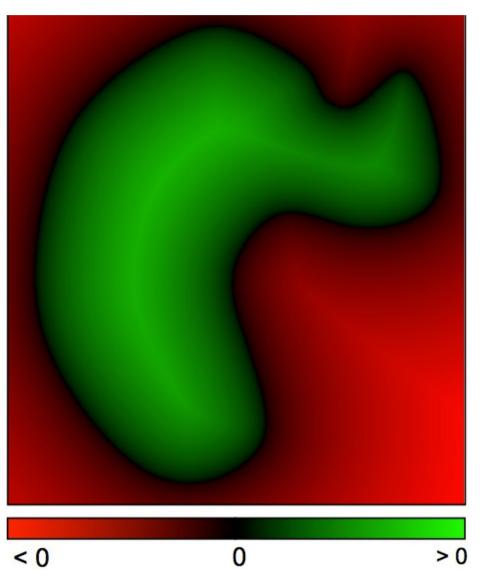


Poisson Surface Reconstruction - I

Siddhartha Chaudhuri http://www.cse.iitb.ac.in/~cs749

Recap: Implicit Function Approach

 Define a function with positive values inside the model and negative values outside

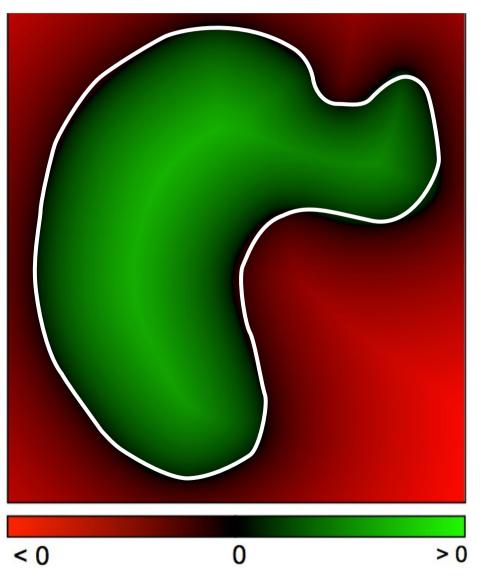


Slides adapted from Kazhdan, Bolitho and Hoppe

Recap: Implicit Function Approach

 Define a function with positive values inside the model and negative values outside

• Extract the zero-set



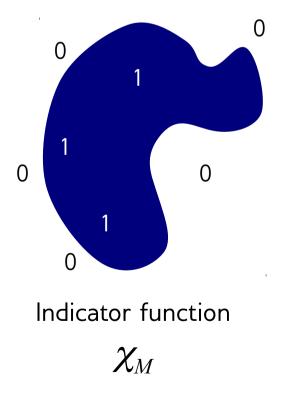
Slides adapted from Kazhdan, Bolitho and Hoppe

Recap: Key Idea

• Reconstruct the surface of the model by solving for the indicator function of the shape

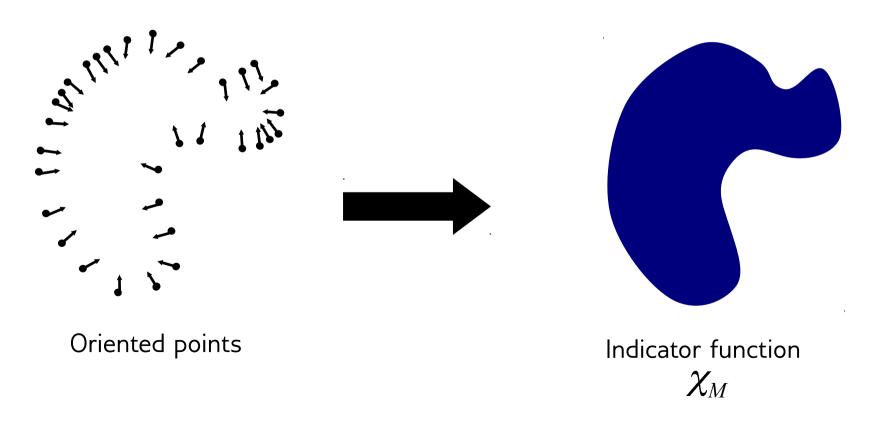
$$\chi_M(p) = \begin{cases} 1 & \text{if } p \in M \\ 0 & \text{if } p \notin M \end{cases}$$

In practice, we define the indicator function to be -1/2 outside the shape and 1/2 inside, so that the surface is the zero level set. We also smooth the function a little, so that the zero set is well defined.



