

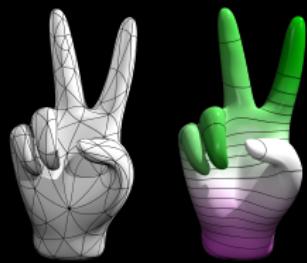
Isogeometric Approximation of Variational Shell Problems

PhD Defense Ricardo Perl



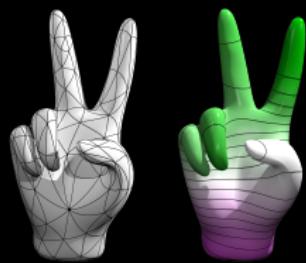
Outlook

Isogeometric
Subdivision Method



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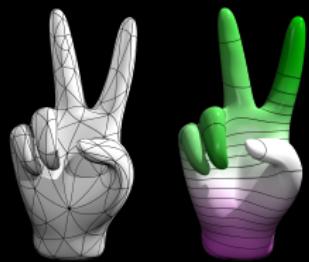
Isogeometric Subdivision Method



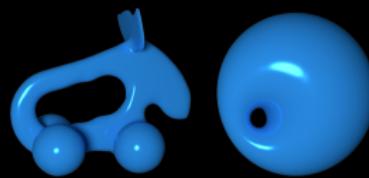
⇒ Robust and efficient
numerical integration

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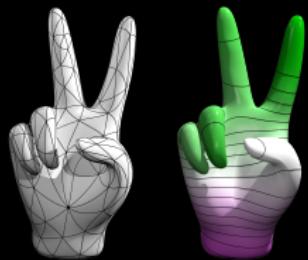
Parametric
Gradient Flows



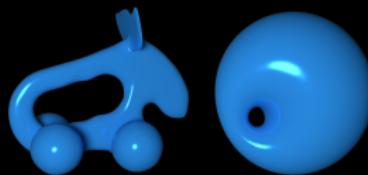
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Parametric Gradient Flows

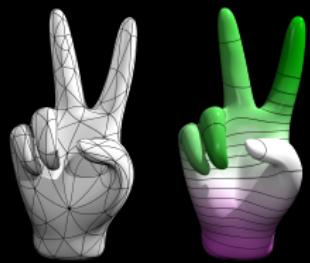


⇒ Robust and efficient
numerical integration

Higher order
⇒ Time and Space
Discretization

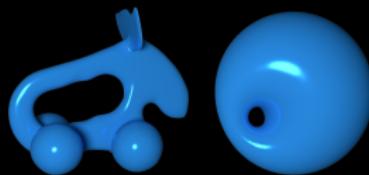
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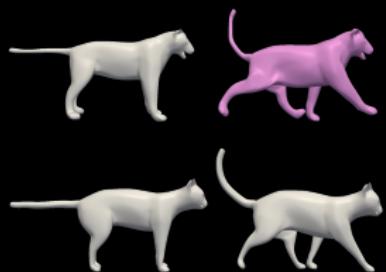
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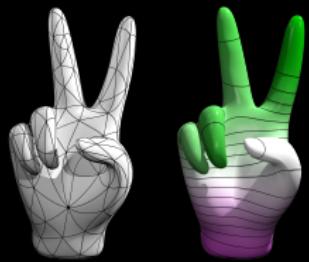
Higher order
⇒ Time and Space
Discretization

Shape Space



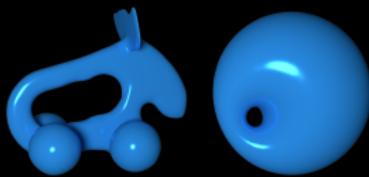
Outlook

Isogeometric Subdivision Method



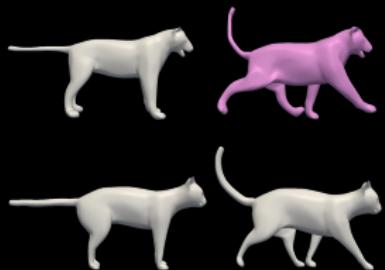
⇒ Robust and efficient numerical integration

Parametric Gradient Flows



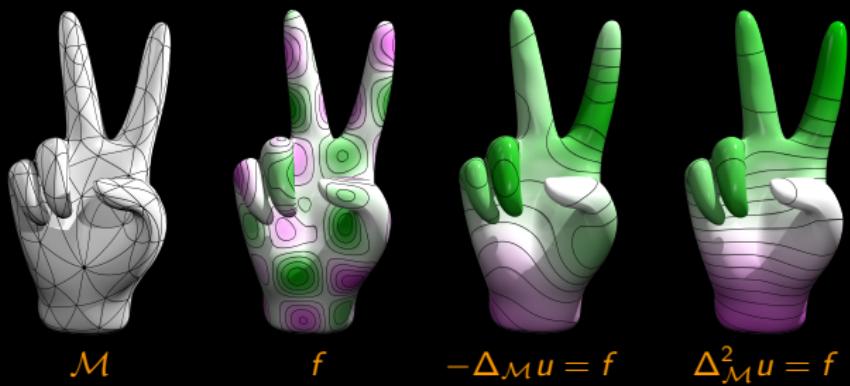
Higher order
⇒ Time and Space Discretization

Shape Space

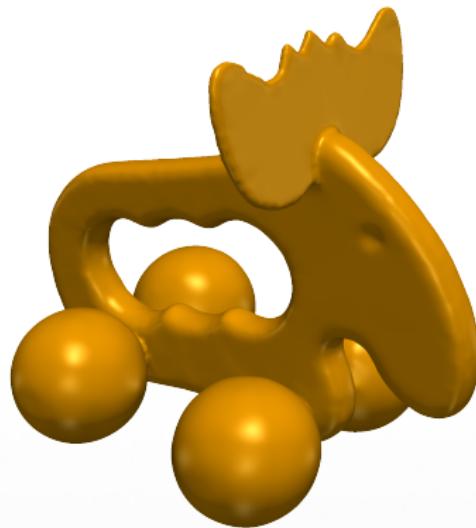


⇒ Bézier curves and splines

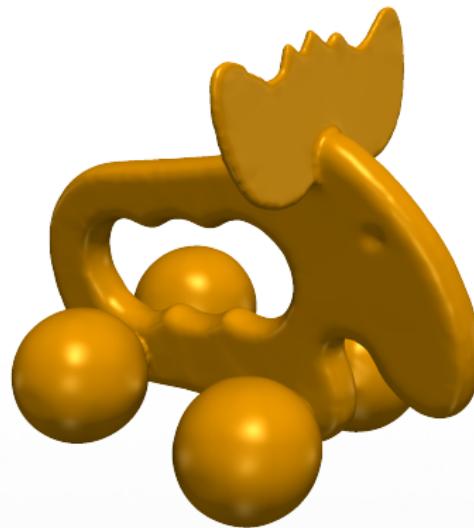
Isogeometric Subdivision Method



Discretization Spaces

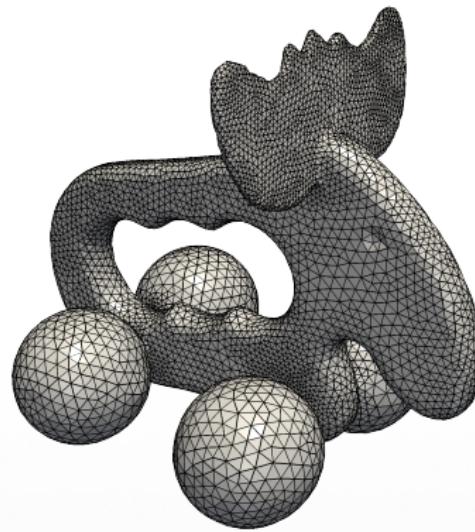


Discretization Spaces



How to discretize smooth surfaces?

Discretization Spaces

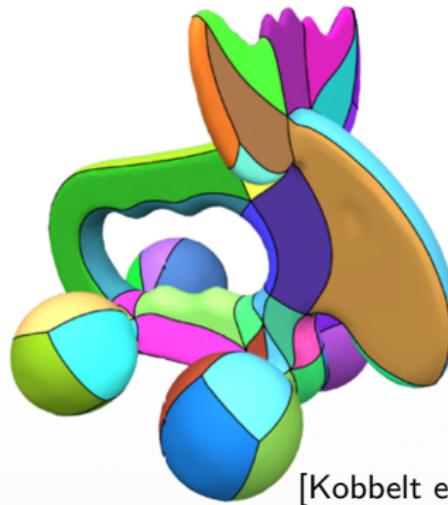


How to discretize smooth surfaces?

Classical FEM

- ✓ Flexibility
- ✗ Smoothness

Discretization Spaces



[Kobbelt et. al.'13]

How to discretize smooth surfaces?

Classical FEM

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NURBS based IgA

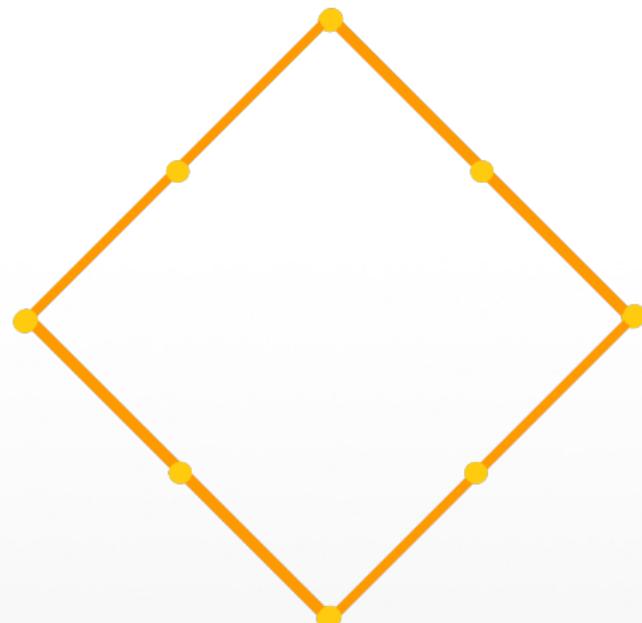
- ✗ Flexibility
- ✓ Smoothness

1D Subdivision



1D Subdivision

1. Subdivision Step
~~ split

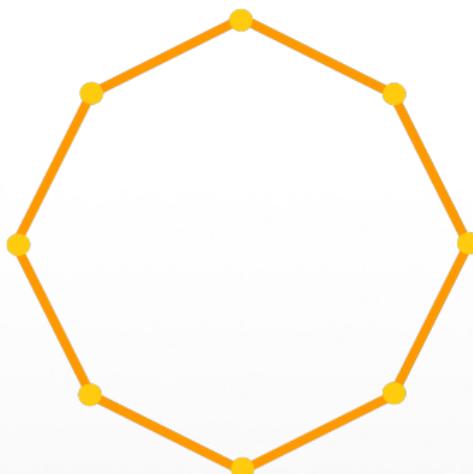


1D Subdivision

1. Subdivision Step

~~ split

~~ smooth



1D Subdivision

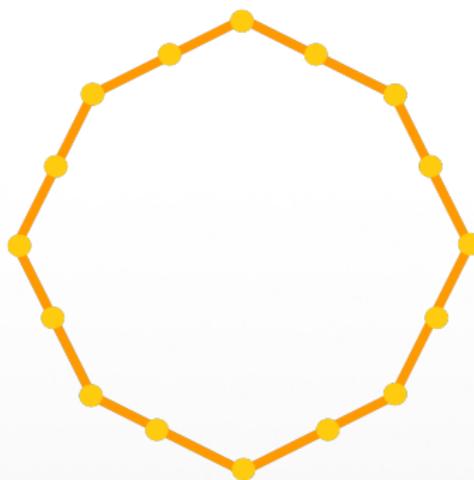
1. Subdivision Step

~~ split

~~ smooth

2. Subdivision Step

~~ split



1D Subdivision

1. Subdivision Step

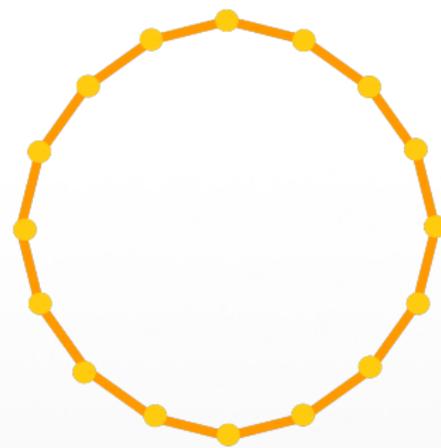
~~ split

~~ smooth

2. Subdivision Step

~~ split

~~ smooth



1D Subdivision

1. Subdivision Step

~~ split

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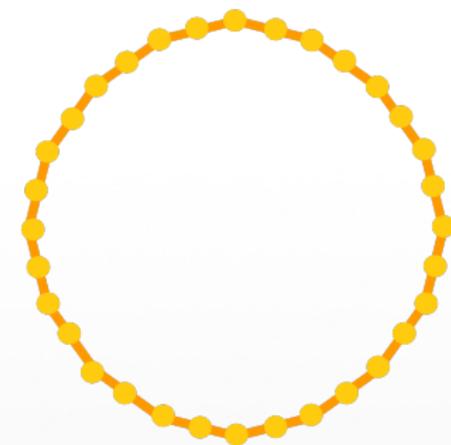
2. Subdivision Step

~~ split

~~ smooth

3. Subdivision Step

~~ split



1D Subdivision

1. Subdivision Step

~~ split

~~ smooth

2. Subdivision Step

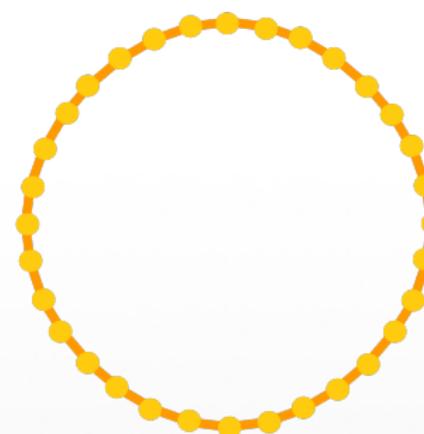
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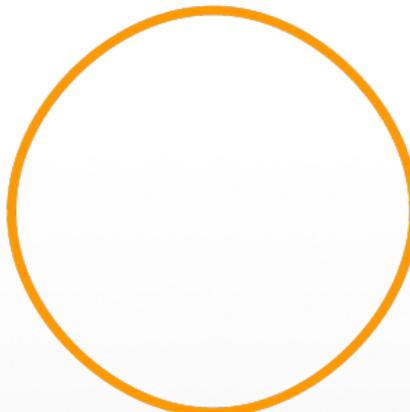
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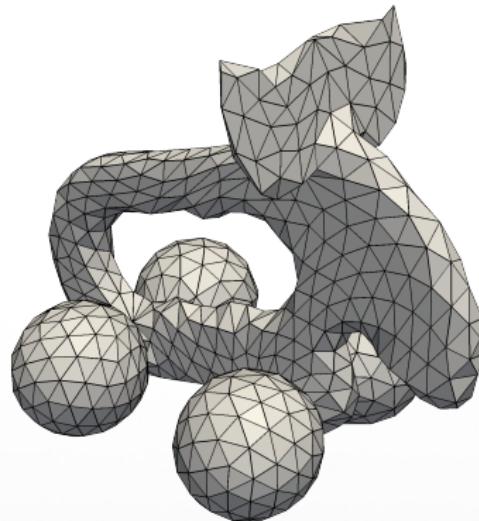
~~ smooth

⋮

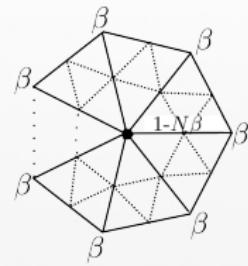
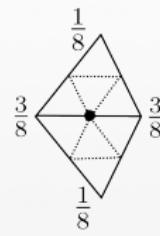
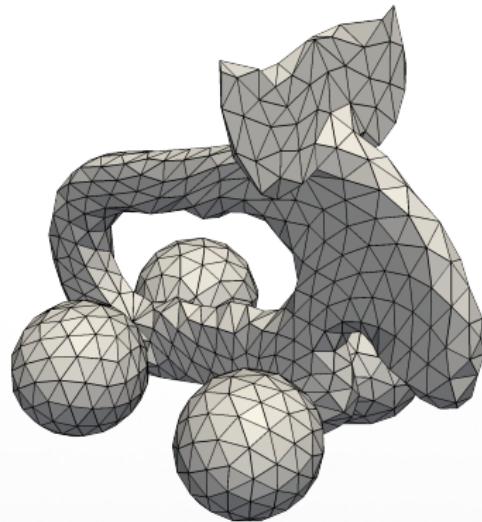
Limit curve



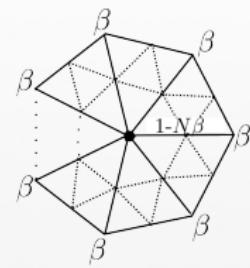
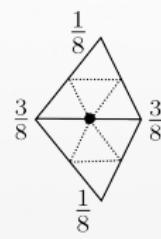
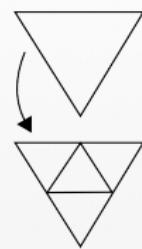
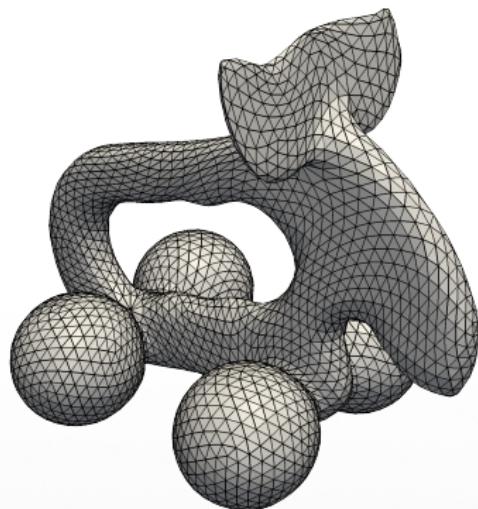
Subdivision Surfaces



