

# Poisson Equation

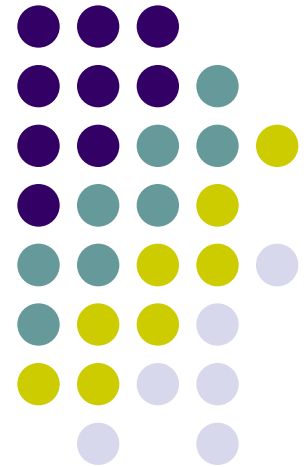
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Hongxin Zhang

2009-05-14

State Key Lab of CAD&CG

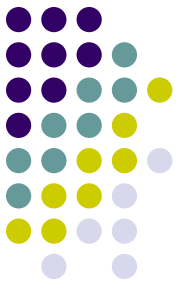
Zhejiang University



# 致谢

- 感谢沈向洋博士提供的部分课件内容





# Outline

- Partial differential equation
- From variational methods to PDE
- Poisson Equation
- Application
  - Poisson Image Editing
  - Poisson/Laplacian Mesh Editing
- How to solve?
- More ...

# Siméon Denis Poisson

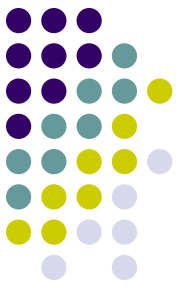


- His teachers: *Laplace, Lagrange, ...*
- Poisson's terms:
  - Poisson's equation
  - Poisson's integral
  - Poisson distribution
  - Poisson brackets
  - Poisson's ratio
  - Poisson's constant



1781-1840, France

*“Life is good for only two things: to study mathematics and to teach it.”*



# Background:

- Partial Differential Equations (PDE)

$$E(f, f_x, f_y, f_{xx}, f_{xy}, f_{yy}) = 0$$

- The PDE's which occur in physics are mostly second order and linear:

$$A \cdot f_{xx} + 2B \cdot f_{xy} + C \cdot f_{yy} + D \cdot f_x + E \cdot f_y + F \cdot f + G = 0$$

$$A \cdot f_{xx} + 2B \cdot f_{xy} + C \cdot f_{yy} + D \cdot f_x + E \cdot f_y + F \cdot f + G = 0$$

$A \cdot C < B^2$  : ● Hyperbolic  
● wave equation:

$$\Delta f = \frac{1}{v^2} \frac{\partial^2 f}{\partial t^2}$$

$A \cdot C = B^2$  : ● Parabolic  
● heat equation:

$$\frac{\partial f}{\partial t} = k \cdot \Delta f$$

$A \cdot C > B^2$  : ● Elliptic  
● Laplace equation:

$$\Delta f = 0$$

● Poisson equation:

$$\Delta f = -\rho$$



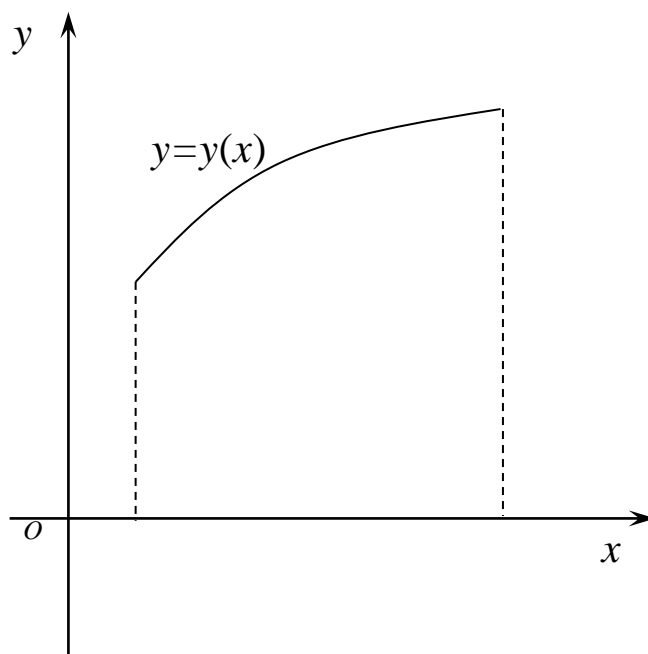
# 变分命题与一般极值问题

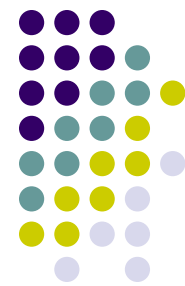
- 历史上有很多有名的极值问题，其求解方法可统称为变分法
  - 两点间的最短连线问题
  - 最速下降线问题
  - 短程线问题
  - ...



# 两点间的最短连线问题

- 为什么“任意两点间的最短连线是连接两端的直线”？





# 两点间的最短连线问题

- 为什么“任意两点间的最短连线是连接两端的直线”？

- 问题的假设：

- 二维平面空间，一点是坐标原点(0,0)，一点在(a,b)

- 两点间的连接曲线是  $y = y(x)$

- 曲线的弧长微元是  $ds^2 = dx^2 + dy^2$  或

$$ds = \sqrt{1 + \left(\frac{dy}{dx}\right)^2} dx$$

- 曲线的总弧长是

$$s = \int_0^a (1 + y'^2)^{1/2} dx$$

$s$ 是标量，是 $y'(x)$ 的一个广义函数，称为泛函，可记为 $s(y')$



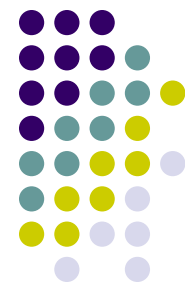
# 两点间的最短连线问题

- 问题的数学描述：找出具有曲线 $y(x)$ 使得

$$\min_{y'} \int_0^a (1 + y'^2)^{1/2} dx$$

- 同时必须满足端点约束条件 (constraint condition)

$$\begin{cases} y(0) = 0 & x = 0 \\ y(a) = b & x = a \end{cases}$$



# 变分命题 (II)

- 第一类变分问题：
  - 被积函数包括一阶导数的变分问题
  - 满足端点约束条件
  - 在所有的足够光滑函数 $y(x)$ 中，求使以下泛函为极值

$$\Pi(y) = \int_{\alpha}^{\beta} F(x, y, y') dx$$

- 第二类变分问题：
  - 两个待定函数： $y(x)$ ,  $z(x)$
  - 满足约束条件： $\varphi(x, y, z) = 0$
  - 满足端点约束条件
  - 在所有的足够光滑函数 $y(x)$ ,  $z(x)$ 中，求使以下泛函为极值

$$\Pi(y, z) = \int_{\alpha}^{\beta} F(x, y, y', z, z') dx$$



# 变分法中的符号

- 给定函数  $y(x)$ 
  - 宗量:  $x$
  - 函数:  $y(x)$
  - 宗量的增量:  $\Delta x$
  - 函数的增量:
    - $\Delta y = y(x + \Delta x) - y(x)$
  - 当两点无限接近:
    - $\Delta x \rightarrow dx, \Delta y \rightarrow dy$
  - 略去高阶微量:
    - $dy = y'(x)dx$
  - 当在  $x$  处取得函数极值
    - $dy = 0$
- 给定泛函  $\Pi(y)$ 
  - 宗量:  $y$
  - 泛函:  $\Pi(y)$
  - 函数的变分:  $\delta y$
  - 泛函的变分:  $\delta \Pi$ 
    - $\delta \Pi = \Pi(y + \delta y) - \Pi(y)$
  - 在计算  $\delta \Pi$  时可以展开  $\Pi(y + \delta y)$  中的被积函数只保留线性项
  - 当在  $y$  处取得泛函极值
    - $\delta \Pi = 0$

函数  $y(x)$  在定义域内与  $y(x) + \delta y(x)$  处处无限接近



# 第一类变分问题

- 设函数 $y(x)$ 是下式的极值解

$$\Pi(y) = \int_{\alpha}^{\beta} F(x, y, y') dx$$

- 且满足端点条件  $y(\alpha) = \bar{y}_1, y(\beta) = \bar{y}_2$
- 设其邻近的函数 $y(x) + \delta y(x)$ 也满足端点条件
- 因此端点变分满足

$$\delta y(\alpha) = \delta y(\beta) = 0$$

- 泛函的变分为

$$\begin{aligned} \delta \Pi &= \Pi(y + \delta y) - \Pi(y) \\ &= \int_{\alpha}^{\beta} \{F(x, y + \delta y, y' + \delta y') - F(x, y, y')\} dx \end{aligned}$$



# 第一类变分问题

- 根据微量计算规则，设 $y(x)$ 和 $y(x)+\delta y(x)$ 是有一阶接近的曲线

$$F(x, y + \delta y, y' + \delta y') = F(x, y, y') + \left[ \frac{\partial}{\partial y} F(x, y, y') \right] \delta y + \left[ \frac{\partial}{\partial y'} F(x, y, y') \right] \delta y'$$

- 引入简写符号

$$F = F(x, y, y'), F_y = \frac{\partial}{\partial y} F(x, y, y'), F_{y'} = \frac{\partial}{\partial y'} F(x, y, y')$$

- 可得

$$\delta F = F_y \delta y + F_{y'} \delta y'$$



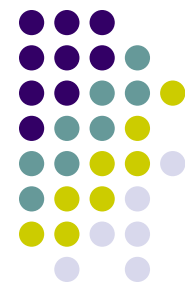
# 第一类变分问题

- 泛函的变分为:

$$\delta\Pi = \int_{\alpha}^{\beta} \delta F dx = \int_{\alpha}^{\beta} [F_y \delta y + F_{y'} \delta y'] dx$$

- 下面将证明函数 $y(x)$ 的导数的变分等于函数 $y(x)$ 的变分的导数，亦即导数和变分两种运算可以互换运算顺序:

$$\delta y' = (\delta y)'$$



# 变分问题的欧拉方程

- 由预备定理可知

$$F_y - \frac{d}{dx} F_{y'} = 0, \alpha \leq x \leq \beta$$

- 如果展开  $\frac{dF_{y'}}{dx}$

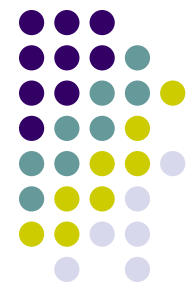
$$F_y - \frac{\partial^2 F}{\partial x \partial y} - \frac{\partial^2 F}{\partial y \partial y'} y' - \frac{\partial^2 F}{\partial y' \partial x} y'' = 0$$

- 其中  $F(x, y, y')$  必须具有二阶偏导数， $y(x)$  也必须具有二阶偏导数。

由此把**变分问题**转化为**微分方程**求解

# 变分法求解(1)

## 最短连线问题



- 其变分极值问题为

$$\delta\Pi = \int_0^{\alpha} [1 + (y' + \delta y')^2]^{1/2} dx - \int_0^{\alpha} [1 + y'^2]^{1/2} dx$$

- 略去 $\delta y'$ 的高次微量得

$$\delta\Pi = \int_0^{\alpha} \frac{y' + \delta y'}{[1 + y'^2]^{1/2}} dx = 0$$

- 分部积分，并利用 $\delta y(0) = 0$ ， $\delta y(a) = 0$ ，得

$$\delta\Pi = -\int_0^{\alpha} \frac{d}{dx} \left[ \frac{y'}{(1 + y'^2)^{1/2}} \right] \delta y dx = 0$$

# 变分法求解(1)

## 最短连线问题



- 由变分法预备定理，给出以下微分方程

$$\frac{d}{dx} \left[ \frac{y'}{(1+y'^2)^{1/2}} \right] = 0$$

- 积分得

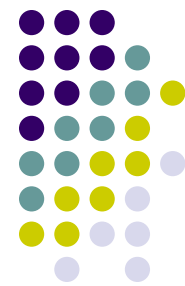
$$\frac{y'}{(1+y'^2)^{1/2}} \equiv \text{const} \quad \Longrightarrow \quad y' \equiv \text{const}$$

- 由端点约束条件即得  $y = \frac{b}{a}x$



# 泛函变分问题的一般求解步骤

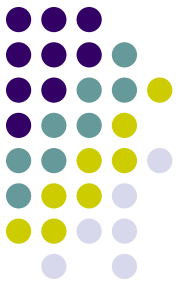
1. 从物理上建立泛函及其条件
2. 通过泛函变分，利用变分法基本预备定理求得欧拉方程
3. 在边界条件下求解欧拉方程，即微分方程求解



# 变分法与欧拉方程

- 变分法与欧拉方程代表同一物理问题
- 欧拉方程求解和从变分法求数值近似解（如有限元，利兹法，伽辽金法等），其效果一样
- 欧拉方程求解很困难，但从泛函求近似解通常很方便，因而变分法一直被广为重视。
- 但并不是所有的微分方程都能找到相对应的泛函问题。

# Poisson Equation



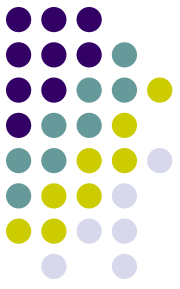
$$\Delta f = -\rho$$

$$\Delta \equiv \frac{\partial^2}{\partial^2 x} + \frac{\partial^2}{\partial^2 y}$$

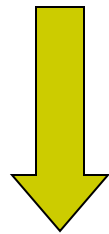
$$\rho = \rho(x, y)$$

平衡膜—泊松方程

# Variational interpretation



$$f^* = \arg \min_f \iint_{\Omega} \underbrace{\|\nabla f - \mathbf{v}\|^2}_F \quad \text{s.t. } f^*|_{\partial\Omega} = f|_{\partial\Omega}$$



$$\text{Euler Equation: } F_f - \frac{\partial}{\partial x} F_{f_x} - \frac{\partial}{\partial y} F_{f_y} = 0$$

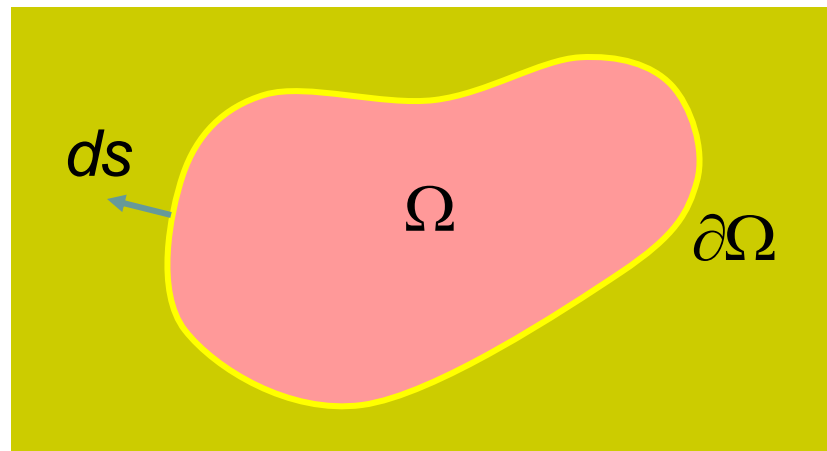
$$\Delta f = \text{div}(\mathbf{v}) \quad \text{s.t. } f^*|_{\partial\Omega} = f|_{\partial\Omega}$$

$\mathbf{V}$  is a **guidance** field, needs not to be a gradient field.