Recap: Challenge

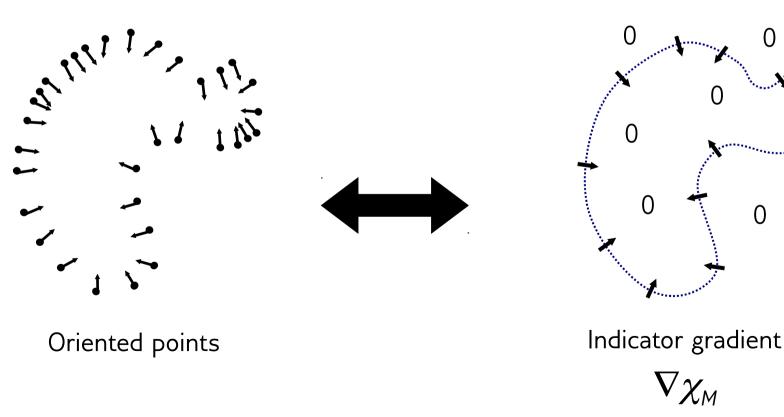
• How to construct the indicator function?



Slides adapted from Kazhdan, Bolitho and Hoppe

Recap: Gradient Relationship

• There is a relationship between the normal field at the shape boundary, and the gradient of the (smoothed) indicator function



Slides adapted from Kazhdan, Bolitho and Hoppe

Ω

Operators

- Let's look at a 1D function $f : \mathbb{R} \to \mathbb{R}$
 - It has a first derivative given by

$$\frac{df}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

• ... a second derivative, and a third...

$$\frac{d^2 f}{dx^2} = \frac{d}{dx} \frac{d}{dx} f \qquad \qquad \frac{d^3 f}{dx^3} = \frac{d}{dx} \frac{d}{dx} \frac{d}{dx} f$$

$$d$$

- $\frac{d}{dx}$ is a general operation mapping functions to functions: it's called an **operator**
 - In fact, it's a linear operator: $\frac{d}{dx}(f+g) = \frac{d}{dx}f + \frac{d}{dx}g$

Variational Calculus

- Imagine we didn't know *f*, but we did know its derivative $g = \frac{df}{dx}$
- Solving for *f* is, obviously, integration

$$f = \int \frac{df}{dx} dx = \int g \, dx$$

- But what if g is not analytically integrable?
 - Then we can look for approximate solutions, drawn from some parametrized family of candidate functions

Variational Calculus

- Assume we have a family of functions F
- Let's minimize the mean squared approximation error over some interval Ω and functions $f \in F$

minimize
$$\int_{\Omega} \left| \frac{df}{dx} - g \right|^2 dx$$

Euler-Lagrange Formulation

• Euler-Lagrange equation: Stationary points (minima, maxima etc) of a functional of the form

$$\int_{\Omega} L(x, f(x), f'(x)) dx$$

are obtained as solutions *f* to the PDE

$$\frac{\partial L}{\partial f} - \frac{d}{dx} \frac{\partial L}{\partial f'} = 0$$

Euler-Lagrange Formulation

- Euler-Lagrange equation: $\frac{\partial L}{\partial f} \frac{d}{dx} \frac{\partial L}{\partial f'} = 0$
- In our case, $L = (f'(x) g(x))^2$, so $\frac{\partial L}{\partial f} = 0$ $\frac{\partial L}{\partial f'} = 2(f'(x) - g(x))$ $\frac{d}{dx} \frac{\partial L}{\partial f'} = 2(f''(x) - g'(x))$
- Substituting, we get (a case of) the 1D Poisson equation:

$$f'' = g'$$
 or $\frac{d^2f}{dx^2} = \frac{dg}{dx}$

• Here, we want to minimize $\int_{\Omega} (f'(x) - g(x))^2 dx$ and end up having to solve

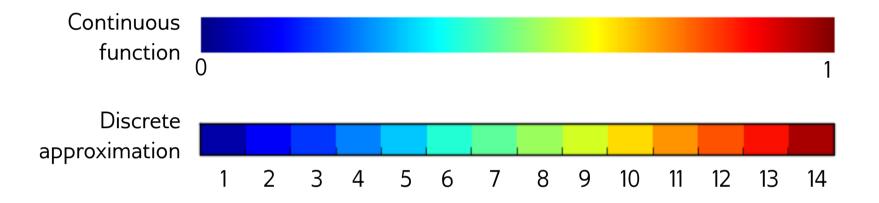
$$\frac{d}{dx}\frac{d}{dx}f = \frac{d}{dx}g$$

i.e. the two sides are equal at all points x

- Let's try to discretize this!
 - Sample *n* consecutive points $\{x_i\}$ from Ω