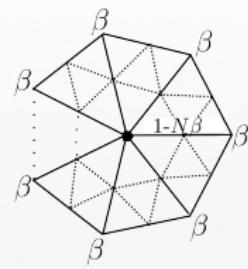
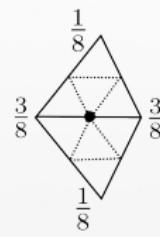
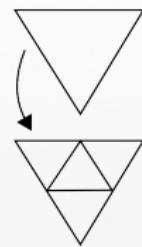
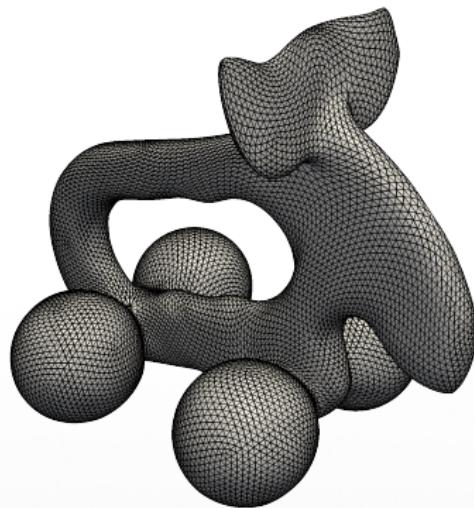
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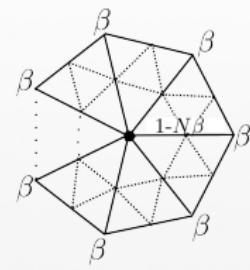
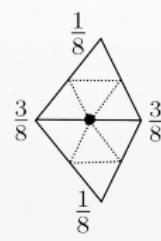
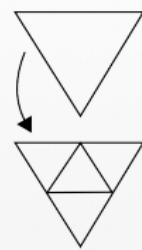
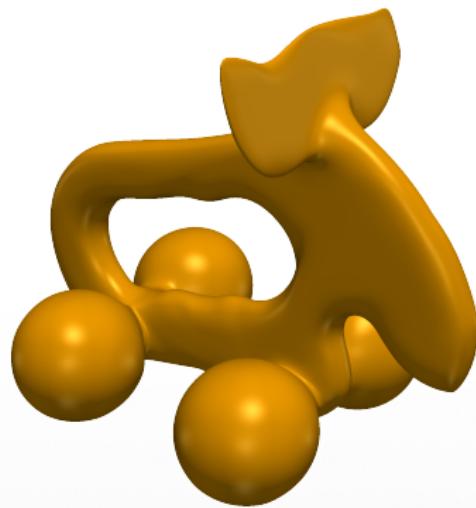
Subdivision Surfaces



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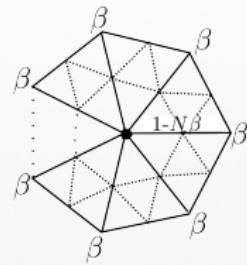
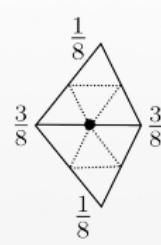
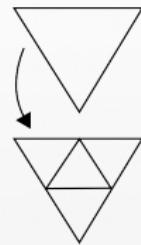
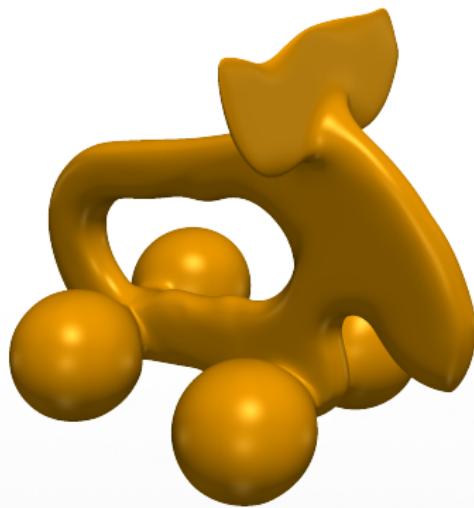


Subdivision Surfaces



Subdivision Surfaces

- ✓ Flexibility
- ✓ Smoothness
 $\Rightarrow C^1$



Isogeometric Subdivision Method

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- [Cirak, Ortiz and Schöder, 2000] use barycenter rule (one point per element)

Reduced Quadrature



■ Given subdivision surface \mathcal{M}

Reduced Quadrature



- Given subdivision surface \mathcal{M}
- Given right-hand side f

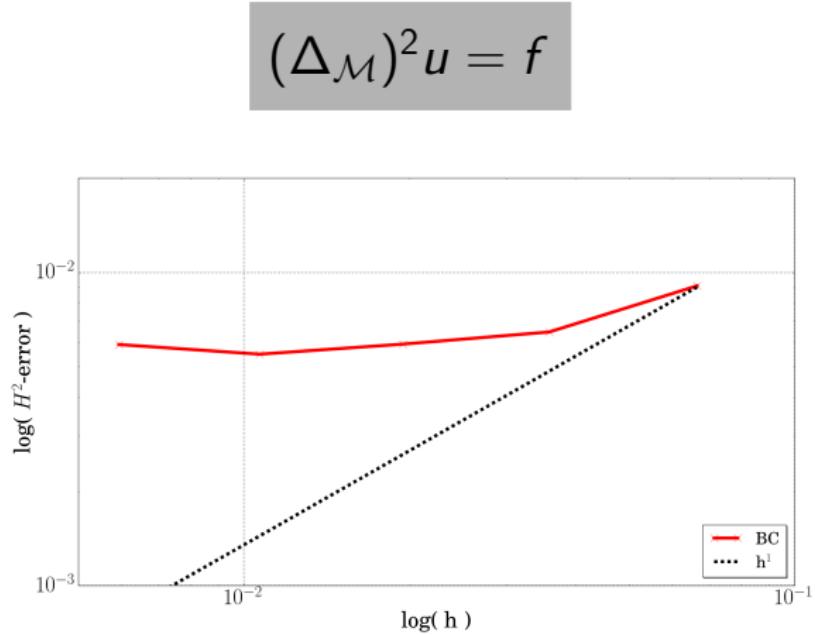
Reduced Quadrature

 \mathcal{M}  f

$$(\Delta_{\mathcal{M}})^2 u = f$$

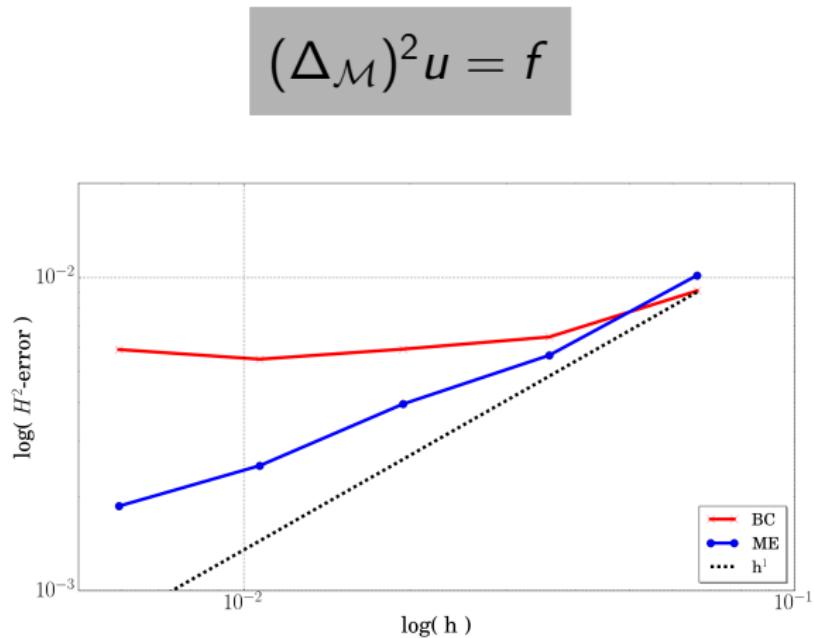
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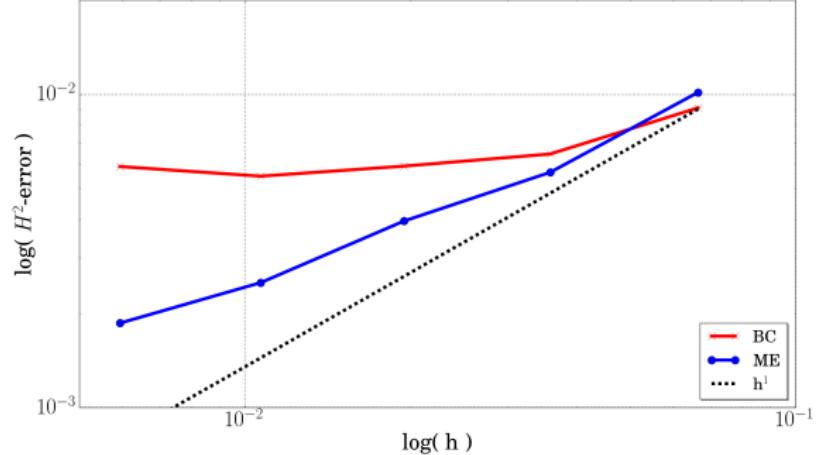
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Reduced Quadrature

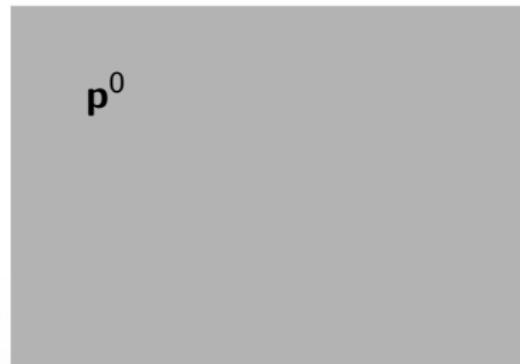
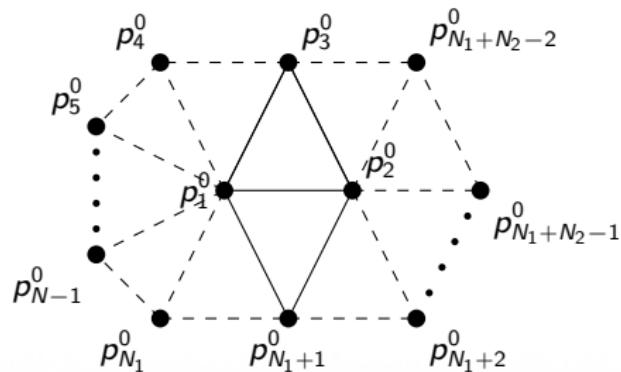


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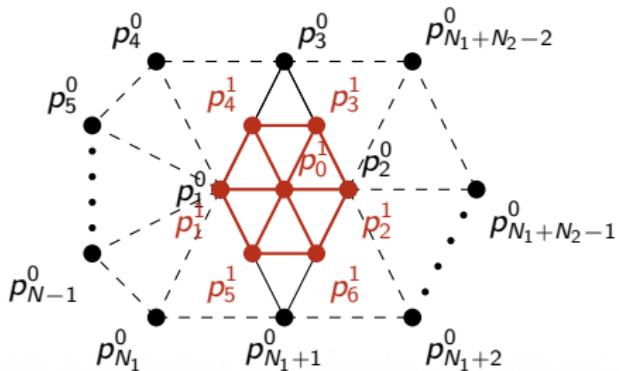


- Given subdivision surface \mathcal{M}
- Given right-hand side f
- Solve bi-Laplacian on \mathcal{M}
- Barycenter (BC) rule can fail!
- Mid-edge (ME) rule works fine, BUT is less efficient.
- Implementation of evaluation process is complex and time consuming.

Mid-edge Lookup Tables

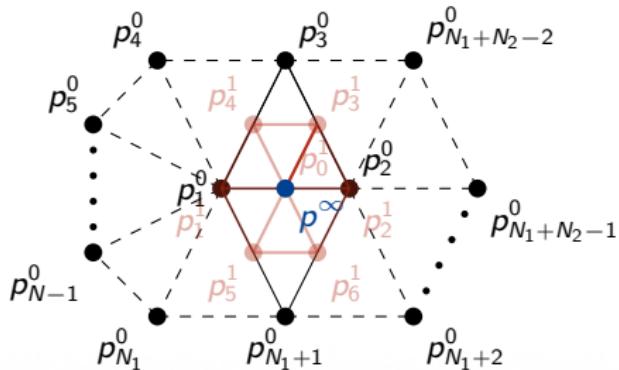


Mid-edge Lookup Tables



$$\mathbf{p}^1 = S\mathbf{p}^0$$

Mid-edge Lookup Tables

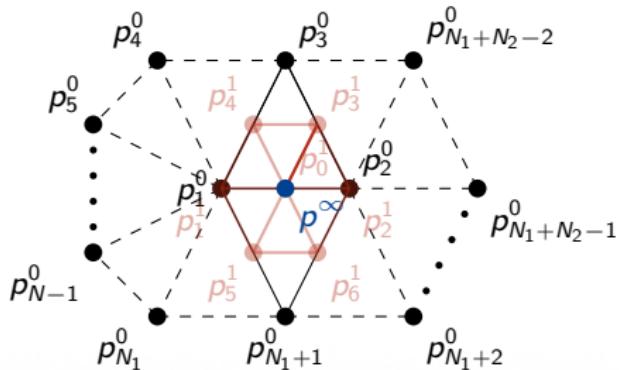


$$\mathbf{p}^\infty = L\mathbf{p}^1 = L \cdot S\mathbf{p}^0$$

$$S = \begin{pmatrix} \frac{3}{\beta_2} & \frac{3}{\beta_2} & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{\beta_2} & 1 - \beta_2 \cdot N_2 & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 & 0 & \beta_2 & \beta_2 & \beta_2 & \dots & \beta_2 & \beta_2 \\ \frac{3}{\beta_1} & \frac{3}{\beta_1} & \frac{1}{\beta_1} & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ 1 - \beta_1 \cdot N_1 & \beta_1 & \beta_1 & \beta_1 & \beta_1 & \dots & \beta_1 & \beta_1 & \beta_1 & 0 & 0 & 0 & \dots & 0 & 0 \\ \frac{3}{\beta_0} & \frac{3}{\beta_0} & \frac{1}{\beta_0} & 0 & 0 & \dots & 0 & 0 & \frac{1}{\beta_0} & \frac{3}{\beta_0} & 0 & 0 & \dots & 0 & 0 \\ \frac{3}{\beta_0} & \frac{3}{\beta_0} & \frac{1}{\beta_0} & 0 & 0 & \dots & 0 & 0 & \frac{1}{\beta_0} & \frac{3}{\beta_0} & 0 & 0 & \dots & 0 & 0 \end{pmatrix}$$

$$L = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ 0 & \frac{3}{2} & \frac{3}{2} & \frac{1}{2} & -\frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} \\ 0 & \frac{3}{2} & \frac{3}{2} & \frac{1}{2} & \frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} \\ -8 & 4 & 0 & 0 & 4 & 0 & 0 \\ -4 & 2 & 2 & -2 & 2 & 2 & -2 \\ -8 & 0 & 4 & 0 & 0 & 4 & 0 \end{pmatrix}$$

Mid-edge Lookup Tables



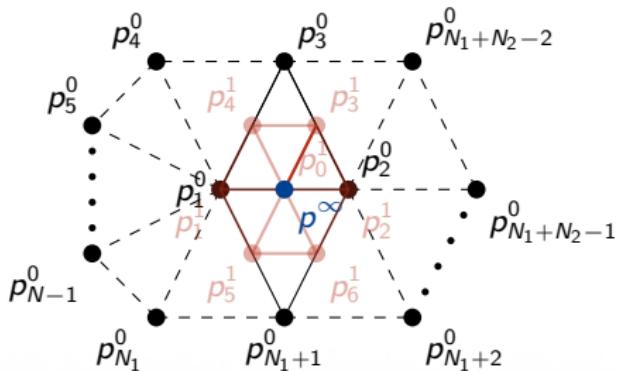
$$\mathbf{p}^\infty = L\mathbf{p}^1 = L \cdot S\mathbf{p}^0$$

Position, first and second derivatives

$$S = \begin{pmatrix} \frac{3}{\beta_2} & \frac{3}{\beta_2} & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{\beta_2} & 1 - \beta_2 \cdot N_2 & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 & 0 & \beta_2 & \beta_2 & \dots & \beta_2 & \beta_2 \\ 1 - \beta_1 \cdot N_1 & \frac{3}{\beta_1} & \frac{1}{\beta_1} & \beta_1 & \beta_1 & \dots & \beta_1 & \beta_1 & 0 & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{\beta_1} & \frac{1}{\beta_1} & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{8} & \frac{1}{8} & 0 & 0 & 0 & \dots & 0 & 0 & \frac{1}{8} & \frac{1}{3} & 0 & \dots & 0 & 0 \end{pmatrix}$$

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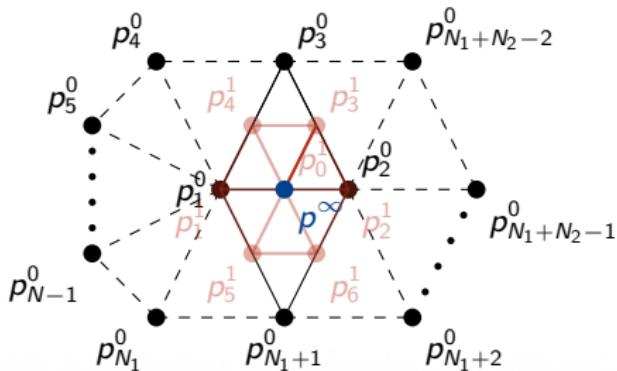
$$\mathbf{p}^\infty = L\mathbf{p}^1 = L \cdot S\mathbf{p}^0$$

