

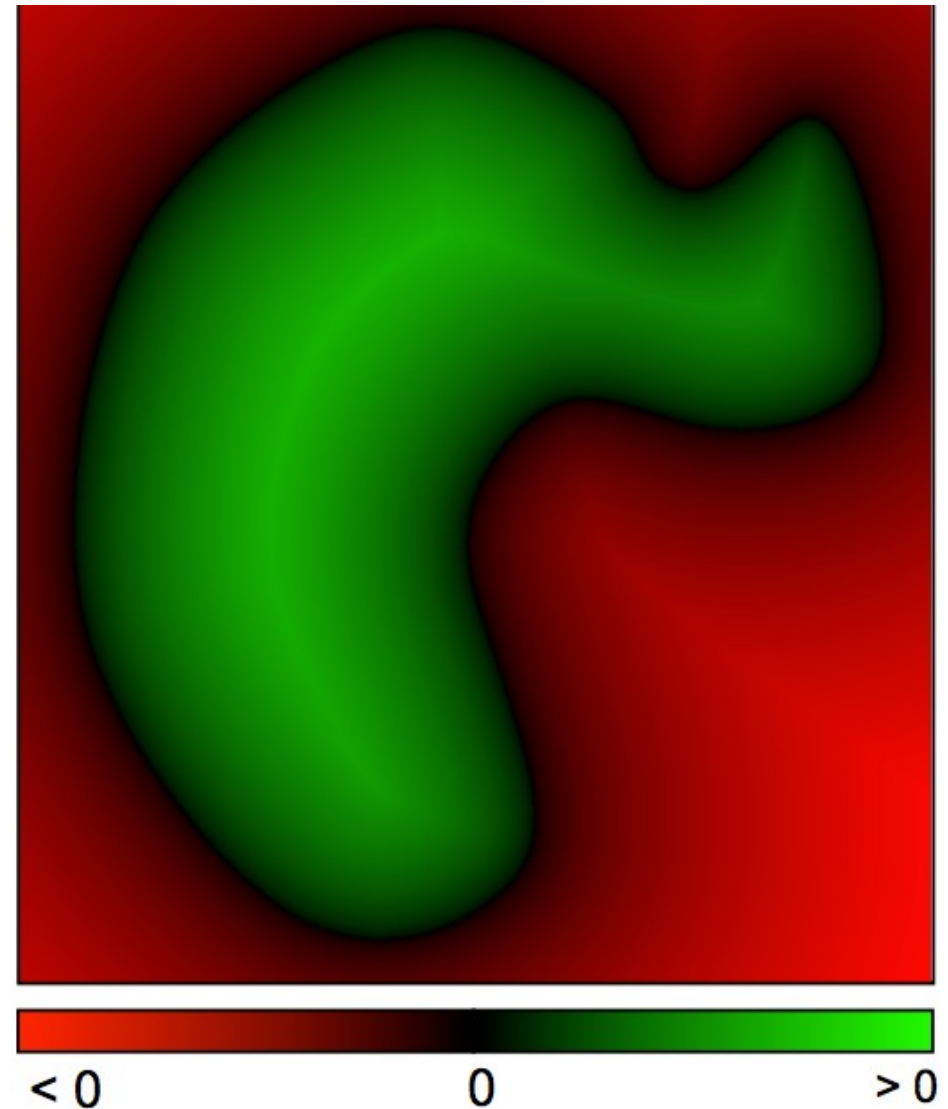
Poisson Surface Reconstruction

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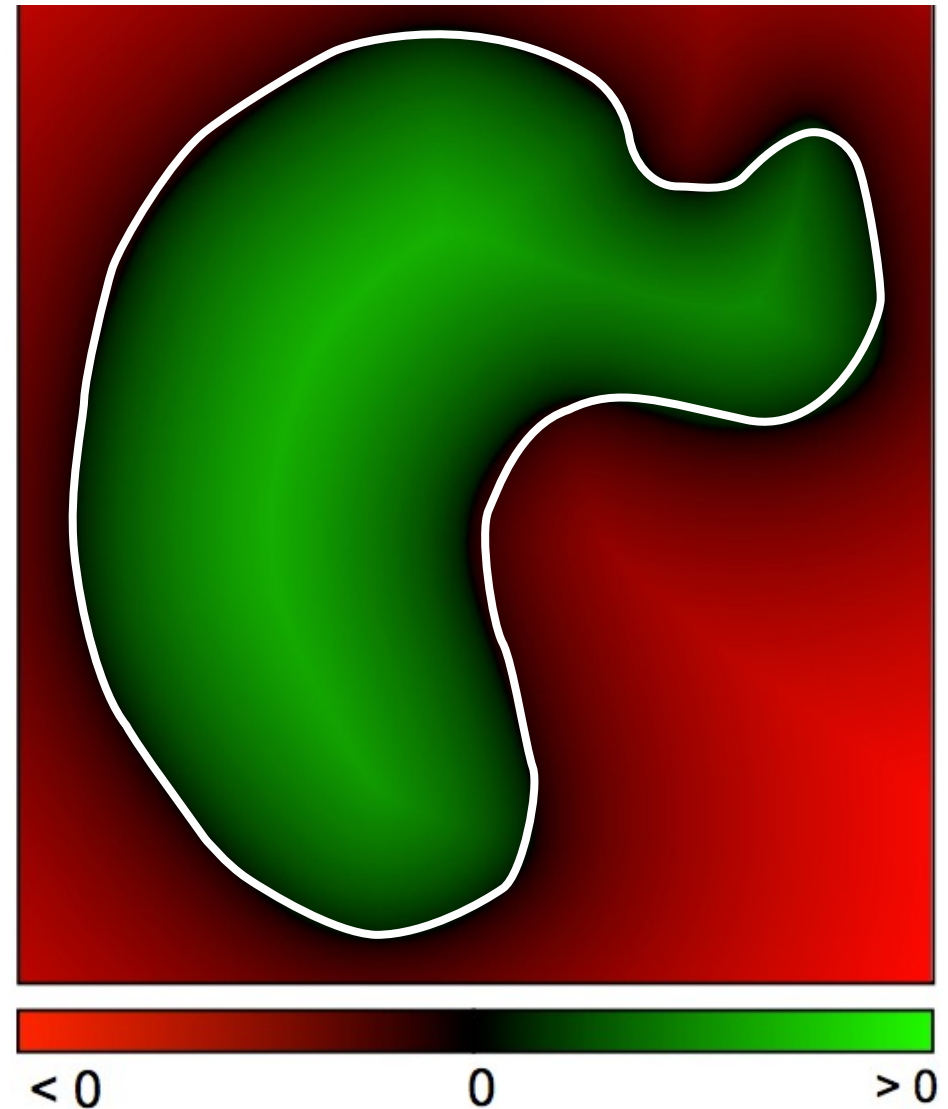
Recap: Implicit Function Approach

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



Recap: Implicit Function Approach

- Define a function with positive values inside the model and negative values outside
- Extract the zero-set

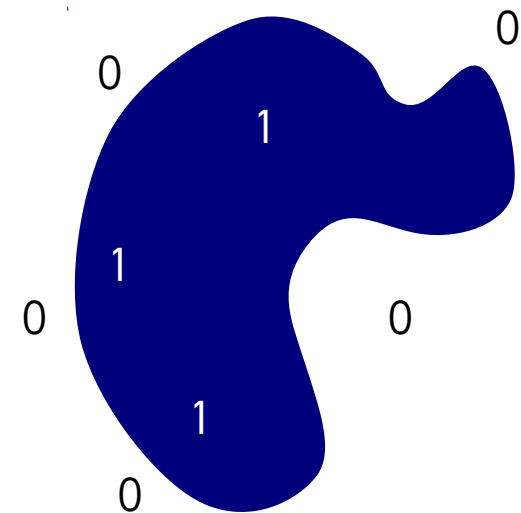


Recap: Key Idea

- 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.