- Assume (for simplicity) they're evenly spaced, so $x_{i+1} - x_i = h$

• We want to minimize $\sum_{i} (f'(x_i) - g(x_i))^2$

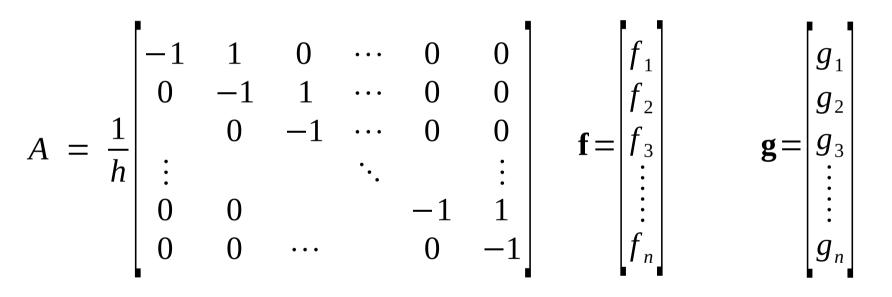


• The derivative at x_i can be approximated as

$$f'(x_i) \approx \frac{f_{i+1} - f_i}{h} = \frac{1}{h} \begin{bmatrix} -1 & 1 \end{bmatrix} \begin{bmatrix} f_i \\ f_{i+1} \end{bmatrix}$$

where f_i is shorthand for $f(x_i)$

 ... and all the derivatives can be listed in one big matrix multiplication: A f = g, where



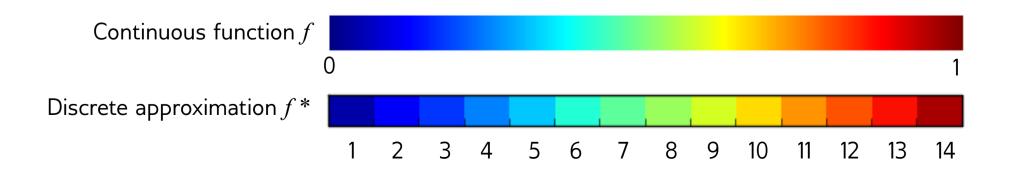
• **f** and **g** are discrete approximations of continuous functions *f* and *g*, and *A* is a discrete approximation for the continuous derivative operator $\frac{d}{dx}$!

Functions as vectors

- Functions from *A* to *B* form a vector space: we can think of functions as "vectors"
 - E.g. we can commutatively add two functions: f + g = g + f
 - Or distribute multiplication with a scalar: s(f+g) = sf + sg
 - If we want, we can also associate a **norm** ("vector length") with a function: e.g. $||f|| = (\int f^2(x) dx)^{1/2}$

A function can be discretized

- Characterize a function *f* by its values at a finite set of *n* sample points
 - This results in a discrete function, let's call it f^*
 - The discrete function is perfectly defined by its values at the *n* points
 - In other words, f^* is represented by a finitedimensional vector $[f(x_1), f(x_2), ..., f(x_n)]$



Linear operators, more formally

- An operator *T* is a mapping from a vector space *U* to another vector space *V*
 - *T* is a linear operator if T(a + b) = T(a) + T(b)
- The set of functions *F* from domain *A* to codomain *B* is a vector space
 - So we can have operators T that map from one function space F to another function space G
 - Note that *T* maps functions to functions!
- The differentials $\frac{d}{dx}$, $\frac{d^2}{dx^2}$, $\frac{d^3}{dx^3}$ etc are linear operators
 - They map functions to their derivatives

Discrete Linear Operators

- Theorem: Any linear operator between finitedimensional vector spaces can be represented by a matrix
 - Let's say we have a set of functions F from A to B
 - The discrete versions of the functions form a finitedimensional vector space F^* equivalent to \mathbb{R}^n
 - Each function is sampled at the same finite set of points
 - Let T be a linear operator from F to itself
 - ... and T^* be a "discrete version" of T acting on F^*
 - Then T^* can be represented by a $n \times n$ matrix (cf. theorem)