- Position, first and second derivatives
- Easy to implement

$$S = \begin{pmatrix} \frac{3}{\beta_2} & \frac{3}{\beta_2} & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{\beta_2} & 1 - \beta_2 \cdot N_2 & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 & 0 & \beta_2 & \beta_2 & \dots & \beta_2 & \beta_2 \\ 1 - \beta_1 \cdot N_1 & \frac{3}{\beta_1} & \frac{1}{\beta_1} & \beta_1 & \beta_1 & \dots & \beta_1 & \beta_1 & 0 & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{\beta_1} & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{8} & 0 & 0 & 0 & 0 & \dots & 0 & 0 & \frac{1}{8} & \frac{1}{3} & 0 & \dots & 0 & 0 \end{pmatrix}$$

$$L = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ 0 & \frac{3}{2} & \frac{1}{2} & \frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\ 0 & \frac{1}{3} & \frac{2}{3} & \frac{2}{3} & \frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} \\ -8 & 4 & 0 & 0 & 4 & 0 & 0 \\ -4 & 2 & 2 & -2 & 2 & 2 & -2 \\ -8 & 0 & 4 & 0 & 0 & 4 & 0 \end{pmatrix}$$

Mid-edge Lookup Tables



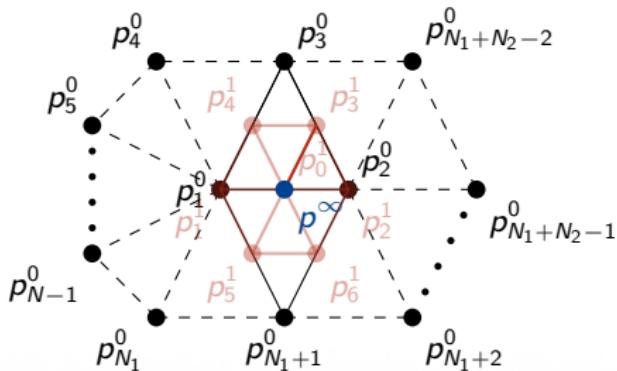
$$\mathbf{p}^\infty = L\mathbf{p}^1 = L \cdot S\mathbf{p}^0$$

- Position, first and second derivatives
- Easy to implement
- Faster than barycenter rule

$$S = \begin{pmatrix} \frac{3}{\beta_2} & \frac{3}{\beta_2} & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{\beta_2} & 1 - \beta_2 \cdot N_2 & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 & 0 & \beta_2 & \beta_2 & \beta_2 & \dots & \beta_2 & \beta_2 \\ 1 - \beta_1 \cdot N_1 & \frac{3}{\beta_1} & \frac{1}{\beta_1} & \beta_1 & \beta_1 & \dots & \beta_1 & \beta_1 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{\beta_1} & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{8} & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \frac{1}{8} & \frac{1}{8} & \frac{1}{8} & \dots & 0 & \frac{1}{8} \\ \frac{1}{8} & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \end{pmatrix}$$

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Mid-edge Lookup Tables



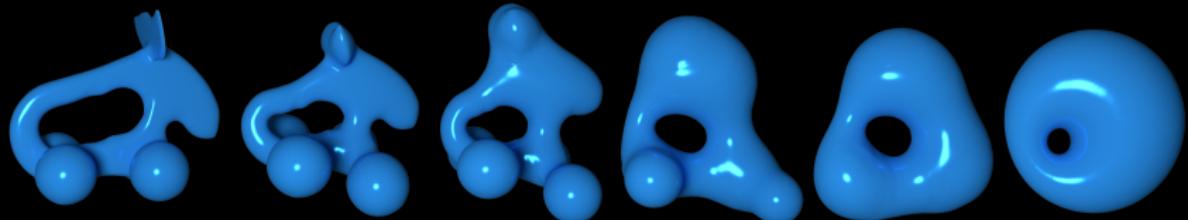
$$\mathbf{p}^\infty = L\mathbf{p}^1 = L \cdot S\mathbf{p}^0$$

- Position, first and second derivatives
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- Arbitrary connectivity

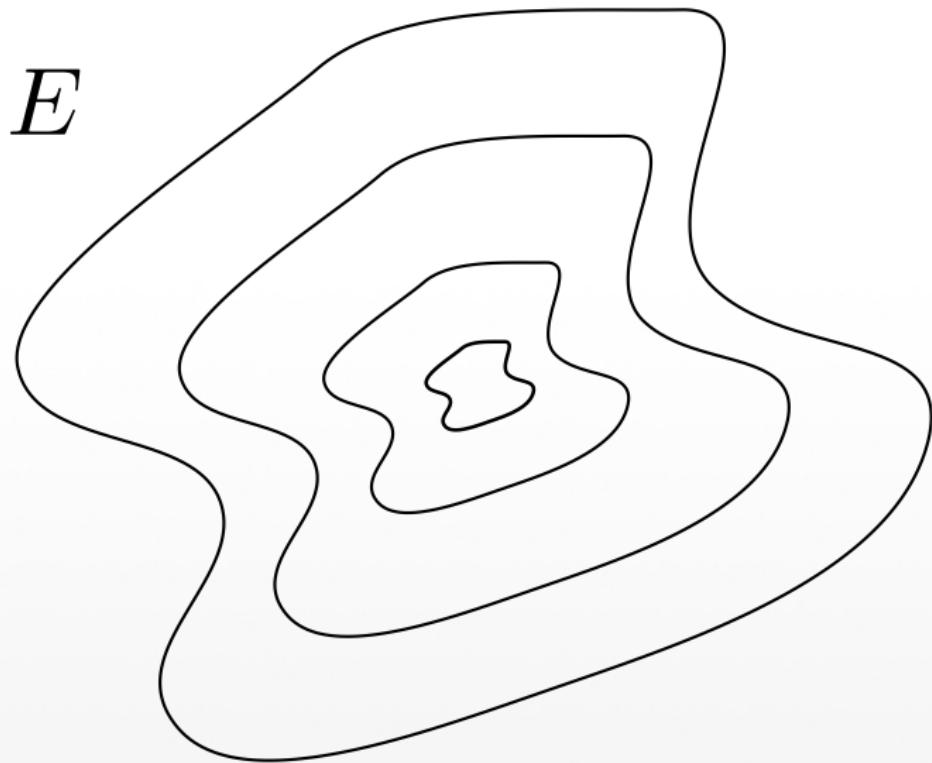
$$S = \begin{pmatrix} \frac{3}{\beta_2} & \frac{3}{\beta_2} & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{\beta_2} & 1-\beta_2 \cdot N_2 & \frac{1}{\beta_2} & 0 & 0 & \dots & 0 & 0 & 0 & \beta_2 & \beta_2 & \dots & \beta_2 & \beta_2 \\ \frac{3}{\beta_1} & \frac{3}{\beta_1} & \frac{1}{\beta_1} & \beta_1 & \beta_1 & \dots & \beta_1 & \beta_1 & 0 & 0 & 0 & \dots & 0 & \frac{1}{\beta_1} \\ 1-\beta_1 \cdot N_1 & \beta_1 & \beta_1 & \beta_1 & \beta_1 & \dots & \beta_1 & \beta_1 & 0 & 0 & 0 & \dots & 0 & 0 \\ \frac{1}{\beta_2} & \frac{1}{\beta_2} & \frac{1}{\beta_2} & \frac{1}{\beta_2} & \frac{1}{\beta_2} & \dots & \frac{1}{\beta_2} & \frac{1}{\beta_2} & 0 & \frac{1}{\beta_2} & \frac{1}{\beta_2} & \dots & \frac{1}{\beta_2} & \frac{1}{\beta_2} \\ \frac{1}{\beta_1} & \frac{1}{\beta_1} & \frac{1}{\beta_1} & \frac{1}{\beta_1} & \frac{1}{\beta_1} & \dots & \frac{1}{\beta_1} & \frac{1}{\beta_1} & 0 & \frac{1}{\beta_1} & \frac{1}{\beta_1} & \dots & \frac{1}{\beta_1} & \frac{1}{\beta_1} \\ \frac{1}{8} & \frac{1}{8} & \frac{1}{8} & \frac{1}{8} & \frac{1}{8} & \dots & \frac{1}{8} & \frac{1}{8} & 0 & \frac{1}{8} & \frac{1}{8} & \dots & \frac{1}{8} & \frac{1}{8} \end{pmatrix}$$

$$L = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ 0 & -\frac{3}{2} & \frac{3}{2} & -\frac{1}{2} & -\frac{5}{2} & -\frac{1}{2} \\ 0 & \frac{3}{2} & -\frac{3}{2} & \frac{1}{2} & -\frac{1}{2} & -\frac{3}{2} \\ -8 & 4 & 0 & 0 & 4 & 0 \\ -4 & 2 & 2 & -2 & 2 & 2 \\ -8 & 0 & 4 & 0 & 0 & 4 \end{pmatrix}$$

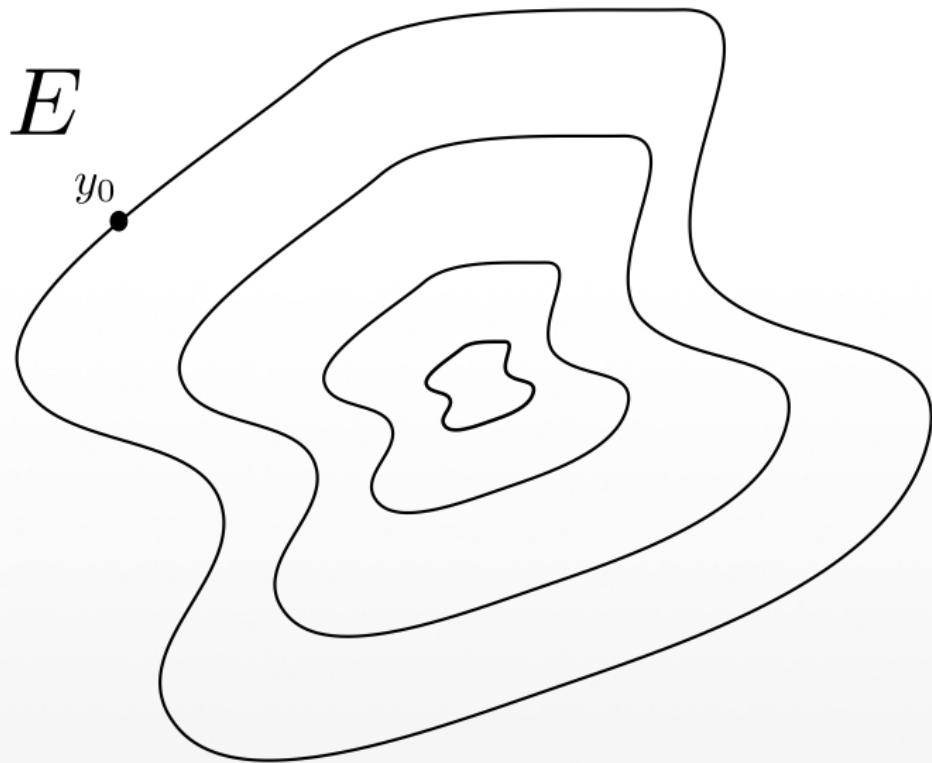
Parametric Gradient Flows



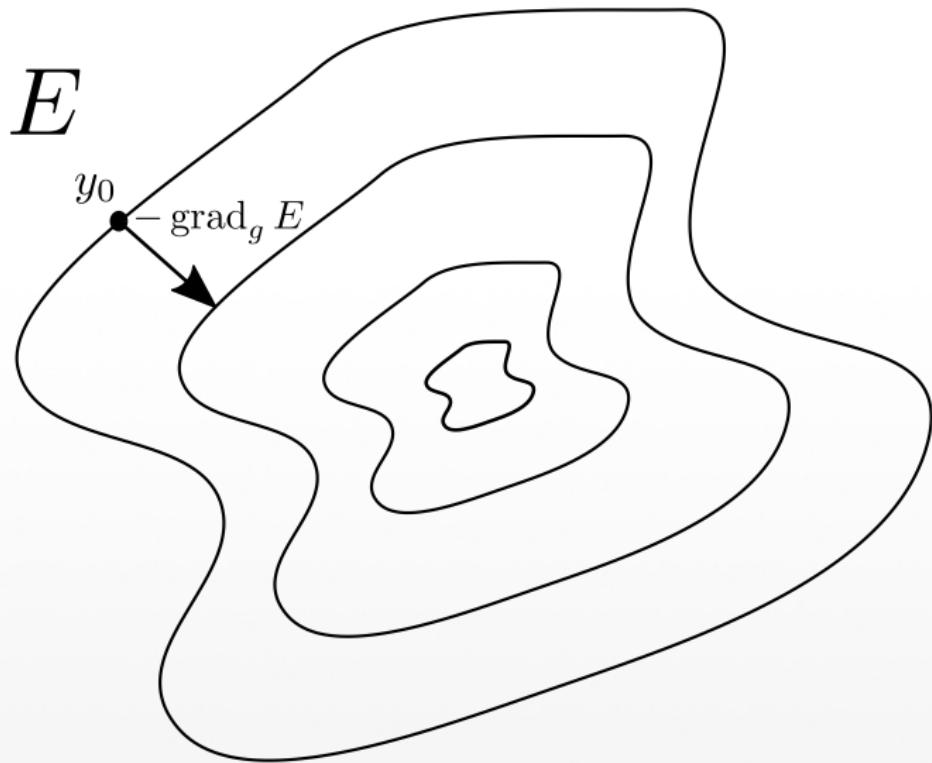
Gradient Flow



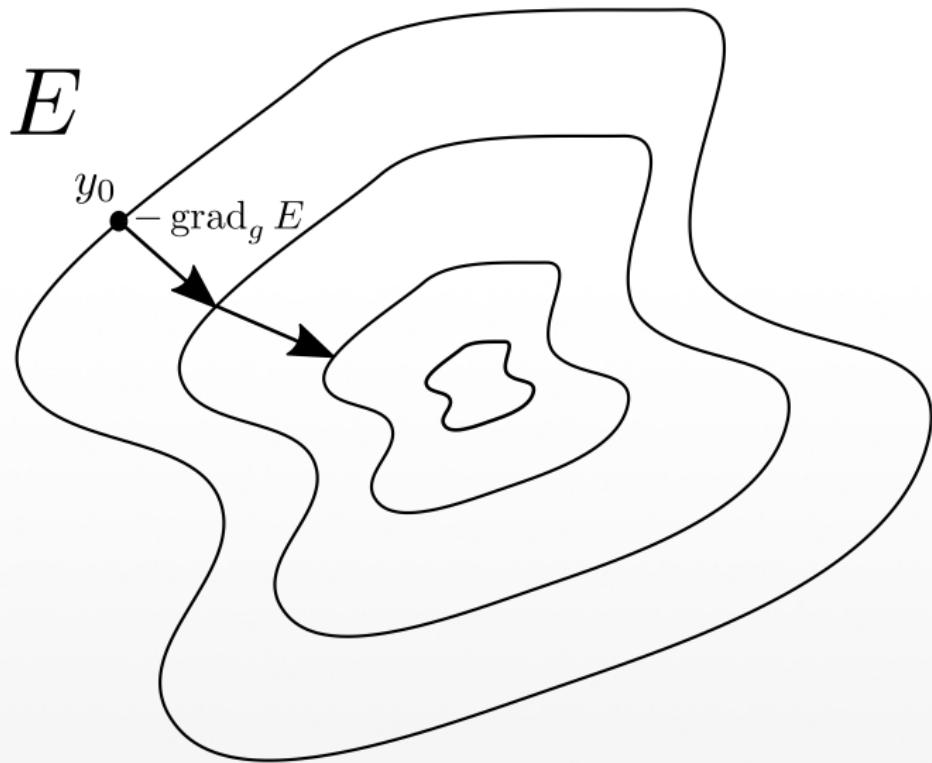
Gradient Flow



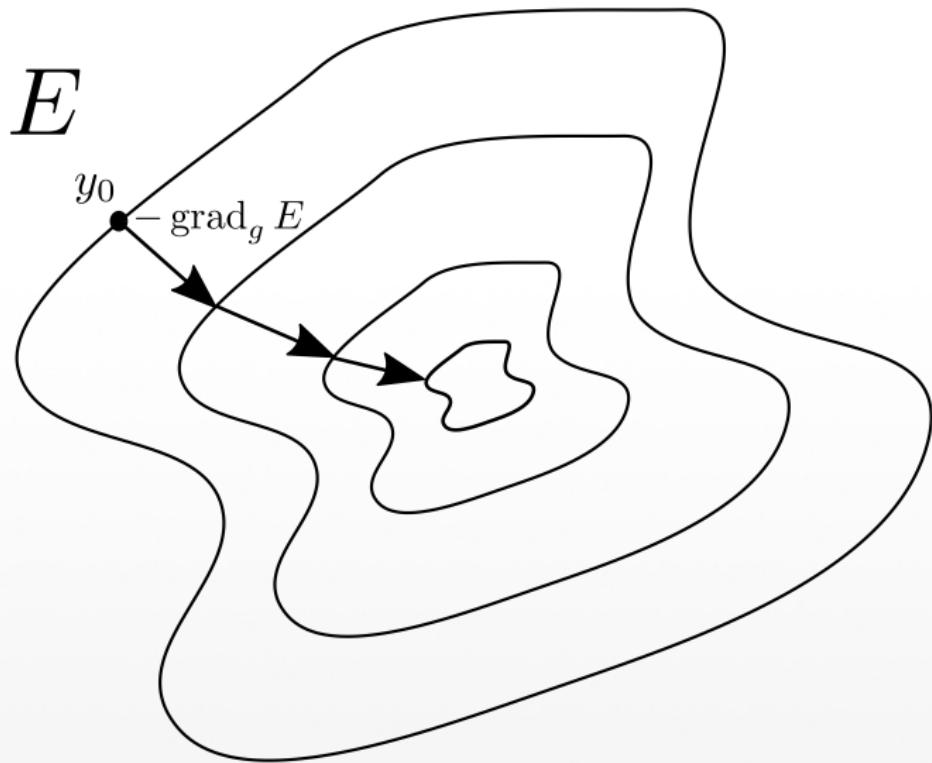
Gradient Flow



Gradient Flow

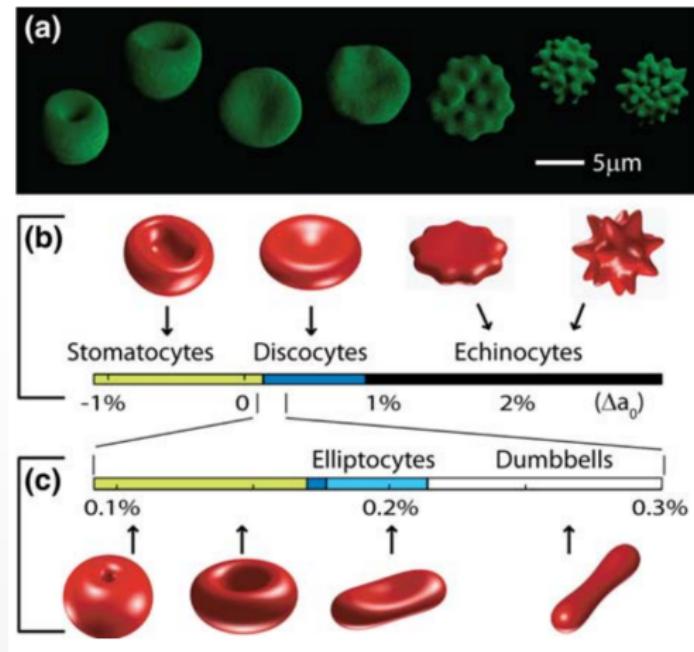


Gradient Flow



Biological Membranes

Computation of biomembranes



[Khairy et al 2008]