# Boundary conditions

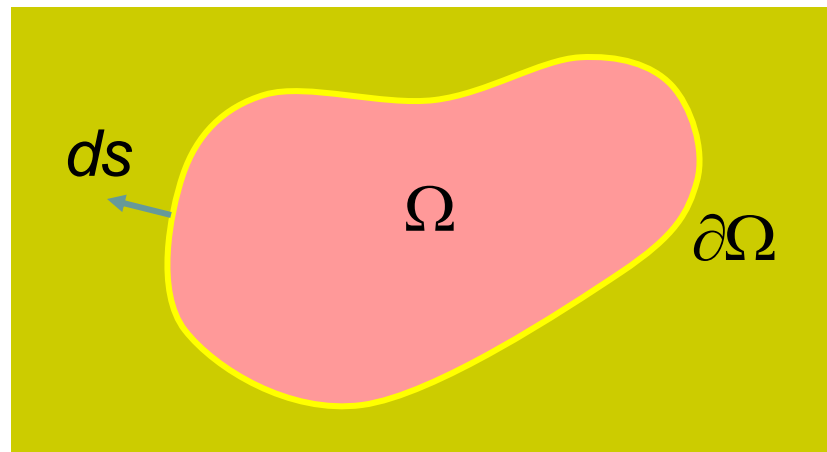
- *Dirichlet* boundary conditions:  $f|_{\partial\Omega}$
- *Neumann* boundary conditions:  $\frac{\partial f}{\partial \mathbf{s}}|_{\partial\Omega}$

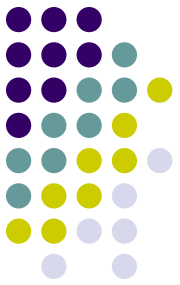




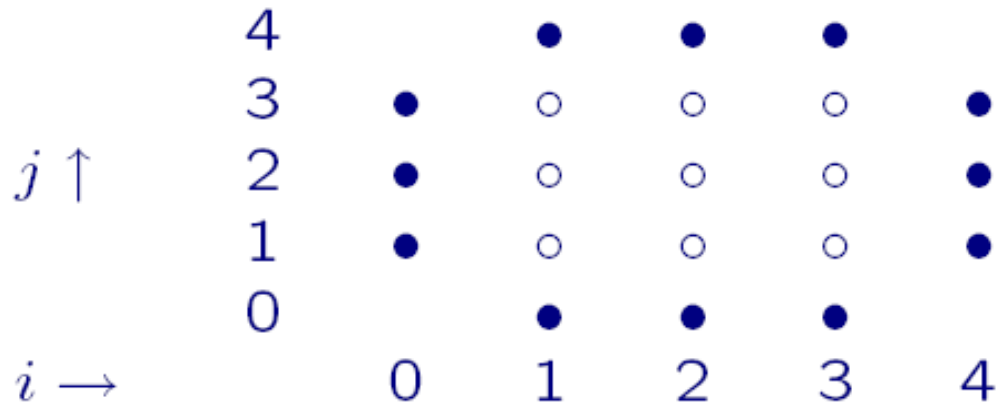
# Existence of solution

The solution of an Poisson Equation is **uniquely** determined in  $\Omega$  , if *Dirichlet* boundary conditions or *Neumann* boundary conditions are specified on  $\partial\Omega$





# Discrete Poisson Equation



$$\Delta f = -\rho$$



$$\frac{f_{i+1,j} + f_{i-1,j} - 2f_{i,j}}{h^2} + \frac{f_{i,j+1} + f_{i,j-1} - 2f_{i,j}}{h^2} = \rho_{i,j}$$

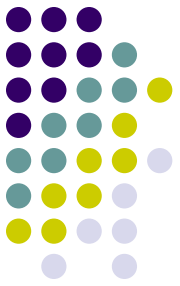




# Poisson Equation Solver

- Direct method
- Iterative methods
  - Jacobi, Gauss-Seidel, SOR
- Multigrid method

# Physical Origins of Poisson Equation



- Electrostatic potential

$$\Delta\Phi = -\frac{\rho(\mathbf{x})}{\epsilon_0}$$

- Gravitational potential

$$\Delta\Phi = -4\pi G\rho(\mathbf{x})$$

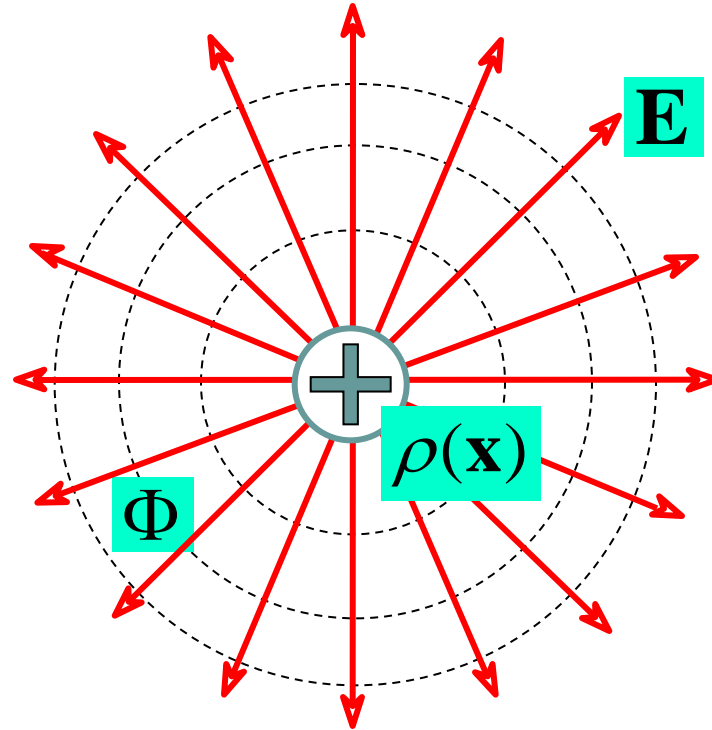
# Electrostatic potential

$$\mathbf{F} = \frac{q_1 q_2 \mathbf{r}}{4\pi\epsilon_0 r^3}$$

$\rho(\mathbf{x})$  Charge Density

$\Phi$  Electric Potential

$\mathbf{E}$  Electric Field



$$\mathbf{E} = -\nabla\Phi$$

# Derivations

*Gauss's Law:*

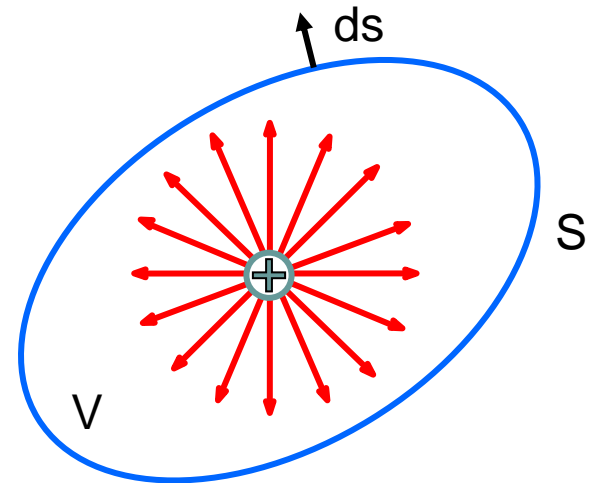
$$\oint_S \mathbf{E} \cdot d\mathbf{s} = \int_V \frac{\rho(\mathbf{x})}{\epsilon_0} dv$$

*Gauss's theorem:*

$$\oint_S \mathbf{E} \cdot d\mathbf{s} = \int_V \nabla \cdot \mathbf{E} dv$$

$$\nabla \cdot \mathbf{E} = \frac{\rho(\mathbf{x})}{\epsilon_0}$$

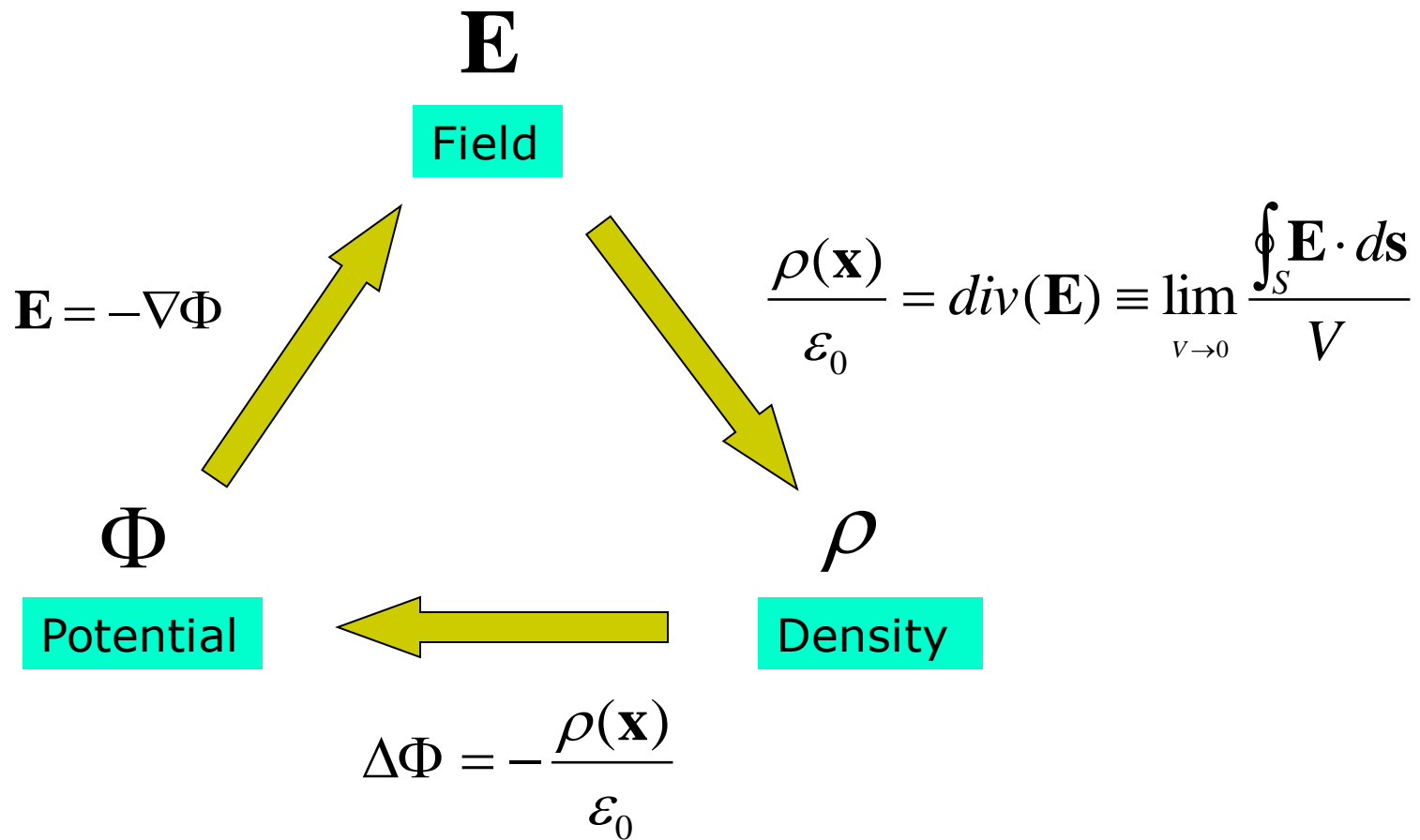
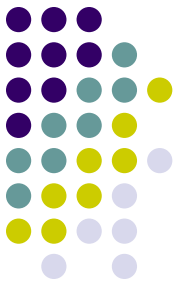
$$\mathbf{E} = -\nabla\Phi$$

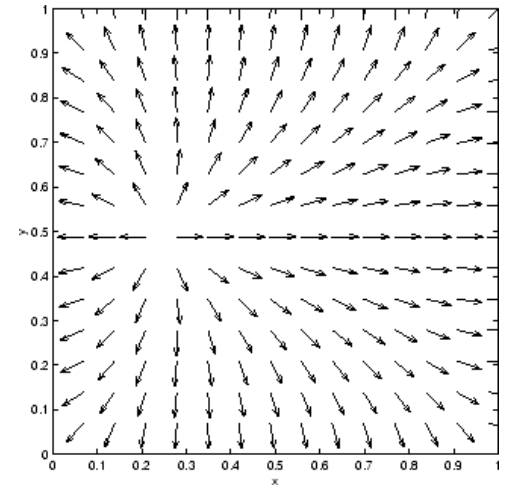
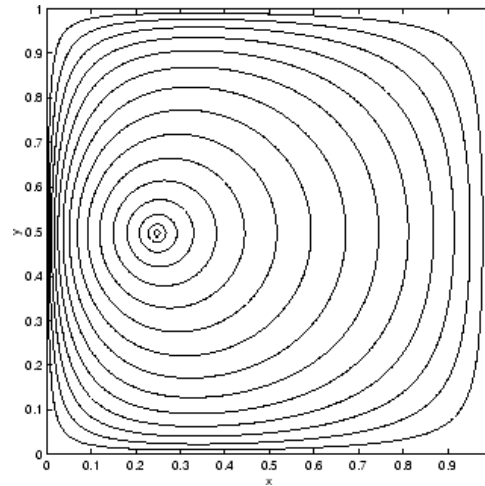
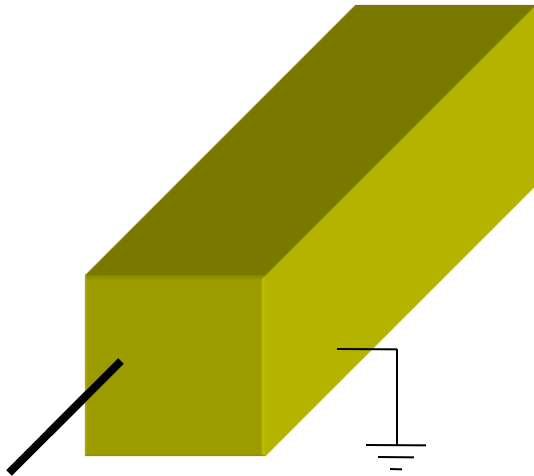
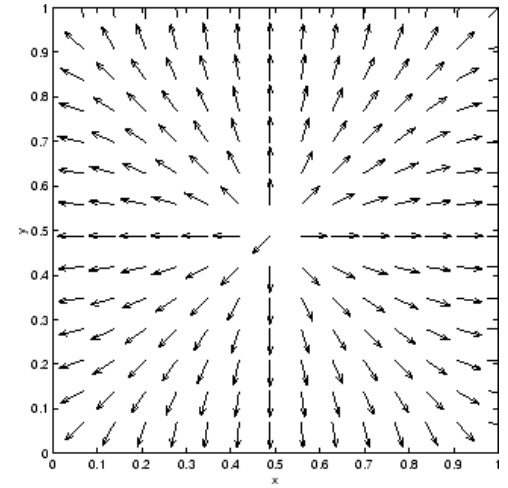
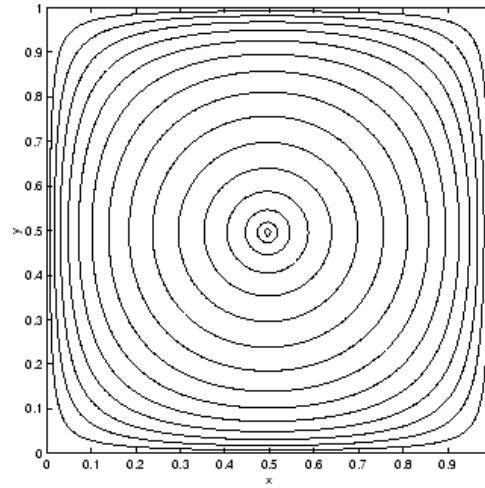
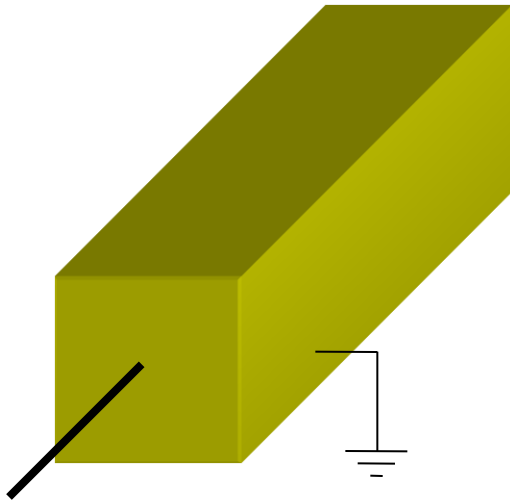


$$\Delta\Phi = -\frac{\rho(\mathbf{x})}{\epsilon_0}$$

Poisson Equation

# Relationships





$$\rho(\mathbf{x}) = \delta(x_0, y_0)$$

$\Phi$

$\mathbf{E}$

# Gravitational potential

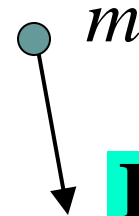
$$\mathbf{F} = \frac{mM\mathbf{G}\mathbf{r}}{r^3}$$