Example: Discrete Derivative

Continuous

- Function: *f*
- Operator: $\frac{d}{dx}$
- Applying operator:

$$\frac{df}{dx} = f'$$

Discrete

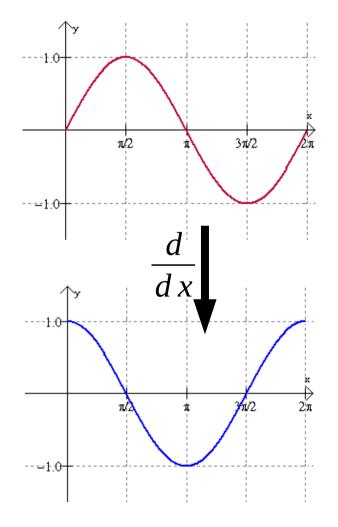
- Vector: $\mathbf{f} = [f(x_1), f(x_2) \dots f(x_n)]$
- Matrix:

$$A = \frac{1}{h} \begin{vmatrix} -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ 0 & -1 & \cdots & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & & & -1 & 1 \\ 0 & 0 & \cdots & 0 & -1 \end{vmatrix}$$

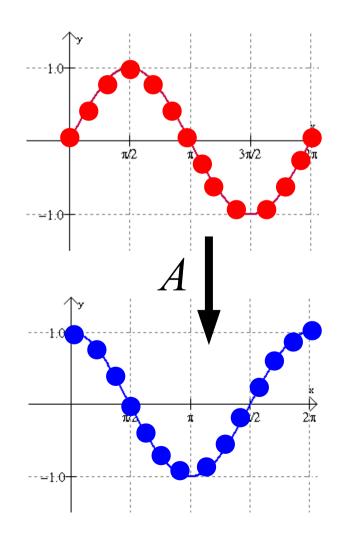
- Applying matrix:
 - $A\mathbf{f} = \mathbf{f}$

Example: Discrete Derivative

Continuous



Discrete



Example: Discrete 2nd Derivative

Continuous

- Function: *f*
- Operator: $\frac{d^2}{dx^2}$
- Applying operator:

$$\frac{d^2f}{dx^2} = f''$$

Discrete

- Vector: $\mathbf{f} = [f(x_1), f(x_2) \dots f(x_n)]$
- Matrix:

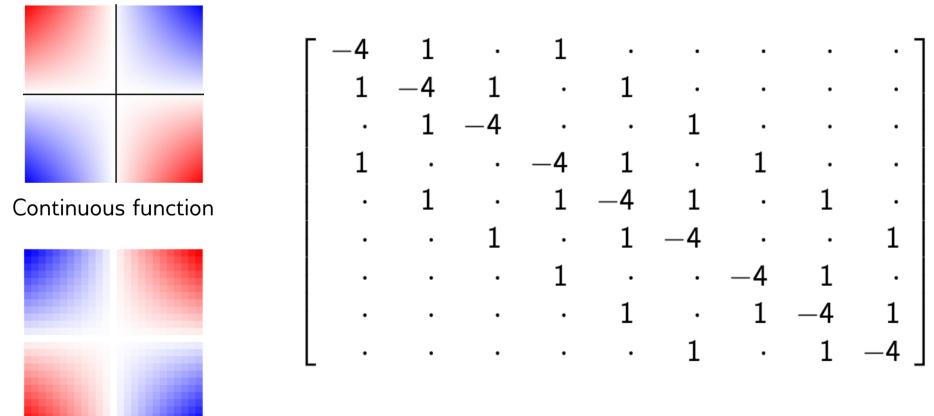
$$L = \frac{1}{h^2} \begin{vmatrix} -2 & 1 & 0 & \cdots & 0 & 0 \\ 1 & -2 & 1 & \cdots & 0 & 0 \\ & 1 & -2 & \cdots & 0 & 0 \\ \vdots & & & \ddots & & \vdots \\ 0 & 0 & & & -2 & 1 \\ 0 & 0 & \cdots & & 1 & -2 \end{vmatrix}$$

• Applying matrix:

 $L\mathbf{f} = \mathbf{f}$ "