Surface Processing and Modeling

Surface denoising



Surface restoration



[Ohlischläger 2010]

Parametric Gradient Flow

Strong formulation

$$y_t = -\text{grad}_g e[y]$$

$$0 = c[y]$$

Parametric Gradient Flow

Strong formulation

$$y_t = -\text{grad}_g e[y]$$

$$0 = c[y]$$

Weak formulation

$$g(y_t, \varphi) = -e'[y](\varphi) \quad \forall \varphi$$

$$0 = c'[y](y_t)$$

Parametric Gradient Flow

Strong formulation

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Energy diminishing property

$$e[y(t)] \leq e[y(s)] \quad \forall t < s$$

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$$e[y] = \int_{\mathcal{M}} da$$

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$$L^2\text{-metric: } g(v, w) = \int_{\mathcal{M}} v \cdot w da$$

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$$L^2\text{-metric: } g(v, w) = \int_{\mathcal{M}} v \cdot w da$$

$$H^1\text{-metric: } g(v, w) = \int_{\mathcal{M}} v \cdot w + \nabla_{\mathcal{M}} v \cdot \nabla_{\mathcal{M}} w da$$

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$$H_{\Delta}^2\text{-metric: } g(v, w) = \int_{\mathcal{M}} v \cdot w + \nabla_{\mathcal{M}} v \cdot \nabla_{\mathcal{M}} w + \Delta_{\mathcal{M}} v \cdot \Delta_{\mathcal{M}} w da$$

Explicit Time Integrators

• Explicit time integrators are simple to implement and can be very efficient.

• They are also very sensitive to numerical errors.

• They are often used in combination with other methods.

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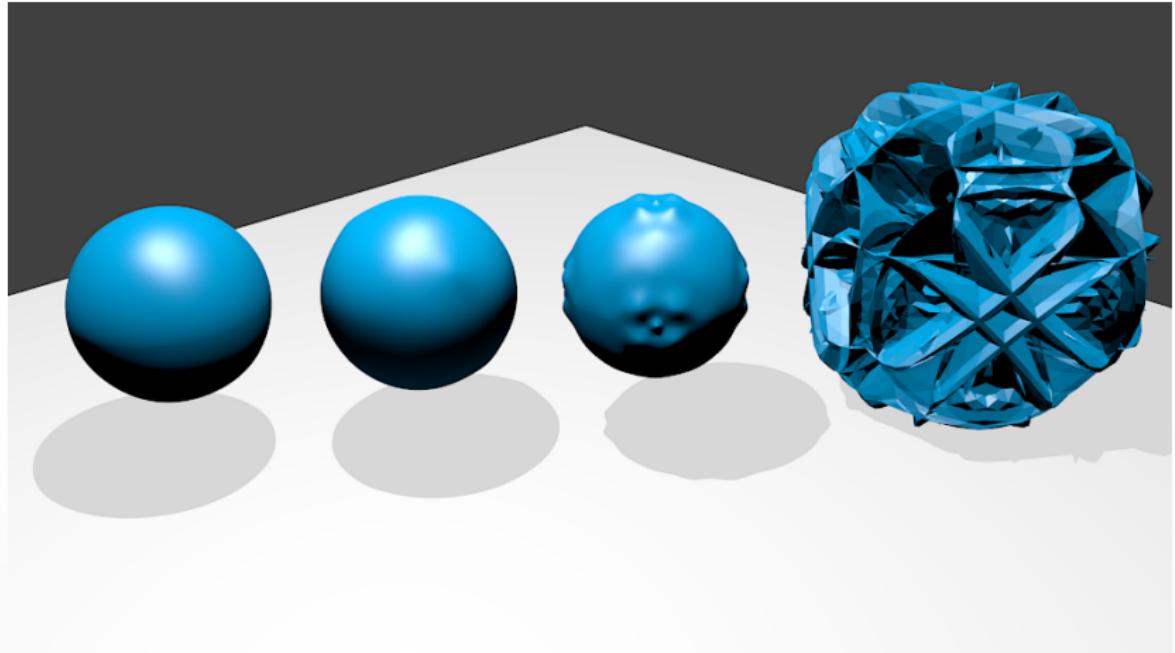
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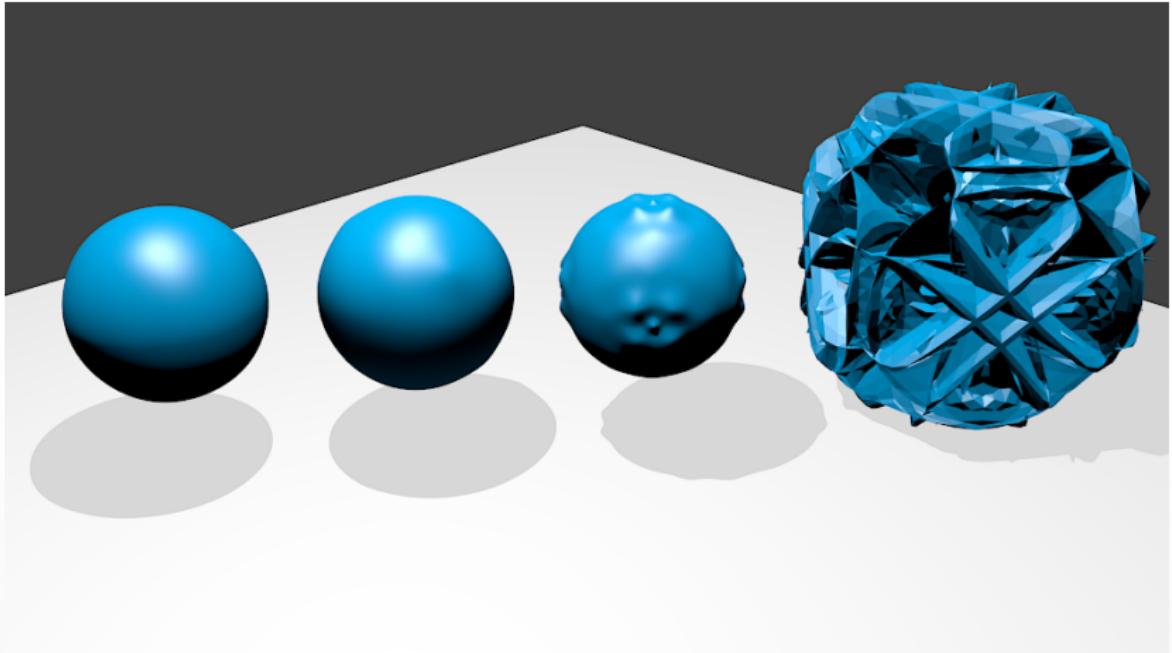
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Explicit Time Integrators



Explicit Time Integrators



⇒Lack of stability

Implicit Time Integrators

Implicit Euler

$$\max_m \|y(t_m) - Y_m\| \leq C(\tau + h^p)$$

- Small time step $\tau = \mathcal{O}(h^p)$ or reduced convergence order

ODE: $\dot{y} = f(t, y), y(0) = y_0$



$$y_{m+1} = y_m + \tau f(t_{m+1}, y_{m+1}) \quad m \geq 0,$$

where $t_{m+1} = t_m + \tau$

Implicit Time Integrators

Higher order implicit Runge-Kutta

$$\max_m \|y(t_m) - Y_m\| \leq C(\tau^p + h^p)$$

ODE: $\dot{y} = f(t, y), y(0) = y_0$

↓

$$y_{m+1} = y_m + \tau \sum_{i=1}^s b_i f(t_m + c_i \tau, y_{mi}) \quad m \geq 0$$

where $t_{m+1} = t_m + \tau$

and

$$y_{mi} = y_m + \tau \sum_{i=1}^s a_{ij} f(t_m + c_i \tau, y_{mj}) \quad i = 1, \dots, s$$

Butcher tableau				
c_1	a_{11}	\dots	a_{1s}	
\vdots	\vdots	\ddots	\vdots	\vdots
c_s	a_{s1}	\dots	a_{ss}	
	b_1	\dots	b_s	

Implicit Time Integrators

Higher order implicit Runge-Kutta

$$\max_m \|y(t_m) - Y_m\| \leq C(\tau^p + h^p)$$

Gradient Flow: $\mathbf{G}_Y(\dot{Y}, \Psi) = -\mathbf{E}'[Y](\Psi) - \Lambda \mathbf{C}'[Y](\Psi), \quad \forall \Psi$
 $\mathbf{C}'[Y](\dot{Y}) = 0$

$$\begin{aligned} &\Downarrow \\ &Y_{m+1} = Y_m + \tau \sum_{i=1}^s b_i \dot{Y}_{mi} \\ &Y_{mi} = Y_m + \tau \sum_{j=1}^s a_{ij} \dot{Y}_{mj}, \quad i = 1, \dots, s, \end{aligned}$$

where the internal stages satisfy

$$\begin{aligned} \mathbf{G}_{Y_{mi}}(\dot{Y}_{mi}, \Psi) &= -\mathbf{E}'[Y_{mi}](\Psi) - \Lambda_i \mathbf{C}'[Y_{mi}](\Psi) \quad \forall \Psi, \quad i = 1, \dots, s, \\ \mathbf{C}'[Y_{mi}](\dot{Y}_{mi}) &= 0 \end{aligned}$$

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c_1	a_{11}	\dots	a_{1s}	
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Implicit Time Integrators

Higher order implicit Runge-Kutta

$$\max_m \|y(t_m) - Y_m\| \leq C(\tau^p + h^p)$$

Theorem

$$\mathbf{E}[Y_{m+1}] \leq \mathbf{E}[Y_m] \quad m \geq 0$$

Gradient Flow: $\mathbf{G}_Y(\dot{Y}, \Psi) = -\mathbf{E}'[Y](\Psi) - \Lambda \mathbf{C}'[Y](\Psi), \quad \forall \Psi$

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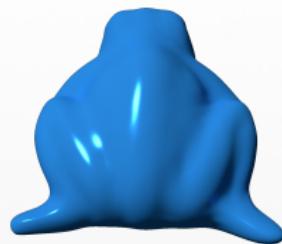
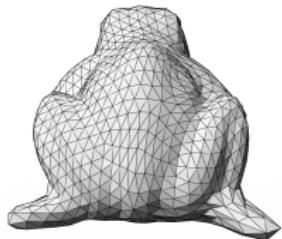
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Results

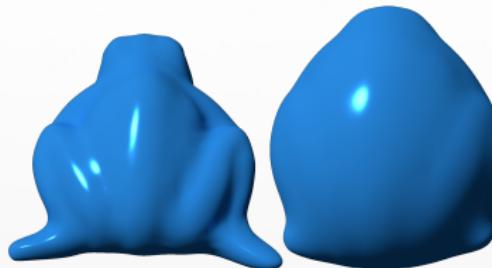
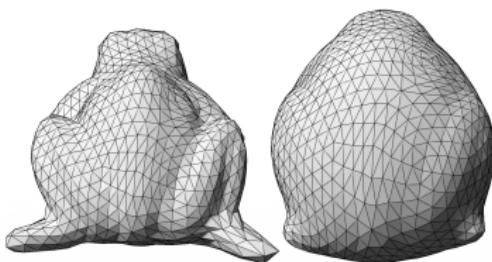
H_{Δ}^2 -Willmore flow



Initial

Results

H_{Δ}^2 -Willmore flow

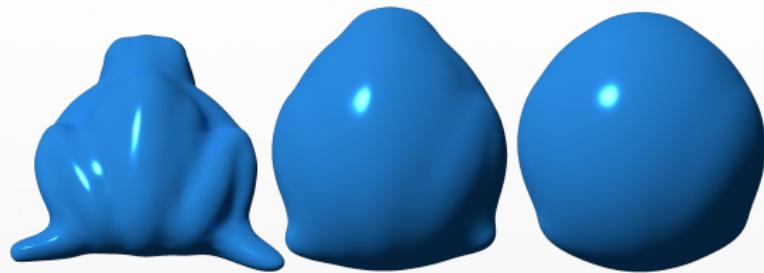
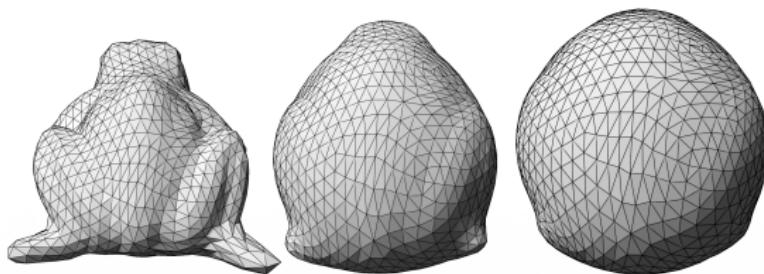