$\rho(\mathbf{x})$  Mass Density

$\Phi$  Gravitational Potential

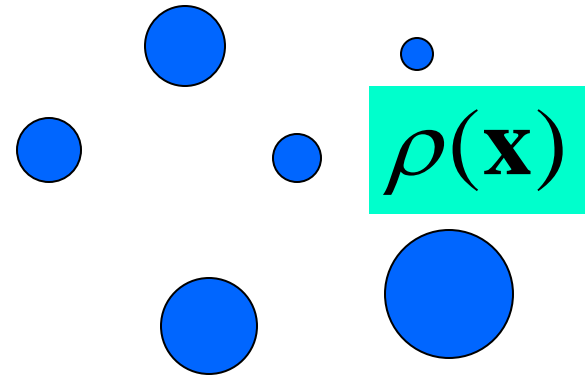
$\mathbf{g}$  Force Field  
(acceleration)

$$\mathbf{g} = -\nabla\Phi$$

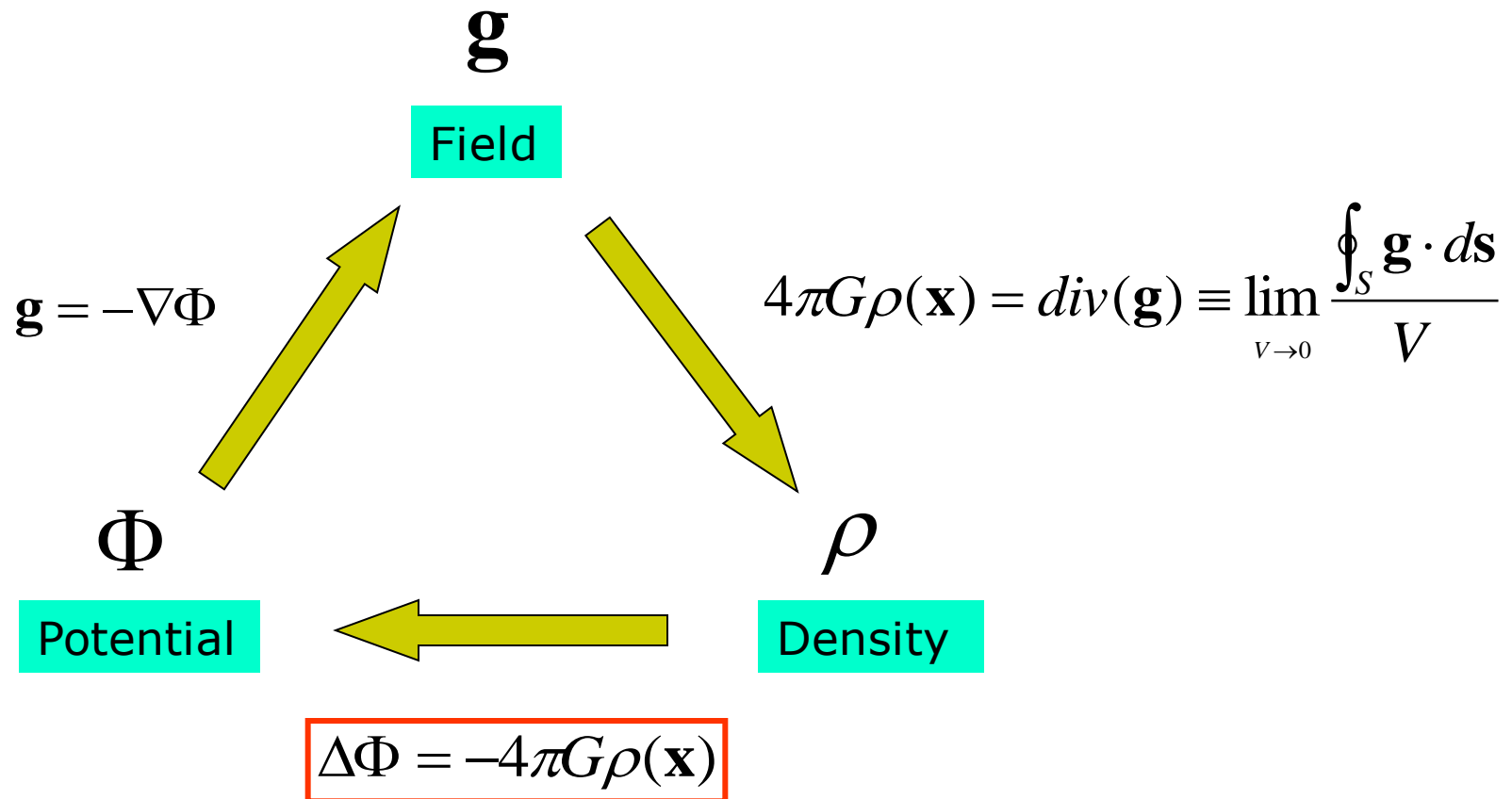
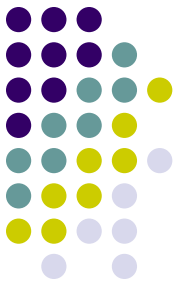


$$\mathbf{F} = m\mathbf{g}$$

$\Phi$



# Relationships

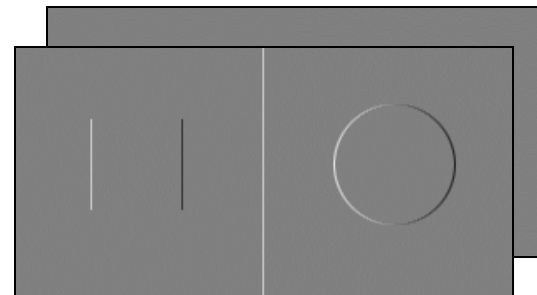
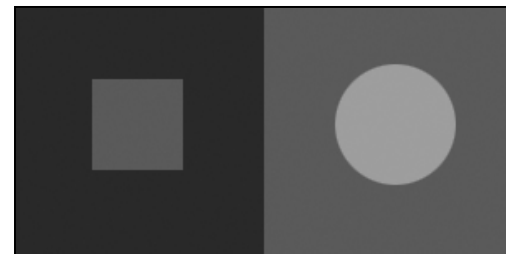
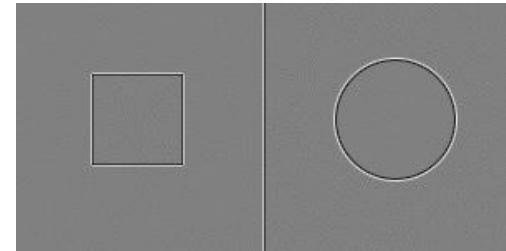


# Analogy for Image

$\rho(\mathbf{x})$  Image Density

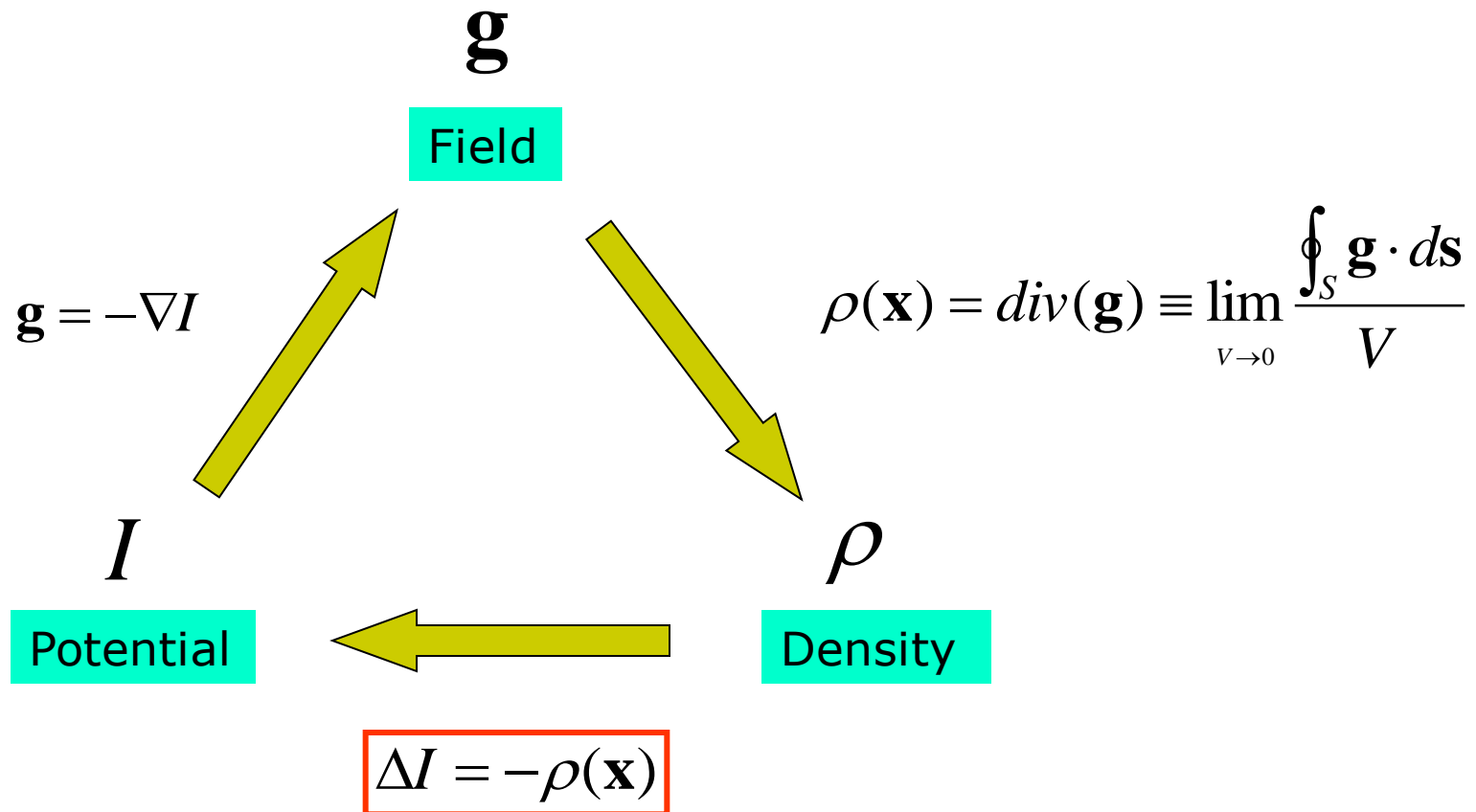
$I$  Image (Potential)

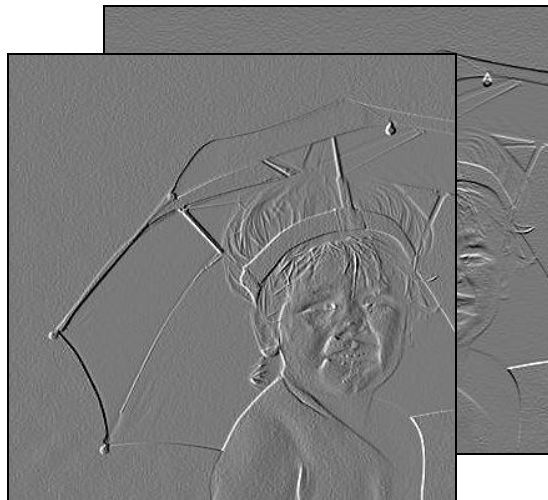
$\mathbf{g}$  Image Gradient



$$\mathbf{g} = -\nabla I$$

# Relationships

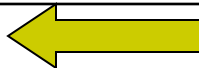




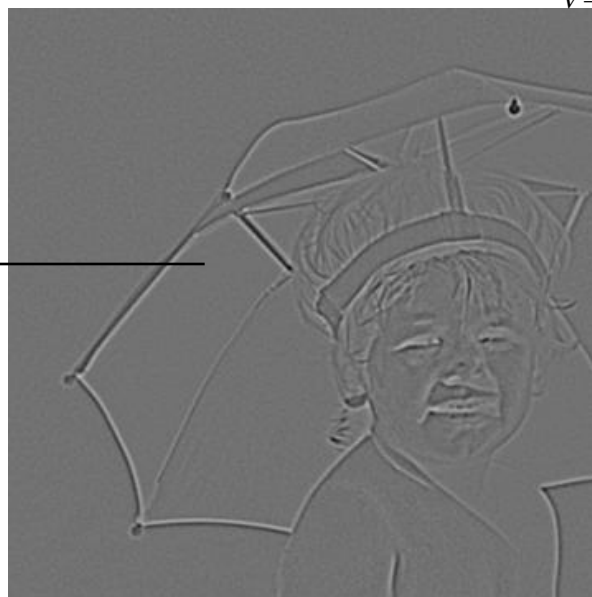
$$\mathbf{g} = -\nabla I$$

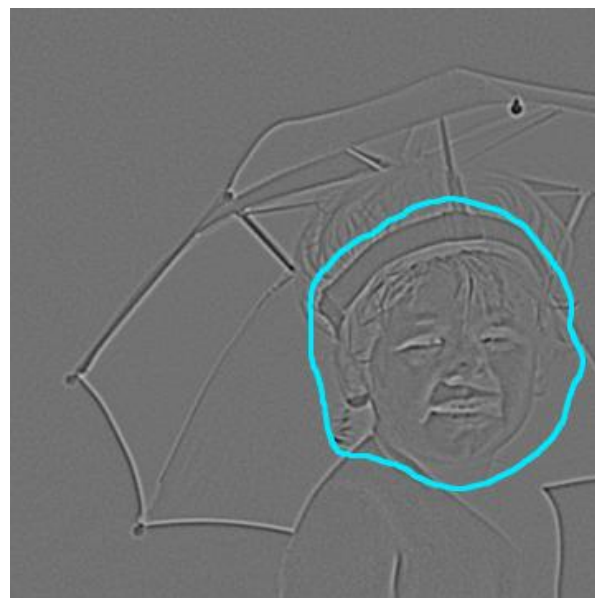


$$\rho(\mathbf{x}) = \text{div}(\mathbf{g}) \equiv \lim_{V \rightarrow 0} \frac{\oint_S \mathbf{g} \cdot d\mathbf{s}}{V}$$



$$\Delta I = -\rho(\mathbf{x})$$

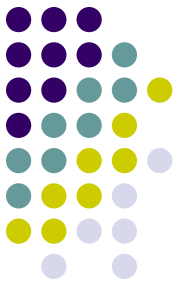




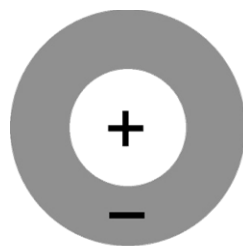
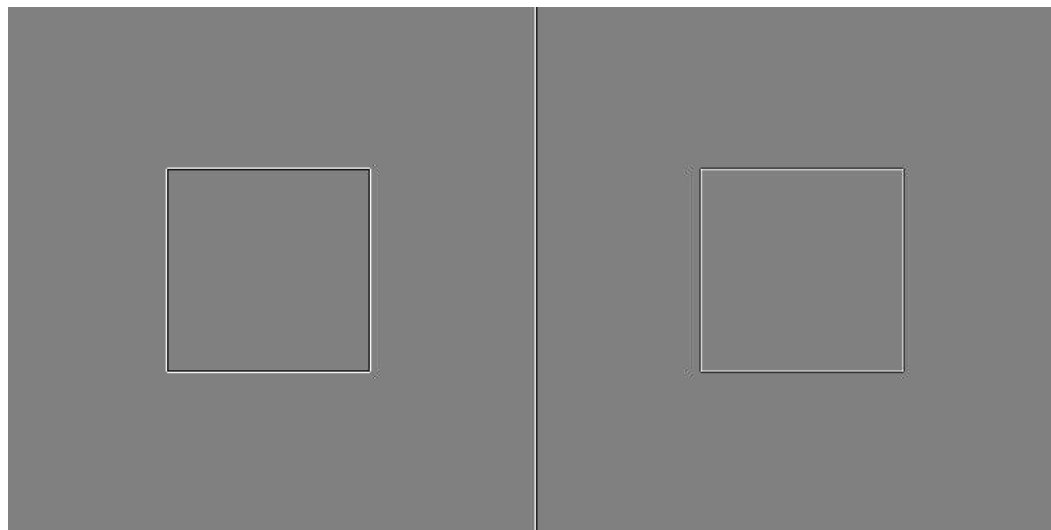
$$\Delta I = -\rho(\mathbf{x})$$