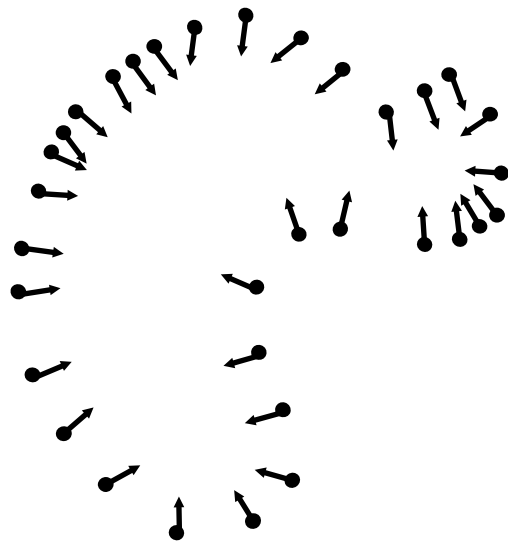


Indicator function

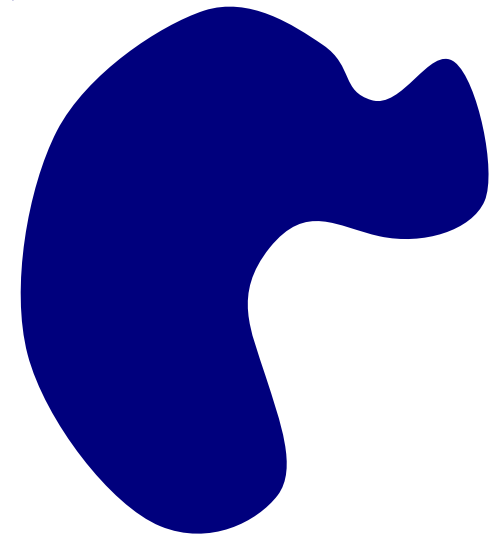
χ_M

Recap: Challenge

- How to construct the indicator function?



Oriented points

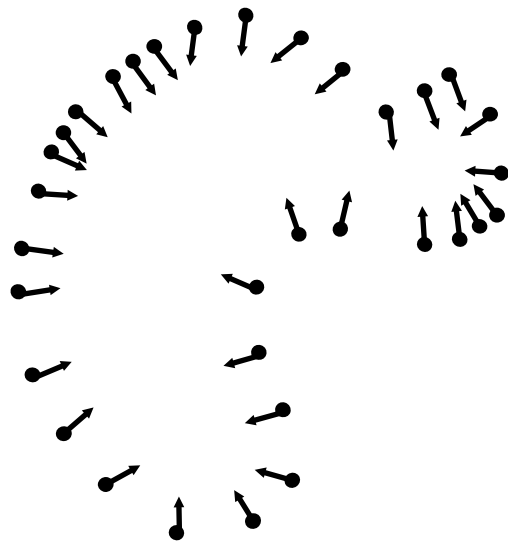


Indicator function

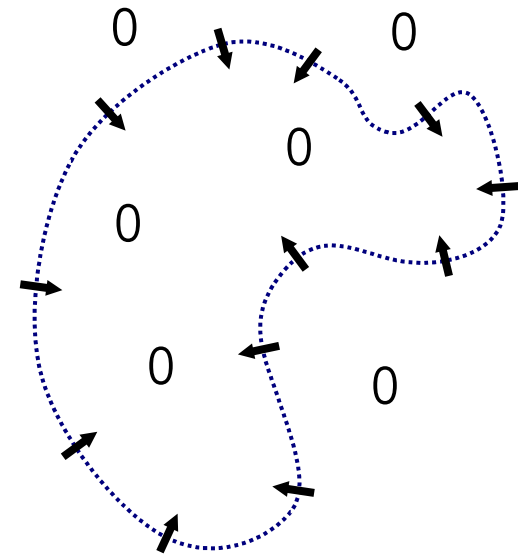
χ_M

Recap: Gradient Relationship

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



Oriented points



Indicator gradient

$$\nabla \chi_M$$

Operators

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

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

- ... a second derivative, and a third...

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

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

- $\frac{d}{dx}$ 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 $f \in F$

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

Euler-Lagrange Formulation

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

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

$$f'(x) = \frac{df}{dx}$$


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

$$\frac{\partial L}{\partial f} = 0 \qquad \frac{\partial L}{\partial f'} = 2(f'(x) - g(x))$$

$$\frac{d}{dx} \frac{\partial L}{\partial f'} = 2(f''(x) - g'(x))$$

- Substituting, we get (a case of) the 1D **Poisson equation:**

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

Link to Linear Least Squares

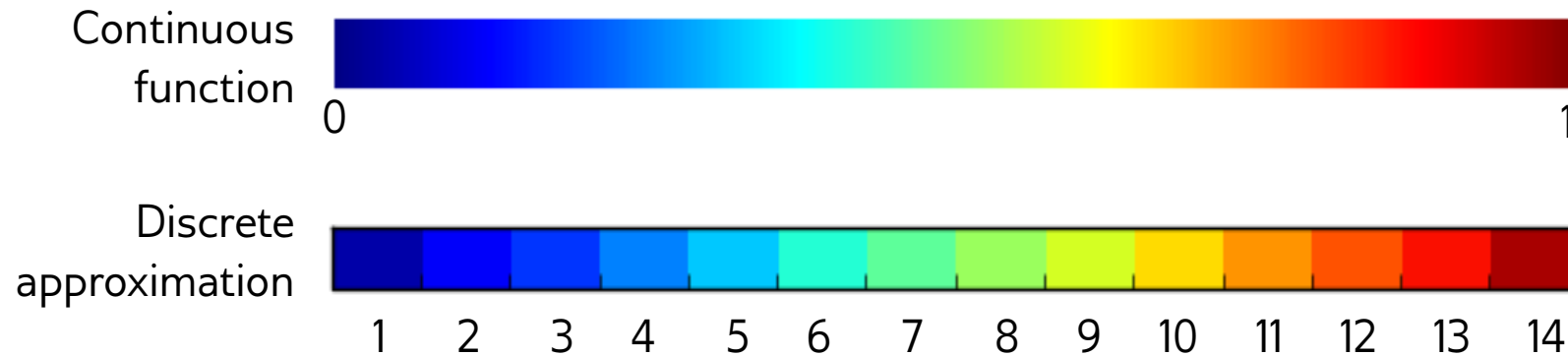
- Here, we want to minimize $\int_{\Omega} (f'(x) - g(x))^2 dx$ and end up having to solve