Operators in higher dimensions

• The underlying function space can have a higherdimensional domain

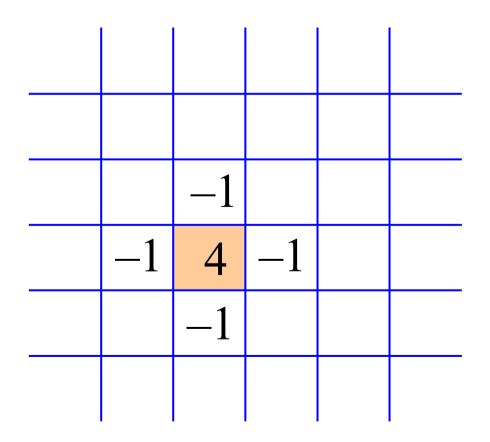


2D discrete Laplace operator

Discrete approximation

Discrete 2D Laplacian

• The Laplacian is computed via differences of a cell from its neighbors



Flashback

 Need to solve set of equations Af = g in a least squares sense

minimize
$$\|\mathbf{r}\|^2 = \|\mathbf{g} - A\mathbf{f}\|^2$$

• The directional derivative in direction $\delta {\bf f}$ is

$$\nabla ||\mathbf{r}||^2 \cdot \delta \mathbf{f} = 2\delta \mathbf{f}^{\mathrm{T}} (A^{\mathrm{T}} \mathbf{g} - A^{\mathrm{T}} A \mathbf{f})$$

• The minimum is achieved when all directional derivatives are zero, giving the normal equations

$$A^{\mathrm{T}}A\mathbf{f} = A^{\mathrm{T}}\mathbf{g}$$

• Thought for the (Previous) Day: Compare this equation to the Poisson equation

- Linear Least Squares: The **f** that minimizes $||A\mathbf{f} \mathbf{g}||^2$ is the solution of $A^T A \mathbf{f} = A^T \mathbf{g}$
- Euler-Lagrange: The *f* that minimizes $\int_{\Omega} \left(\frac{df}{dx}(x) - g(x) \right)^2 dx \text{ is a solution of } \frac{d}{dx} \frac{d}{dx} f = \frac{d}{dx} g$
- Knowing that A is the discrete version of $\frac{a}{dx}$, everything lines up *except* for the transpose bit
 - How do we reconcile this?

• The derivative at x_i can *also* be approximated as

$$f'(x_i) \approx \frac{f_i - f_{i-1}}{h} = \frac{1}{h} \begin{bmatrix} -1 & 1 \end{bmatrix} \begin{bmatrix} f_{i-1} \\ f_i \end{bmatrix}$$

... and derivatives at all x_i as B f, where

$$B = \frac{1}{h} \begin{vmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 \\ & -1 & 1 & \cdots & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & & & 1 & 0 \\ 0 & 0 & \cdots & -1 & 1 \end{vmatrix}$$

... which is just $-A^{T}$!

• Can rewrite normal equations as $(-A^T)A\mathbf{f} = (-A^T)\mathbf{g}$

Uniqueness of Solutions

- The discrete operator A we constructed is full-rank (invertible), and gives a unique solution $A^{-1}\mathbf{g}$ for \mathbf{f}
- But the corresponding continuous problem has multiple solutions (e.g. if *f* is a solution, (*f*+*constant*) is also a solution)
- Explanation: $A\mathbf{f} = \mathbf{g}$ implicitly imposes the boundary condition $f_n = -g_n$ (see the last row of the matrix)
 - In higher dimensions, the operator matrix *A* is non-square (maps scalar field to vector field) and not invertible. The system is overdetermined and we seek least-squares solutions

Discrete Second Derivative

• Multiplying the matrices, we get the discrete second derivative operator (the 1D Laplacian)

If you actually do the multiplication, this term is -1 and not -2. This is because our discretization does not correctly model the derivative at the end of the range. If you swap the matrices, the discrepancy occurs in the *last* element of the product instead. $\frac{d^2}{dx^2} = \frac{d}{dx}\frac{d}{dx}$ discretized to $(-A^T)A = \frac{1}{h^2} \begin{bmatrix} -2 & 1 & 0 & \cdots & 0 & 0 \\ 1 & -2 & 1 & \cdots & 0 & 0 \\ 1 & -2 & 1 & \cdots & 0 & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & & -2 & 1 \\ 0 & 0 & \cdots & 1 & -2 \end{bmatrix}$

... which is the same as the Taylor series approximation for the second derivative

In higher dimensions

- We have a function $f: \mathbb{R}^p \to \mathbb{R}^q$
- Differential operators (in 3D):

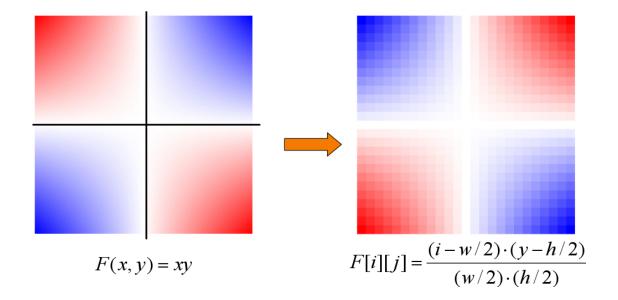
• **Gradient** (of scalar-valued function):
$$\nabla f = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}\right)$$