Initial

Step 1

Results

H_{Δ}^2 -Willmore flow



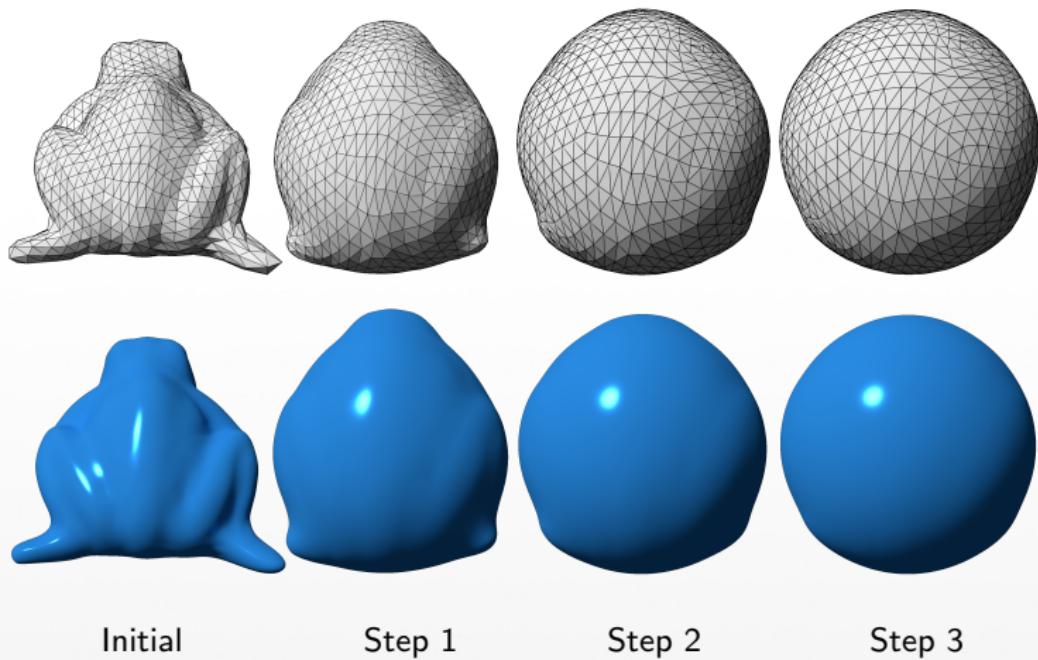
Initial

Step 1

Step 2

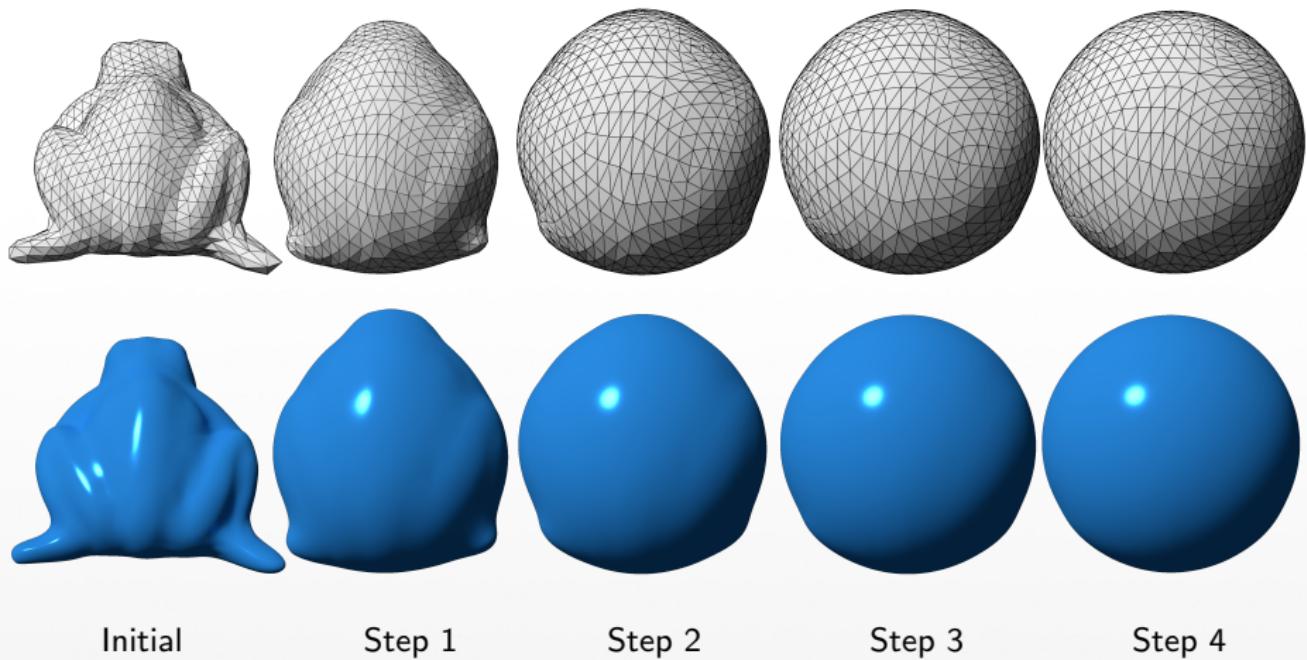
Results

H_{Δ}^2 -Willmore flow

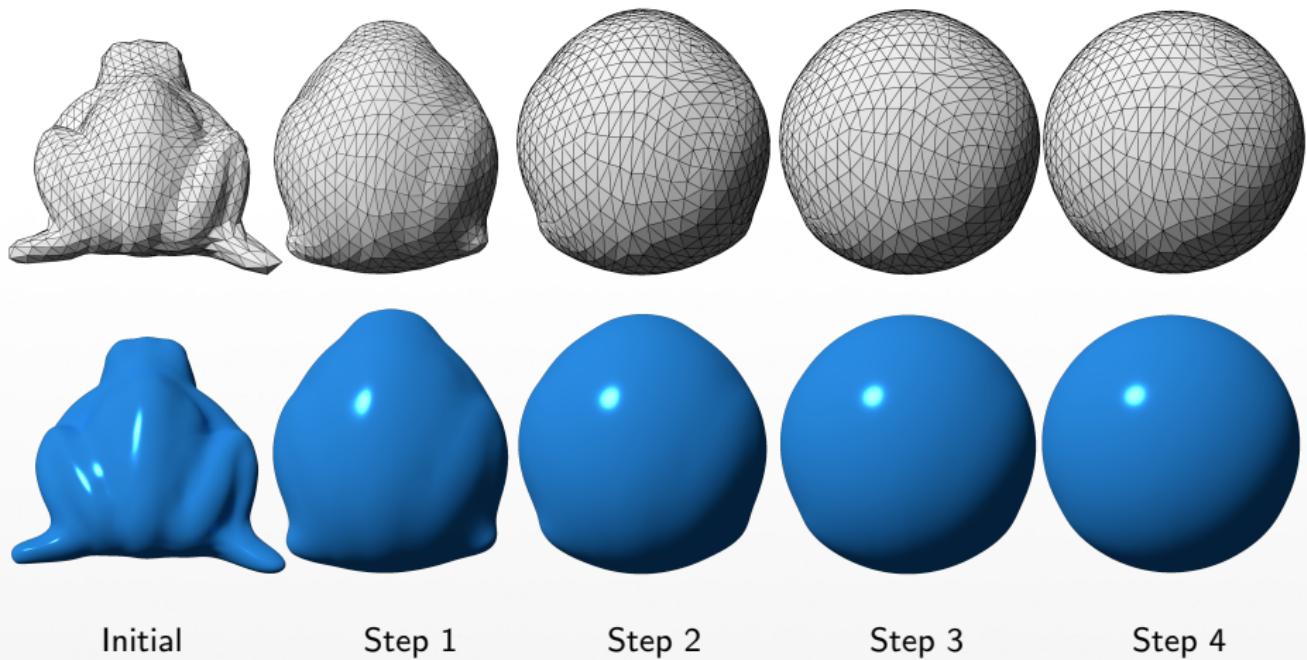


Results

H_{Δ}^2 -Willmore flow



H_{Δ}^2 -Willmore flow



Large Time Steps: $\tau = 0.75$, $h = 0.11$

Results

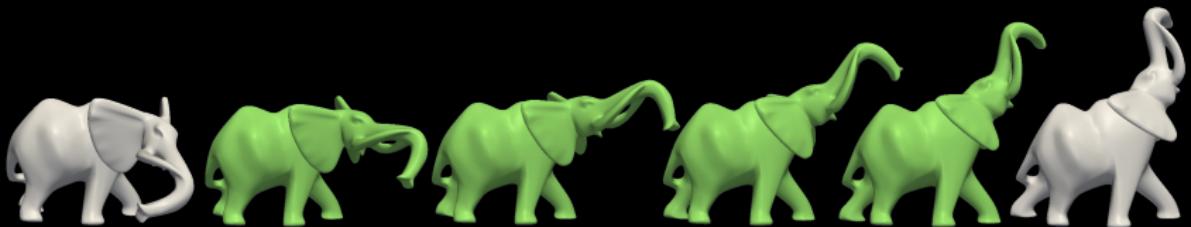
H^1 -Willmore flow



H^2_Δ -Willmore flow



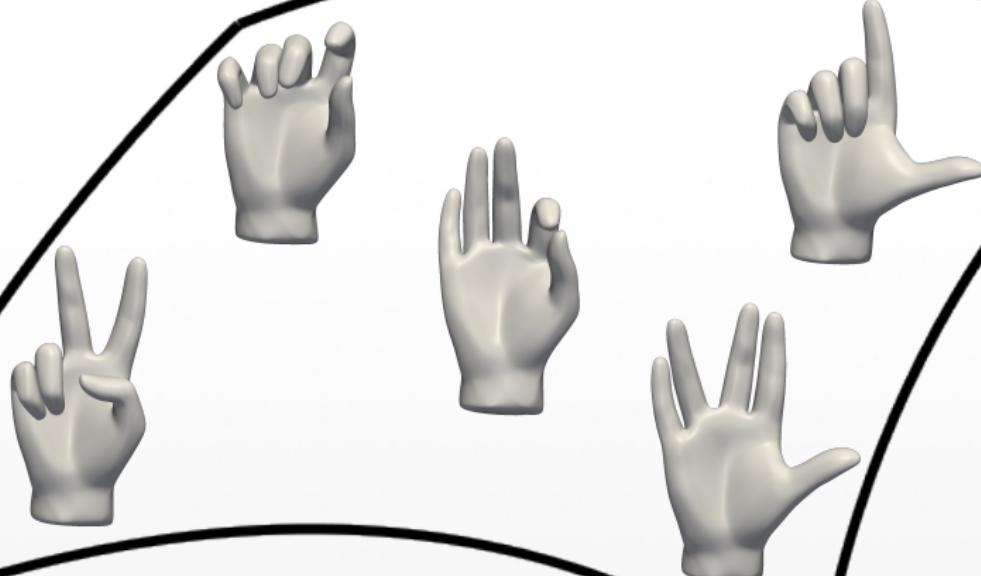
Bézier curves and Splines in Shape Space



Shape Space



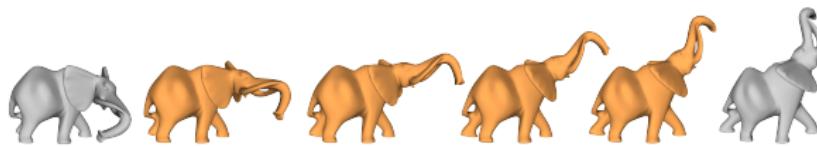
Shell space as Riemannian manifold



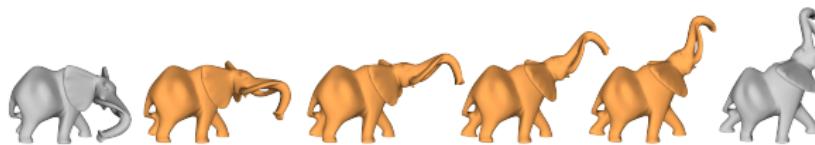
Geodesic Calculus



Geodesic Calculus

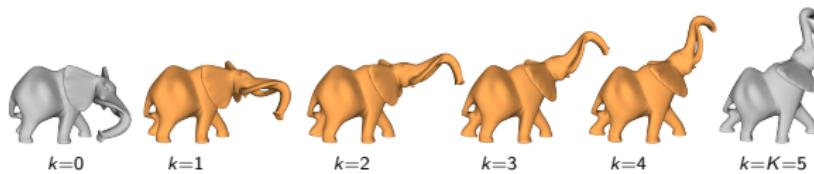


Geodesic Calculus



[Heeren et al 2012, 2014] developed a **time discrete geodesic calculus in shell space**

Geodesic Calculus



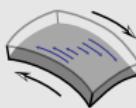
[Heeren et al 2012, 2014] developed a **time discrete geodesic calculus in shell space**

Discrete geodesics are (local) minimizers of the discrete path energy

$$\mathcal{E}[y_0, \dots, y_K] = K \sum_{k=1}^K \mathcal{W}[y_{k-1}, y_k]$$

$$\text{dist}^2(y_{k-1}, y_k) \approx \mathcal{W}[y_{k-1}, y_k] = \delta \mathcal{W}_{\text{tang}}[y_{k-1}, y_k] + \delta^3 \mathcal{W}_{\text{bend}}[y_{k-1}, y_k]$$

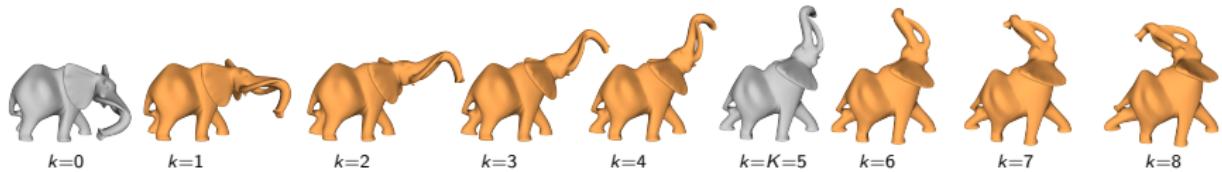
tangential distortion



bending



Geodesic Calculus



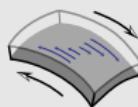
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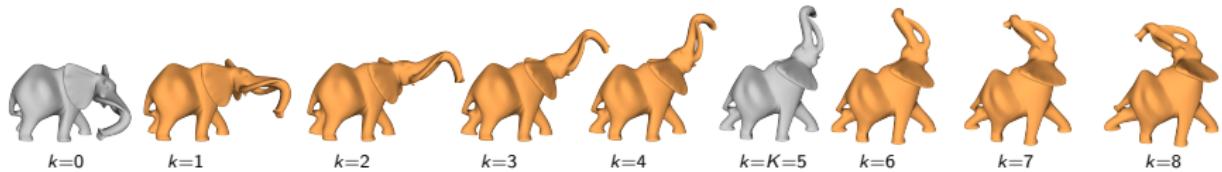
bending



Discrete exponential map defined variationally based on short discrete geodesics

$$y_k = \arg \min_y 2(\mathcal{W}[y_{k-2}, y_{k-1}] + \mathcal{W}[y_{k-1}, y])$$

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tangential distortion



bending

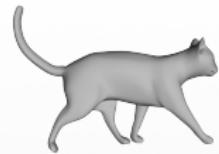
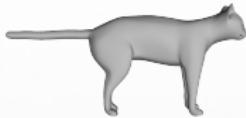


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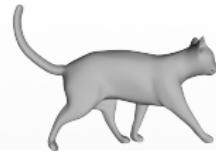
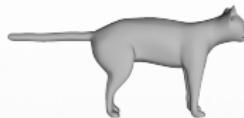
Discrete logarithm defined as initial displacements of shortest discrete geodesics

Geodesic Calculus



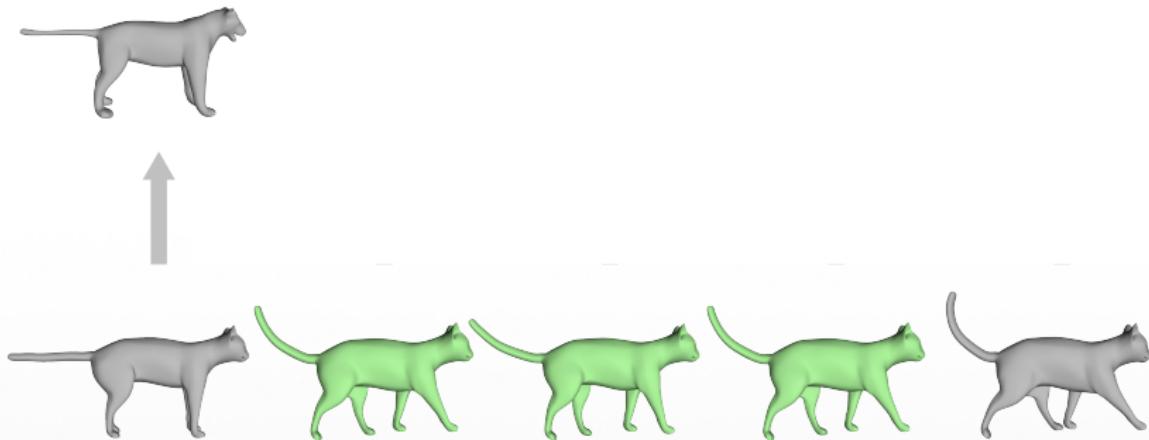
Discrete parallel transport defined via the construction of discrete
Riemannian parallelograms

Geodesic Calculus



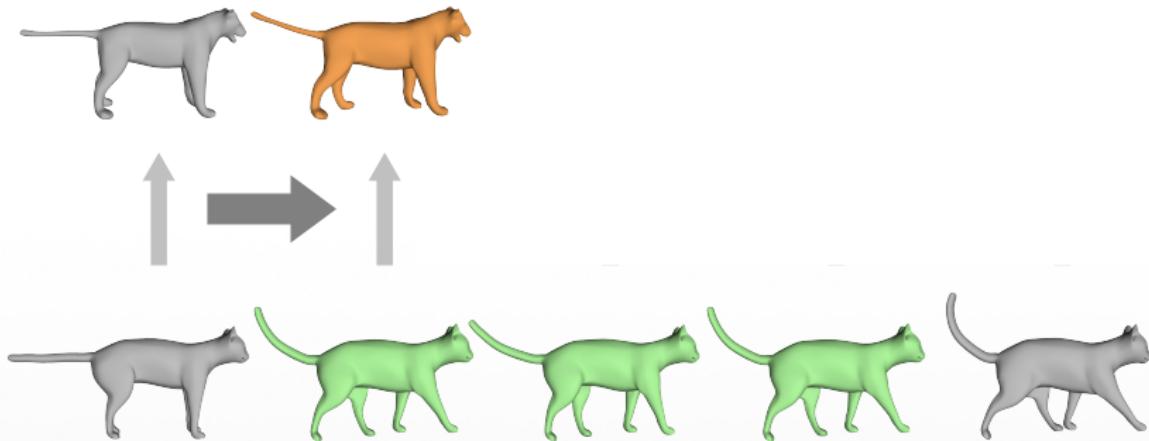
Discrete parallel transport defined via the construction of discrete
Riemannian parallelograms