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

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 $\sum_i (f'(x_i) - g(x_i))^2$

Link to Linear Least Squares



- 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 $f(x_i)$

Link to Linear Least Squares

- ... and all the derivatives can be listed in one big matrix multiplication: $A \mathbf{f} = \mathbf{g}$, where

$$A = \frac{1}{h} \begin{bmatrix} -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ & 0 & -1 & \cdots & 0 & 0 \\ \vdots & & & \ddots & \vdots & \\ 0 & 0 & & & -1 & 1 \\ 0 & 0 & \cdots & & 0 & -1 \end{bmatrix} \quad \mathbf{f} = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ \vdots \\ f_n \end{bmatrix} \quad \mathbf{g} = \begin{bmatrix} g_1 \\ g_2 \\ g_3 \\ \vdots \\ g_n \end{bmatrix}$$

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

Flashback

- Need to solve set of equations $A\mathbf{f} = \mathbf{g}$ in a least squares sense

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

- The directional derivative in direction $\delta\mathbf{f}$ is

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

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

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

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

Link to Linear Least Squares

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

Link to Linear Least Squares

- 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 $B \mathbf{f}$, where

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

... 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, $(f + \text{constant})$ 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.

$$\frac{d^2}{dx^2} = \frac{d}{dx} \frac{d}{dx} \quad \text{discretized to} \quad (-A^T)A = \frac{1}{h^2} \begin{bmatrix} -2 & 1 & 0 & \dots & 0 & 0 \\ 1 & -2 & 1 & \dots & 0 & 0 \\ & 1 & -2 & \dots & 0 & 0 \\ \vdots & & & \ddots & & \vdots \\ 0 & 0 & & & -2 & 1 \\ 0 & 0 & \dots & & 1 & -2 \end{bmatrix}$$

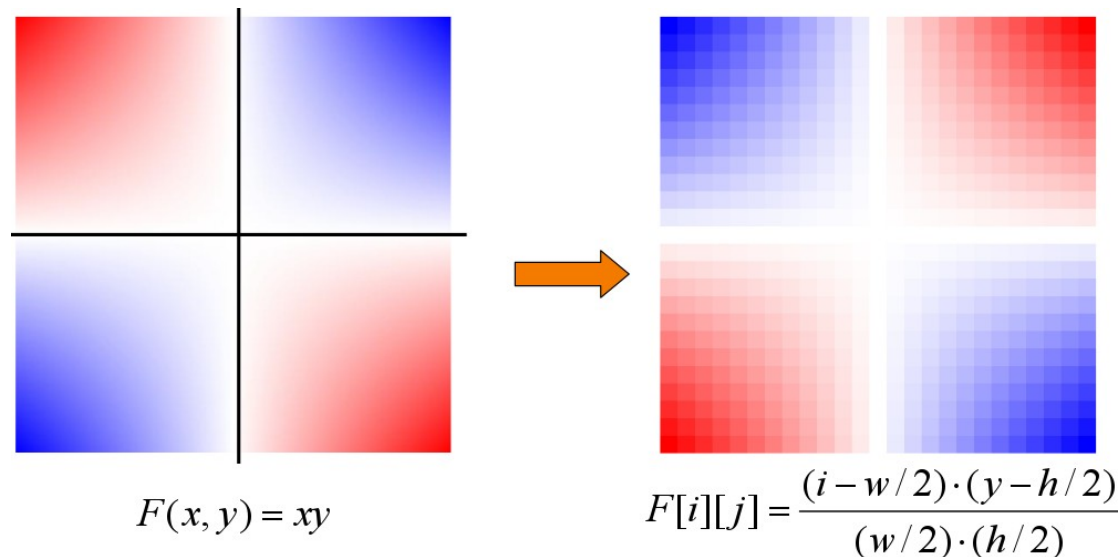
... which is the same as the Taylor series approximation for the second derivative

In higher dimensions

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



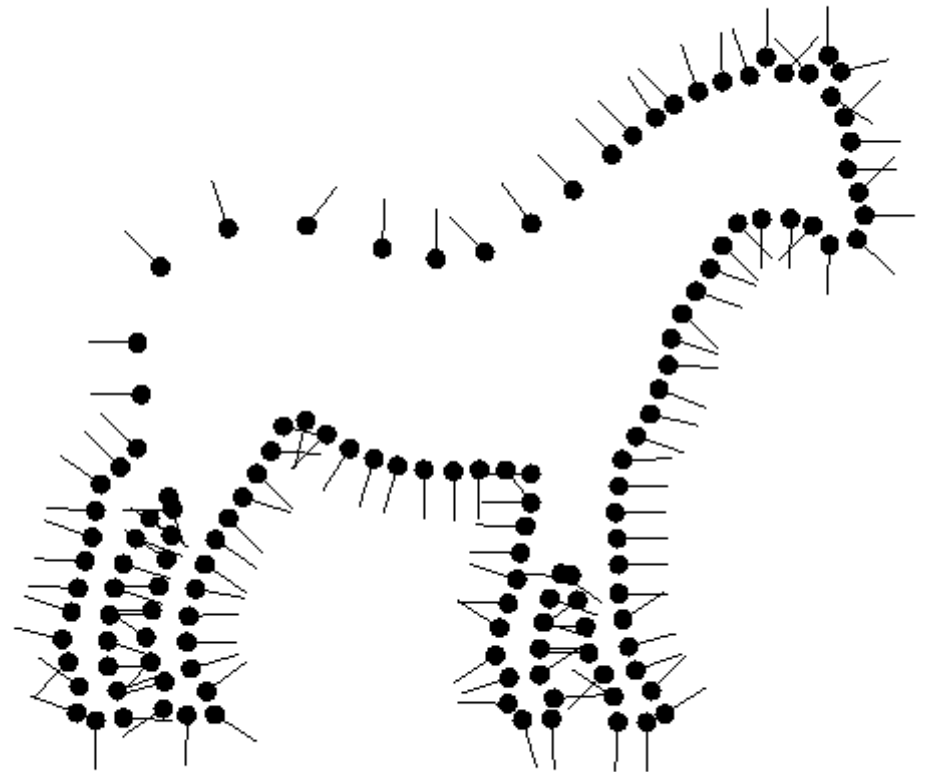
Takeaway

- 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

Given the Points:

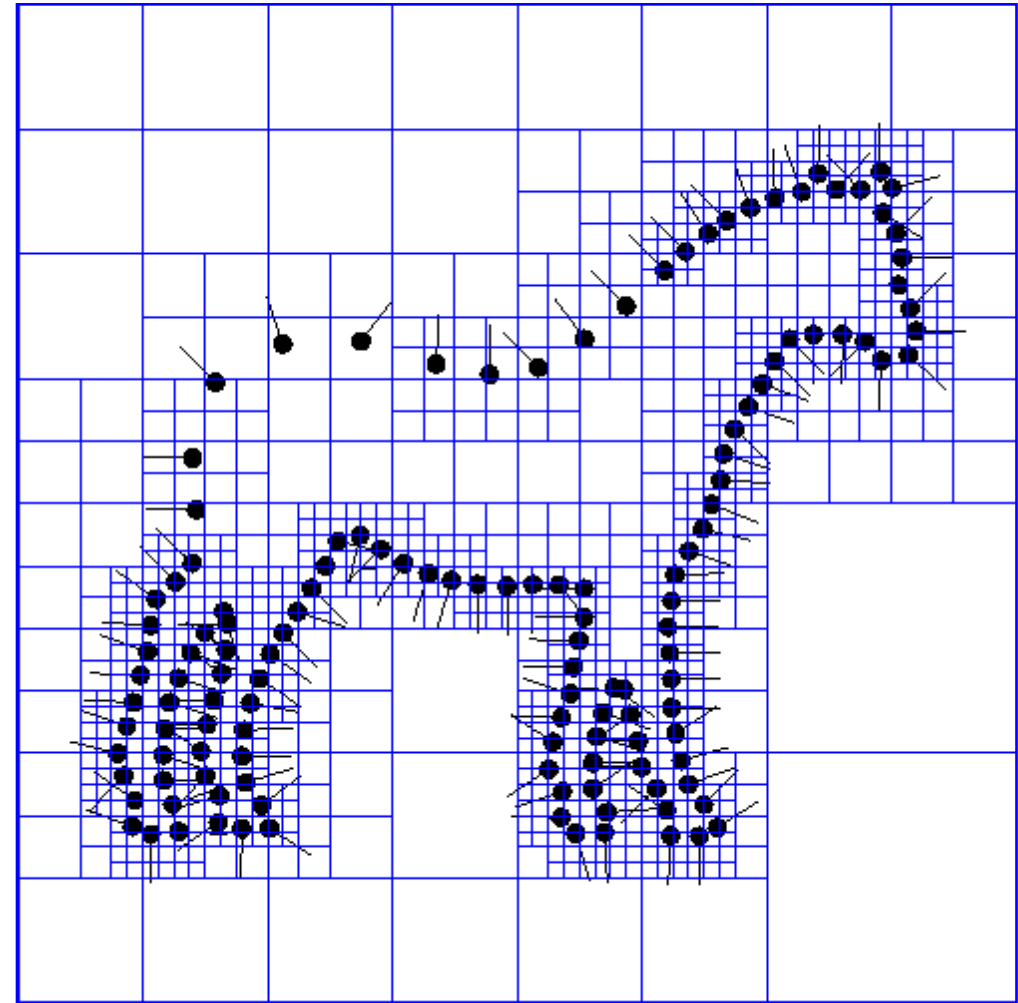
- Set octree
- Compute vector field
- Compute indicator function
- Extract iso-surface



Implementation: Adaptive Octree

Given the Points:

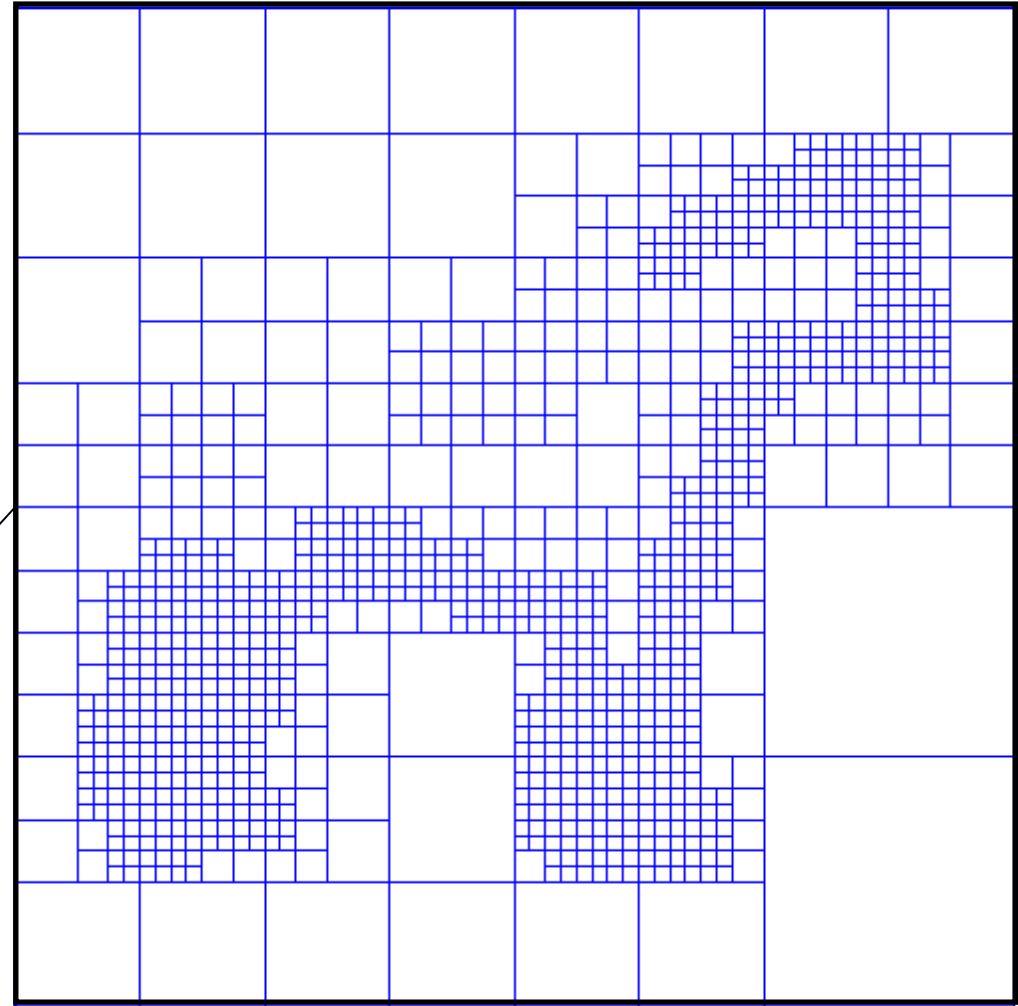
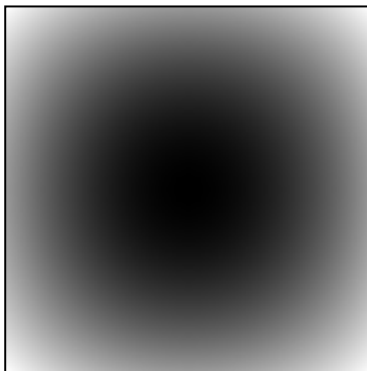
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Implementation: Vector Field

Given the Points:

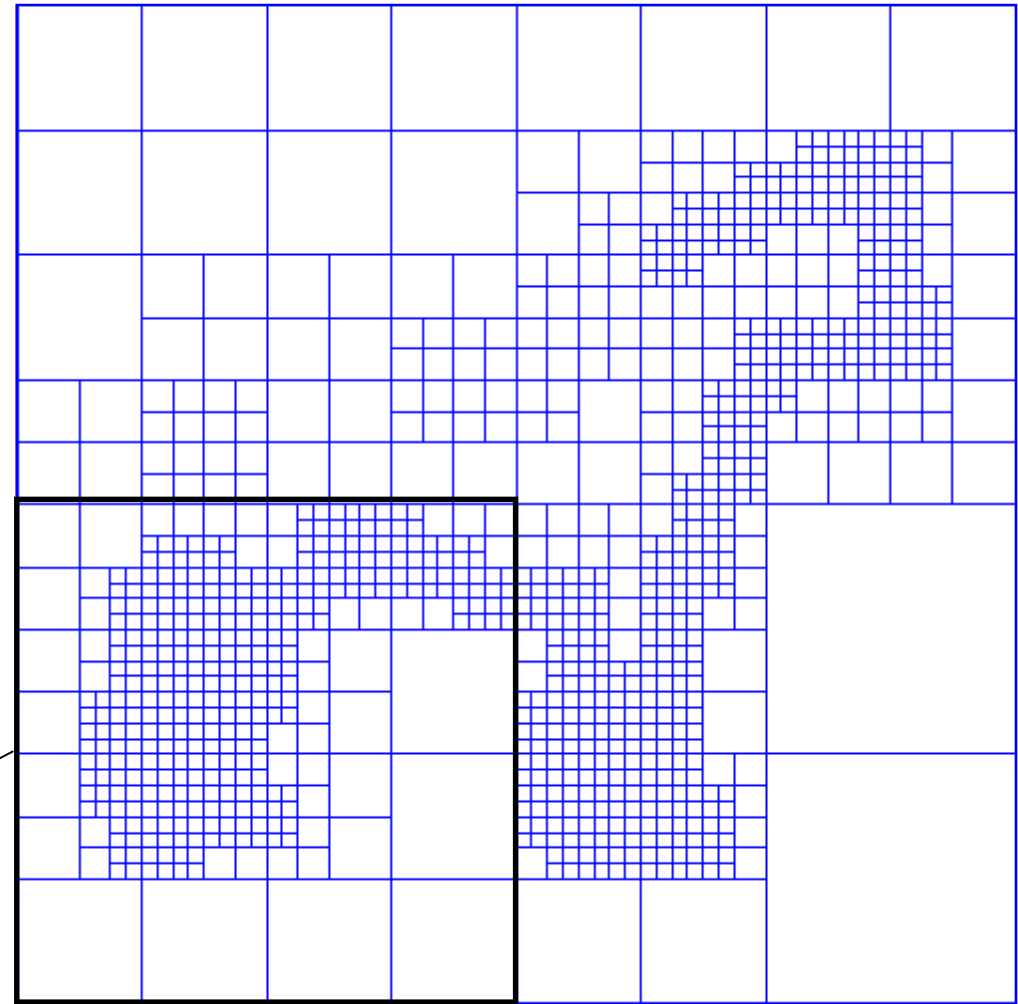
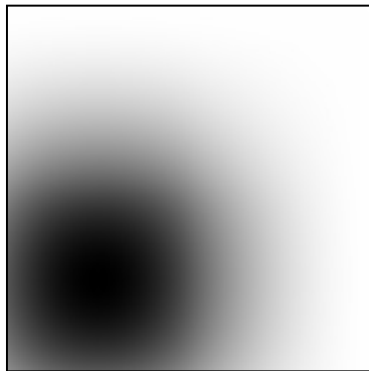
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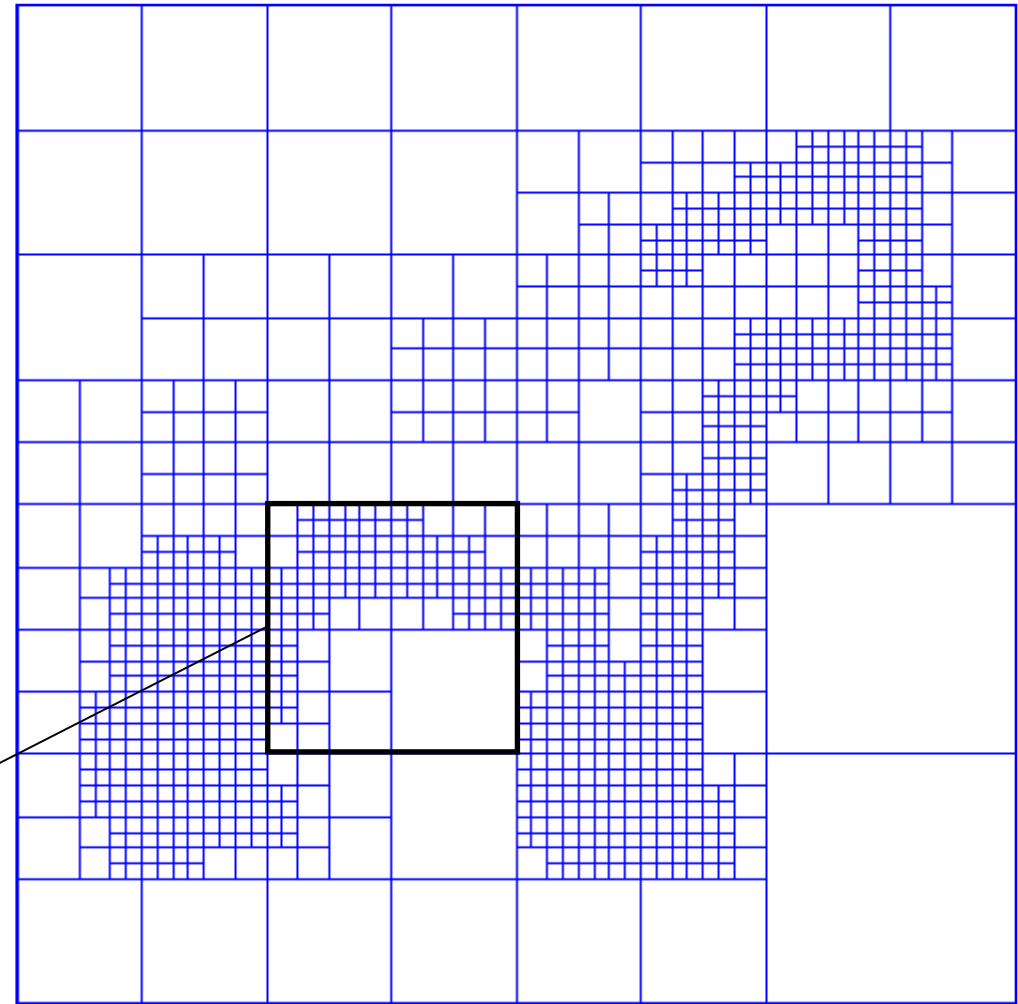
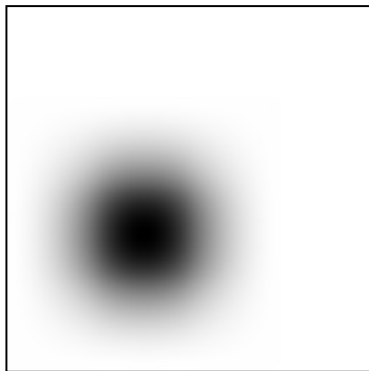
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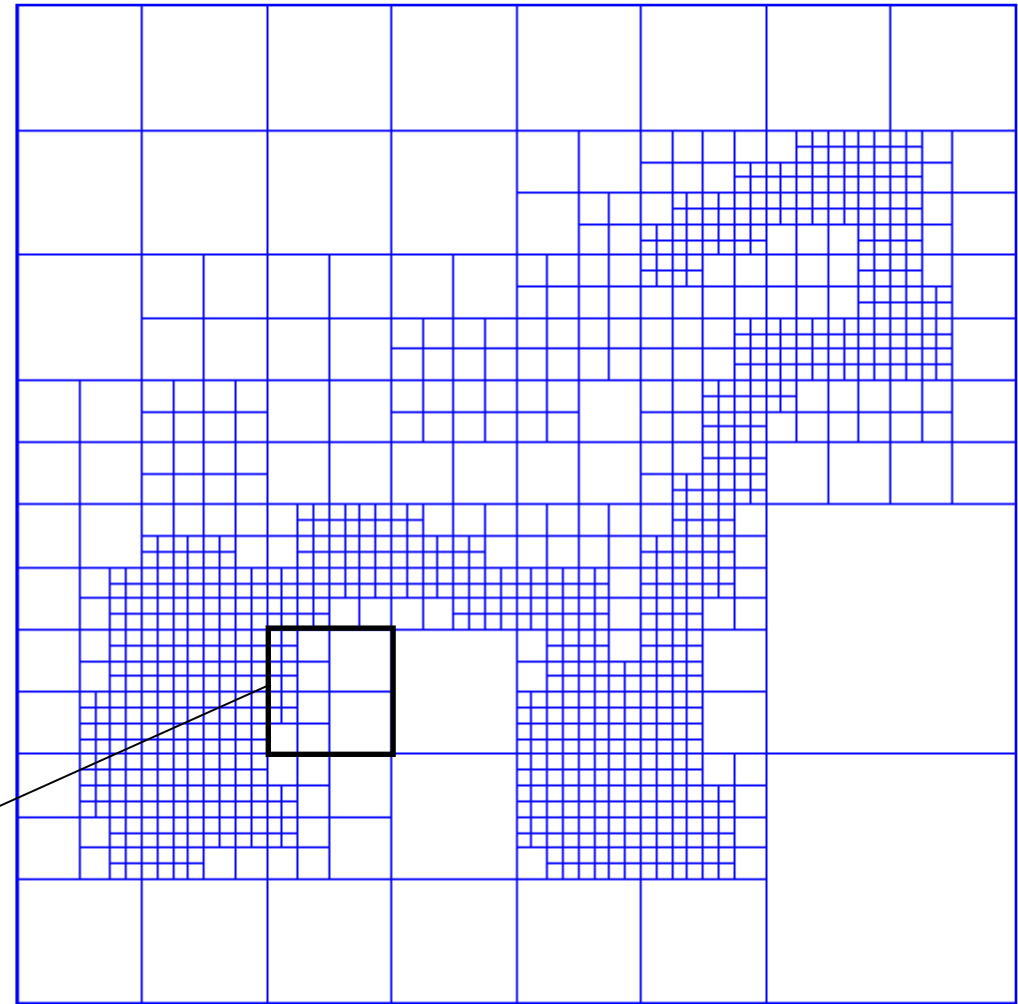
