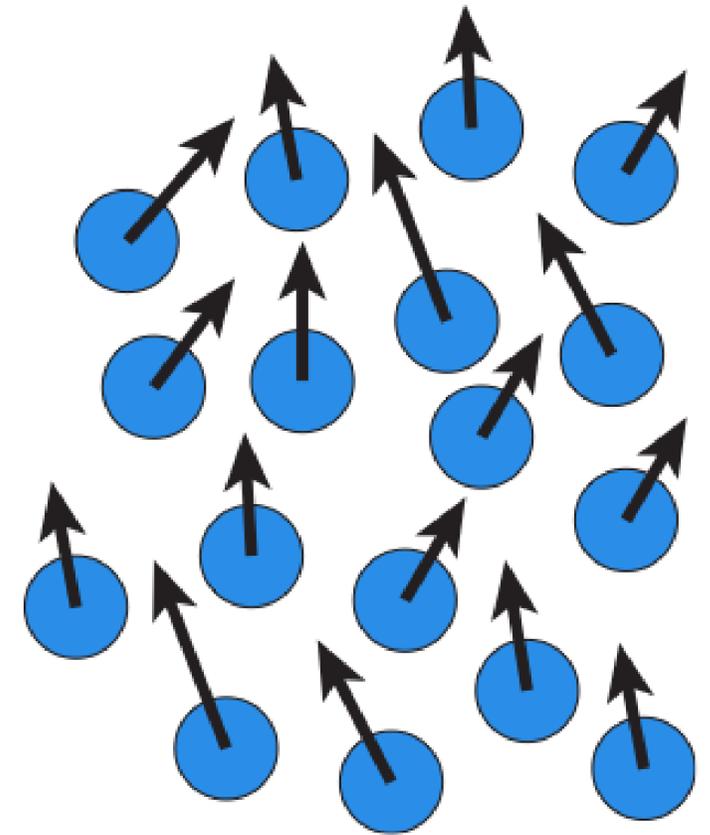


record temperature at fixed locations in space

# Lagrangian vs. Eulerian—Trade-Offs

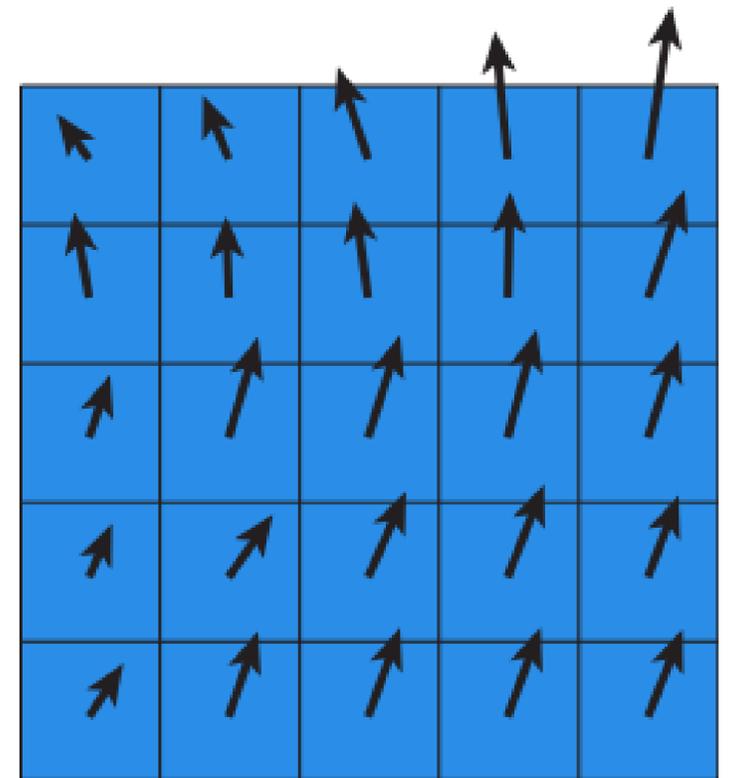
## ■ Lagrangian

- conceptually easy (like polygon soup!)
- resolution/domain not limited by grid
- good particle distribution can be tough
- finding neighbors can be expensive



## ■ Eulerian

- fast, regular computation
- easy to represent, e.g., smooth surfaces
- simulation “trapped” in grid
- grid causes “numerical diffusion” (blur)
- need to understand PDEs



# Mixing Lagrangian & Eulerian

- Of course, no reason you have to choose just one!
- Many modern methods mix Lagrangian & Eulerian:
  - PIC/FLIP, particle level sets, mesh-based surface tracking, Voronoi-based, arbitrary Lagrangian-Eulerian (ALE), ...
- *Pick the right tool for the job!*

*Maya Bifrost*



**Ok, but we're getting *way* ahead of ourselves.  
How do we solve *easy* PDEs?**

# Numerical PDEs—Basic Strategy

- Pick PDE that models phenomenon of interest
  - Which quantity do we want to solve for?
- Pick spatial discretization
  - How do we approximate derivatives in space?
- Pick time discretization
  - How do we approximate derivatives in time?
  - When do we evaluate forces?
  - Forward Euler, backward Euler, symplectic Euler, ...
- Finally, we have an *update rule*
- Repeatedly solve to generate an animation

# The Laplace Operator

- All of our model equations used the Laplace operator
- Different conventions for symbol:



← same symbol used for “change”



← same symbol used for Hessian!

