

# Embodied Vision

Physical Modeling: Time Integration, Mass-Spring System  
and Finite Element Method

Tsung-Wei Ke

Spring 2026

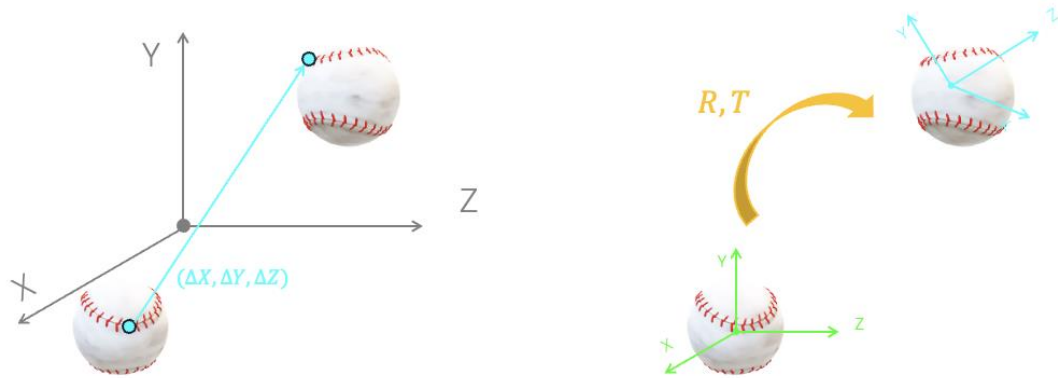


# Disclaimer

- This lecture borrows contents heavily from
  - [Physics-based Animation](#) by David I.W Levin at University of Toronto
  - [Physics-based Animation of Solids and Fluids](#) by Minchen Li at CMU
- This is an introductory lecture to physical modeling. Check the advanced courses in physic-based simulation for more details.

# Recap

## Rigid-body Motion



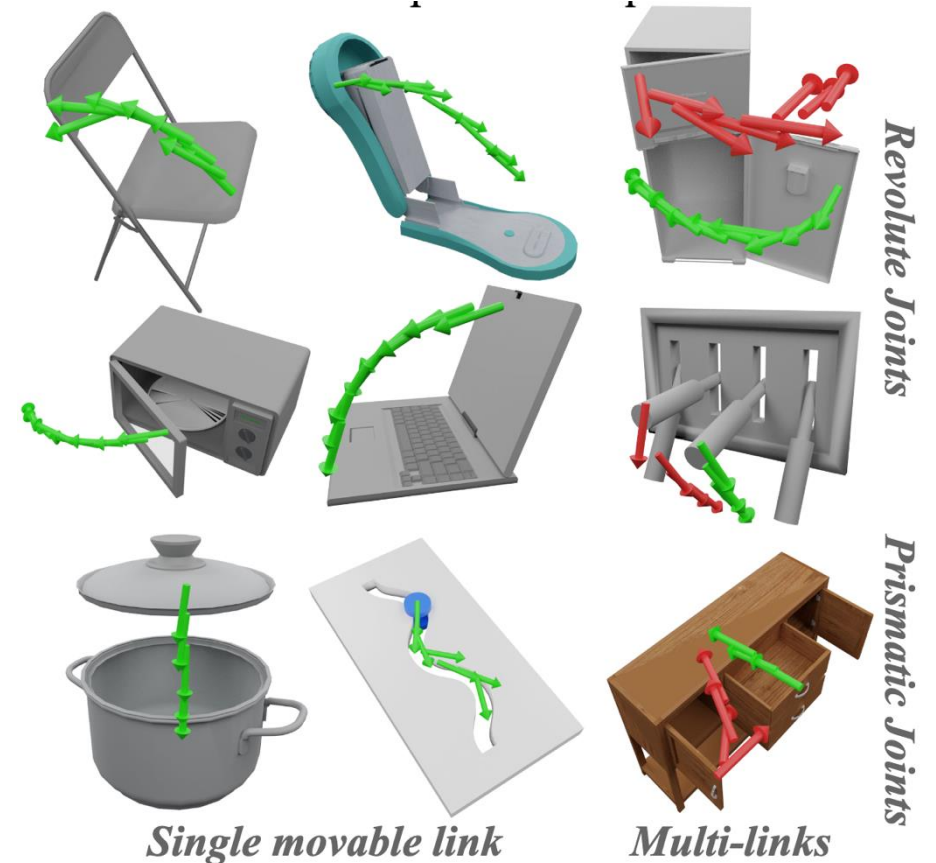
Rigid-body physic law:

$$\frac{d}{dt} \mathbf{q}(t) = \frac{d}{dt} \begin{bmatrix} \mathbf{t}(t) \\ \mathbf{R}(t) \\ \mathbf{v}(t) \\ \boldsymbol{\omega}(t) \end{bmatrix} = \begin{bmatrix} \mathbf{v}(t) \\ \boldsymbol{\omega}(t) \times \mathbf{R}(t) \\ \frac{\mathbf{F}(t)}{M} \\ \mathbf{I}(t)^{-1} (\boldsymbol{\tau} - \boldsymbol{\omega}(t) \times \mathbf{I}(t) \boldsymbol{\omega}(t)) \end{bmatrix}$$