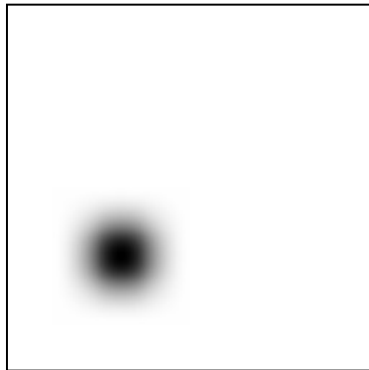
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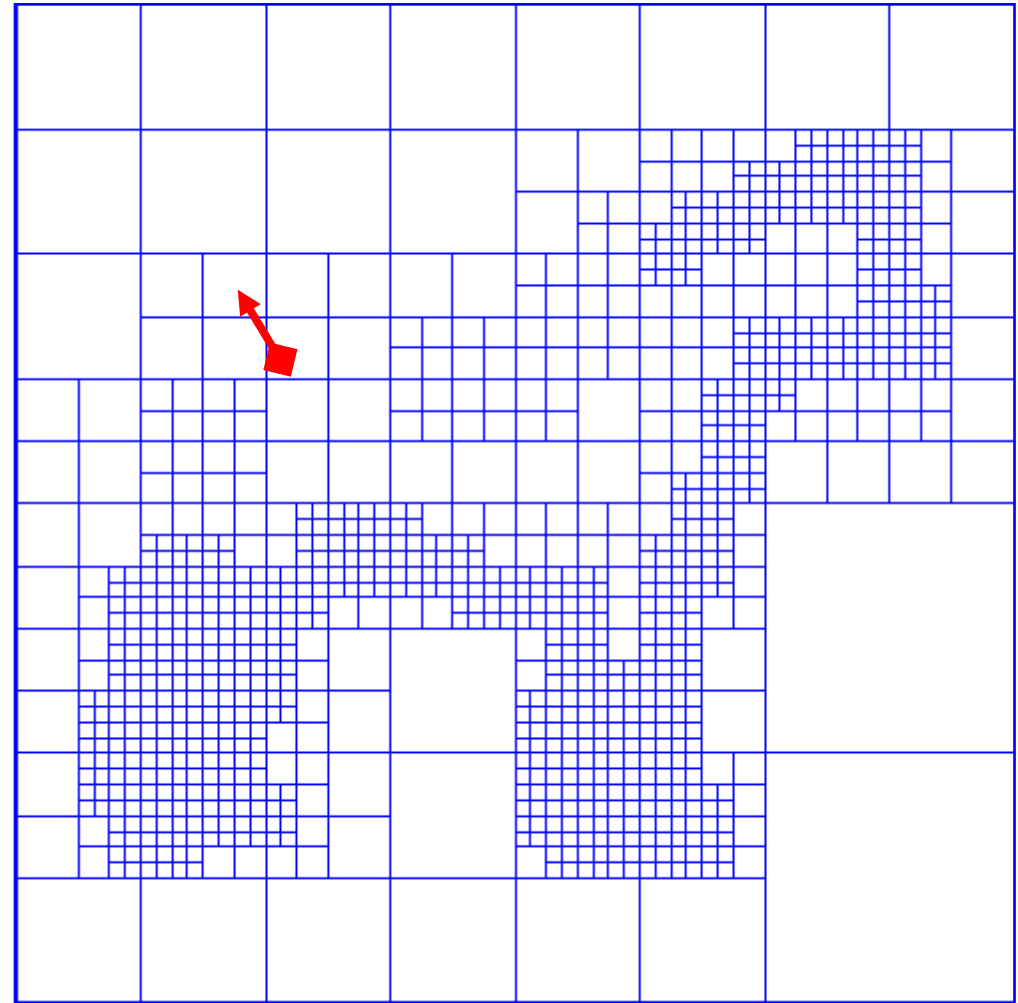
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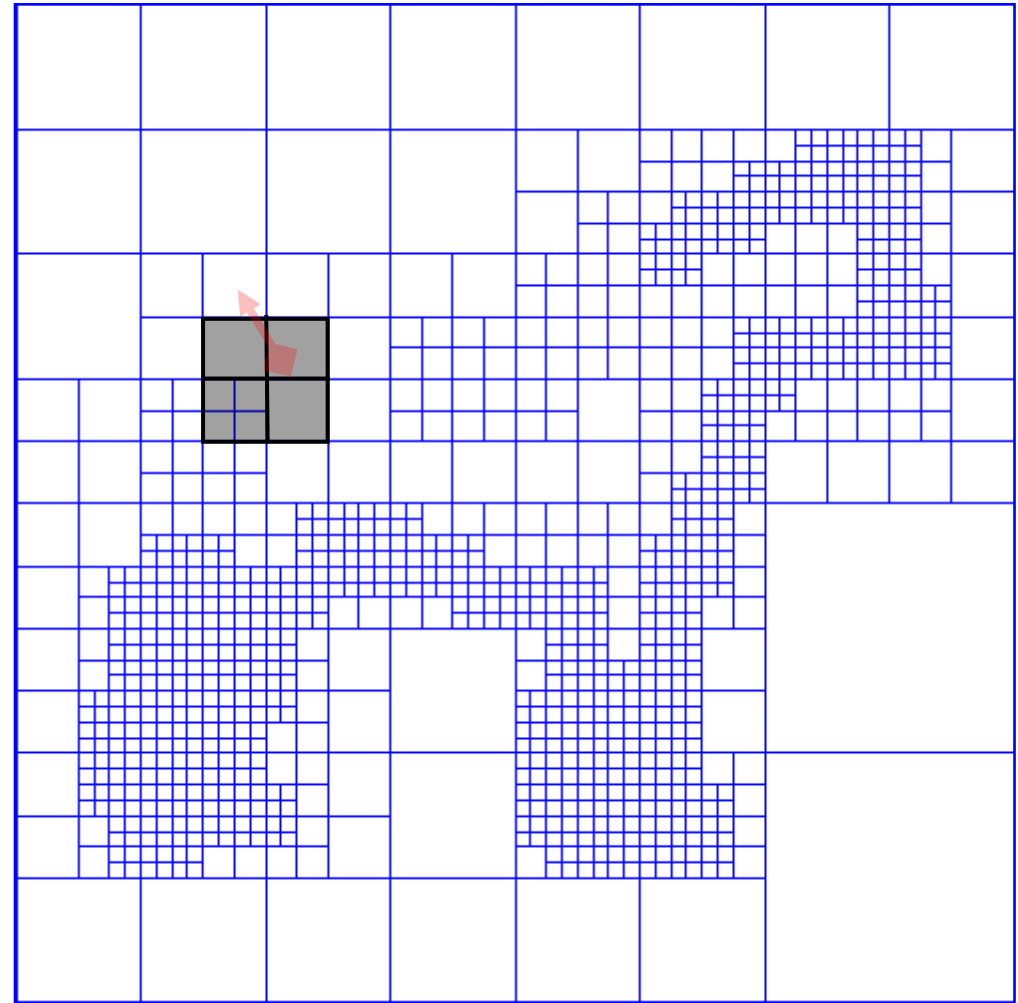
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Implementation: Vector Field