- Differential operators

Nabla operator

$$\nabla = \left( \frac{\partial}{\partial x_1}, \dots, \frac{\partial}{\partial x_d} \right)^t \quad \nabla u = \left( \frac{\partial u}{\partial x_1}, \dots, \frac{\partial u}{\partial x_d} \right)^t$$

Laplace operator

$$\Delta = \nabla \cdot \nabla = \sum_{k=1}^d \frac{\partial^2}{\partial x_k^2} \quad \Delta u = \nabla \cdot \nabla u$$

**div**      **grad**

$$\Delta u = \frac{\partial^2 u}{\partial x_1^2} + \dots + \frac{\partial^2 u}{\partial x_n^2}$$

# The Laplace Operator

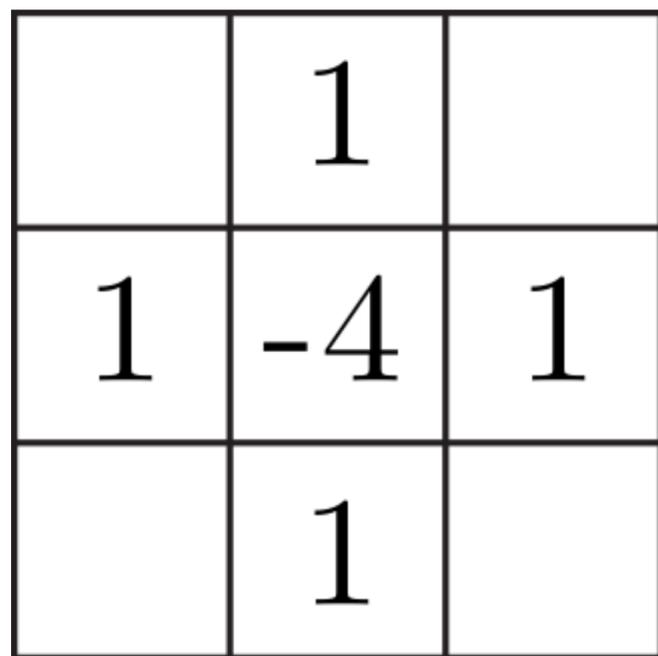
- All of our model equations used the Laplace operator
- *Unbelievably* important object showing up everywhere across physics, geometry, signal processing, ...
- Ok, but what does it mean?
- *Differential operator*: eats a function, spits out its “2nd derivative”
- What does that mean for a function  $u: \mathbb{R}^n \rightarrow \mathbb{R}$ ?
  - divergence of gradient
  - trace of hessian
  - sum of second derivatives
  - “average” curvature

$$\Delta u = \frac{\partial^2 u}{\partial x_1^2} + \dots + \frac{\partial^2 u}{\partial x_n^2}$$

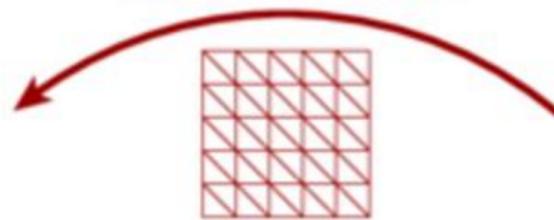
# Discretizing the Laplacian

- How do we approximate the Laplacian?
- Depends on discretization (Eulerian, Lagrangian, grid, mesh, ...)
- Two extremely common ways in graphics:

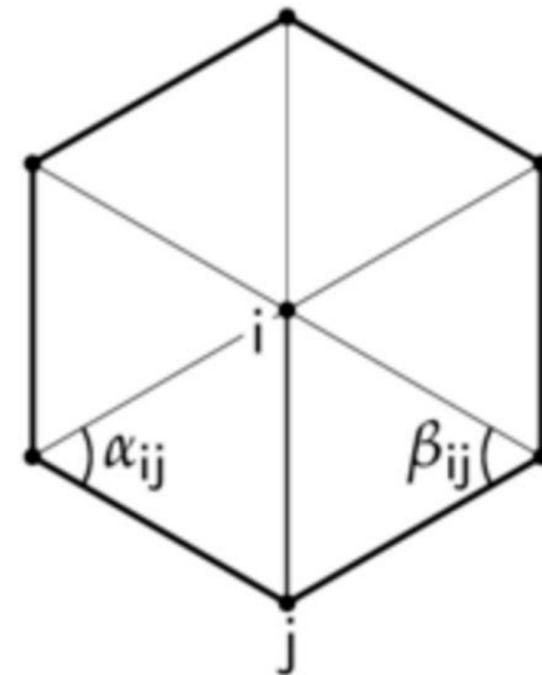
GRID  $h$



(actually, this becomes that)



TRIANGLE MESH



$$\frac{4u_{ij} - u_{i+1,j} - u_{i-1,j} - u_{i,j+1} - u_{i,j-1}}{h^2}$$

$$\frac{1}{2} \sum_j (\cot \alpha_{ij} + \cot \beta_{ij})(u_j - u_i)$$

- $u$  could be displacement in normal direction, for example
- Also not too hard on point clouds, polygon meshes, ...

# Numerically Solving the Laplace Equation

- Want to solve  $\Delta u = 0$
- Plug in one of our discretizations, e.g.,

	$c$	
$d$	$a$	$b$
	$e$	

$$\frac{4a - b - c - d - e}{h} = 0$$
$$\iff a = \frac{1}{4}(b + c + d + e)$$

- At solution that solves the Laplace Equation, each value is the average of neighboring values.
- How do we solve this?
- One idea: keep averaging with neighbors! (“Jacobi method”)
- Correct, but *slow* convergence

# Boundary Conditions for Discrete Laplace

- What values do we use to compute averages near the boundary?