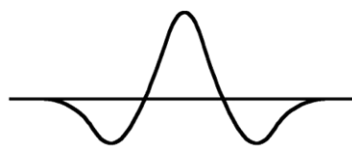
# simultaneous contrast effect



# Why Laplace operator?



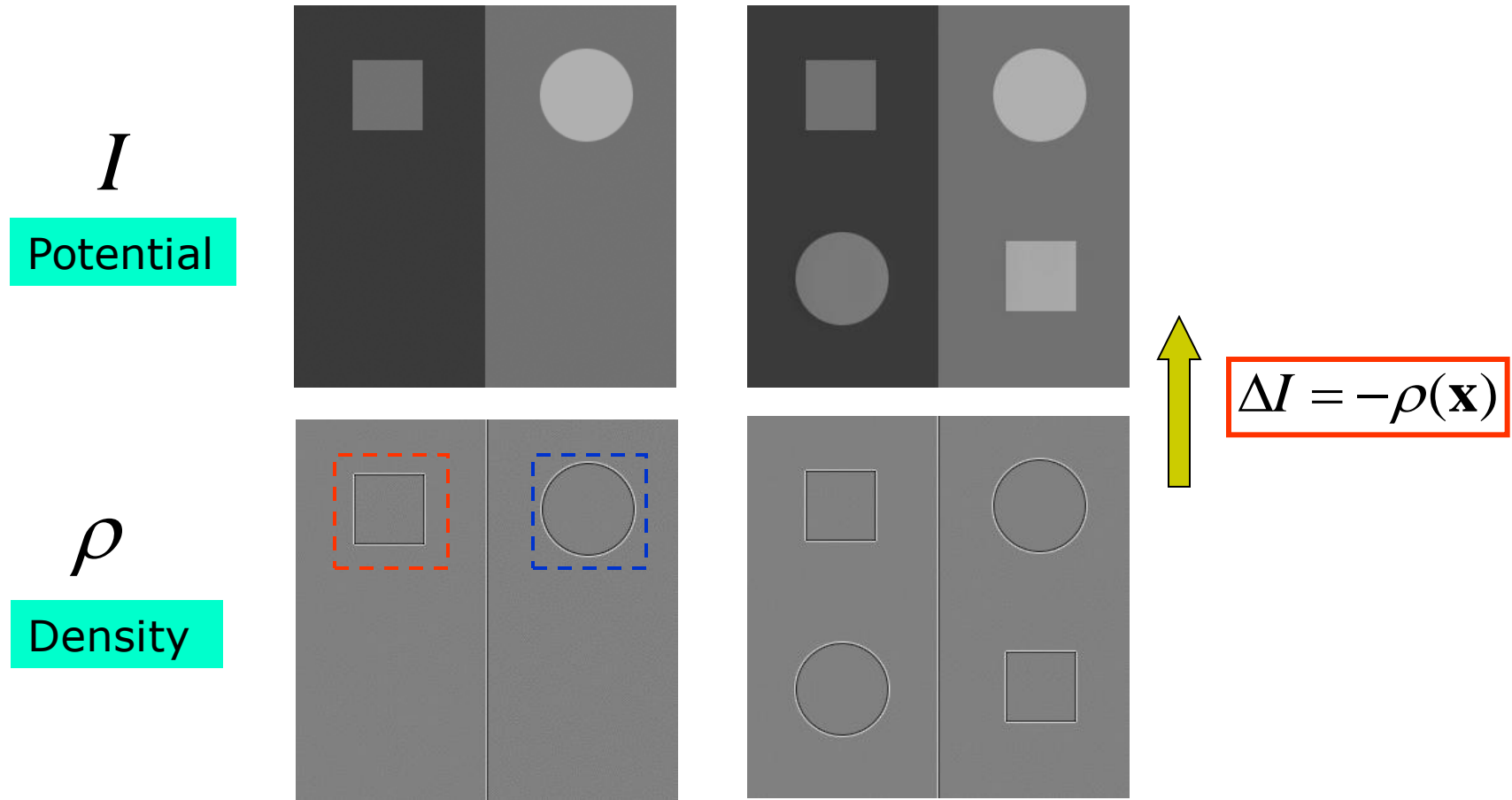
a



b



# Motivation for Image Editing

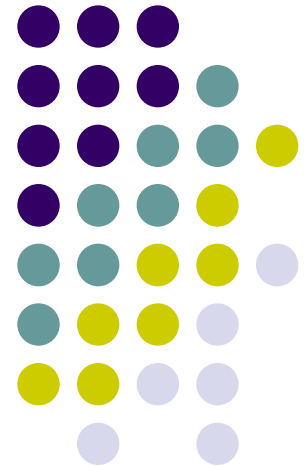


# Poisson Image Editing

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P. Pérez, M. Gangnet, and A. Blake

Poisson Image Editing. *SIGGRAPH*  
2003

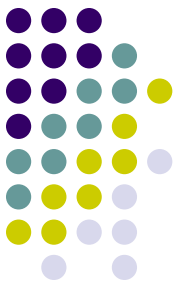




# Seamless Cloning

- Precise selection: tedious and unsatisfactory
- Alpha-Matting: powerful but involved
- **Seamless cloning**: loose selection but no seams?

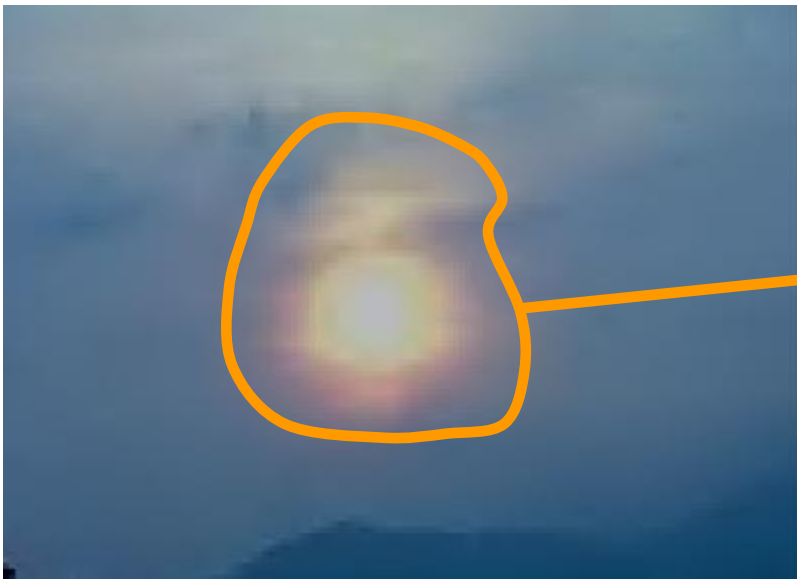




# Cloning by solving Poisson Equation

$$\Delta I = \text{div}(\nabla I_A) \quad \text{s.t.} \quad I|_{\partial\Omega} = I_B|_{\partial\Omega}$$

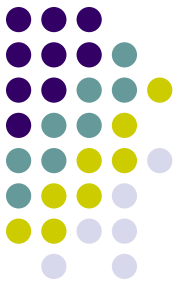
$I_A$



$I_B$



# Why we do analogy for image?

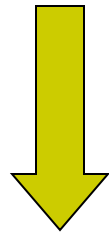


- Easier in the image gradient domain
  - *Local* editing → *global* effects
  - *Seamless* - cloning, editing, tiling

# Variational interpretation



$$I^* = \arg \min_f \iint_{\Omega} \underbrace{\|\nabla I - \nabla I_A\|}_{F}^2 \quad \text{s.t. } I^* |_{\partial\Omega} = I_B |_{\partial\Omega}$$



$$\text{Euler Equation: } F_f - \frac{\partial}{\partial x} F_{f_x} - \frac{\partial}{\partial y} F_{f_y} = 0$$

$$\Delta I = \text{div}(\nabla I_A) \quad \text{s.t. } I |_{\partial\Omega} = I_B |_{\partial\Omega}$$

$\nabla I_A$  is a **gradient** field to be cloned.

**conceal**



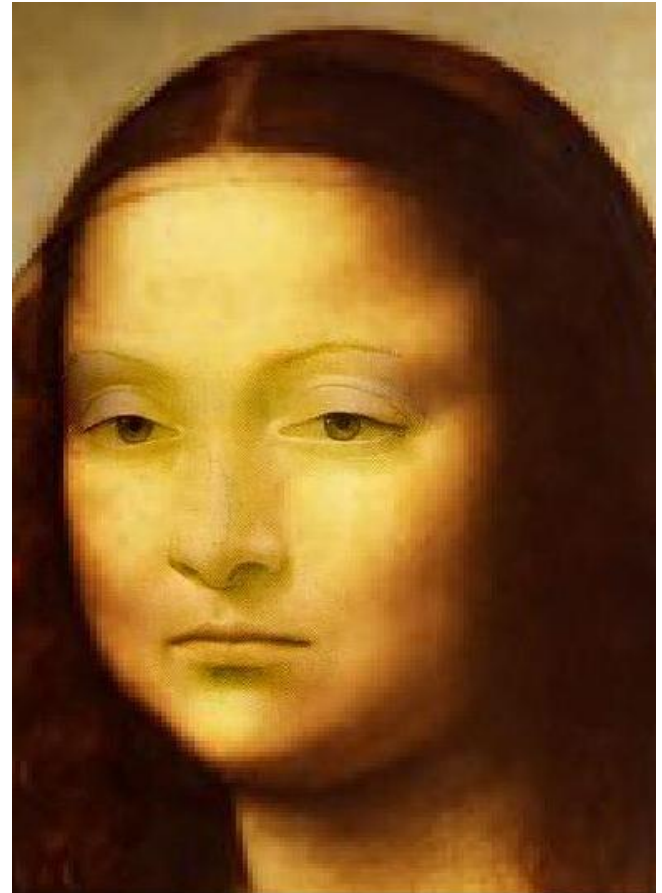
# compose



**change texture**



# change features



# mix lights



# Seamless Editing



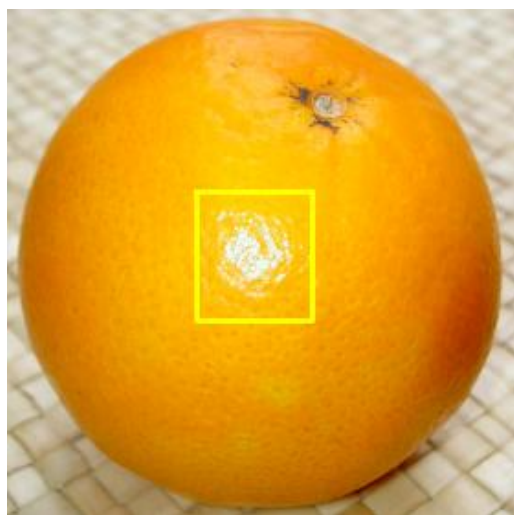
$I_A$



$I$

$$\Delta I = \operatorname{div}(T(\nabla I_A))$$

$$\text{s.t. } I|_{\partial\Omega} = I_A|_{\partial\Omega}$$



**change colors**



**change colors**



# Seamless Tiling

Single image



# Seamless Tiling

Multiple  
images  
tiled at  
random

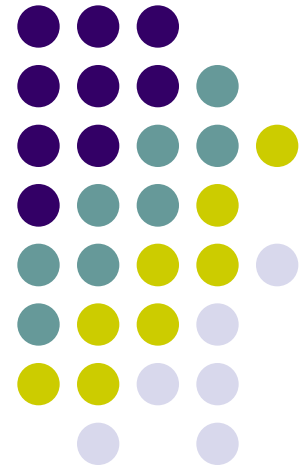


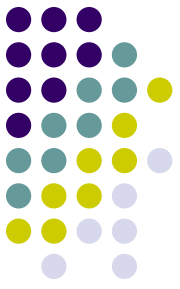
# Poisson Matting

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J. Sun, J. Jia, C. K. Tang, H. Y. Shum

Poisson Matting. *SIGGRAPH 2004*.





# Image Composition

- Composition Equation

$$I = \alpha F + (1 - \alpha)B$$



$I$



$\alpha F$



$\alpha$



$B$



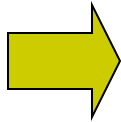
# Matting – pulling of Matte

- Matting Equation

$$I = \alpha F + (1 - \alpha)B$$



$I$



$\alpha F$



$\alpha$



$B$

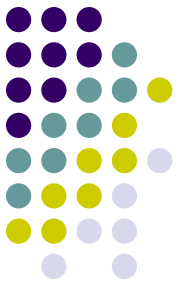
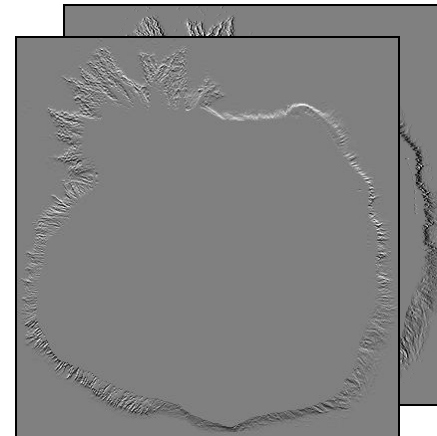
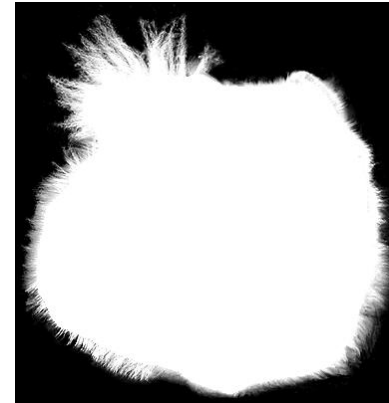
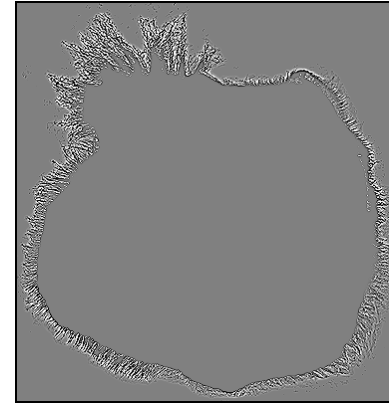
# Analogy for Matte

$\rho(\mathbf{x})$  Matte Density

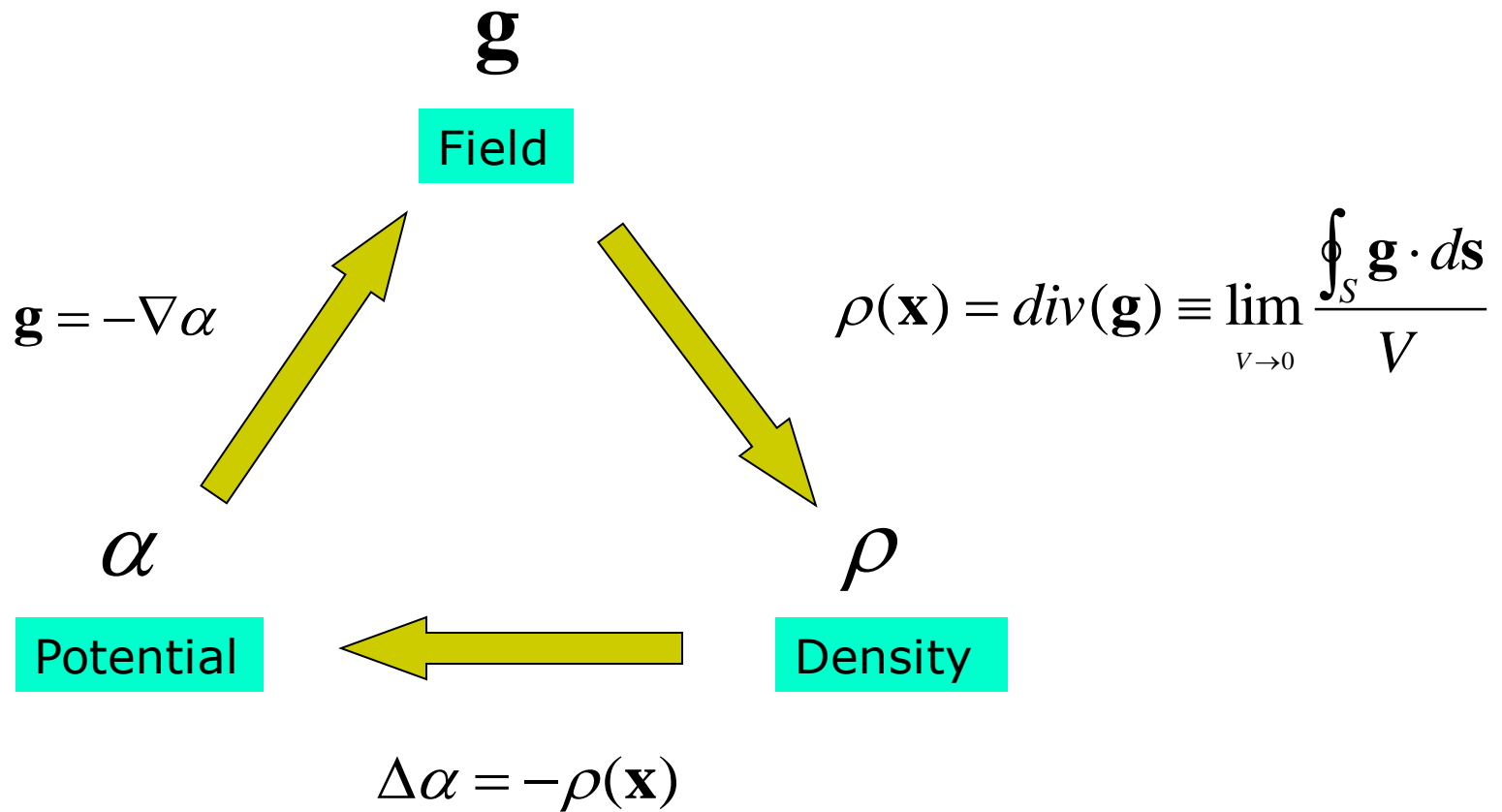
$\alpha$  Matte (Potential)