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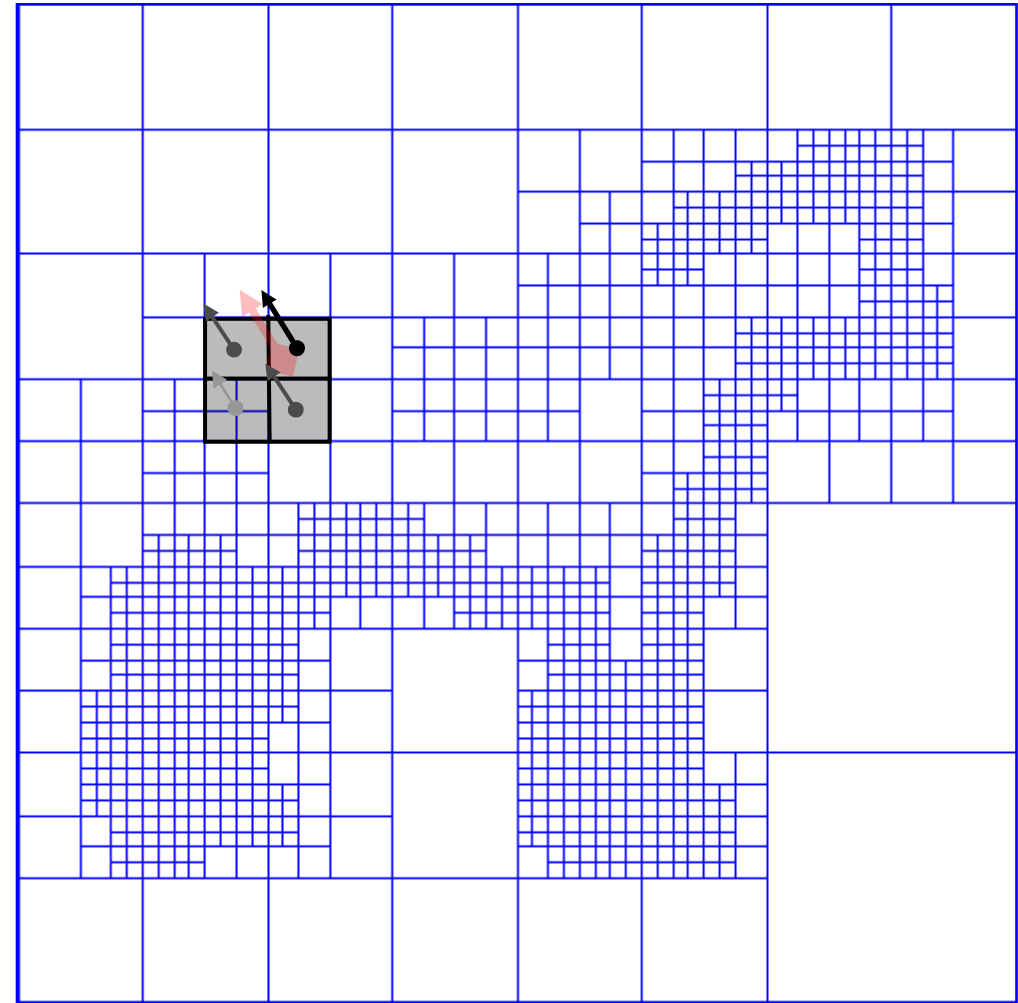
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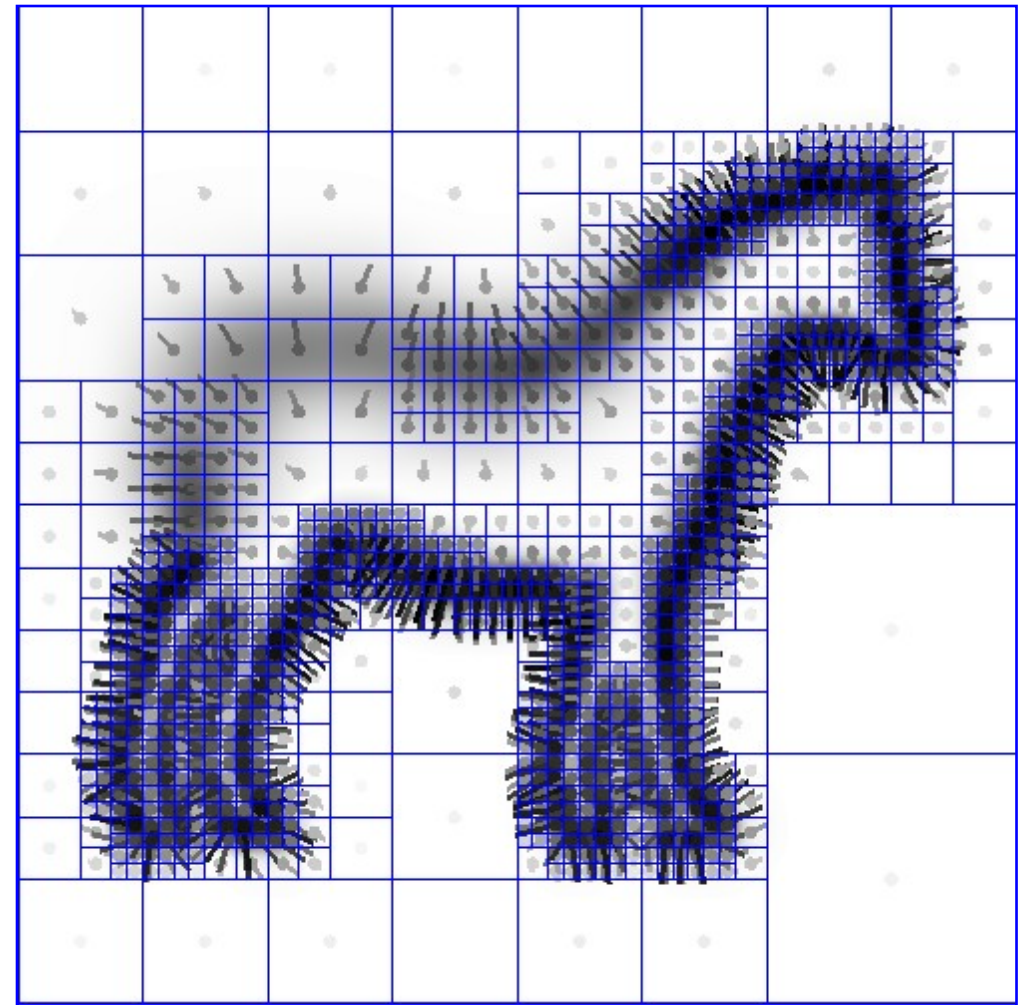
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Implementation: Vector Field