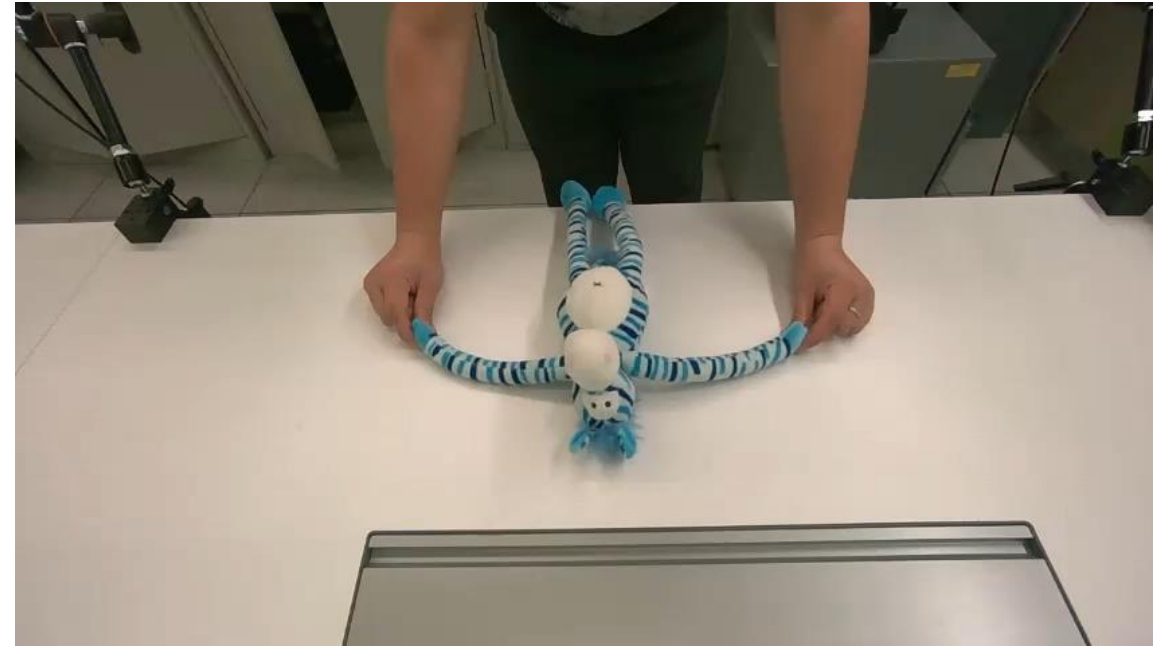
Simulation:

$$\mathbf{q}(t) = \mathbf{q}(0) + \int_0^t \frac{d}{dt} \mathbf{q}(t) dt = \mathbf{q}(0) + \sum_{i=1}^T \frac{d}{dt} \mathbf{q}(t)|_{t=t_i} \Delta t$$