$\mathbf{g}$  Matte Gradient

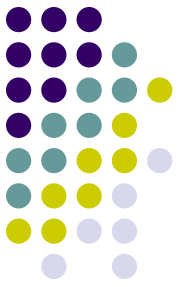
$$\mathbf{g} = -\nabla \alpha$$



# Relationships



# Poisson Matting (Global)



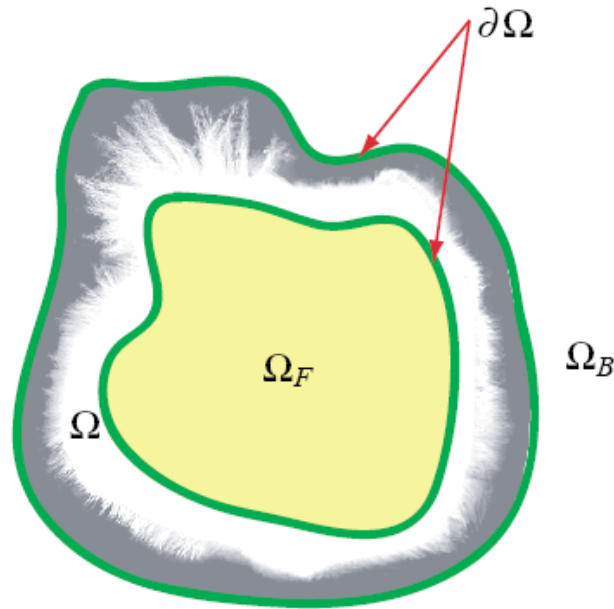
$$I = \alpha F + (1 - \alpha)B$$

$$\nabla I = (F - B)\nabla \alpha + \alpha\nabla F + (1 - \alpha)\nabla B$$

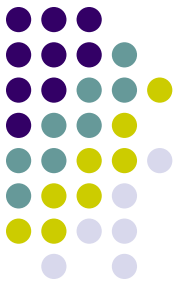
$$\nabla I \approx (F - B)\nabla \alpha$$

$$\nabla \alpha \approx \frac{\nabla I}{F - B} \quad \rho(\mathbf{x}) \approx \operatorname{div}\left(\frac{\nabla I}{F - B}\right)$$

# Matting by solving Poisson Equation

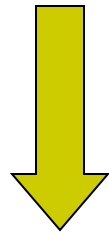


$$\Delta\alpha = \operatorname{div}\left(\frac{\nabla I}{F - B}\right) \quad \text{s.t. } \alpha|_{\partial\Omega} = \begin{cases} 1 & \mathbf{x} \in \Omega_F \\ 0 & \mathbf{x} \in \Omega_B \end{cases}$$



# Variational interpretation

$$\alpha^* = \arg \min_f \iint_{\Omega} \left\| \nabla \alpha - \frac{\nabla I}{F - B} \right\|^2 \quad \text{s.t. } \alpha^* |_{\partial\Omega} = \alpha |_{\partial\Omega}$$



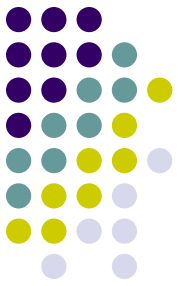
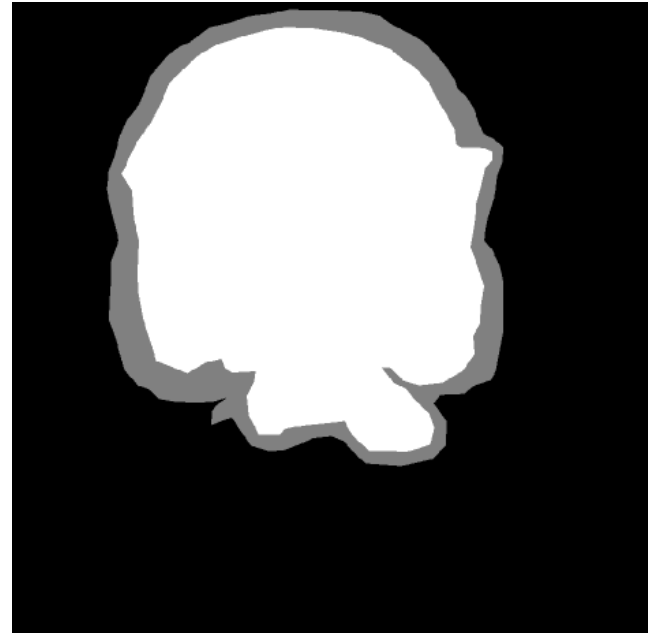
$J$

Euler Equation:  $J_f - \frac{\partial}{\partial x} J_{f_x} - \frac{\partial}{\partial y} J_{f_y} = 0$

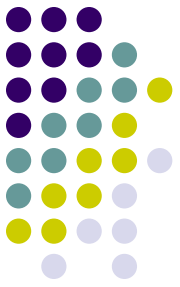
$$\Delta \alpha = \operatorname{div} \left( \frac{\nabla I}{F - B} \right) \quad \text{s.t. } \alpha |_{\partial\Omega} = \alpha |_{\partial\Omega}$$

$\frac{\nabla I}{F - B}$  is a **guidance** field, an approximation of matte gradient.





# Local Poisson Matting



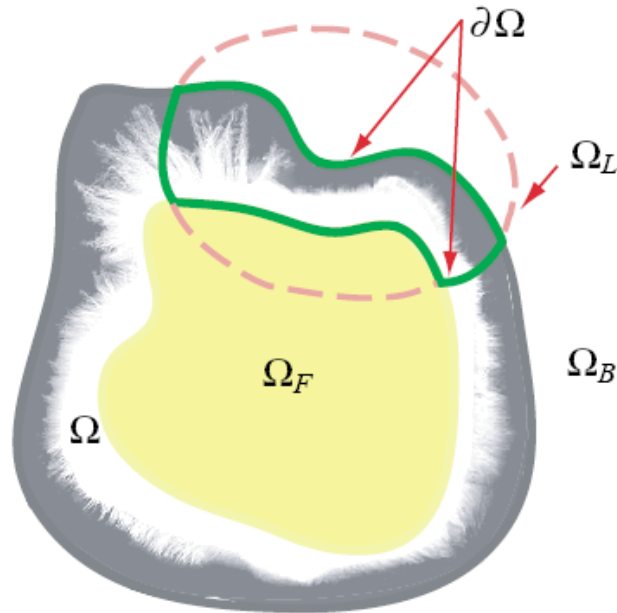
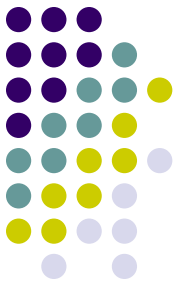
$$I = \alpha F + (1 - \alpha)B$$

$$\nabla I = (F - B)\nabla \alpha + \alpha\nabla F + (1 - \alpha)\nabla B$$

$$\nabla \alpha = \frac{1}{F - B} (\nabla I - \alpha\nabla F - (1 - \alpha)\nabla B)$$

$$\nabla \alpha = A(\nabla I - D)$$

# Matting by solving Poisson Equation



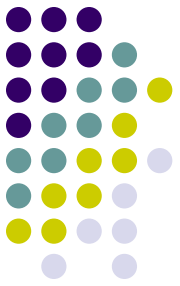
$$\Delta \alpha \approx \operatorname{div}(A(\nabla I - D)) \quad \text{s.t. } \alpha|_{\partial \Omega} = \begin{cases} 1 & \mathbf{x} \in \Omega_F \\ 0 & \mathbf{x} \in \Omega_B \\ \alpha_g & \mathbf{x} \in \Omega \cap \Omega_L \end{cases}$$

# Why we do analogy for Matte?



- Editing Matte directly at pixel-level is very tedious and impractical!
  - *Local* editing → *global* effects
  - *Seamless* local refinement

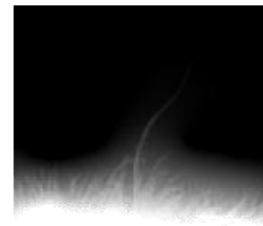
# Key Observation



Image



$$A \approx A^*$$



$$A < A^*$$



$$A > A^*$$



Image



$$|D| \approx |D^*|$$



$$|D| < |D^*|$$



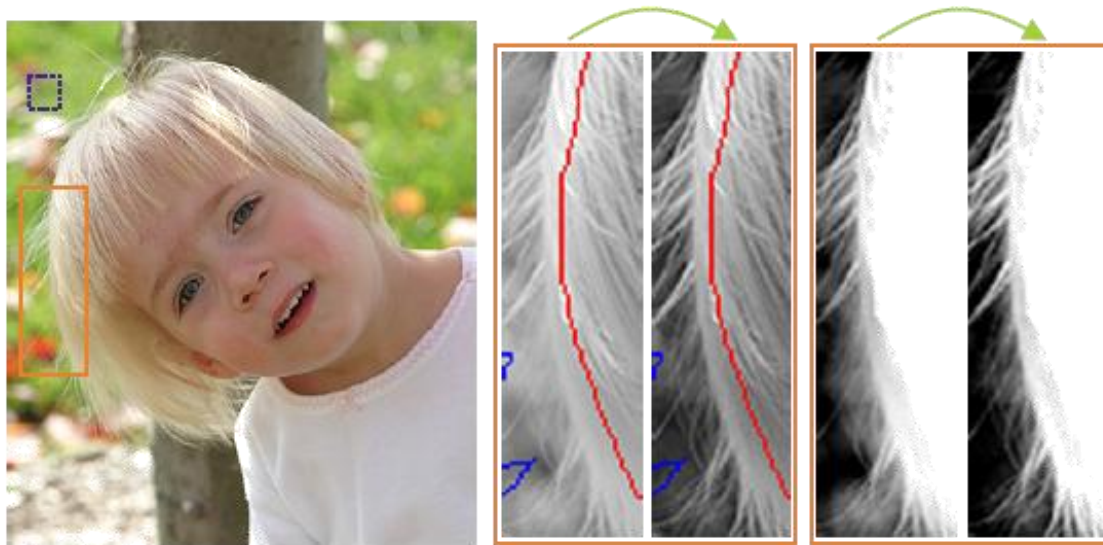
$$|D| > |D^*|$$



# Human-in-the-loop

- In Global Poisson Matting:
  - $A$  and  $D$  are estimated automatically.
- In Local Poisson Matting:
  - $A$  and  $D$  are manipulated interactively.
  - $A$  and  $D$  are manipulated more efficiently by a set of tools we designed.

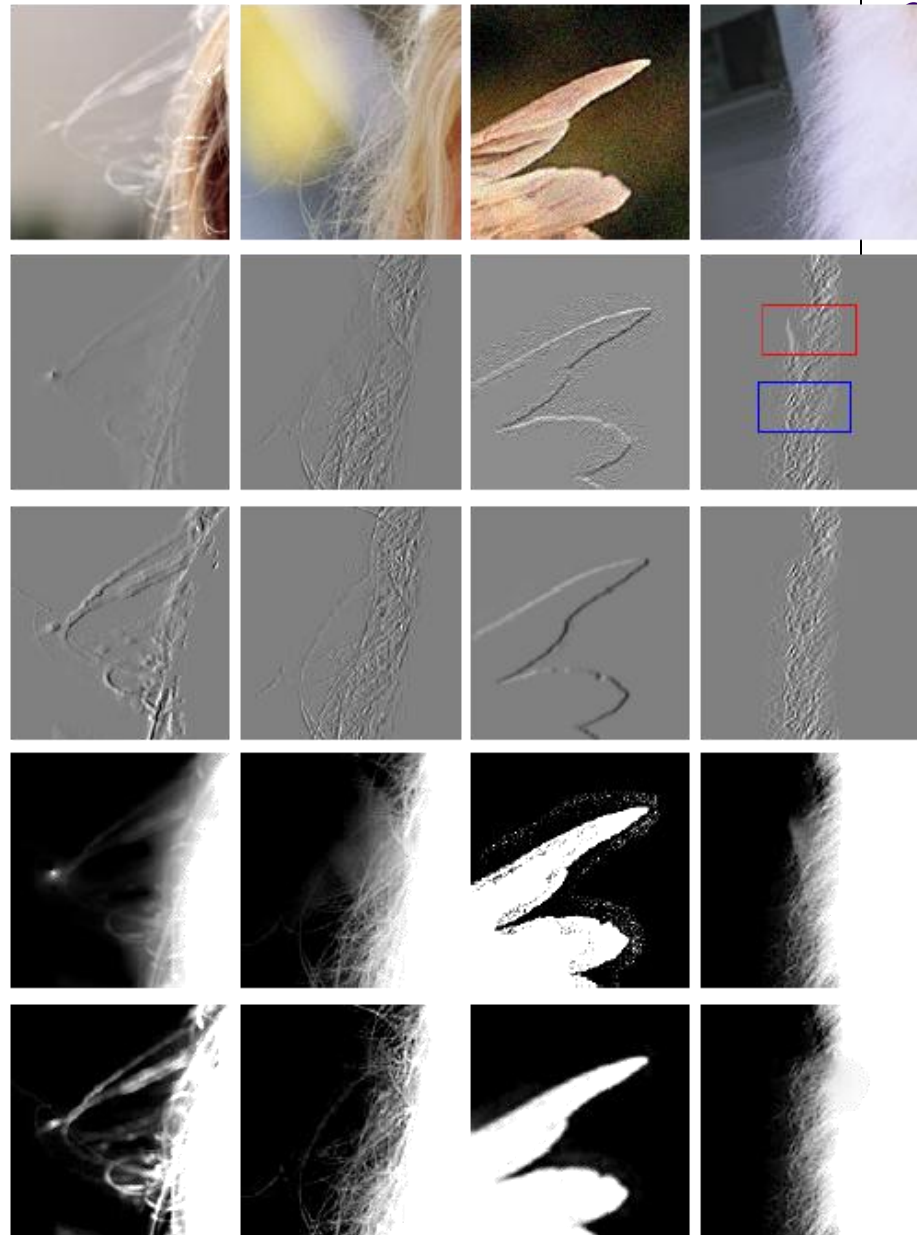
# Tool I: channel selection



Minimize the variance of the foreground or background colors.