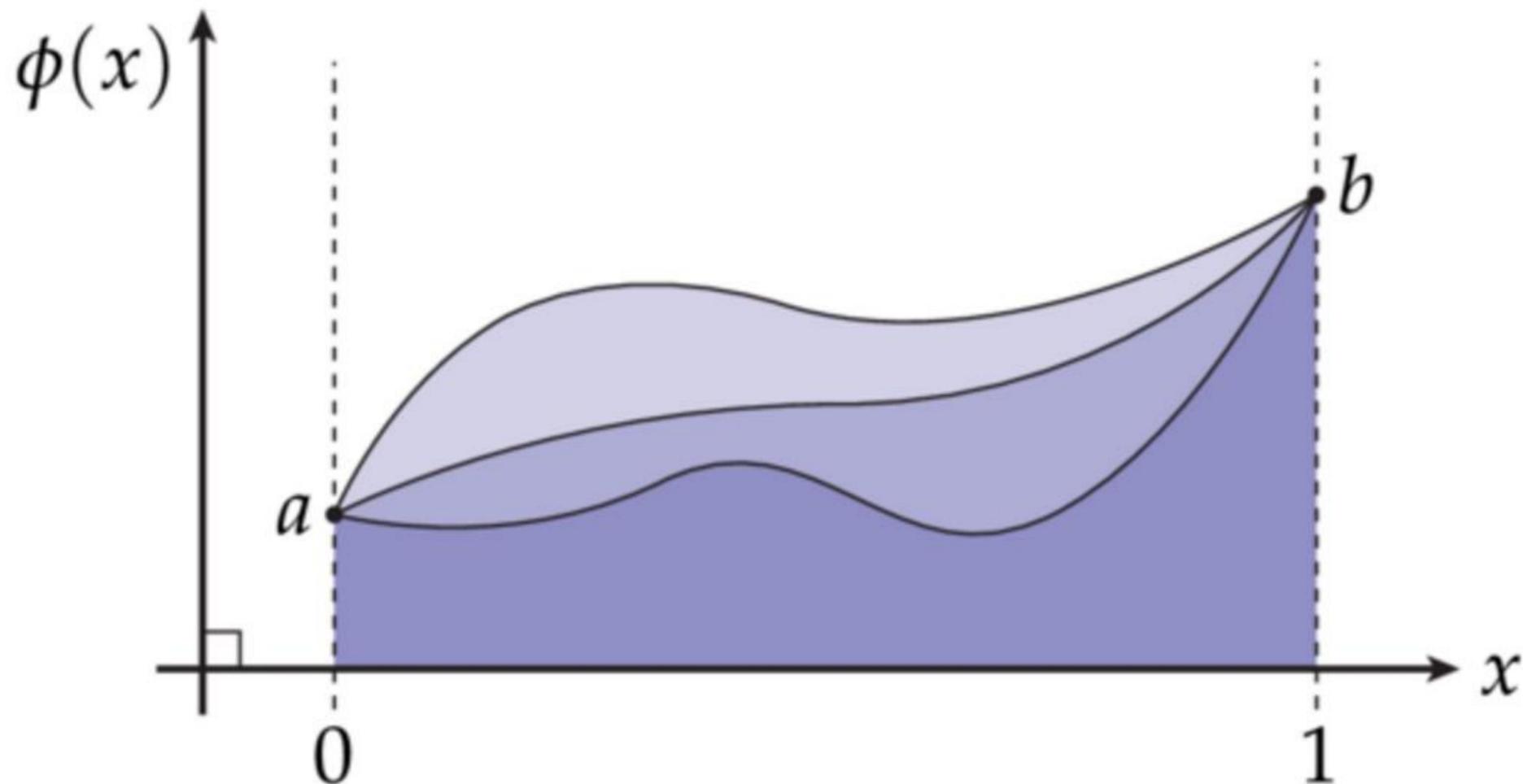
	$c$	
$?$	$a$	$b$
	$e$	

$$a = \frac{1}{4}(b + c + ? + e)$$

- **A: We get to choose—this is the data we want to interpolate!**
- **Two basic boundary conditions:**
  - 1. *Dirichlet*—boundary data always set to fixed values**
  - 2. *Neumann*—specify derivative (difference) across boundary**
- **Also mixed (*Robin*) boundary conditions (and more, in general)**