Geodesic Calculus



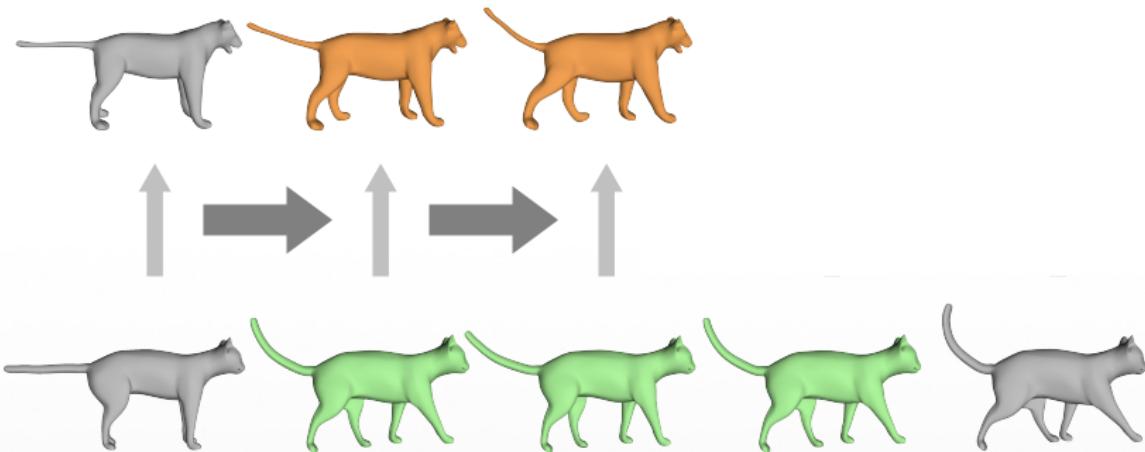
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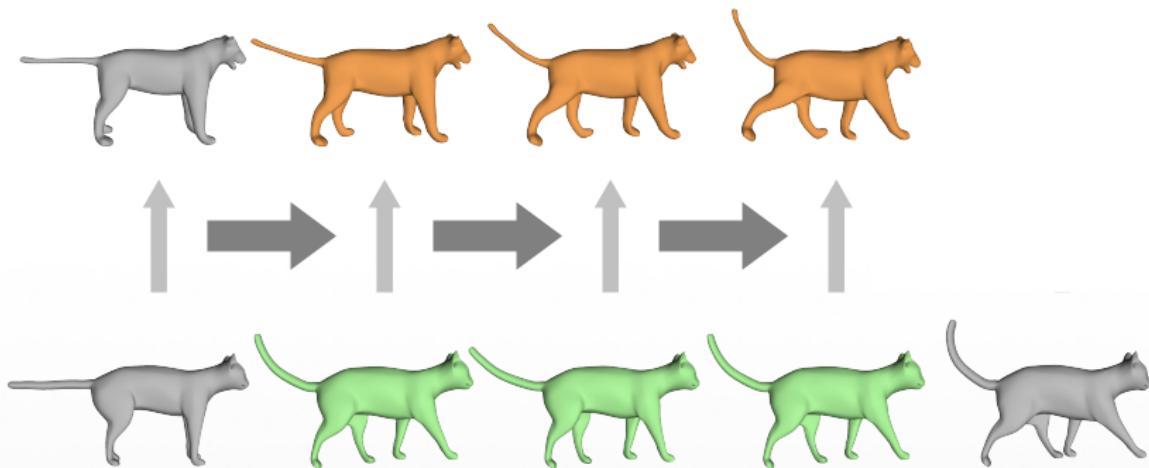
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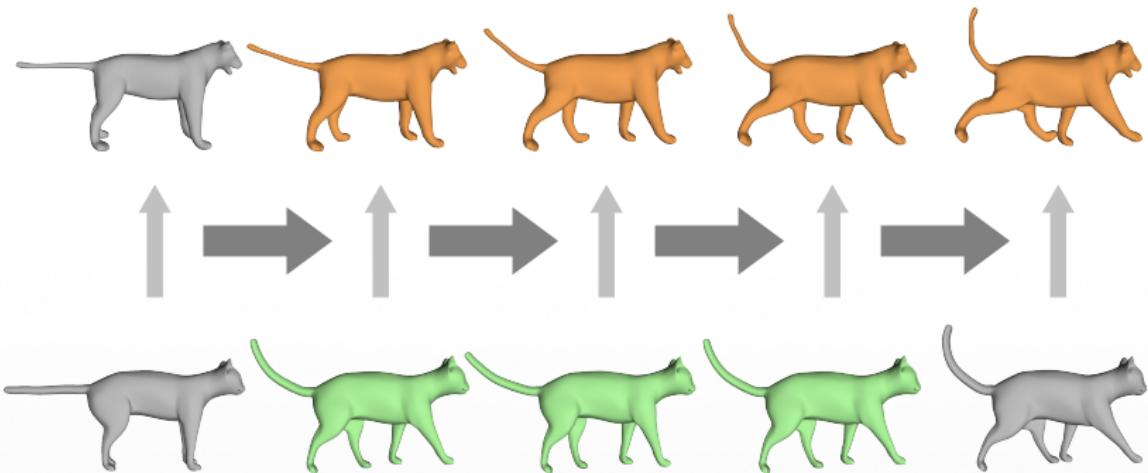
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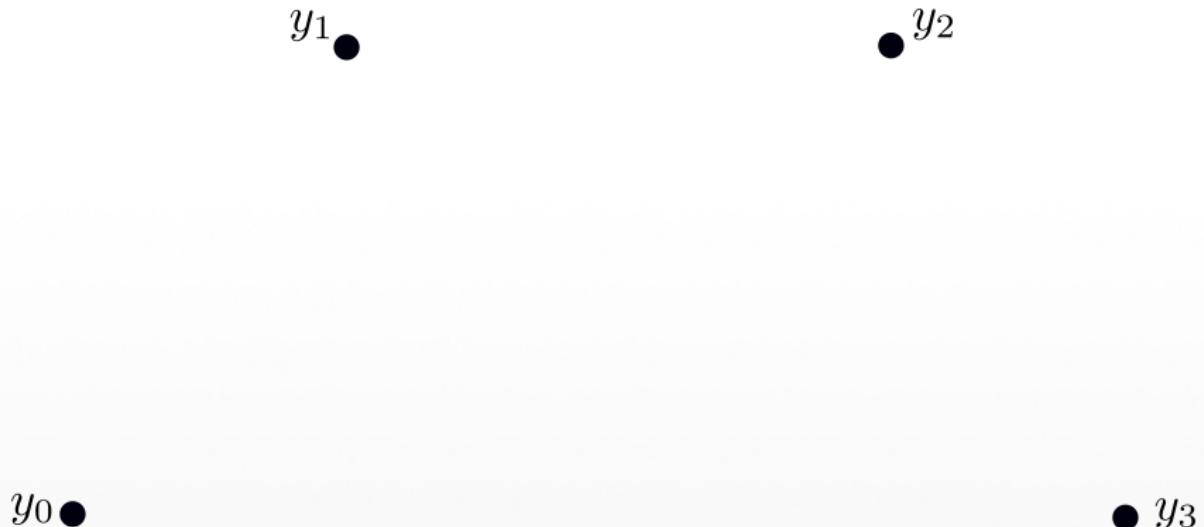


Discrete parallel transport defined via the construction of discrete Riemannian parallelograms

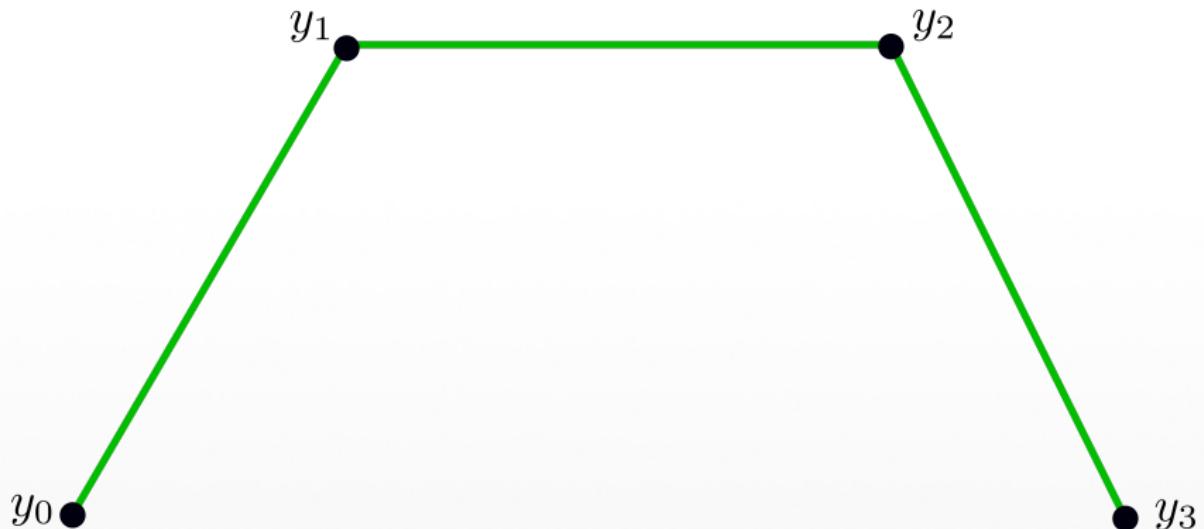
Bézier curves/De Casteljau Algorithm in \mathbb{R}^n

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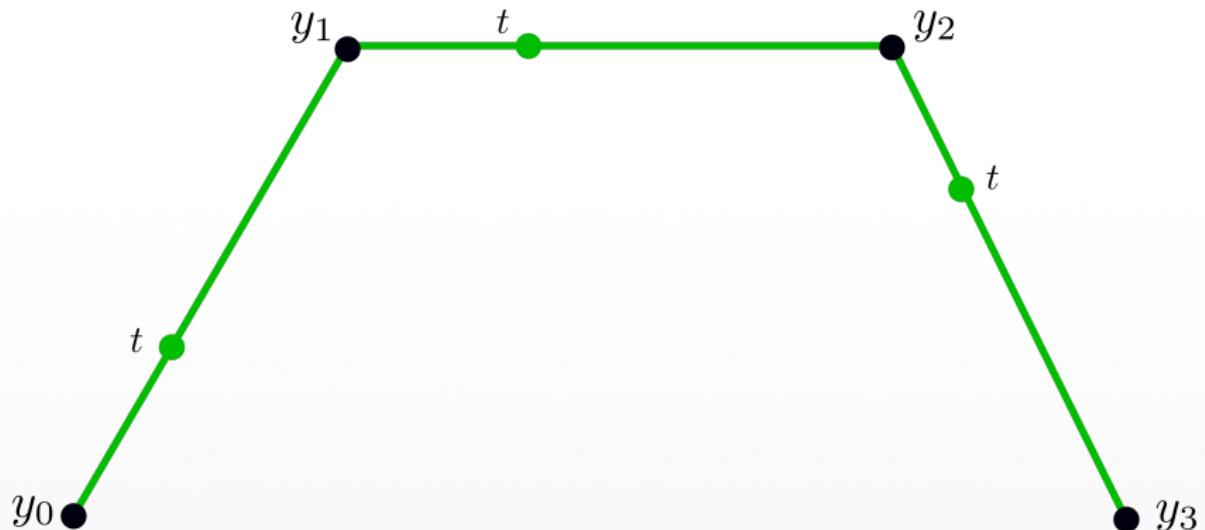
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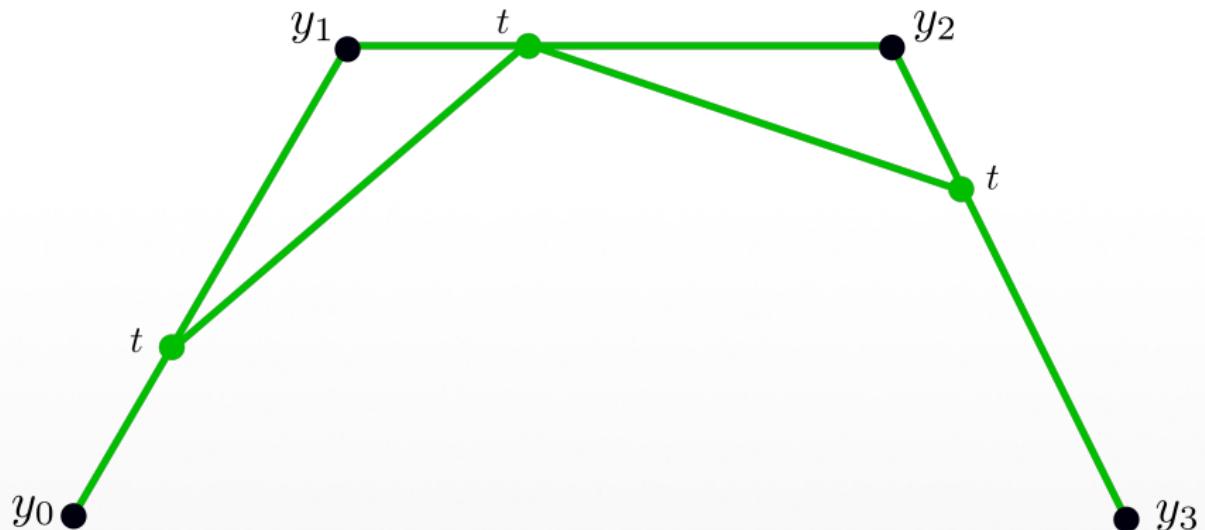
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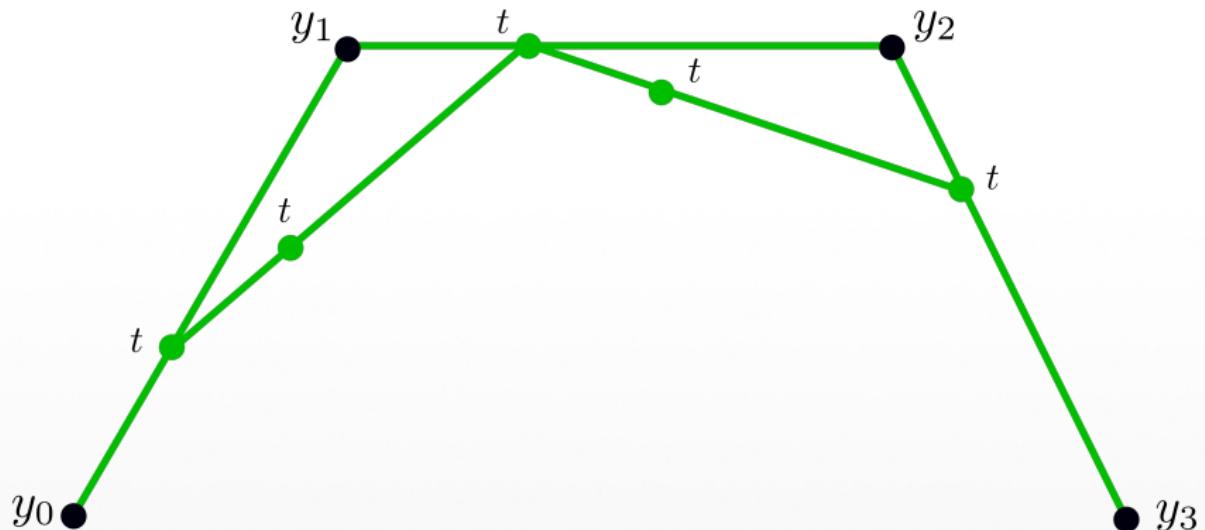
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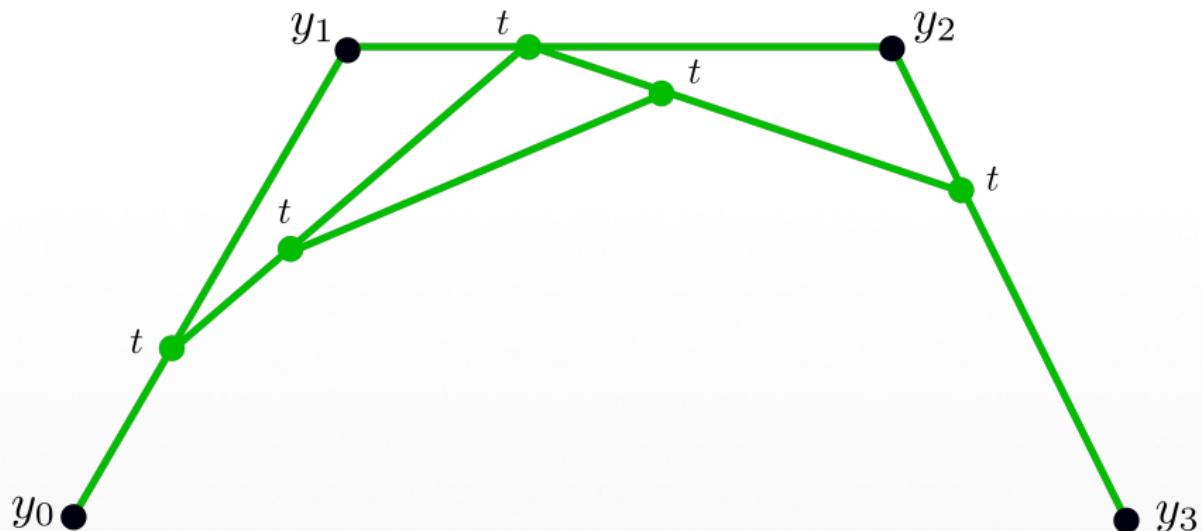
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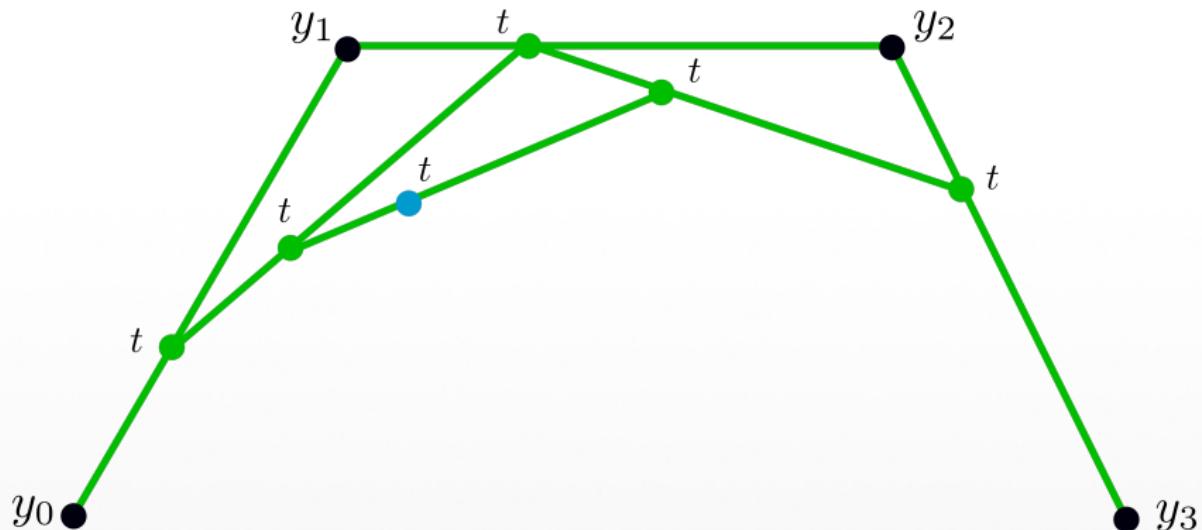
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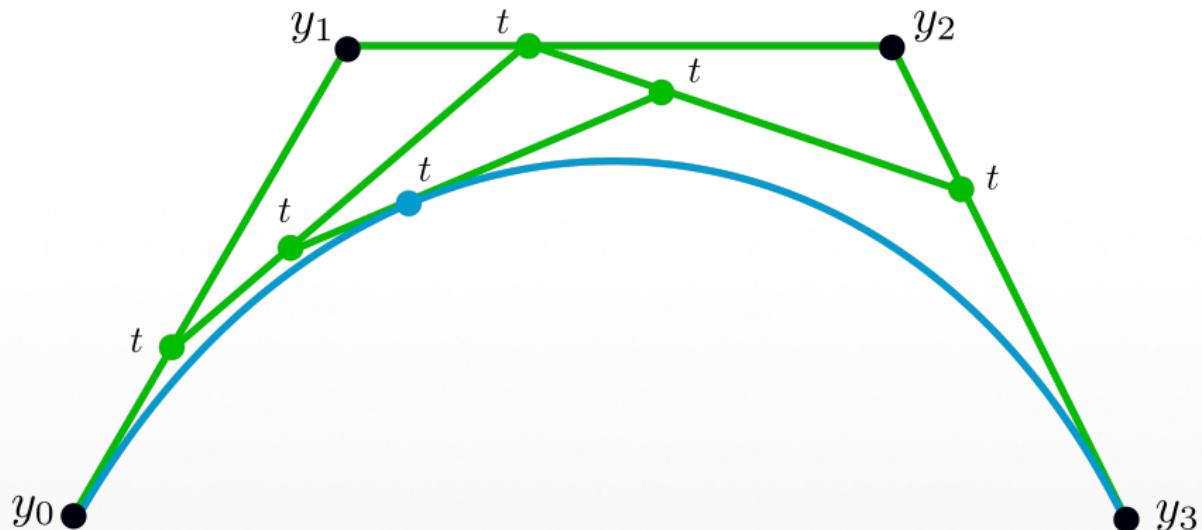
Bézier curves/De Casteljau Algorithm in \mathbb{R}^n