Given the Points:

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Implementation: Indicator Function

Given the Points:

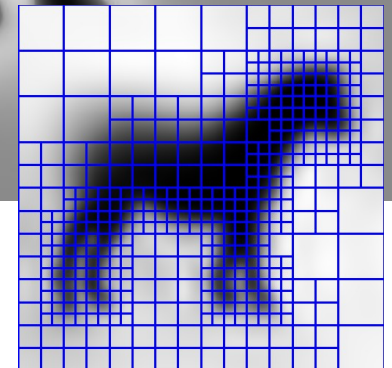
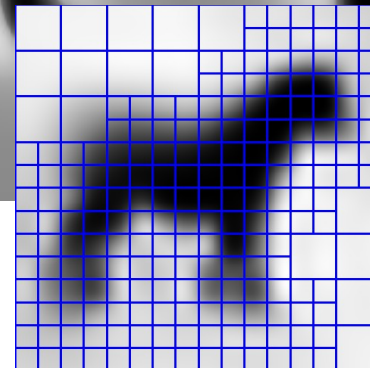
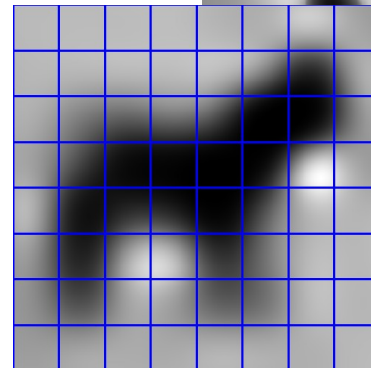
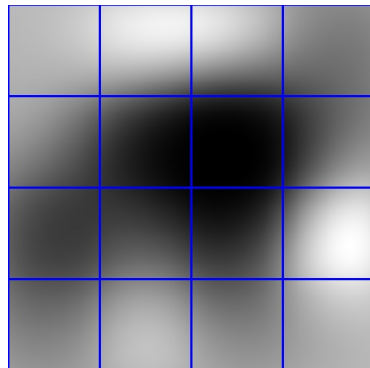
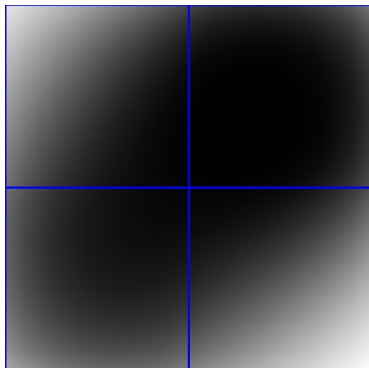
- Set octree
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- Compute indicator function
 - Compute divergence
 - Solve Poisson equation
- Extract iso-surface



Implementation: Indicator Function

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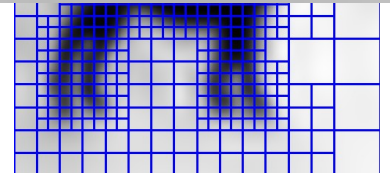
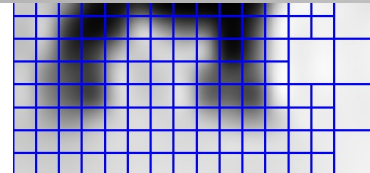
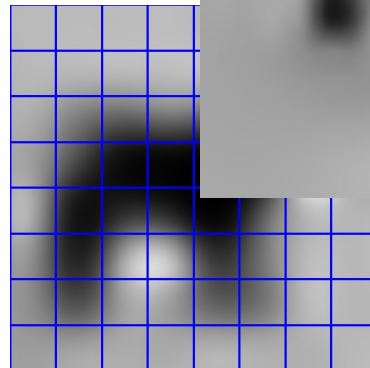
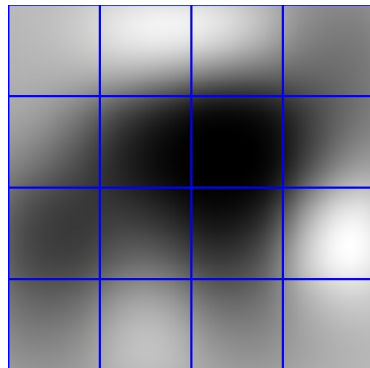
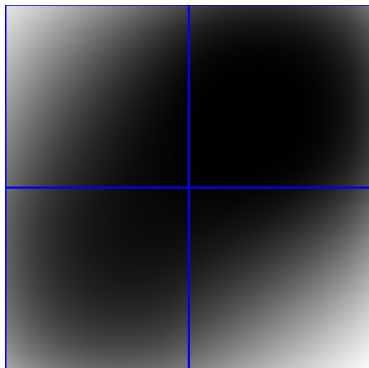
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Implementation: Indicator Function

Given the Points:

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Implementation: Surface Extraction

Given the Points:

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