• **Divergence** (of vector-valued function): $\nabla \cdot V = \frac{\partial V_x}{\partial x} + \frac{\partial V_y}{\partial y} + \frac{\partial V_z}{\partial z}$

• Laplacian (of scalar-valued function): $\Delta f = \nabla \cdot \nabla f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} + \frac{\partial^2 f}{\partial z^2}$

In higher dimensions

- We have a function $f : \mathbb{R}^p \to \mathbb{R}^q$
 - We can discretize the domain as before, and obtain discrete analogues of the gradient ∇ (A), divergence ∇· (-A^T) and Laplacian Δ = (∇·)∇ (-A^TA)
 - Note that the gradient and divergence matrices are no longer square (more on this next class)



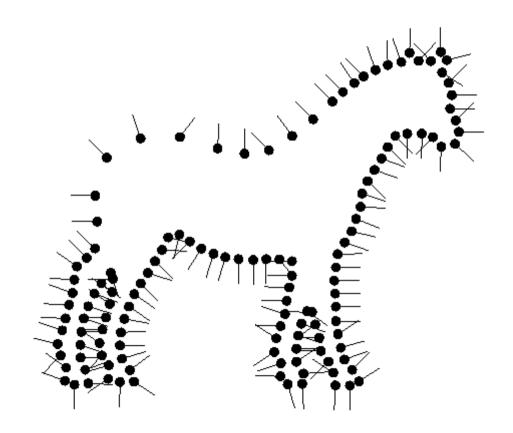
Misha Kazhdan

Takeaway

- A continuous variational problem can be approximated by a discrete one
 - Continuous function → Discrete vector of values
 - Continuous operator → Discrete matrix
 - Function composition → Matrix multiplication
 - Euler-Lagrange solution → Linear Least Squares
- Rest of this class: Overview of the pipeline of Poisson surface reconstruction
- Next class: The Galerkin approximation for recovering a continuous function from the discrete setup

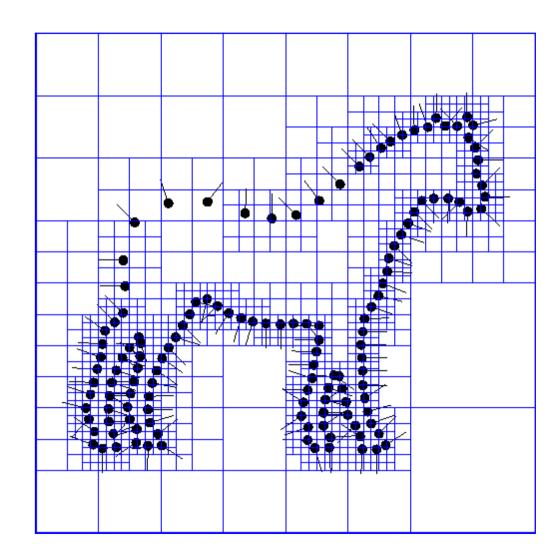
Implementation

- Set octree
- Compute vector field
- Compute indicator function
- Extract iso-surface