## Articulated-object Motion



# However, Most Objects are not Rigid Bodies...



# However, Most Objects are not Rigid Bodies...



Cloth



Rope



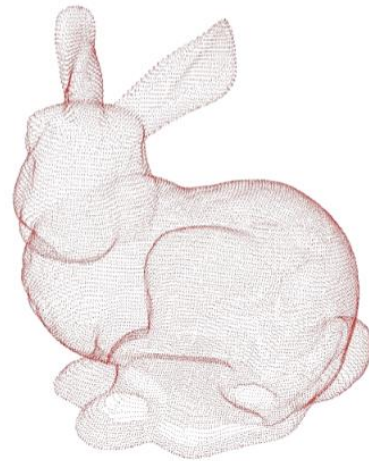
Fluid



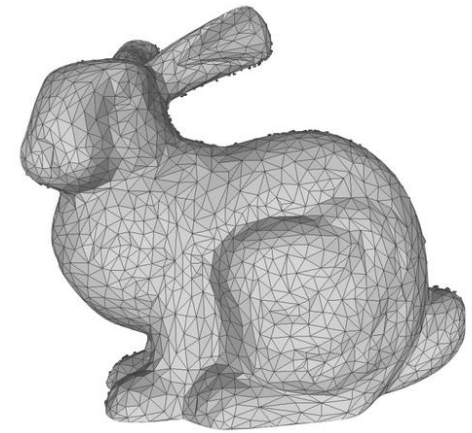
Soft body

# How to Physically Model Non-Rigid-Body Motion?

1. How to represent 3D model of non-rigid bodies?



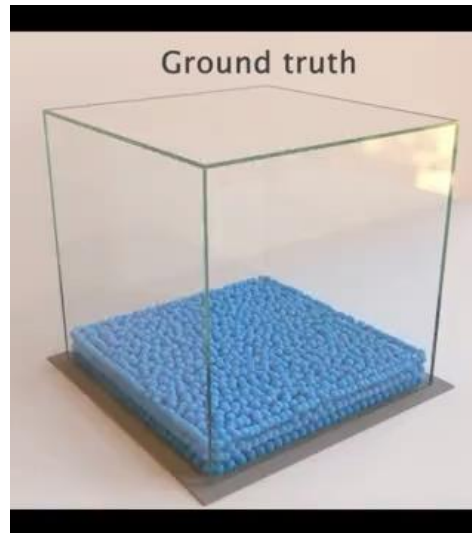
point



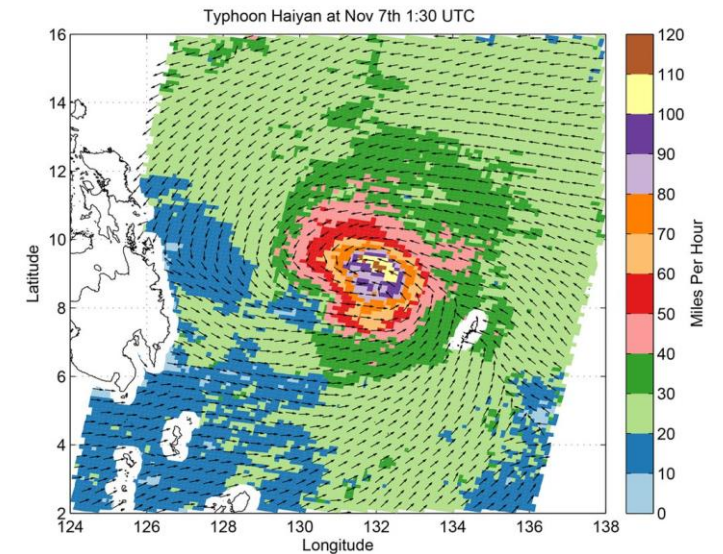
mesh

# How to Physically Model Non-Rigid-Body Motion?

1. How to represent 3D model of non-rigid bodies?
2. How to represent non-rigid-body motion?



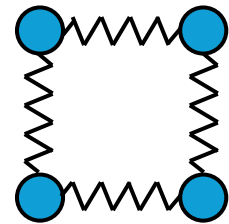
Particle motion



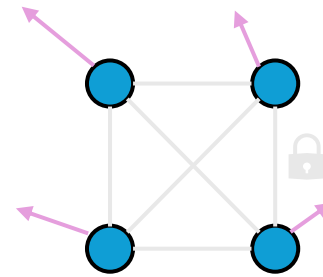
Motion field

# How to Physically Model Non-Rigid-Body Motion?

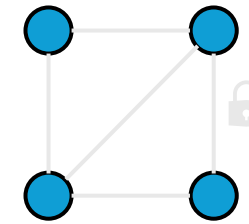
1. How to represent 3D model of non-rigid bodies?
2. How to represent non-rigid-body motion?
3. How to physically model non-rigid-body motion?  
Note that point motions are correlated