# Dirichlet Boundary Conditions

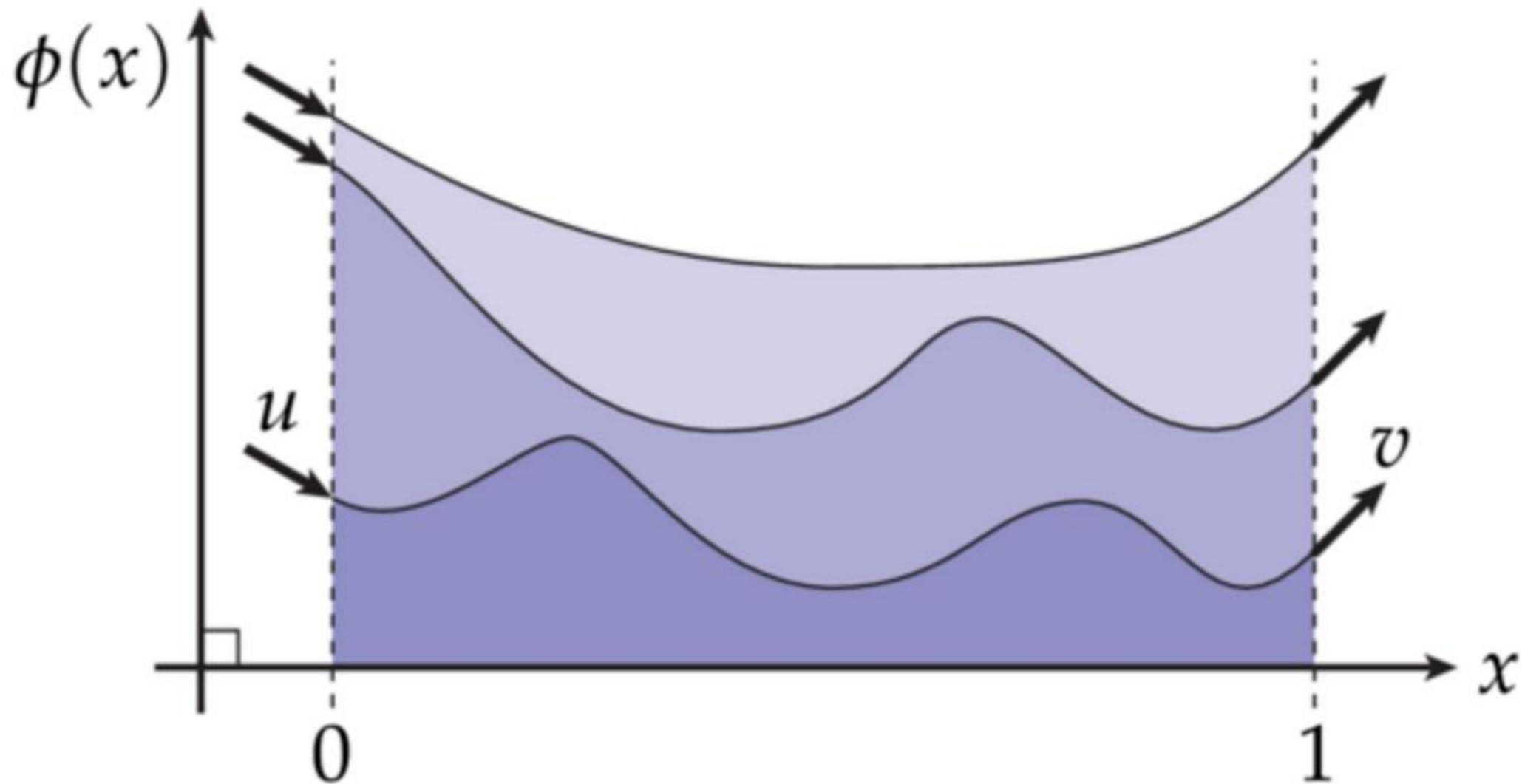
- Let's go back to smooth setting, function on real line
- *Dirichlet* means “prescribe values”
- E.g.,  $\Phi(0)=a$ ,  $\Phi(1) = b$



- Many possible functions “in between”!

# Neumann Boundary Conditions

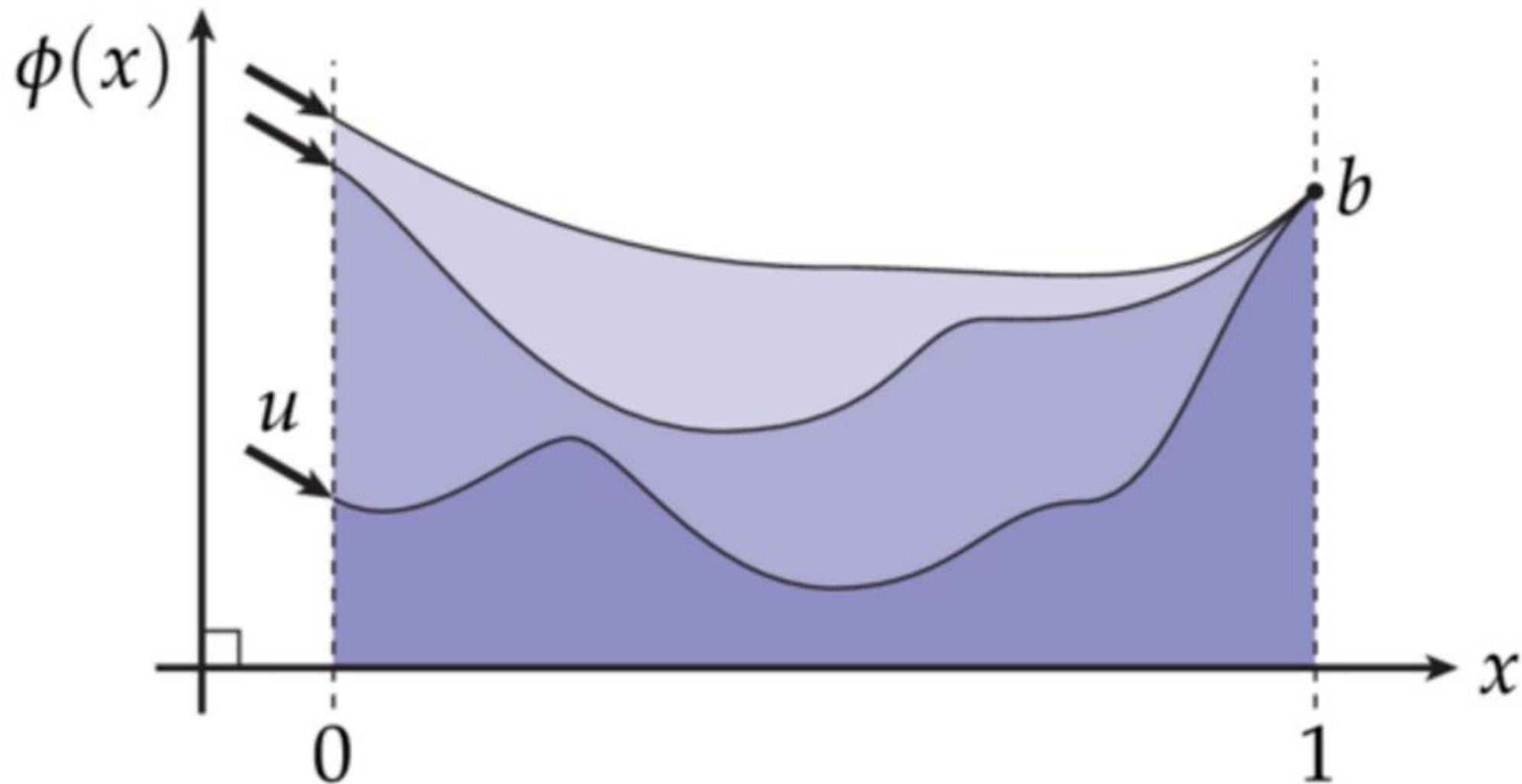
- *Neumann* means “prescribe derivatives”
- E.g.,  $\Phi'(0)=u$ ,  $\Phi'(1) = v$