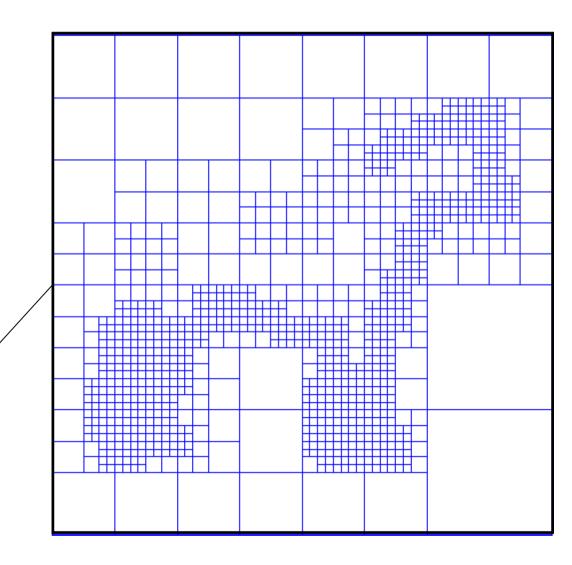


Implementation: Adaptive Octree

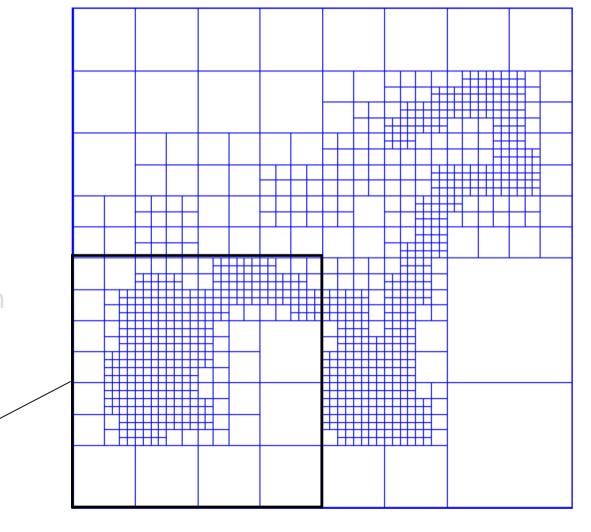
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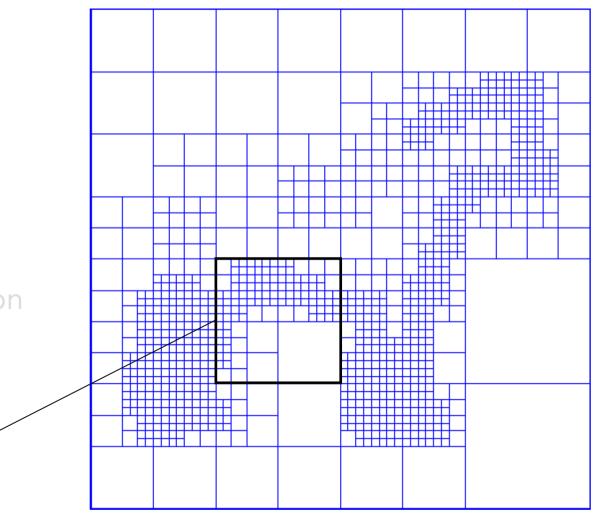
- Set octree
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 - Define a function space
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- Extract iso-surface



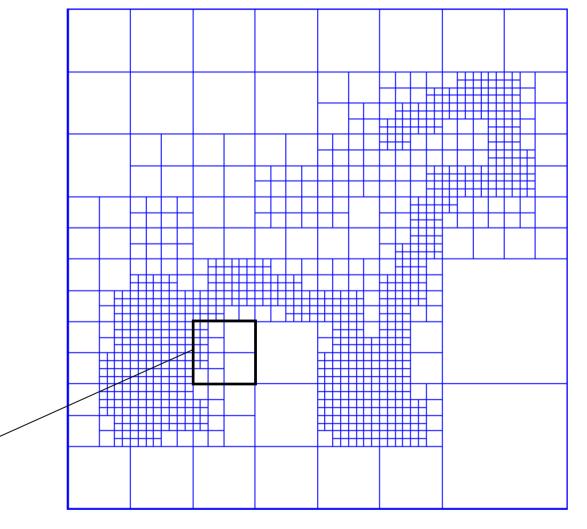
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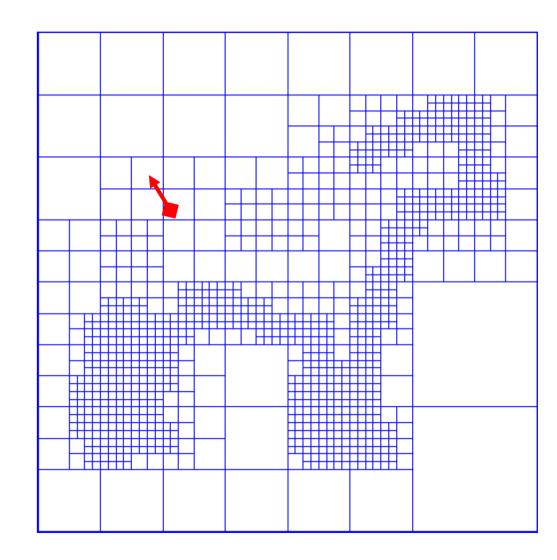
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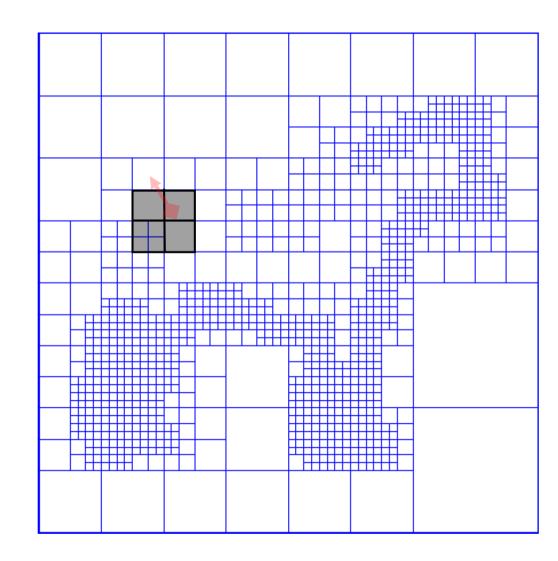
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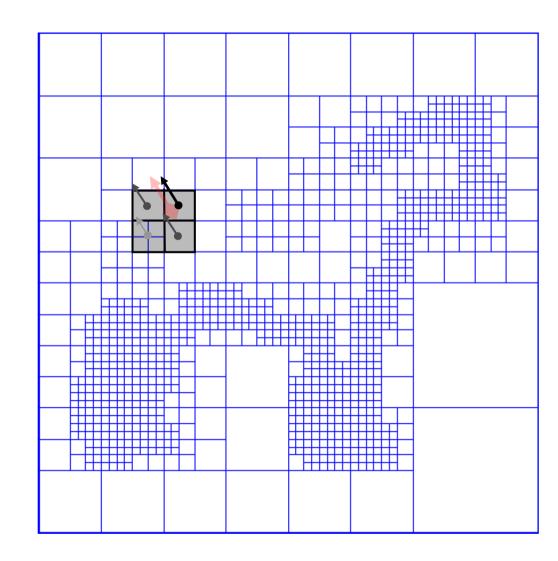
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- Extract iso-surface