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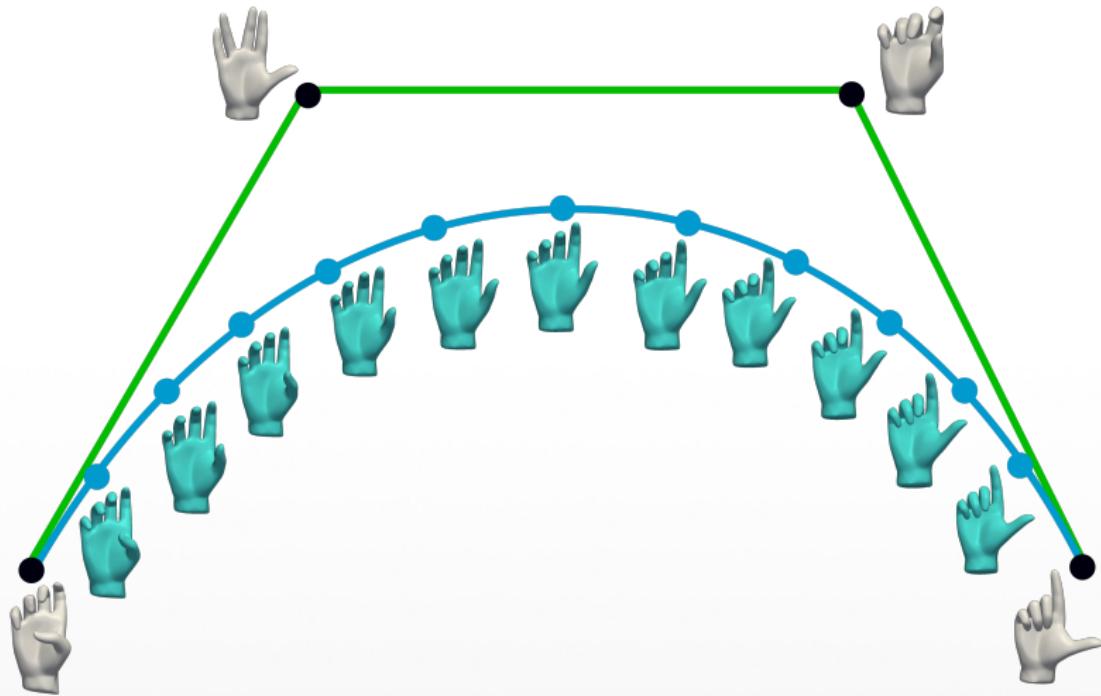
Bézier curves/De Casteljau Algorithm in \mathbb{R}^n



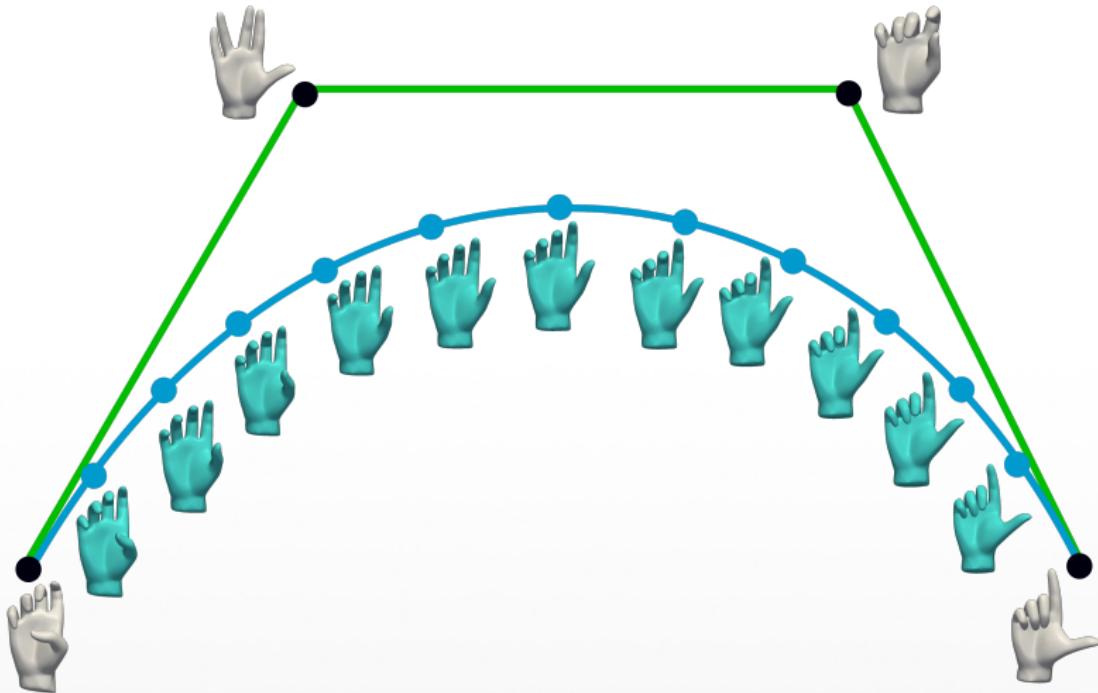
Bézier Curves in Shape Space



Bézier Curves in Shape Space



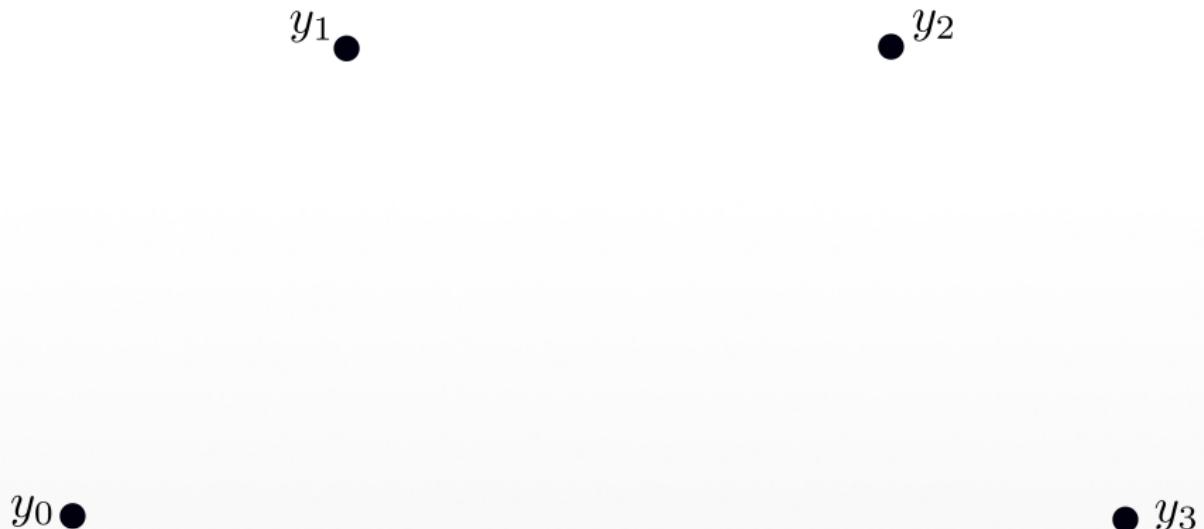
Bézier Curves in Shape Space



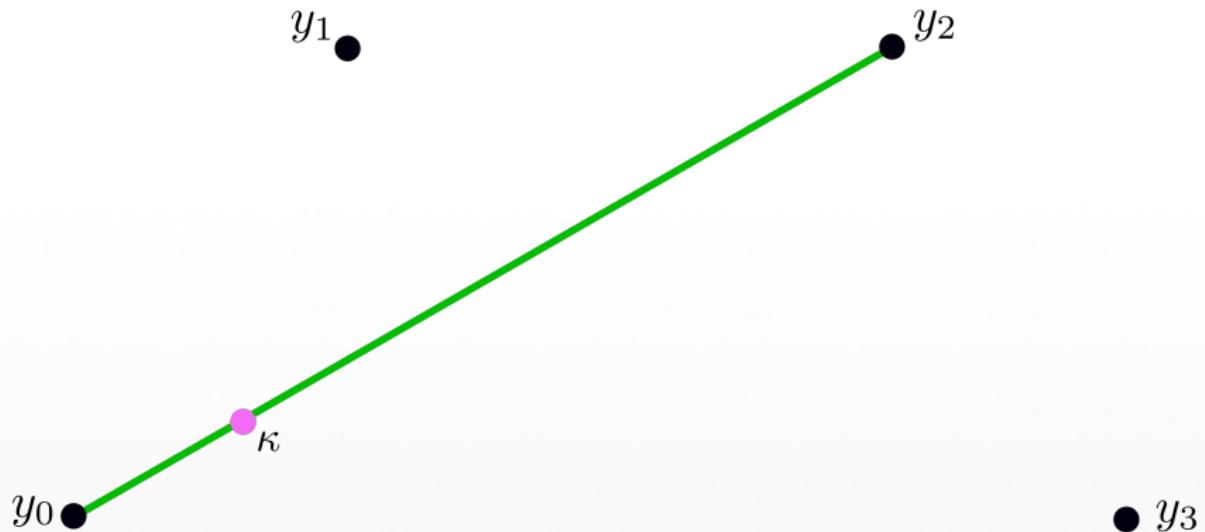
Problems

- Do not interpolate input data
- Evaluation at parameter value depends on all input shapes