Mass-spring system

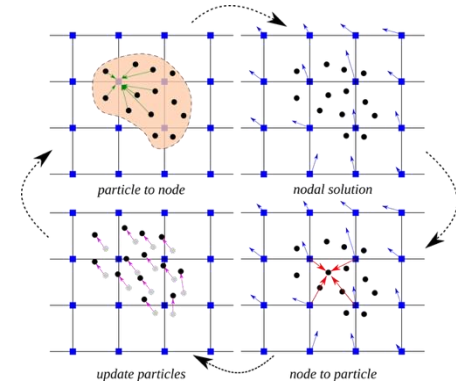


Position Based Dynamics



$$\min_x E(x, x^t, v^t) \quad \text{s.t.} \quad g(x) \geq 0.$$

Incremental Potential Solver



Material Point Method

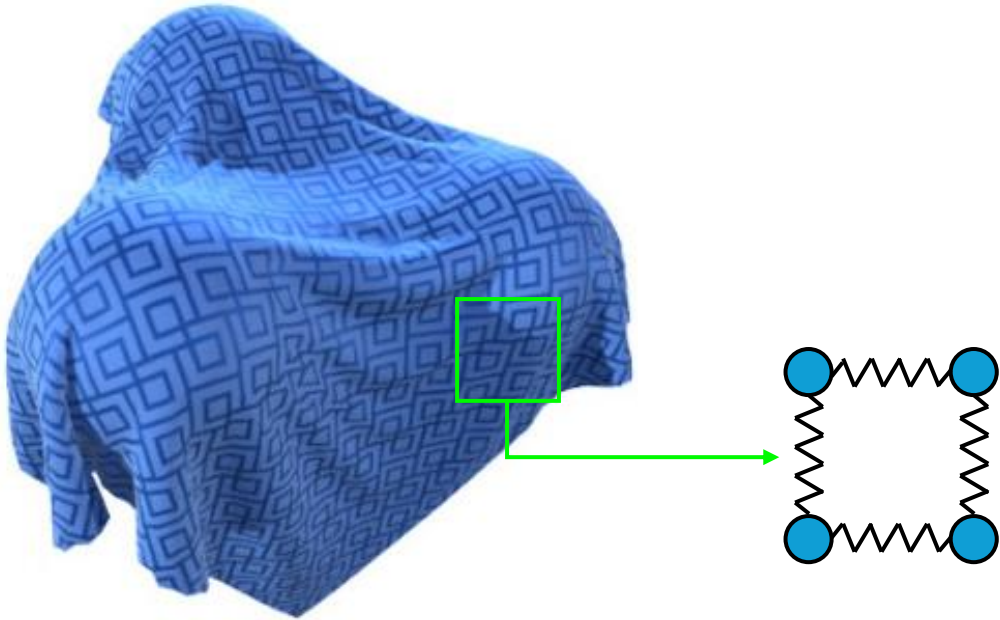
# Content

- Non-Rigid Modeling
  - Mass-spring system
  - Position-based Dynamics
  - Tetrahedral and Deformation

# Content

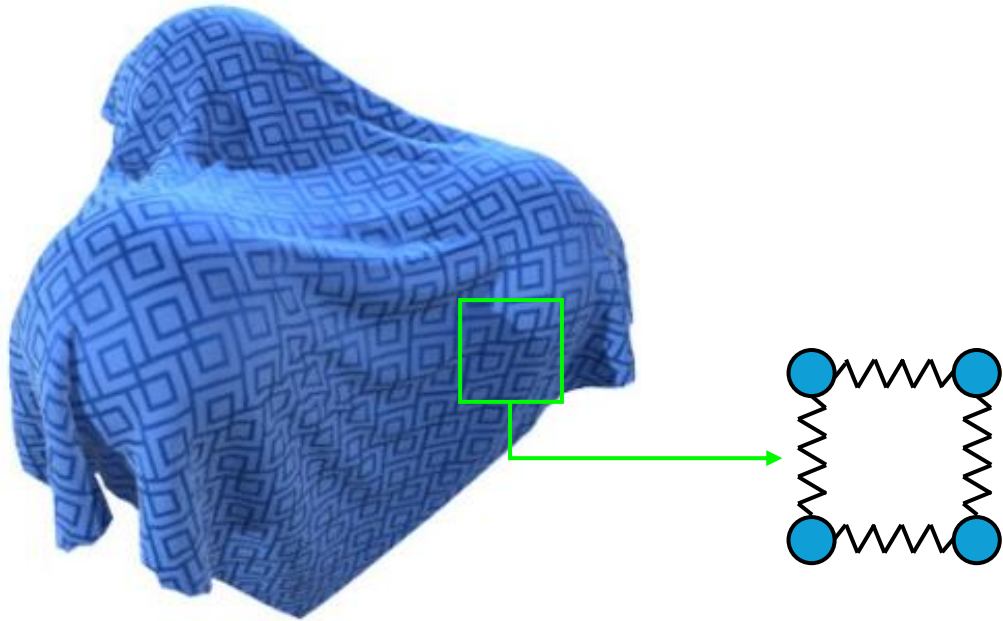
- Non-Rigid Modeling
  - Mass-spring system
  - Position-based Dynamics
  - Tetrahedral and Deformation

# Mass-Spring System



- **Idea:** Represent a deformable object as a set of mass nodes  $\mathcal{V}$  connected by spring-based edges  $\mathcal{E}$ , forming a graph  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$
- The connectivity pattern is pre-defined
- The dynamic formulation of a mass-spring system:
  - Calculate the total force on each node
  - Update the velocity and position of each node

# Mass-Spring System



- The dynamic formulation of a mass-spring system:
  - The total force on node  $i$ :

$$F_i = \sum_{i,j \in \mathcal{E}} F_{i,j}^{spring} + F_{i,j}^{dashpot} + F_i^{ext}$$

- Spring force describes the bounding force between nodes:

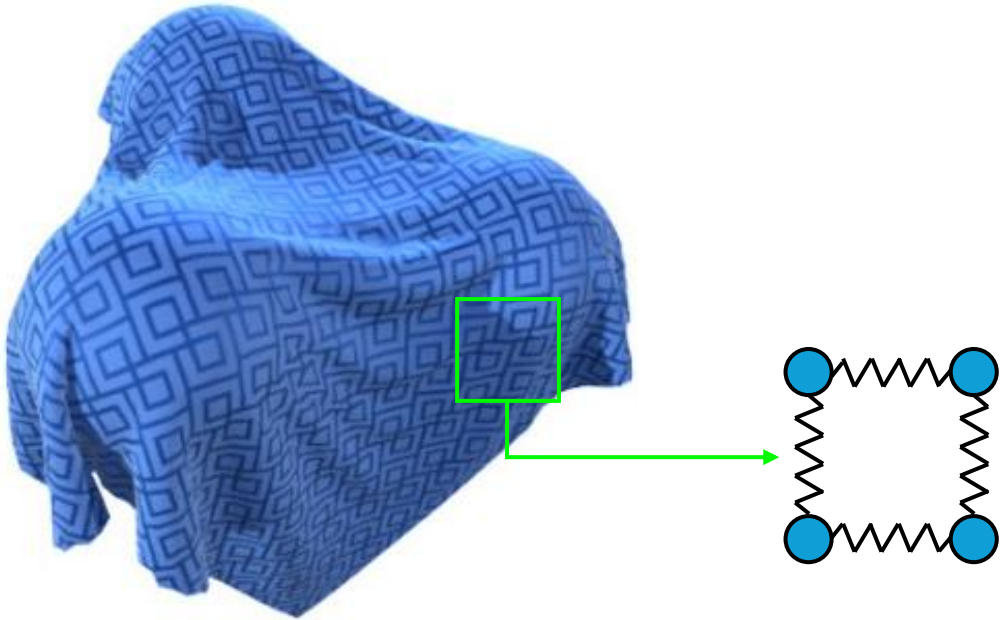
$$F_{i,j}^{spring} = k_{i,j} (\|x_j - x_i\| - l_{i,j}) \frac{x_j - x_i}{\|x_j - x_i\|}$$

- The dashpot dissipates energy, preventing oscillations:

$$F_{i,j}^{dashpot} = -\gamma (\|v_i - v_j\|)$$

- External forces accounts for collision, gravity and user interactions

# Mass-Spring System



- The dynamic formulation of a mass-spring system:

- The total force on node  $i$ :

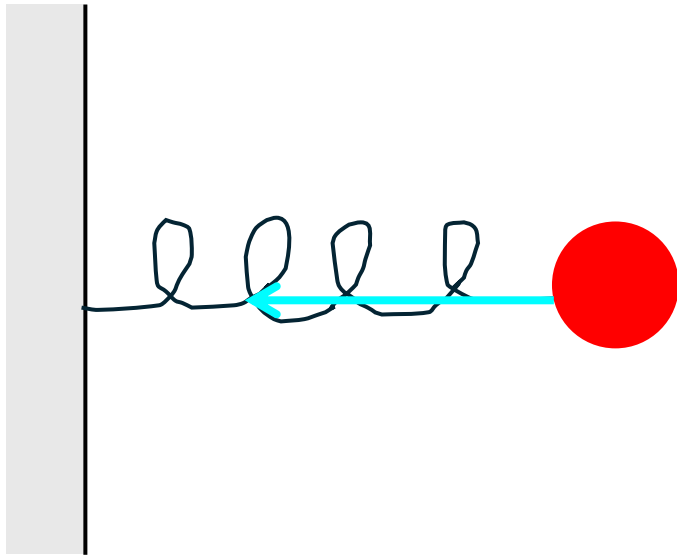
$$F_i = \sum_{i,j \in \mathcal{E}} F_{i,j}^{spring} + F_{i,j}^{dashpot} + F_i^{ext}$$

- The updated velocity and position of node  $i$ :

$$\begin{aligned} v_i^{t+1} &= \delta \left( v_i^t + \Delta t \frac{F_i}{m_i} \right) \\ x_i^{t+1} &= x_i^t + \Delta t v_i^{t+1} \end{aligned}$$

How do we derive this update rule?  
Is this update rule optimal?

# Let's Consider a Simple Case



- The total force on node  $i$ :

$$F_i = \sum_{i,j \in \mathcal{E}} F_{i,j}^{spring} + F_{i,j}^{dashpot} + F_i^{ext}$$

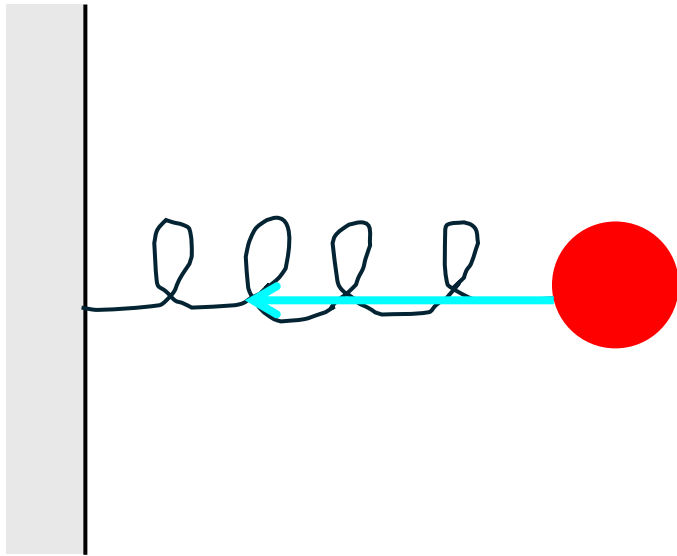
- Another end is attached to the wall:  $x_j = 0$
- The rest length of the spring is zero:  $l_{i,j} = 0$
- Spring force:

$$F_i^{spring} = -kx_i(t)$$

- Newton's second law:

$$F_i = m\ddot{x}_i(t) \Rightarrow \underbrace{-kx_i(t)}_{\text{2nd order ODE}} = m\ddot{x}_i(t)$$