- Again, many possible functions!

# Both Neumann & Dirichlet

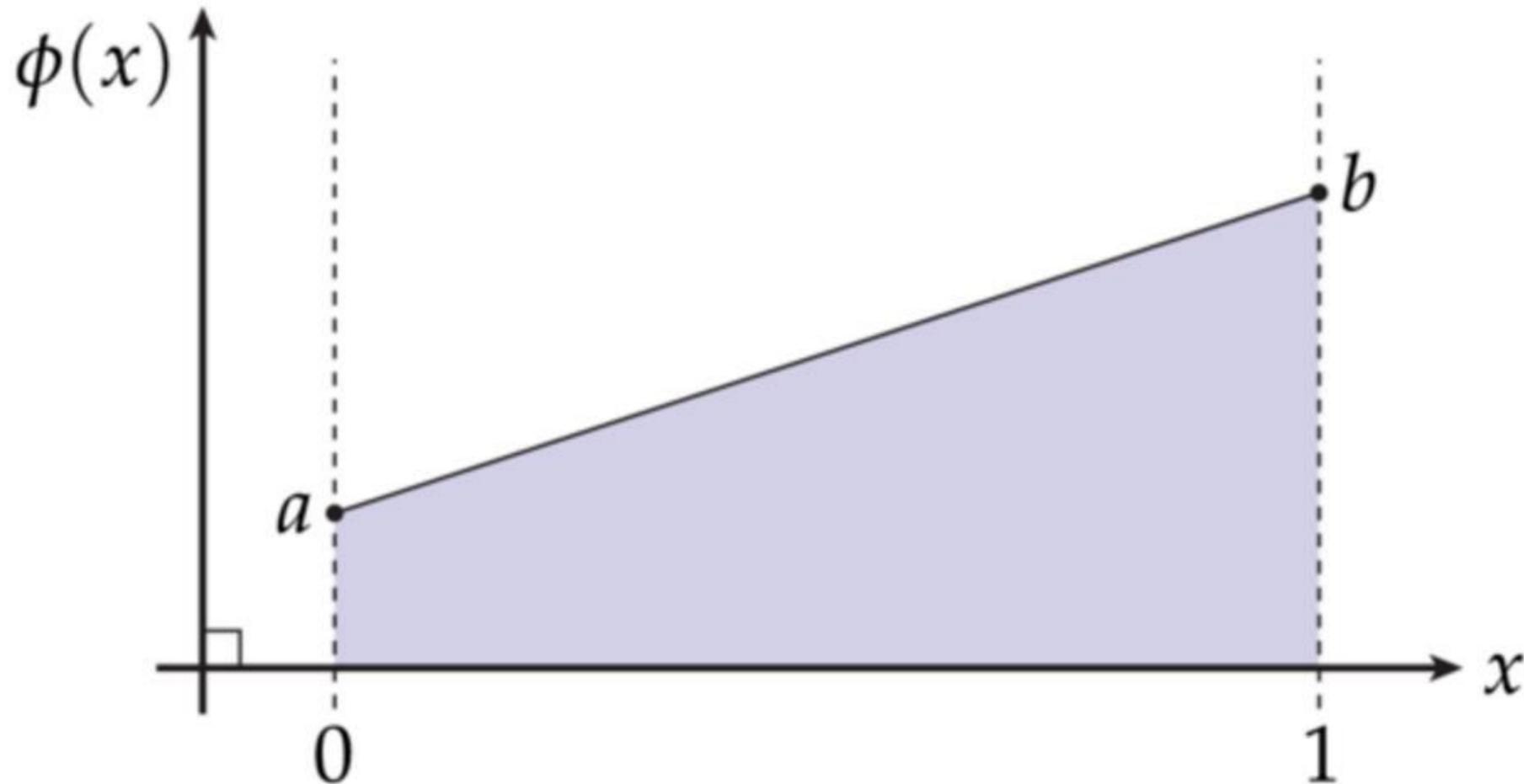
- Or: prescribe some values, some derivatives
- E.g.,  $\Phi'(0)=u$ ,  $\Phi(1) = b$



- Q: What about  $\Phi'(1)=v$ ,  $\Phi(1) = b$ ? Does that work?
- Q: What about  $\Phi'(0) + \Phi(0) = p$ ,  $\Phi'(1) + \Phi(1) = q$ ?  
(Robin)