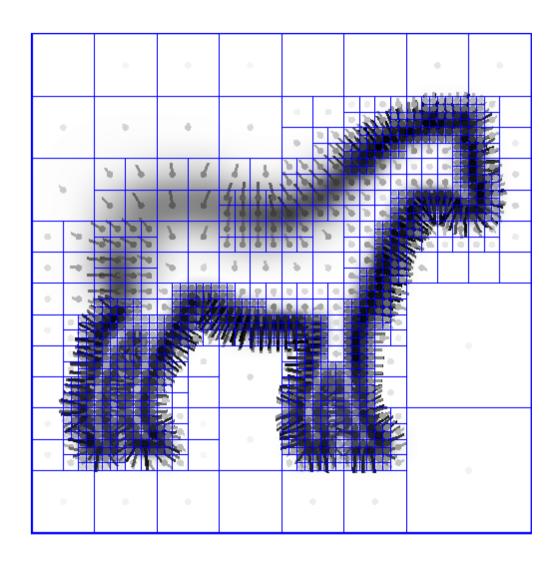
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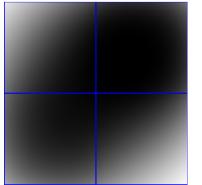
Implementation: Indicator Function

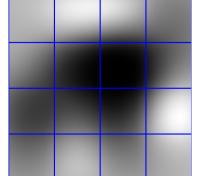
- Set octree
- Compute vector field
- Compute indicator function
 - Compute divergence
 - Solve Poisson equation
- Extract iso-surface

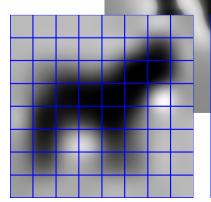


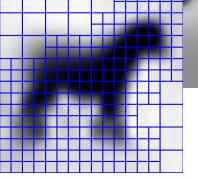
Implementation: Indicator Function

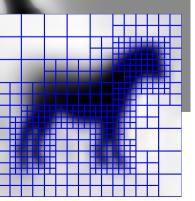
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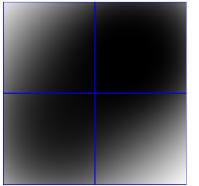


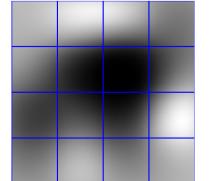




Implementation: Indicator Function

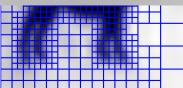
- Set octree
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- Compute indicator function
 - Compute divergence
 - Solve Poisson equation
- Extract iso-surface











Implementation: Surface Extraction

- Set octree
- Compute vector field
- Compute indicator function
- Extract iso-surface