# Idea: Simplify One 2<sup>nd</sup> Order ODE to Two 1<sup>st</sup> Order ODE



- 2<sup>nd</sup> order ODE:

$$-kx_i(t) = m\ddot{x}_i(t)$$

- We know that:

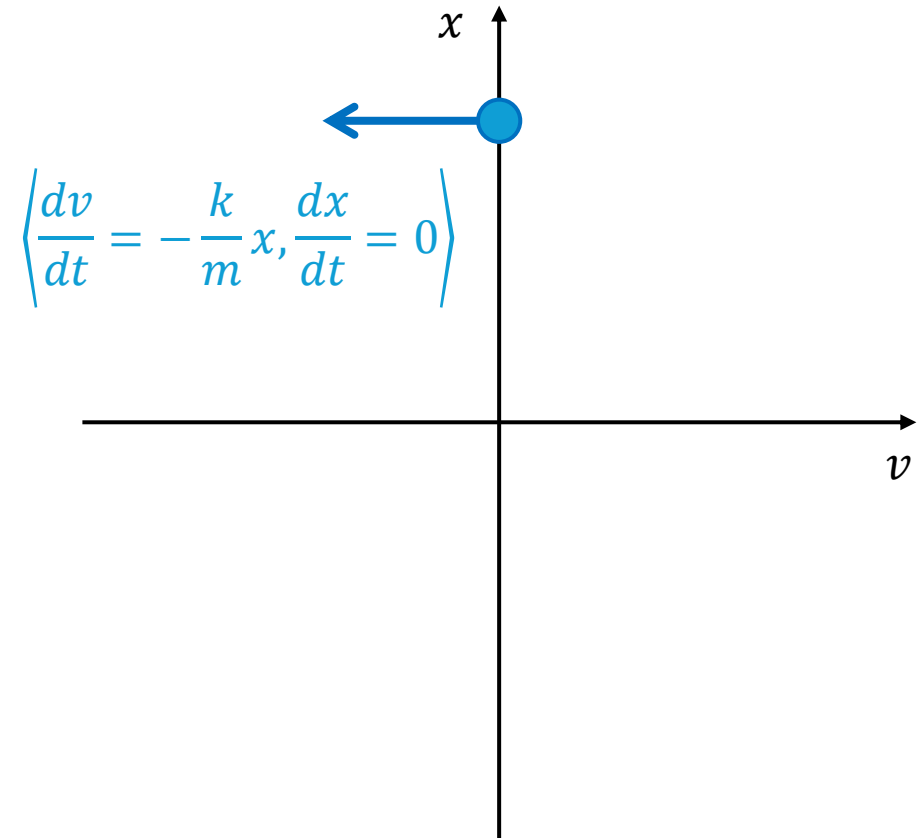
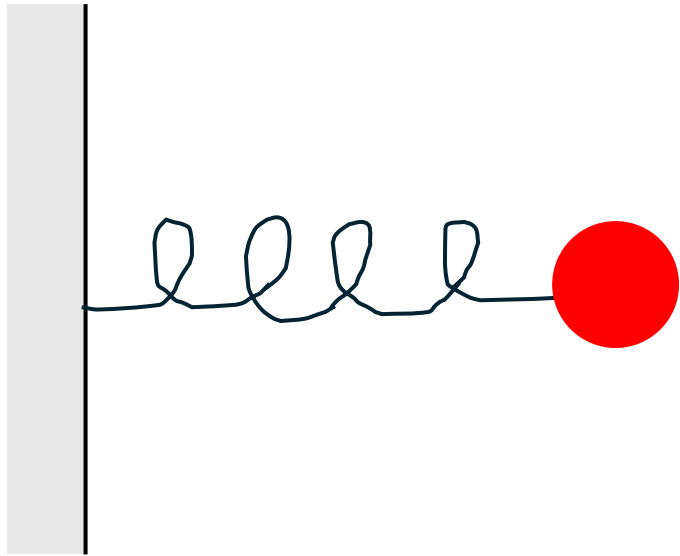
$$\ddot{x} = \dot{v}$$

$$\dot{x} = v$$

- We convert a 2<sup>nd</sup> order ODE to two 1<sup>st</sup> order ODEs:

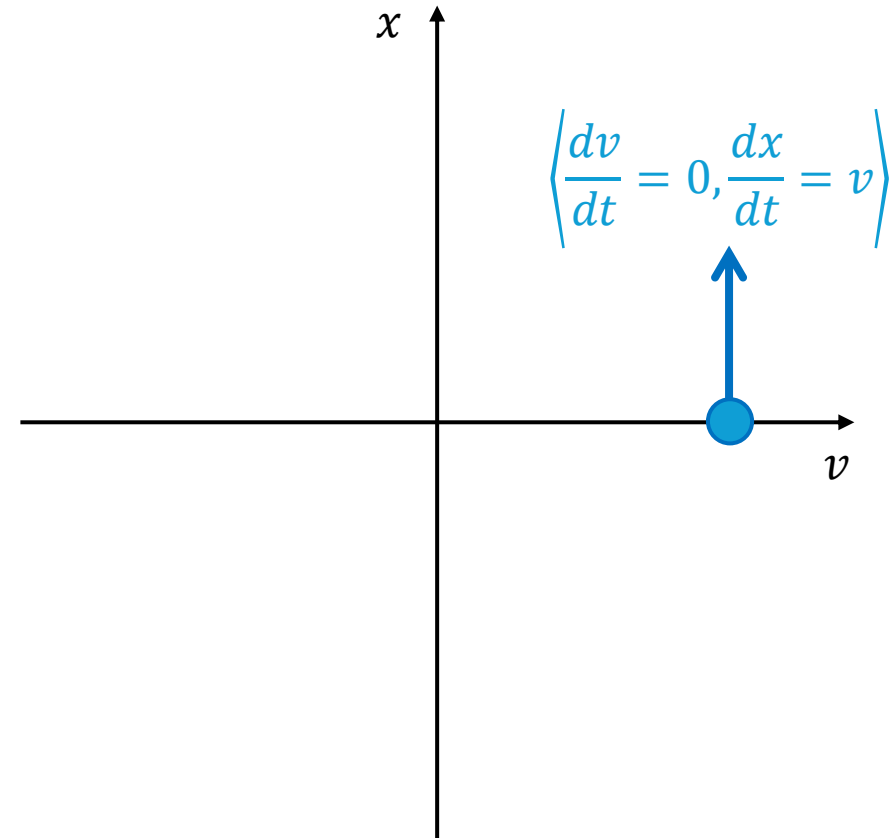
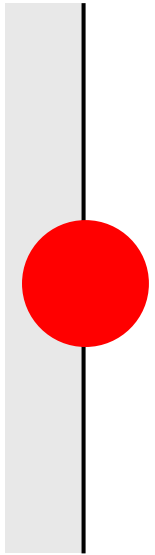
$$\underbrace{\begin{pmatrix} m & 0 \\ 0 & 1 \end{pmatrix}}_A \underbrace{\frac{d}{dt} \begin{pmatrix} v \\ x \end{pmatrix}}_{\dot{y}} = \underbrace{\begin{pmatrix} 0 & -k \\ 1 & 0 \end{pmatrix}}_{f(y)} \underbrace{\begin{pmatrix} v \\ x \end{pmatrix}}_y$$

# Idea: Simplify One 2<sup>nd</sup> Order ODE to Two 1<sup>st</sup> Order ODE



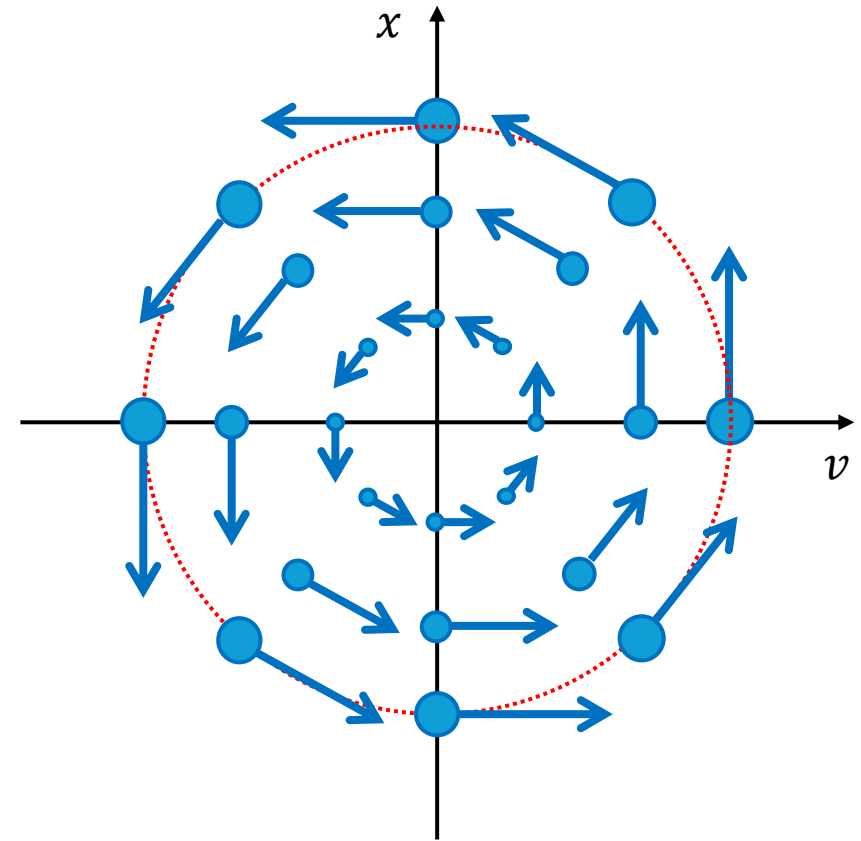
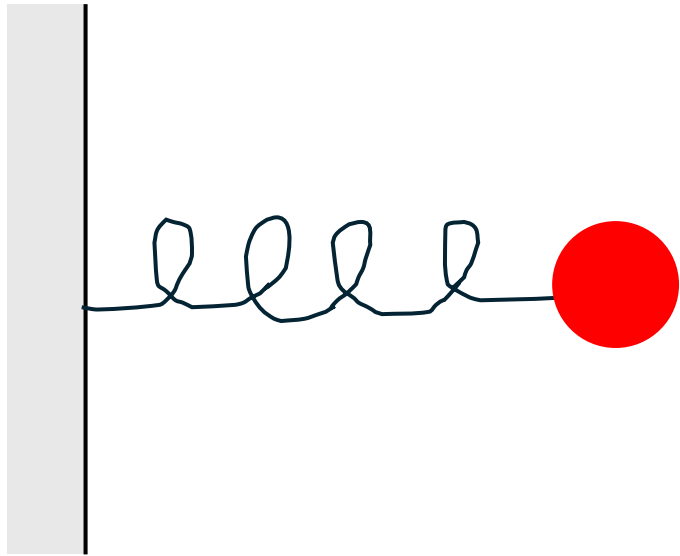
$$\begin{pmatrix} m & 0 \\ 0 & 1 \end{pmatrix} \frac{d}{dt} \begin{pmatrix} v \\ x \end{pmatrix} = \begin{pmatrix} 0 & -k \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 0 \\ x \end{pmatrix}$$