# 1D Laplace w/ Dirichlet BCs

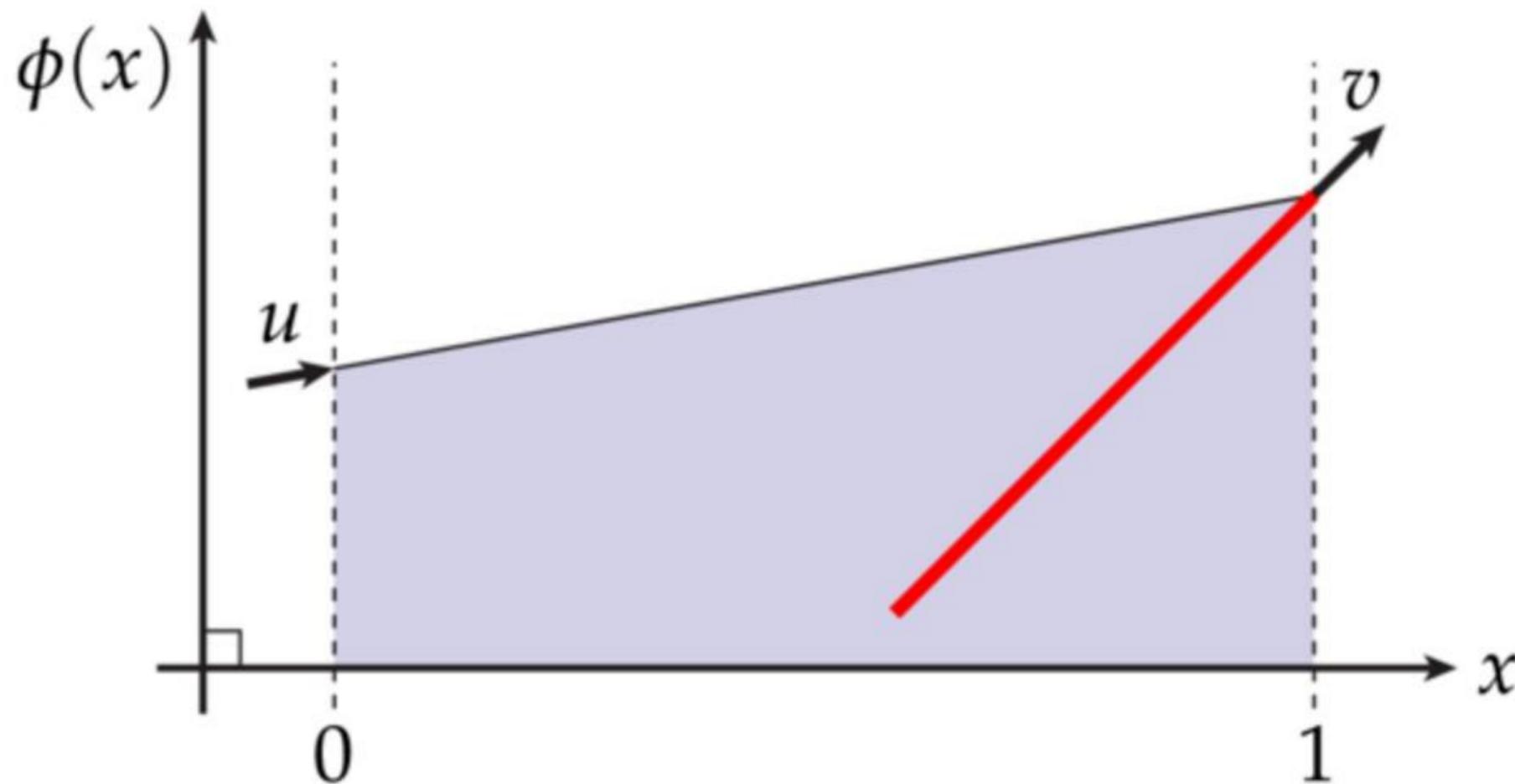
- 1D Laplace:  $\partial^2\Phi/\partial x^2 = 0$
- Solutions:  $\Phi(x) = cx + d$
- Q: Can we *always* satisfy given Dirichlet boundary conditions?



- Yes: a line can interpolate any two points.