# Tool 2: local filtering

- Boosting
- Highpass
- Diffusion
- Clone



(a) Boosting

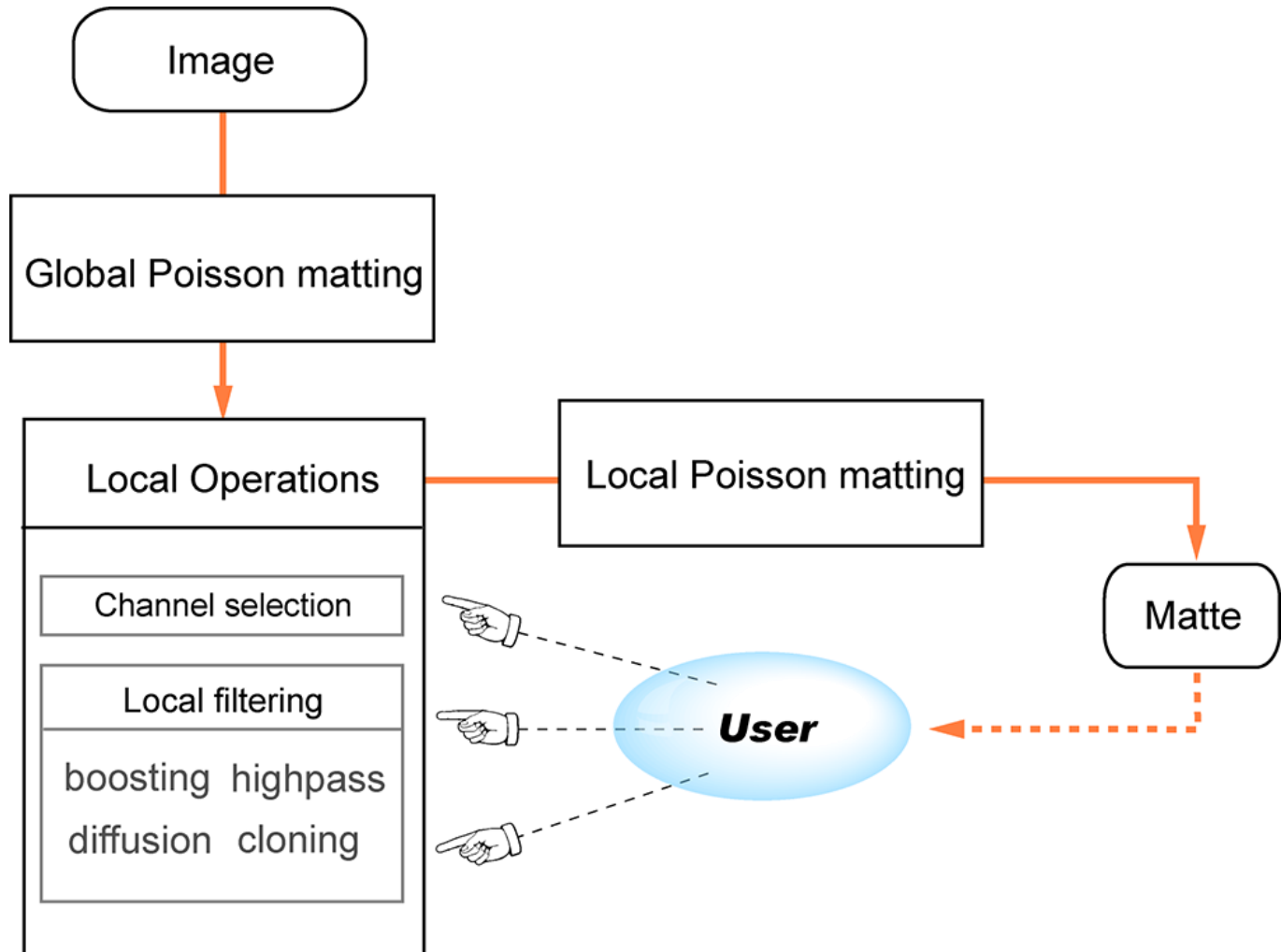
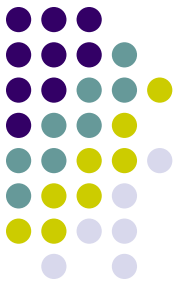
(b) Highpass

(c) Diffusion

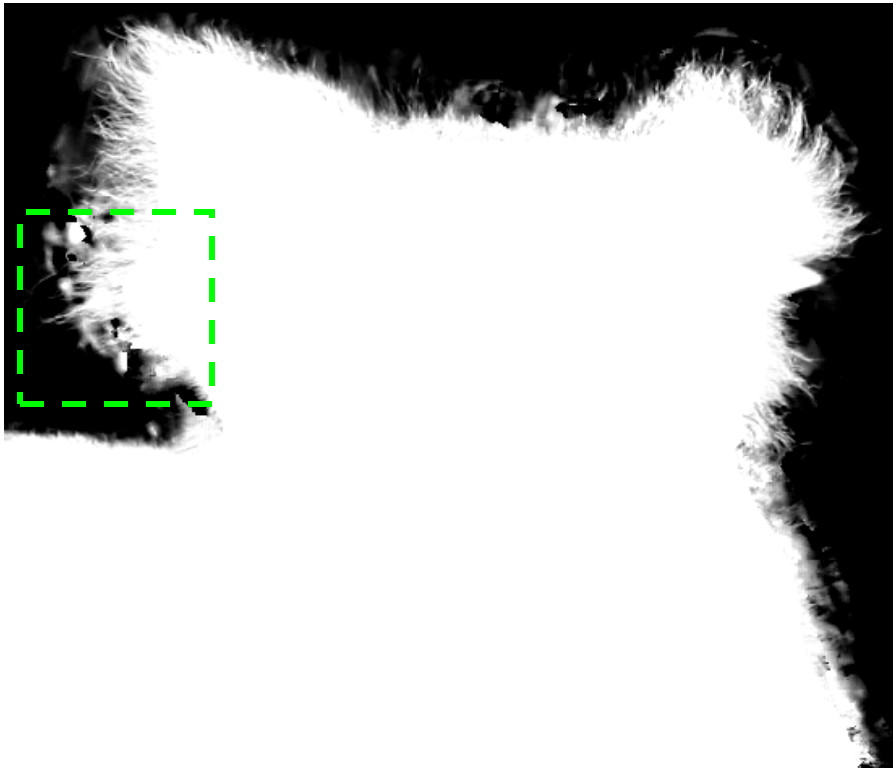
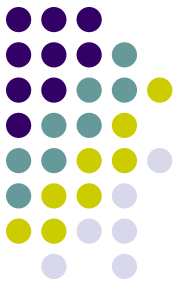
(d) Clone



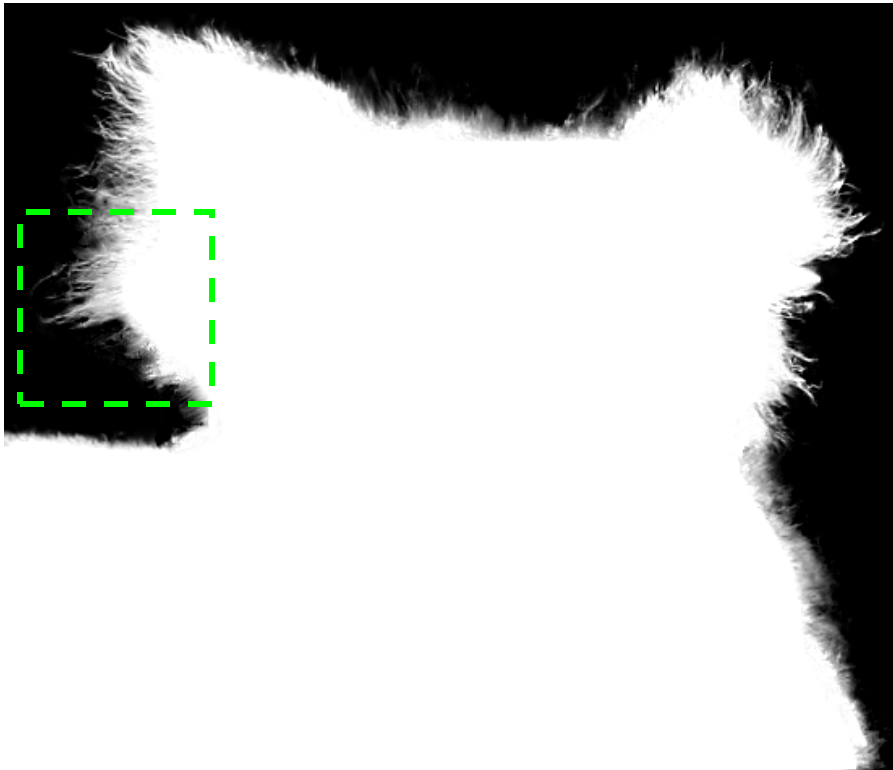
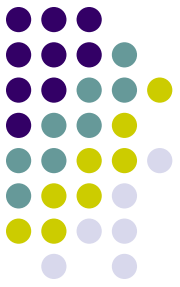
# Poisson Matting



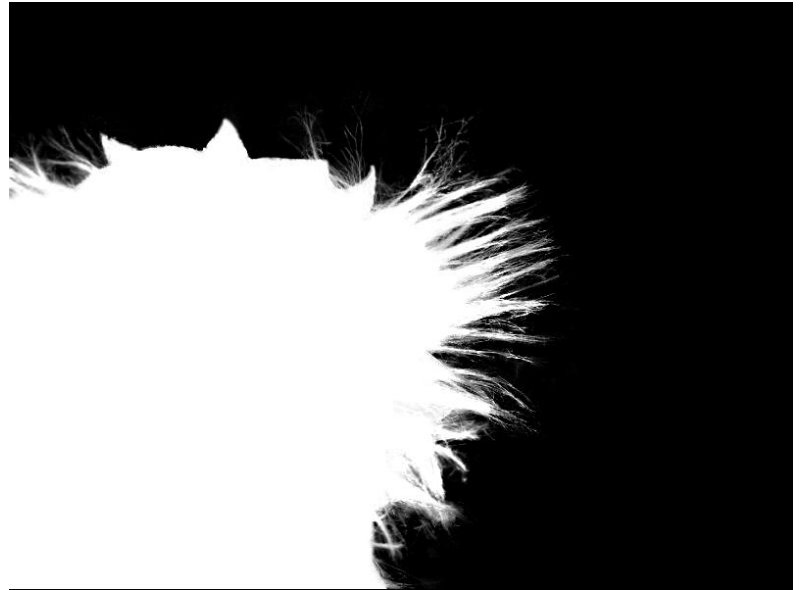
# Bayesian Matting result

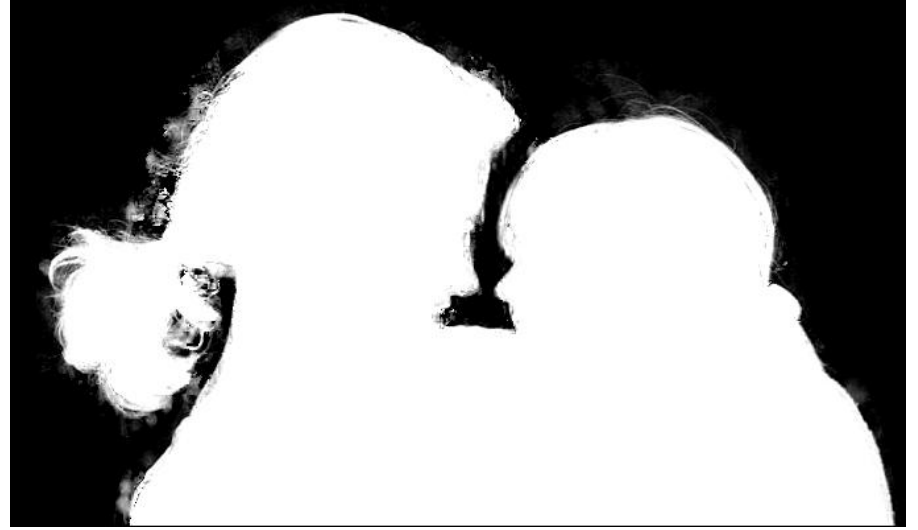


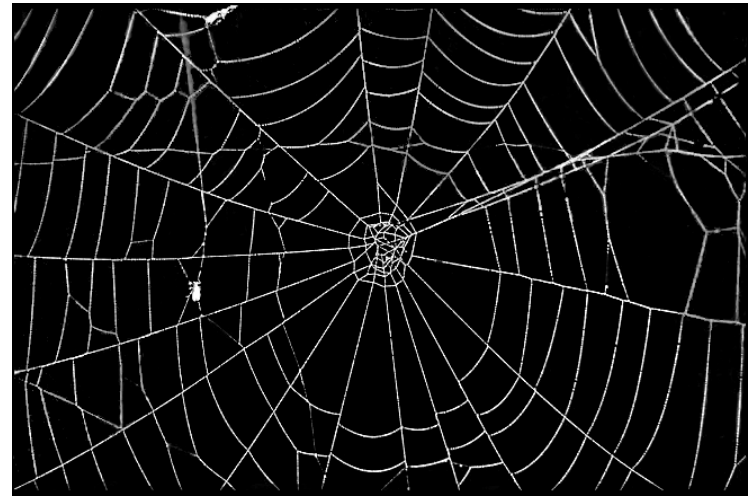
# Poisson Matting result









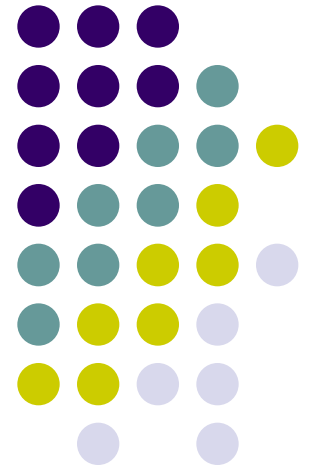


# De-fogging



---

Video Demo

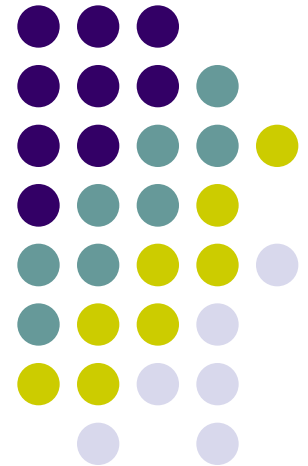


# Poisson Mesh Editing

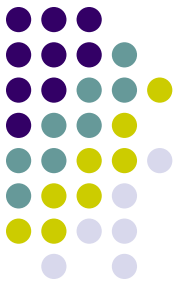
---

Yizhou Yu, et al.

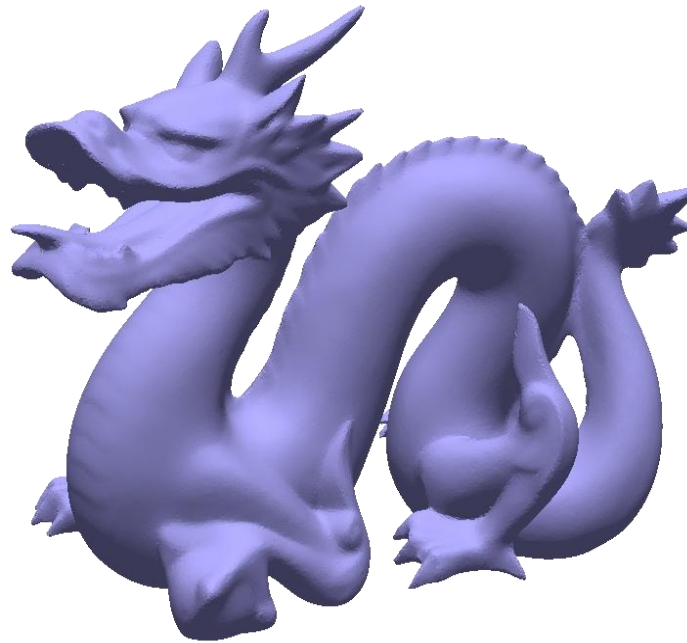
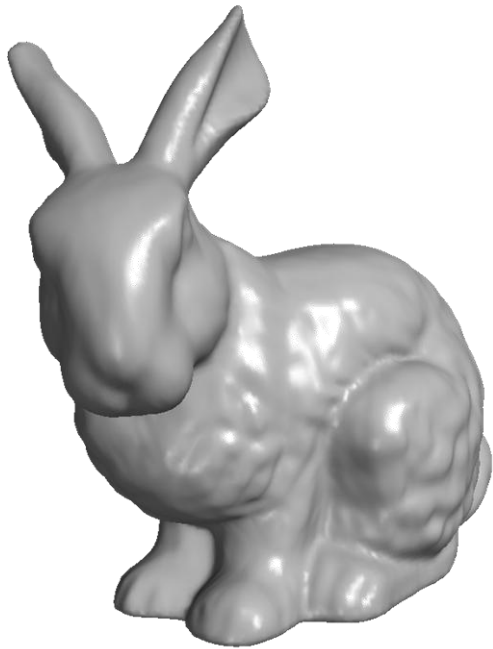
Poisson Mesh Editing. *SIGGRAPH 2004*.