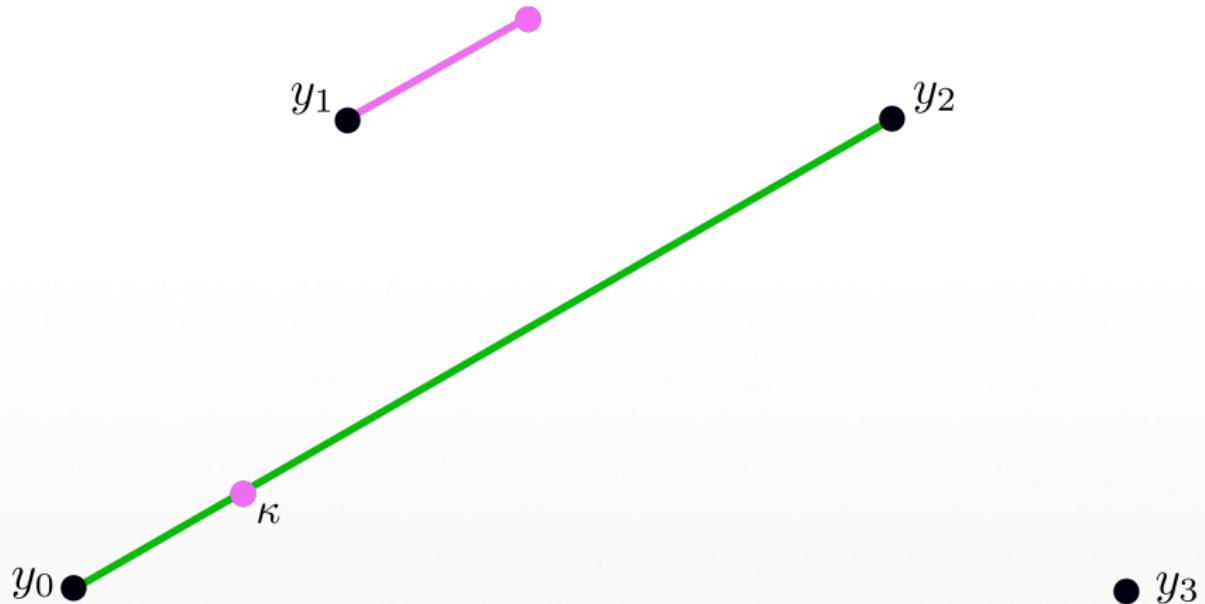
Cardinal Splines in \mathbb{R}^n



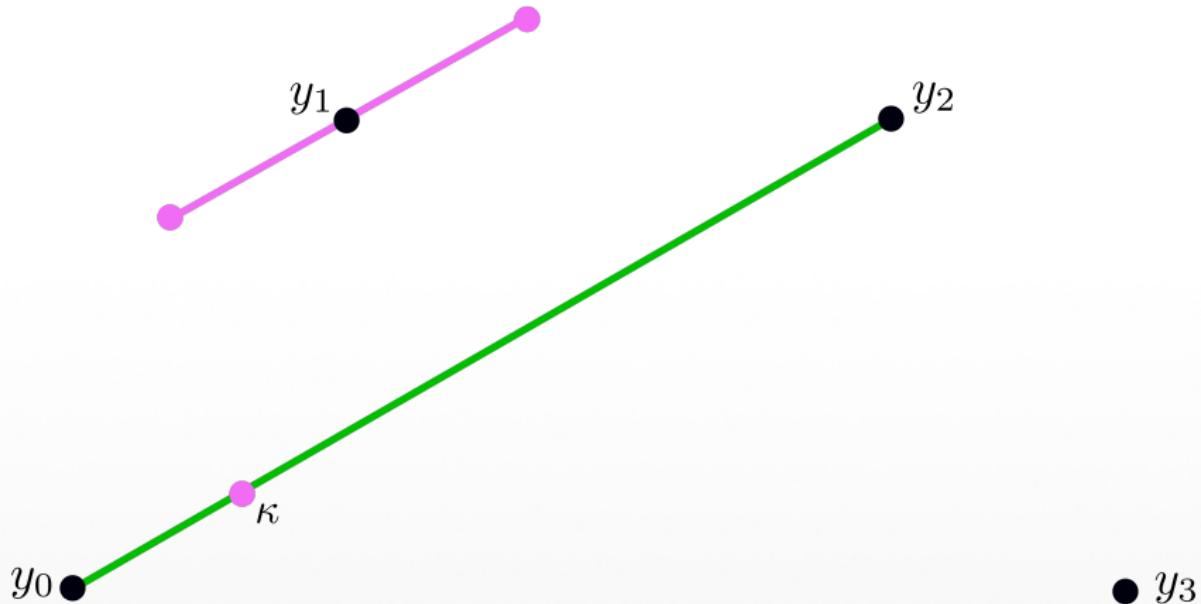
Cardinal Splines in \mathbb{R}^n



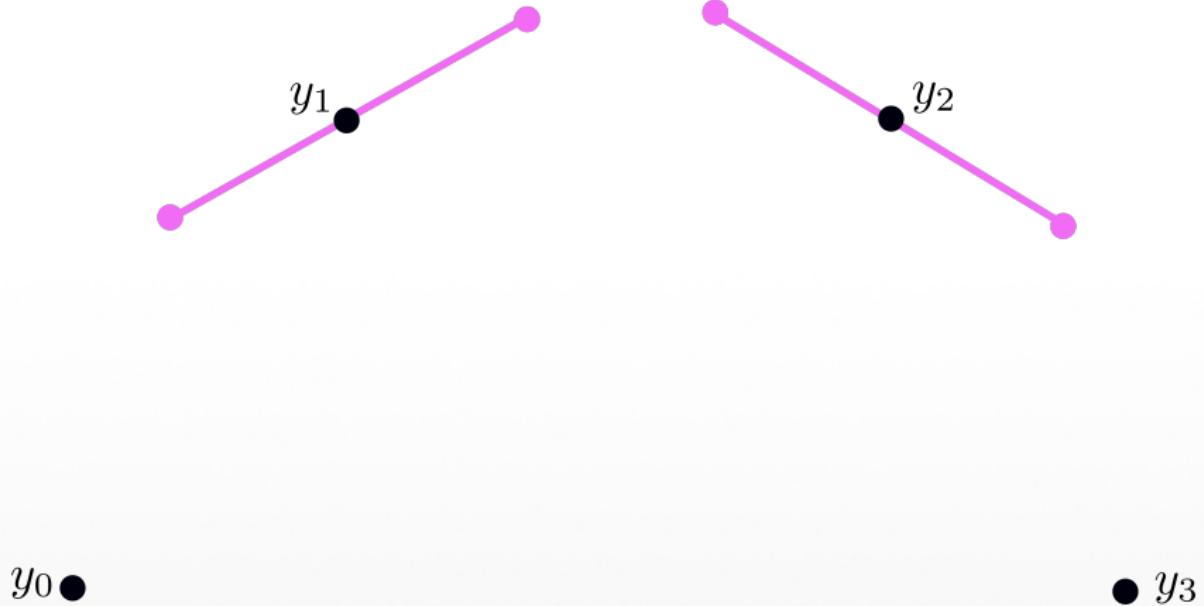
Cardinal Splines in \mathbb{R}^n



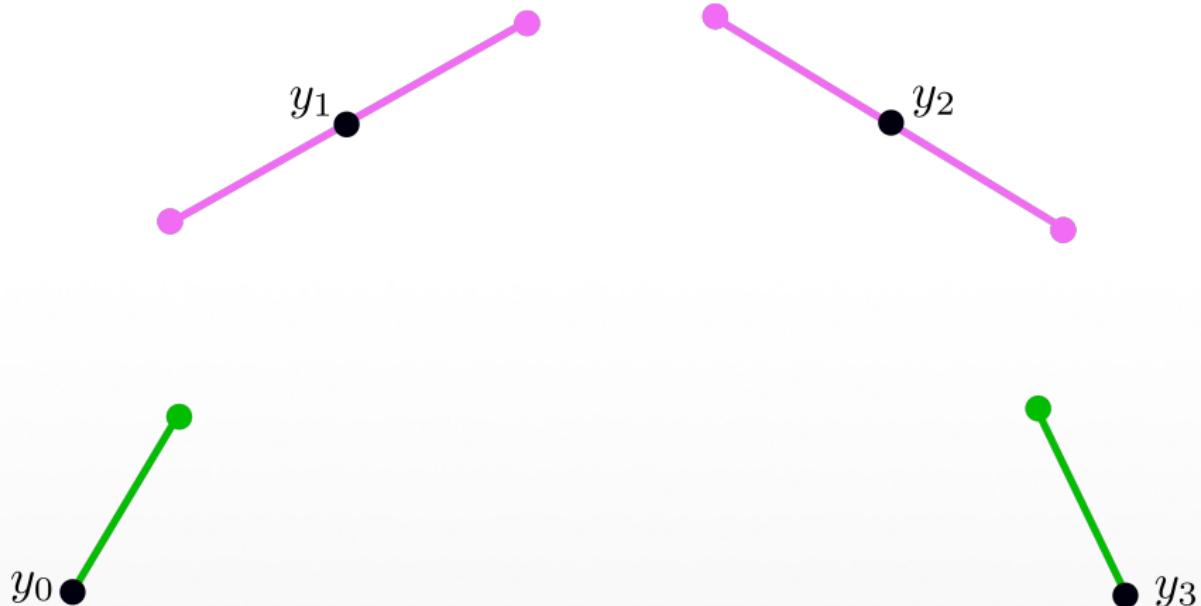
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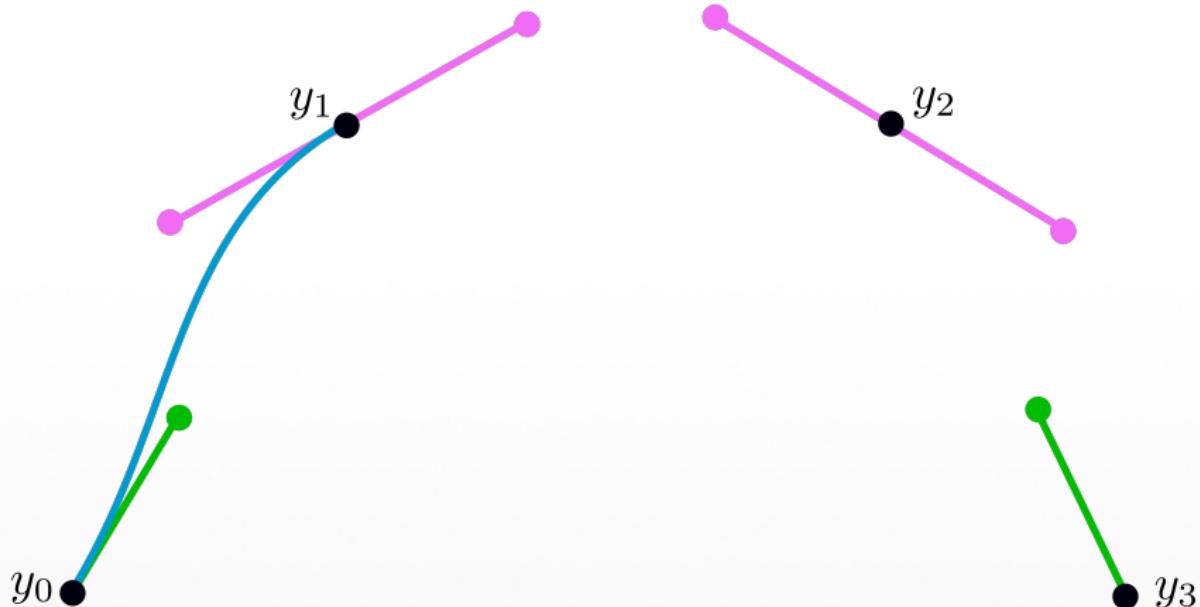
Cardinal Splines in \mathbb{R}^n



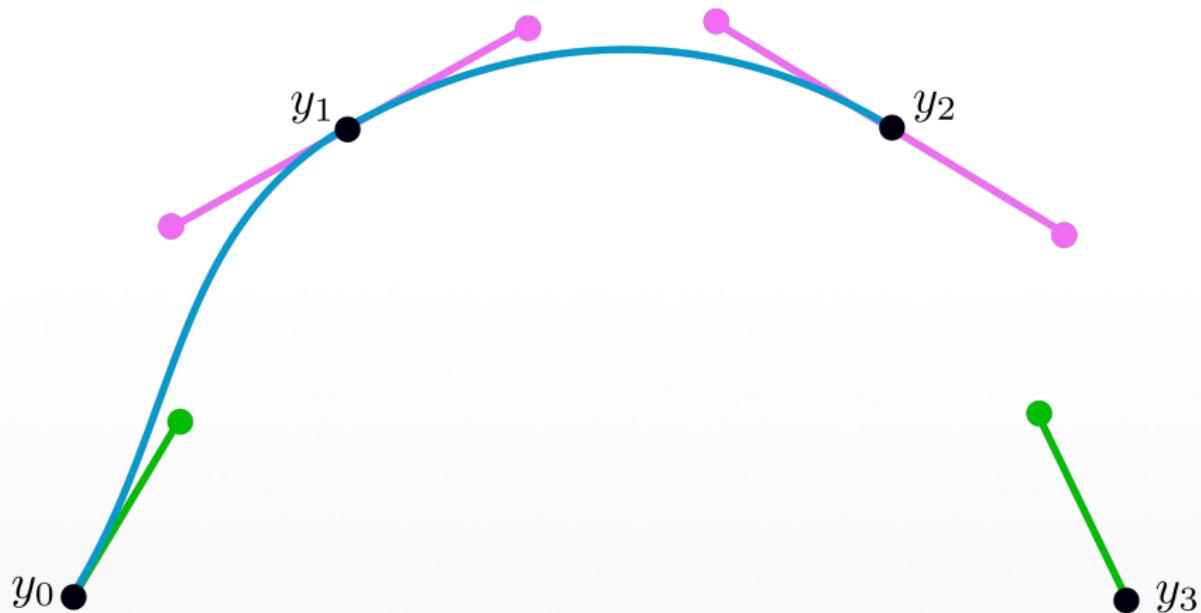
Cardinal Splines in \mathbb{R}^n



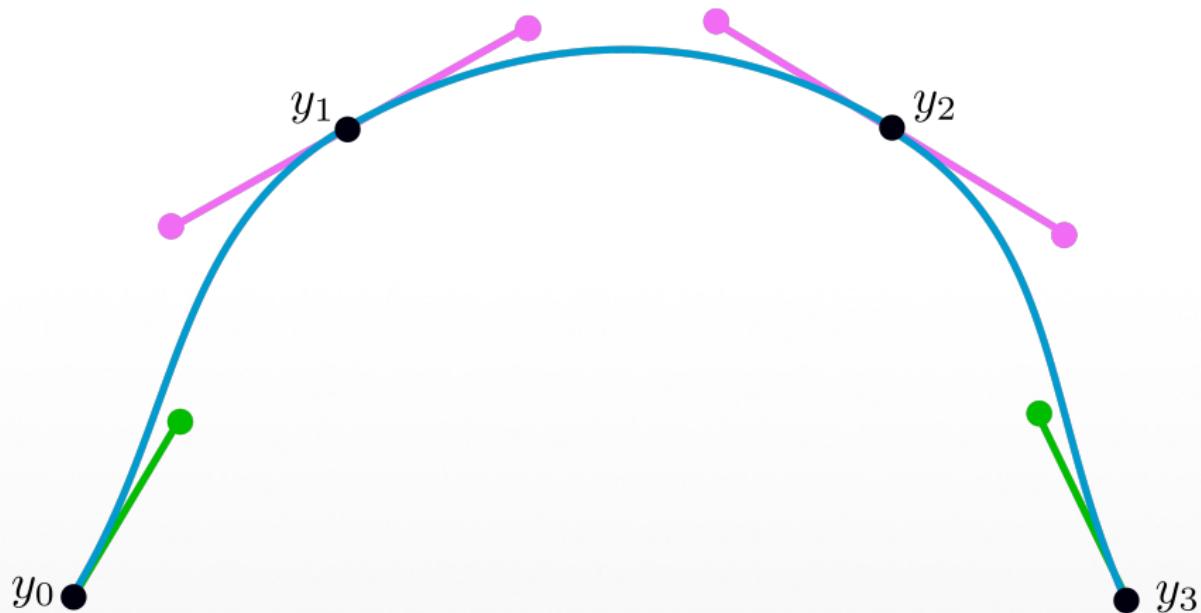
Cardinal Splines in \mathbb{R}^n



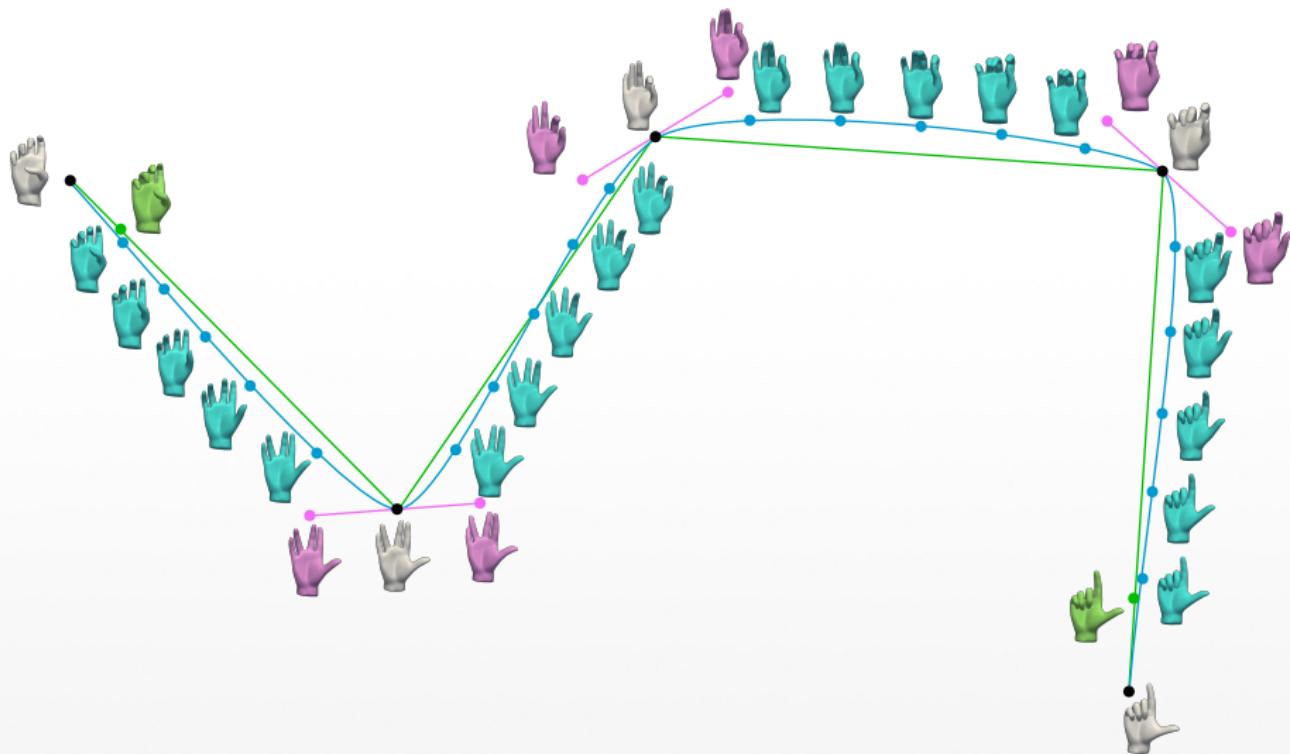
Cardinal Splines in \mathbb{R}^n



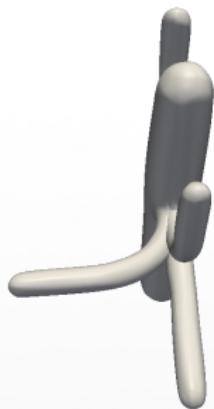
Cardinal Splines in \mathbb{R}^n



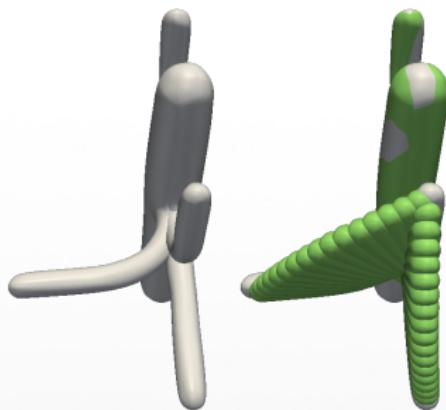
Cardinal Splines in Shape Space



Tension parameter

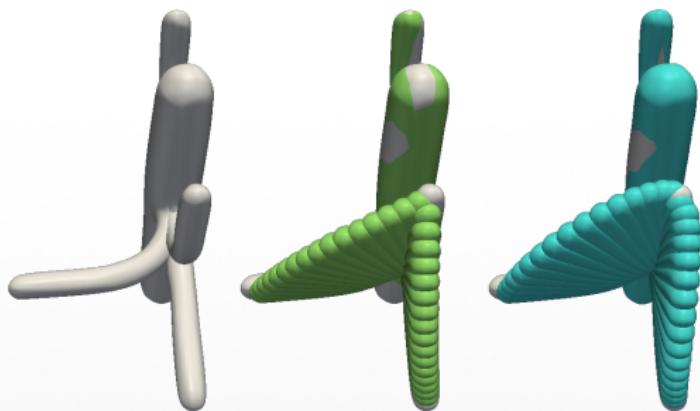


Tension parameter



$$\kappa = 0$$

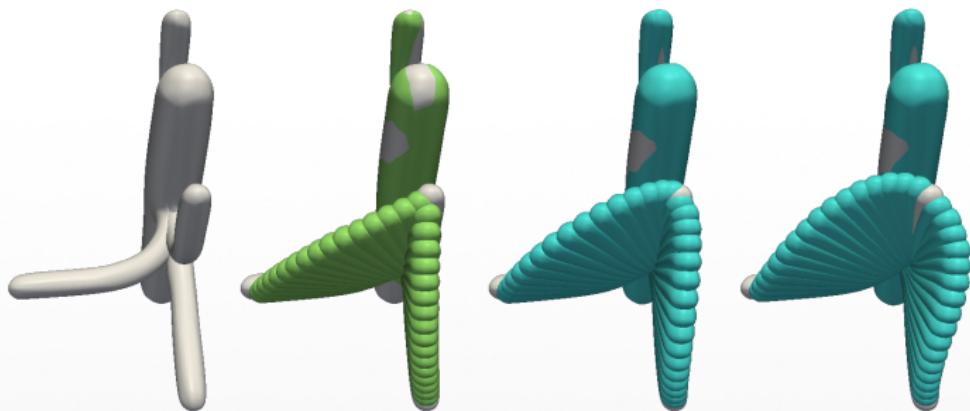
Tension parameter



$\kappa = 0$

$\kappa = 0.5$

Tension parameter

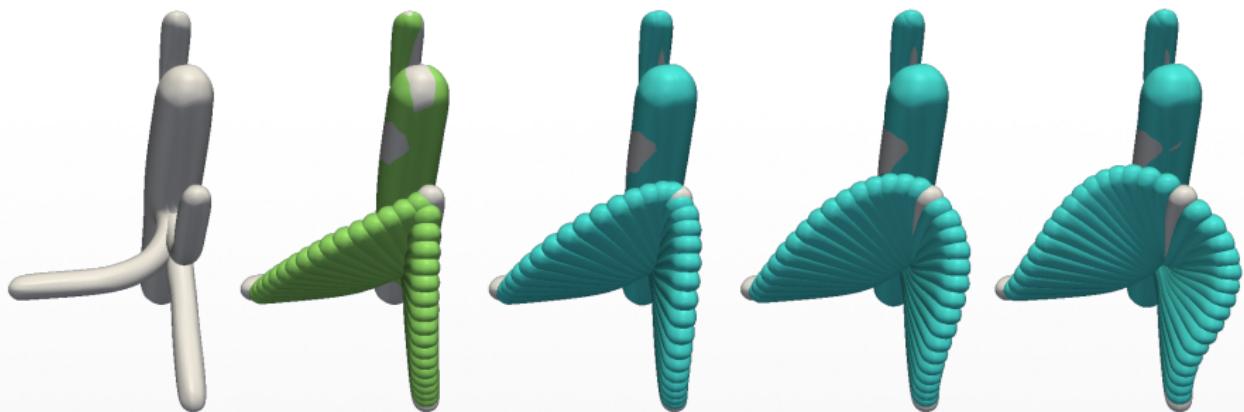


$\kappa = 0$

$\kappa = 0.5$

$\kappa = 1$

Tension parameter



$\kappa = 0$

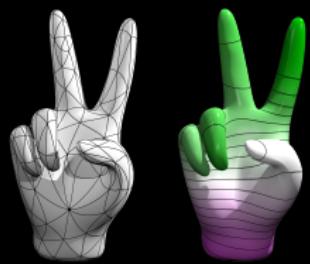
$\kappa = 0.5$

$\kappa = 1$

$\kappa = 1.5$

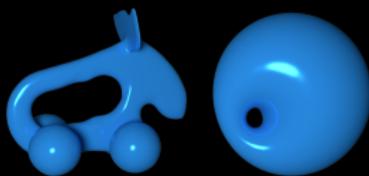
Overview

Isogeometric
Subdivision Method



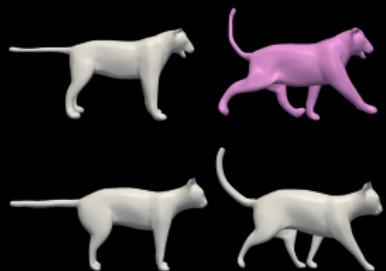
⇒ Robust and efficient
numerical integration

Parametric
Gradient Flows



Higher order
⇒ Time and Space
Discretization

Shape Space



⇒ Bézier curves
and splines