# 1D Laplace w/ Neumann BCs

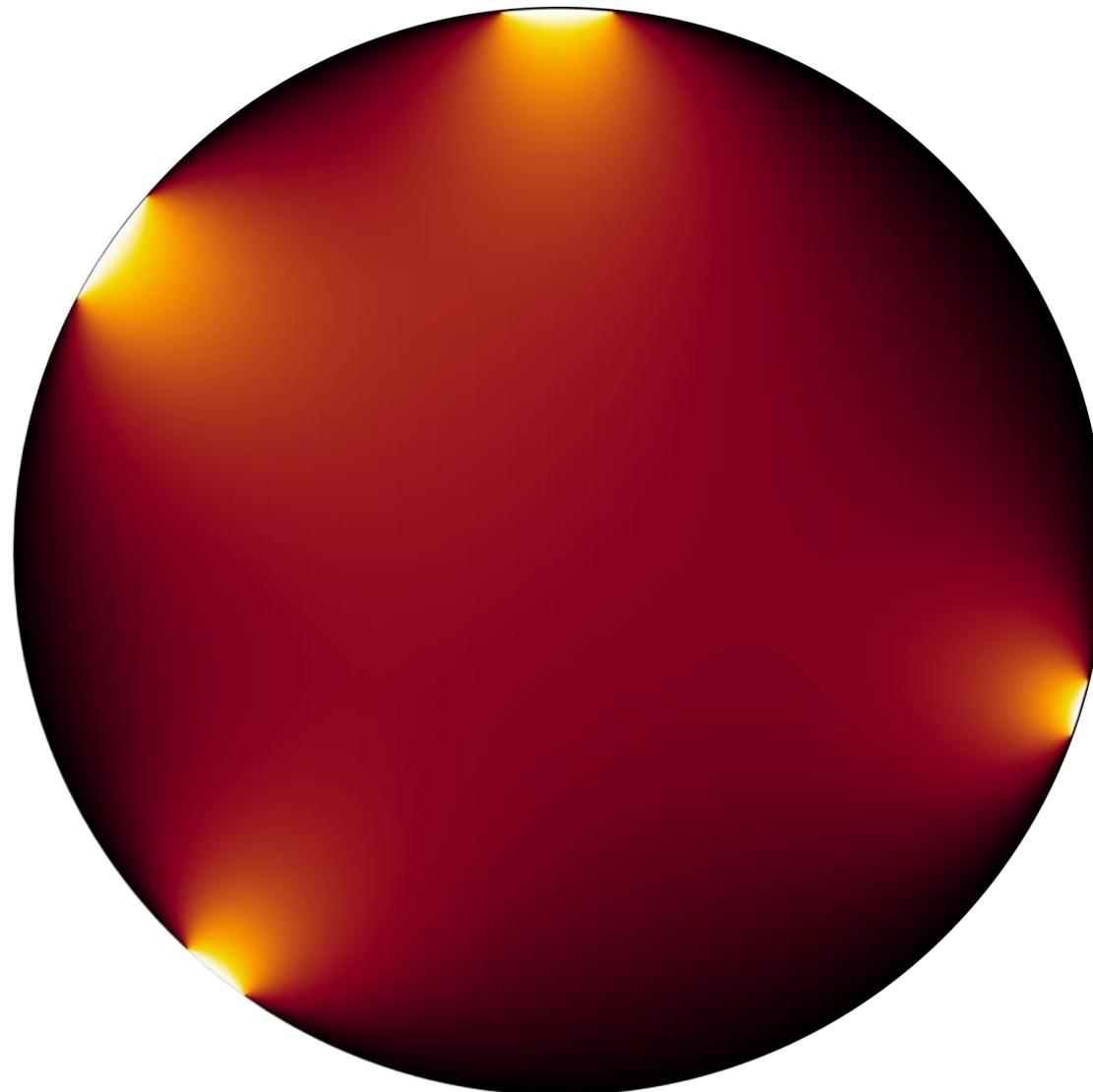
- What about Neumann BCs?
- Q: Can we prescribe the derivative at both ends?



- Only if  $u$  and  $v$  are equal! A straight line only has one slope.
- In general, solution to a PDE may not exist for given BCs.

# 2D Laplace w/ Dirichlet BCs

- 2D Laplace:  $\Delta \Phi = 0$
- Q: Can satisfy any Dirichlet BCs? (given data along boundary)



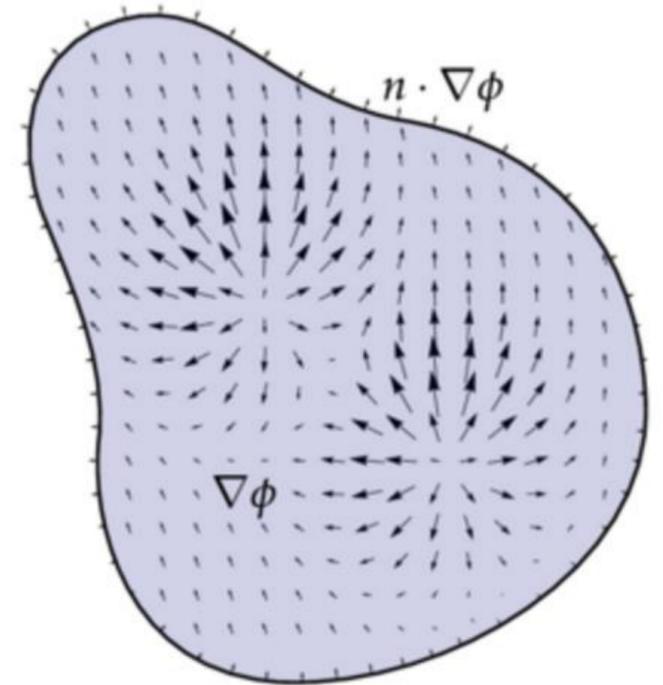
- Yes: Laplace is long-time solution to heat flow
- Data is “heat” at boundary. Then just let it flow...

# 2D Laplace w/ Neumann BCs

- What about Neumann BCs for  $\Delta\Phi=0$ ?
- Neumann BCs prescribe derivative in normal direction:  $n \cdot \nabla\Phi$
- Q: Can it always be done? (Wasn't possible in 1D...)
- In 2D, we have the *divergence theorem*:

$$\int_{\partial\Omega} n \cdot \nabla\phi = \int_{\Omega} \nabla \cdot \nabla\phi = \int_{\Omega} \Delta\phi \stackrel{!}{=} 0$$

- Should be called, “what goes in must come out theorem!”
- Can't have a solution unless the net flux through the boundary is zero.
- Numerical software will *not* always tell you if there's a problem! (Especially if you wrote it yourself...)



# Solving the Heat Equation

- Back to our three model equations, want to solve *heat diffusion equation*

$$\dot{u} = \Delta u$$

- Just saw how to discretize Laplacian
- Also know how to do time (forward Euler, backward Euler, ...)