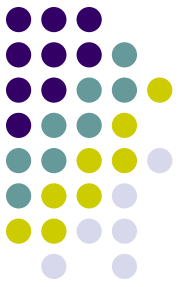
# Mesh Editing



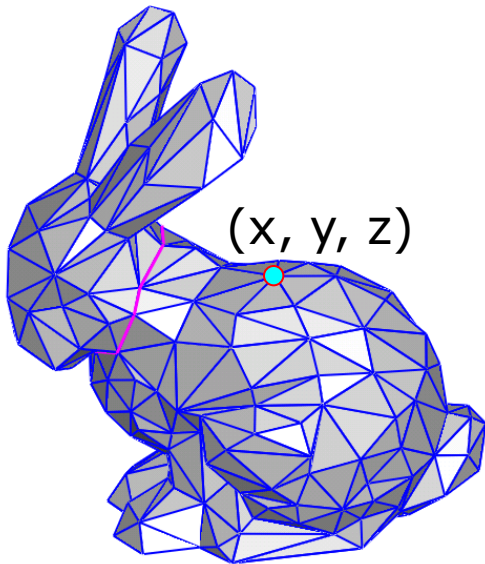
- Tools for 3D Content Creation
  - Deformation, Smoothing, Merging



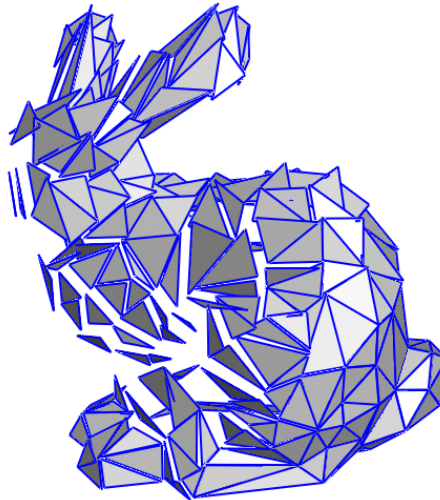
# Poisson Mesh Editing



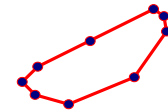
$$\Delta \boxed{f} = \operatorname{div} \boxed{\mathbf{W}} \quad \text{s.t.} \quad f|_{\partial\Omega} = \boxed{f^*|_{\partial\Omega}}$$



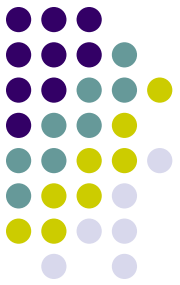
Mesh Geometry



Guidance Field

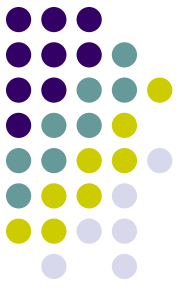


Boundary Condition



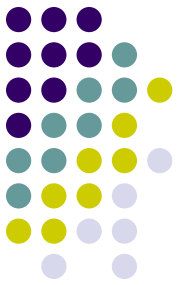
# Why Poisson Mesh Editing?

- Editing mesh geometry explicitly is very tedious and impractical!
- *Local* editing → *global* effects
- *Avoid artifacts* by distributing errors using least-square minimization

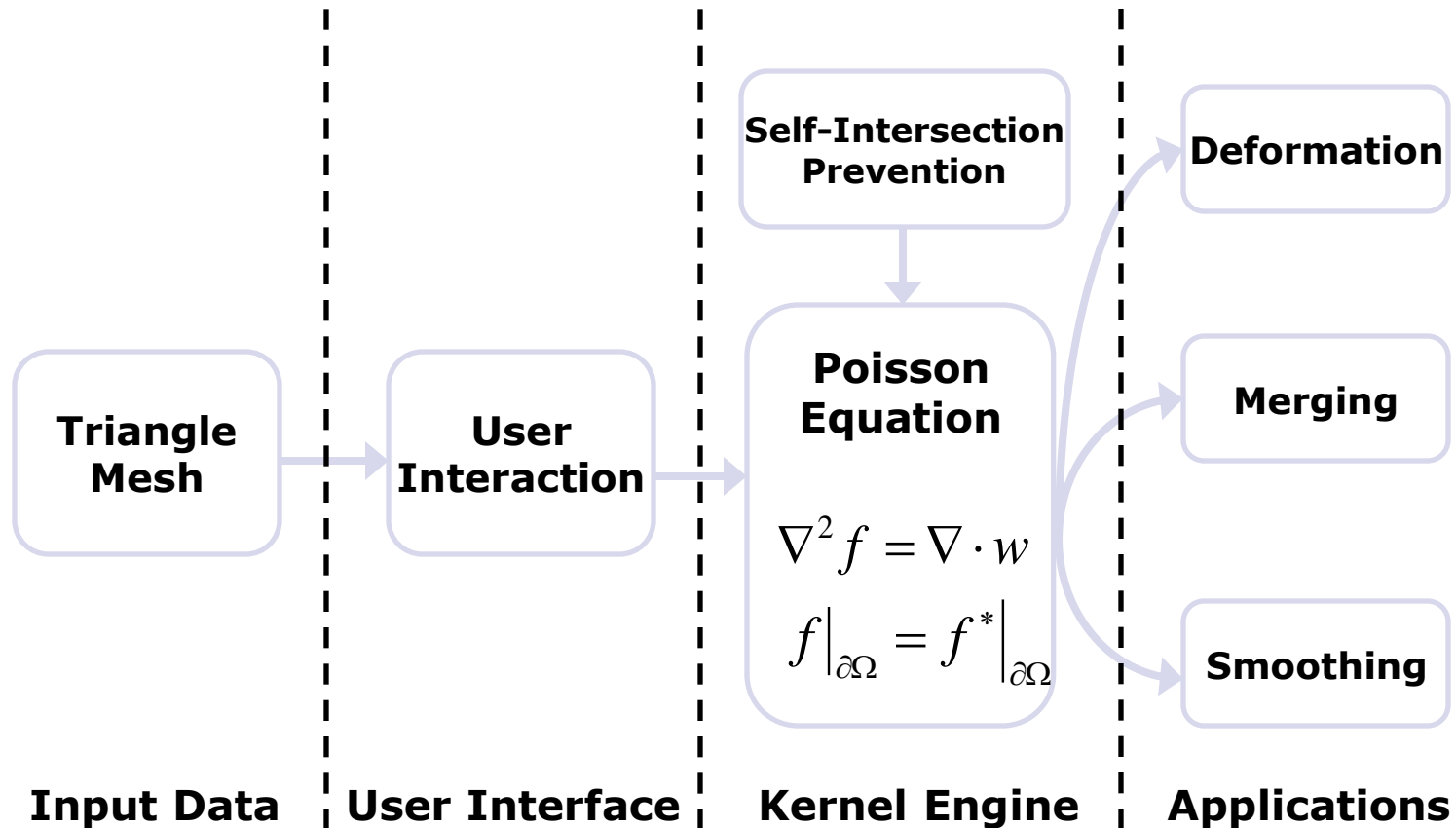


# Challenges

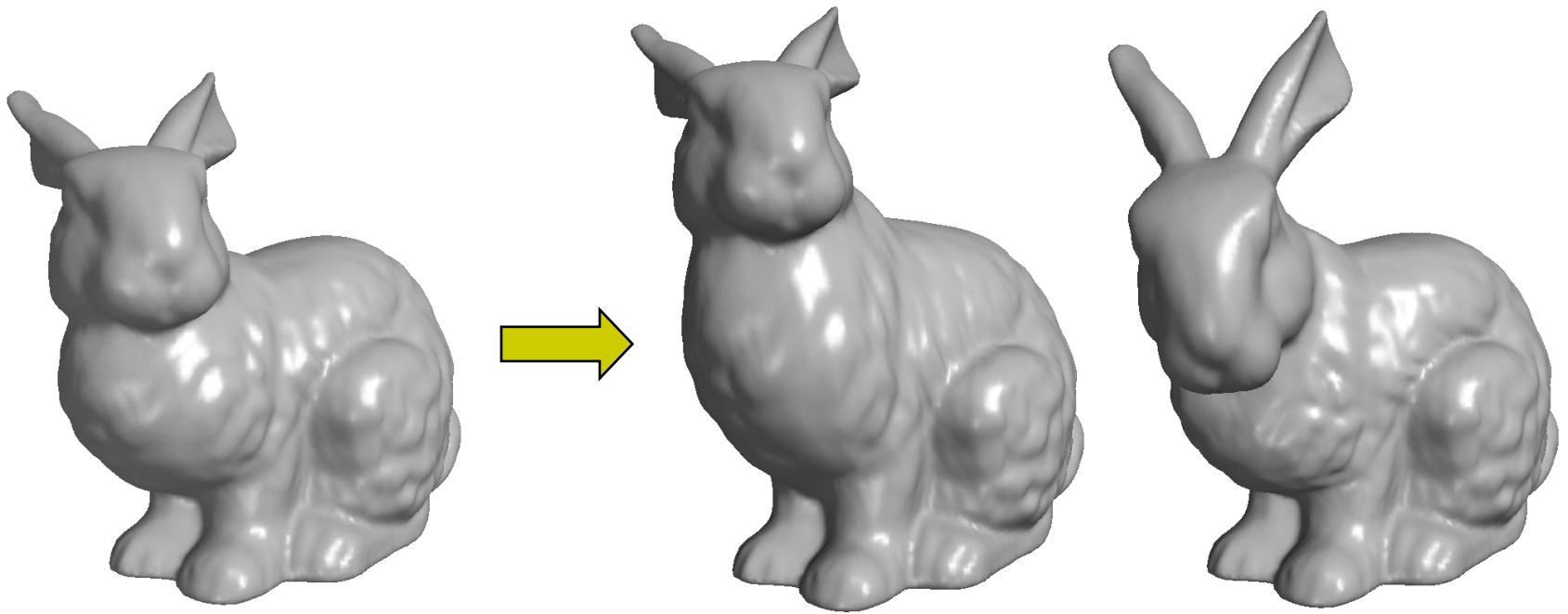
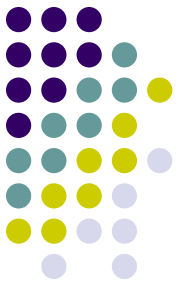
- Apply Poisson equation to mesh
  - *Parameterization mesh*: define vertex positions as signal on 2d-manifold
  - Define discrete Laplace and divergence operators for mesh
- How to modify the guidance field and boundary conditions?
  - *Local frame propagation*



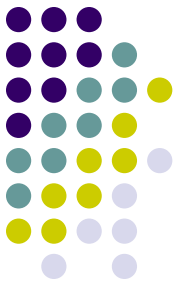
# A Generic Editing Framework



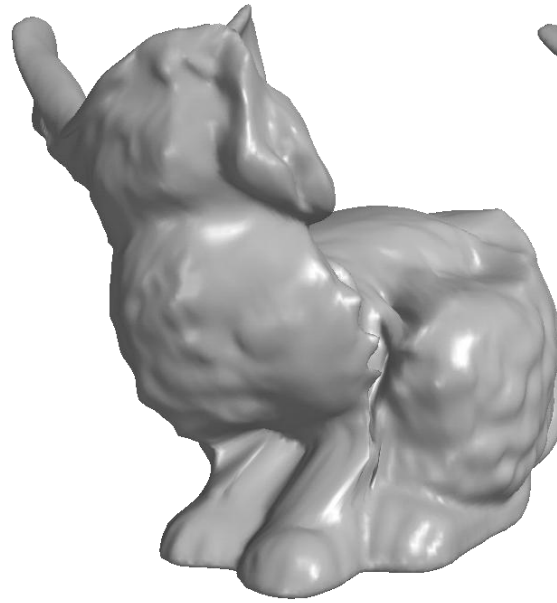
# Deformation



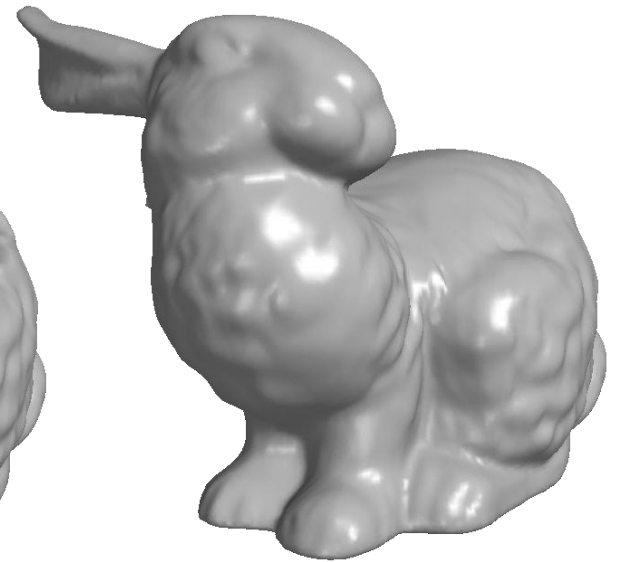
# Deformation



Naïve Poisson

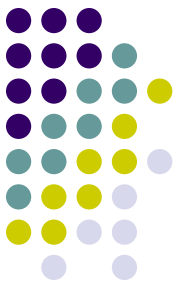


WIRE (Maya)

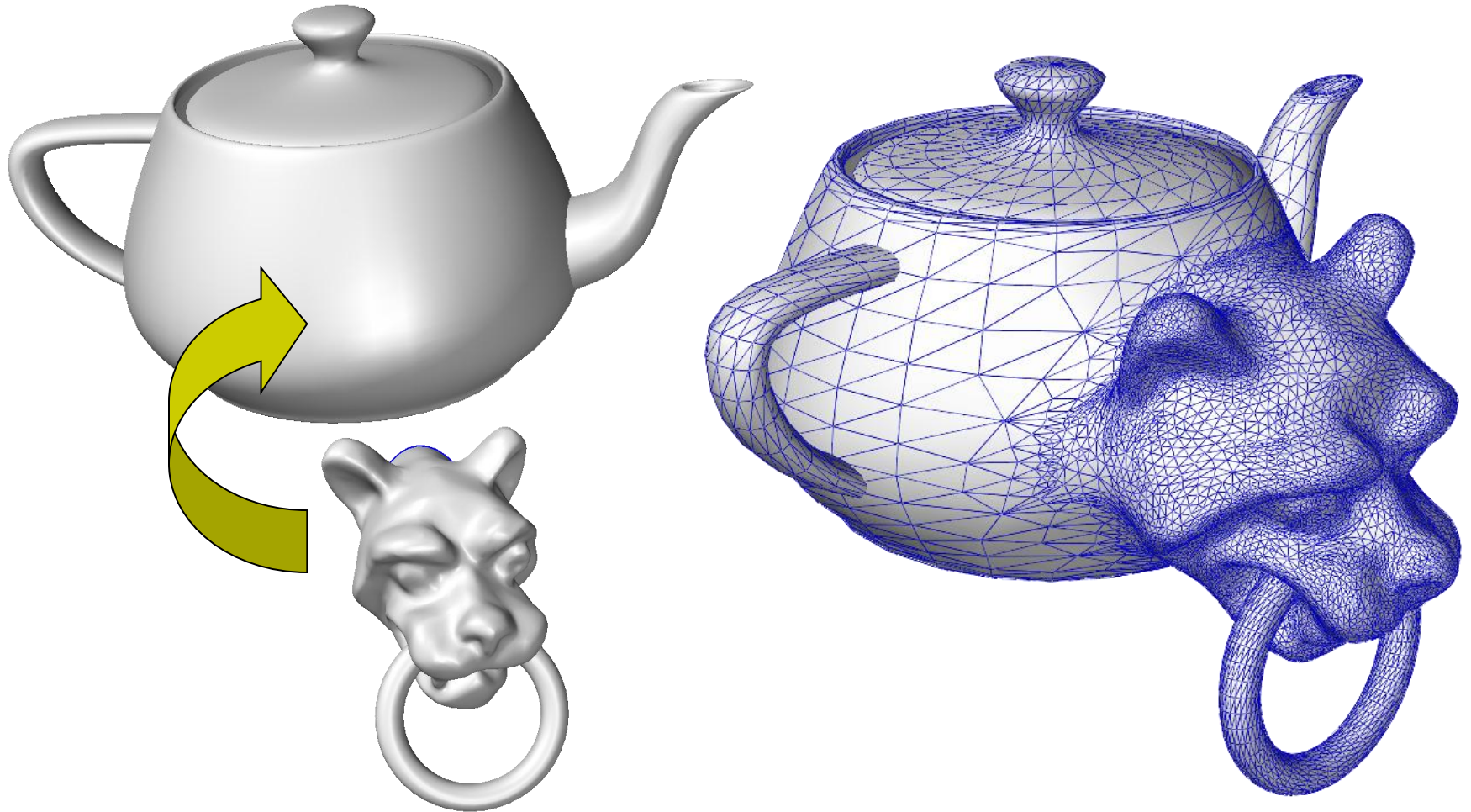
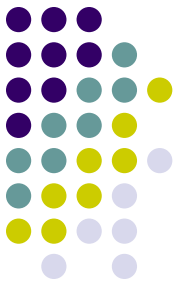