- E.g., forward Euler:

$$u^{k+1} = u^k + \Delta u^k$$

- Q: On a grid, what's our overall update now at  $u_{i,j}$ ?

$$u_{i,j}^{k+1} = u^k + \frac{\tau}{h^2} (4u_{i,j}^k - u_{i+1,j}^k - u_{i-1,j}^k - u_{i,j+1}^k - u_{i,j-1}^k)$$

- **Not hard to implement!** Loop over grid, add up some neighbors.

# Solving the Wave Equation

- Finally, wave equation:

$$\ddot{u} = \Delta u$$

- Not much different; now have 2nd derivative in time
- By now we've learned two different techniques:

- Convert to two 1st order (in time) equations:

$$\dot{u} = v, \quad \dot{v} = \Delta u$$

- Or, use centered difference (like Laplace) in time:

$$\frac{u^{k+1} - 2u^k + u^{k-1}}{\tau^2} = \Delta u^k$$

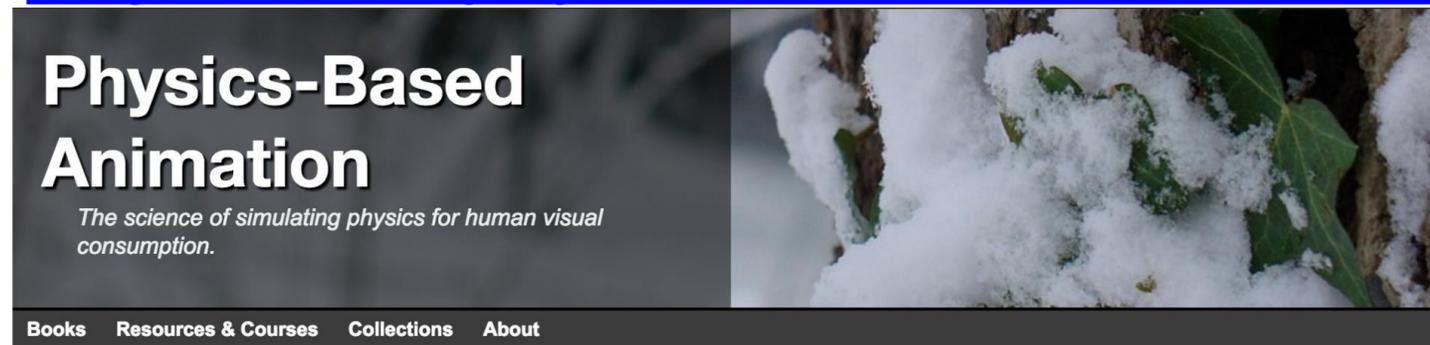
- Plus all our choices about how to discretize Laplacian.
- *So many choices!* And many, many (*many*) more we didn't discuss.

**Wait, what about all those cool fluids  
and stuff?**

# Want to Know More?

- There are some good books:
- And papers:

<http://www.physicsbasedanimation.com/>



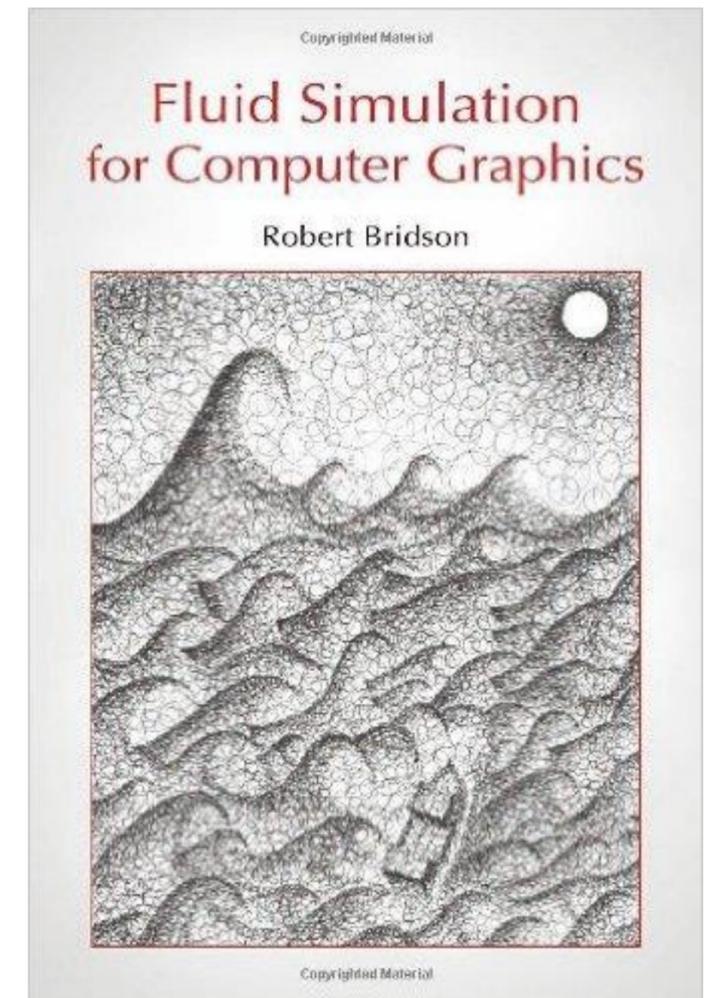
**Biomechanical Simulation and Control of Hands and Tendinous Systems**

Prashant Sachdeva, Shinjiro Sueda, Susanne Bradley, Mikhail Fain, Dinesh K. Pai

Search...

Contact

This site is managed by Christopher Batty from the University of Waterloo



- Also, what did the folks who *wrote* these books & papers read?