Poisson

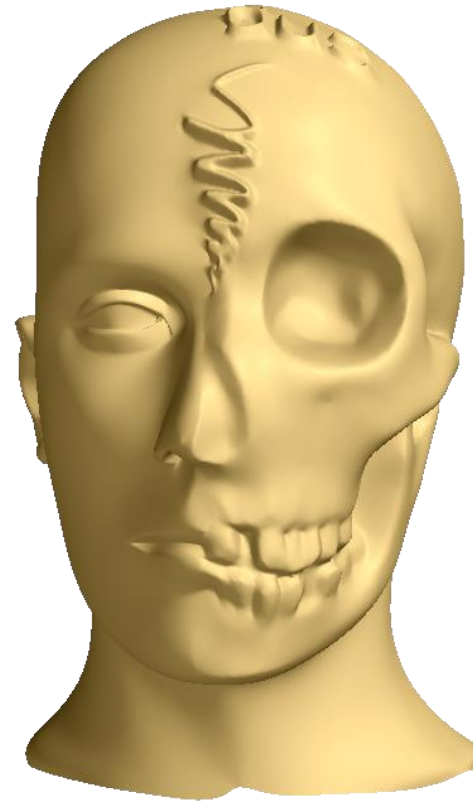
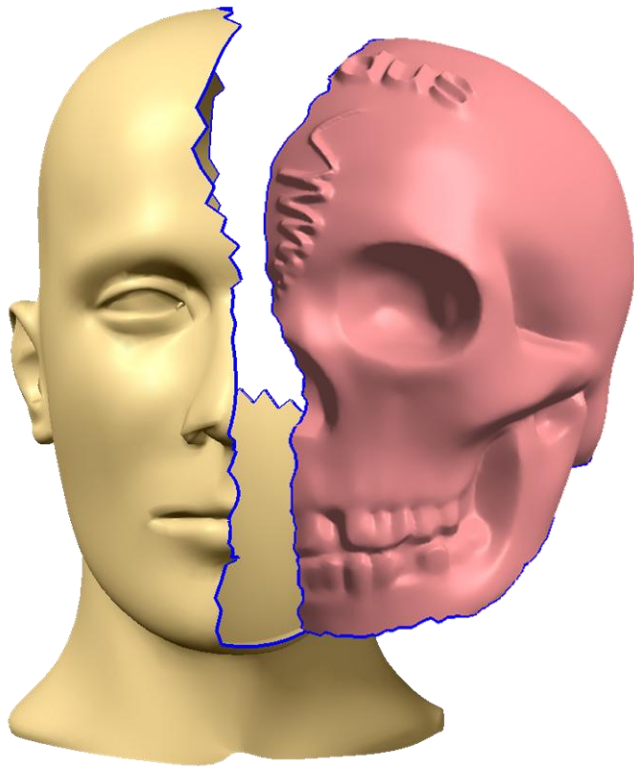
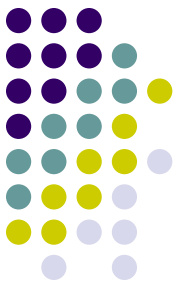
# Deformation



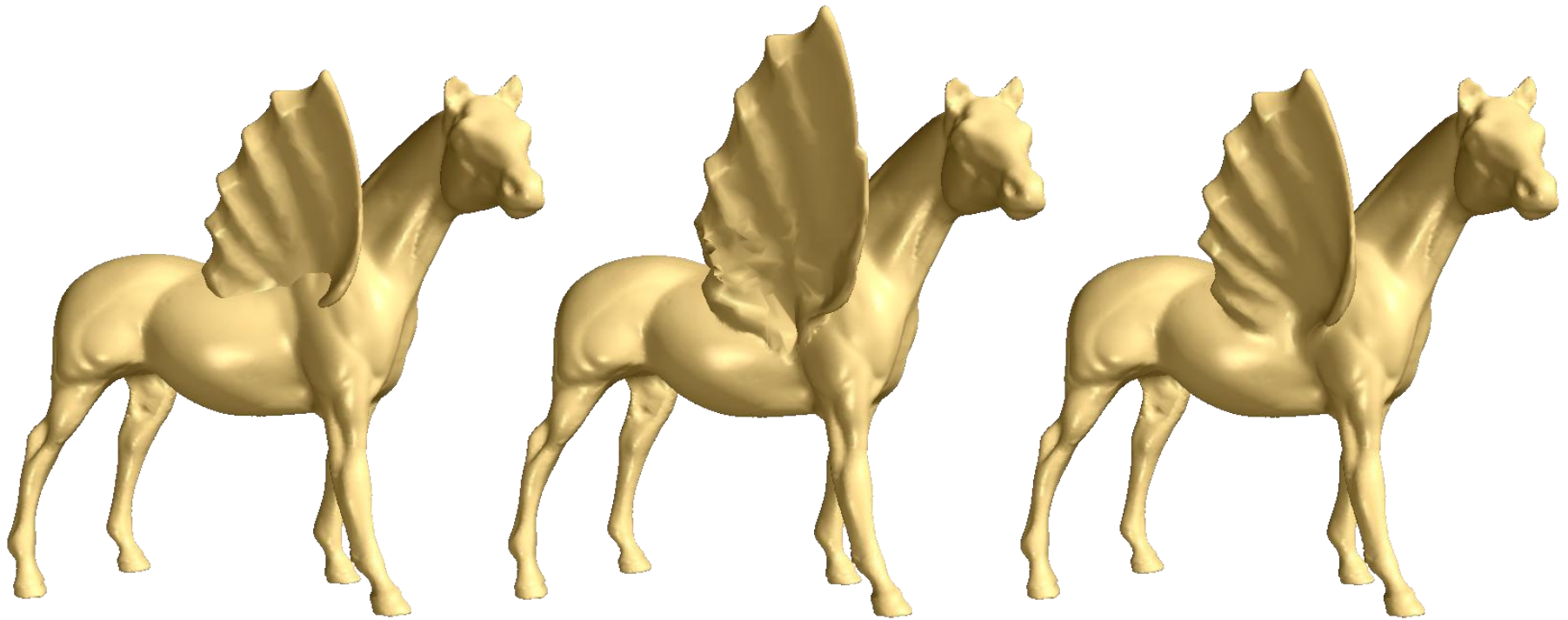
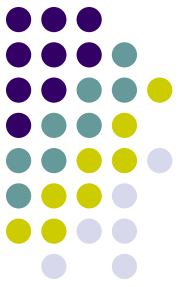
# Object Merging



# Object Merging



# Object Merging

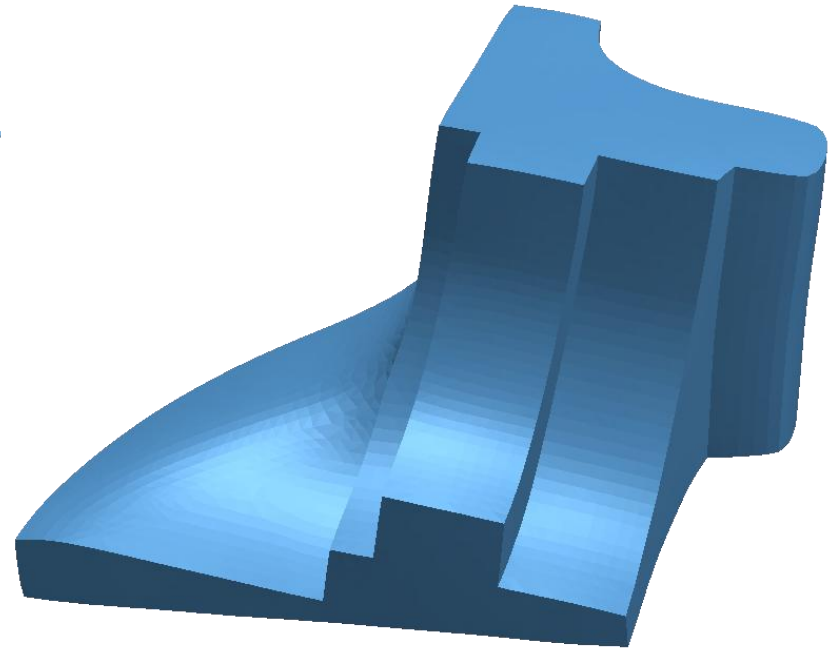
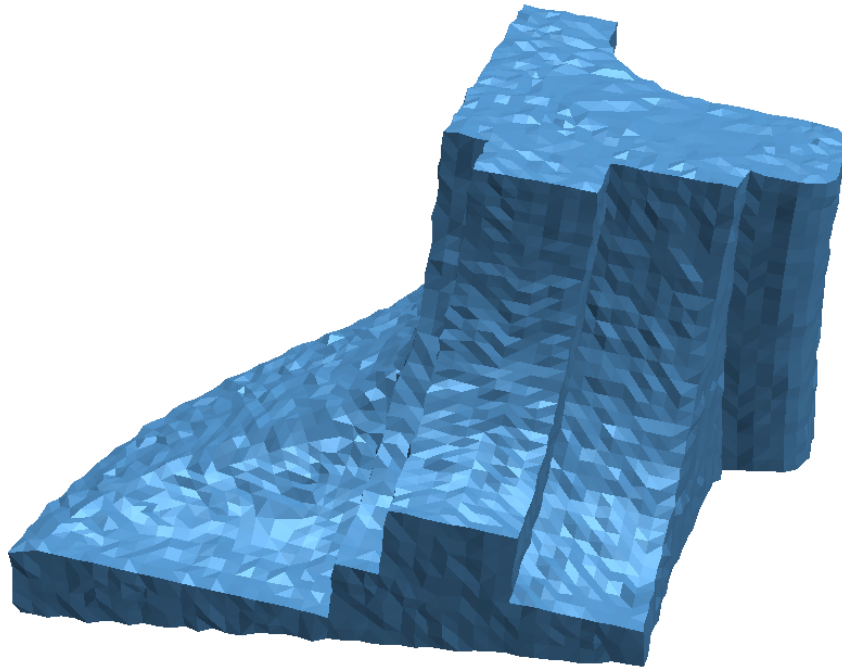
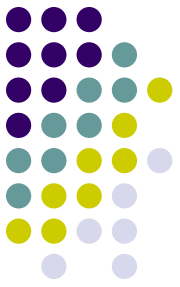


Boolean Operation

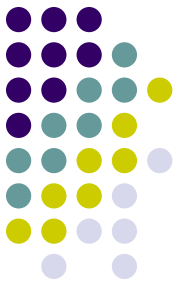
WIRE (Maya)

Poisson

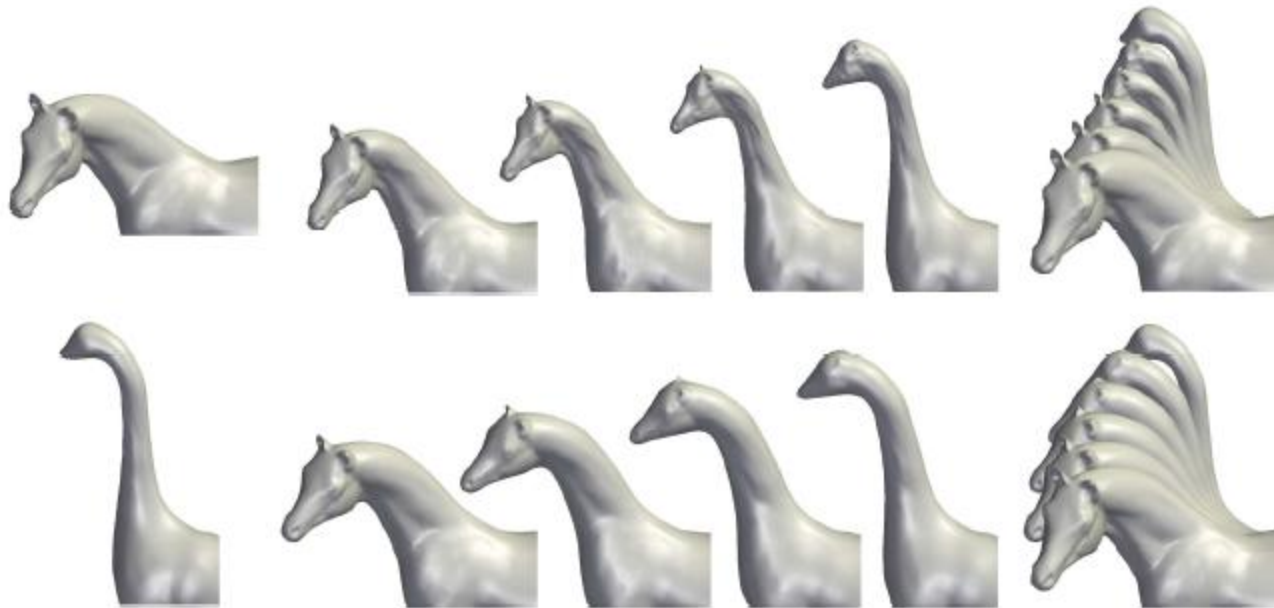
# Smoothing



# Other Applications



- Mesh Morphing



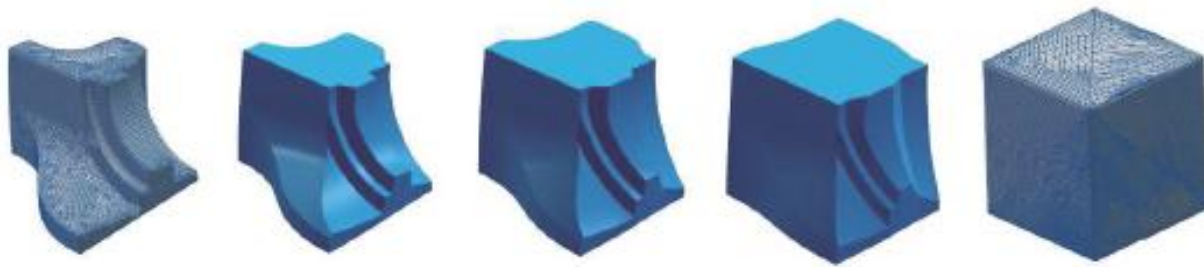
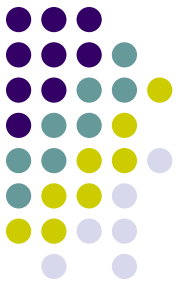


Fig. 5. Morphing between the fan-disk and the cube model.



Fig. 6. Morphing between the bunny and the rabbit model.





# Poisson

- Poisson equation is important
  - so is Laplacian ...
- Understanding the graphics problem
  - Formulating Image editing using Poisson
- Extending to similar problems
  - Poisson mesh editing
  - From 2D image to mesh
- Creatively applying to different problems
  - Poisson matting