# Idea: Simplify One 2<sup>nd</sup> Order ODE to Two 1<sup>st</sup> Order ODE



$$\begin{pmatrix} m & 0 \\ 0 & 1 \end{pmatrix} \frac{d}{dt} \begin{pmatrix} v \\ x \end{pmatrix} = \begin{pmatrix} 0 & -k \\ 1 & 0 \end{pmatrix} \begin{pmatrix} v \\ x \end{pmatrix}$$

# Idea: Simplify One 2<sup>nd</sup> Order ODE to Two 1<sup>st</sup> Order ODE



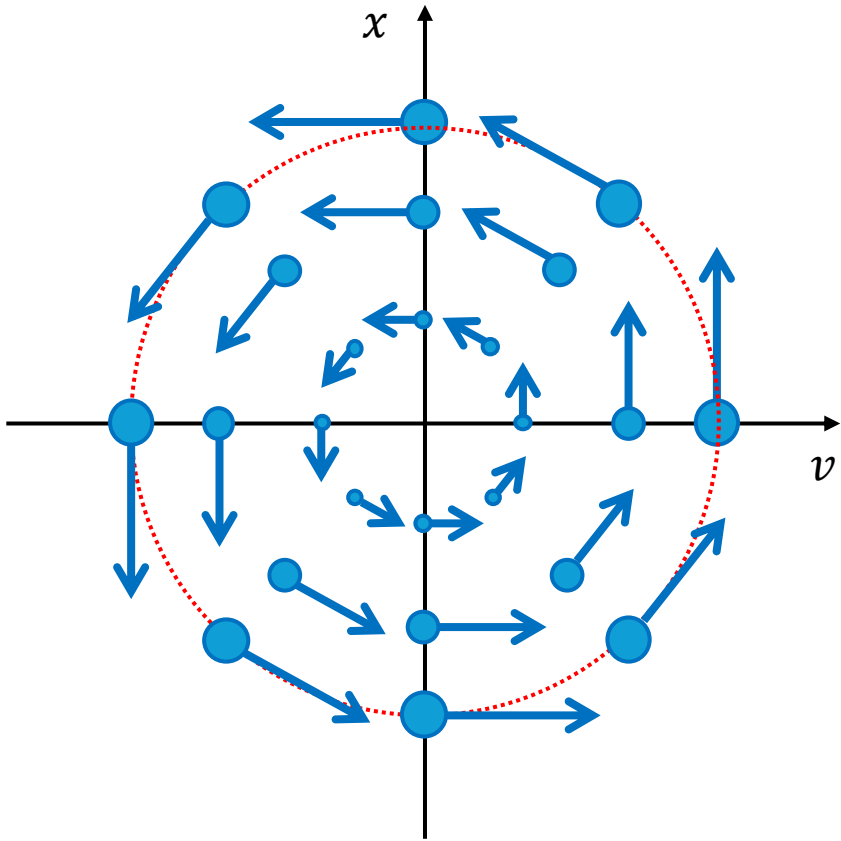
$$\begin{pmatrix} m & 0 \\ 0 & 1 \end{pmatrix} \frac{d}{dt} \begin{pmatrix} v \\ x \end{pmatrix} = \begin{pmatrix} 0 & -k \\ 1 & 0 \end{pmatrix} \begin{pmatrix} v \\ x \end{pmatrix}$$

We can't always solve this equation analytically.  
What are the numerical approximators?

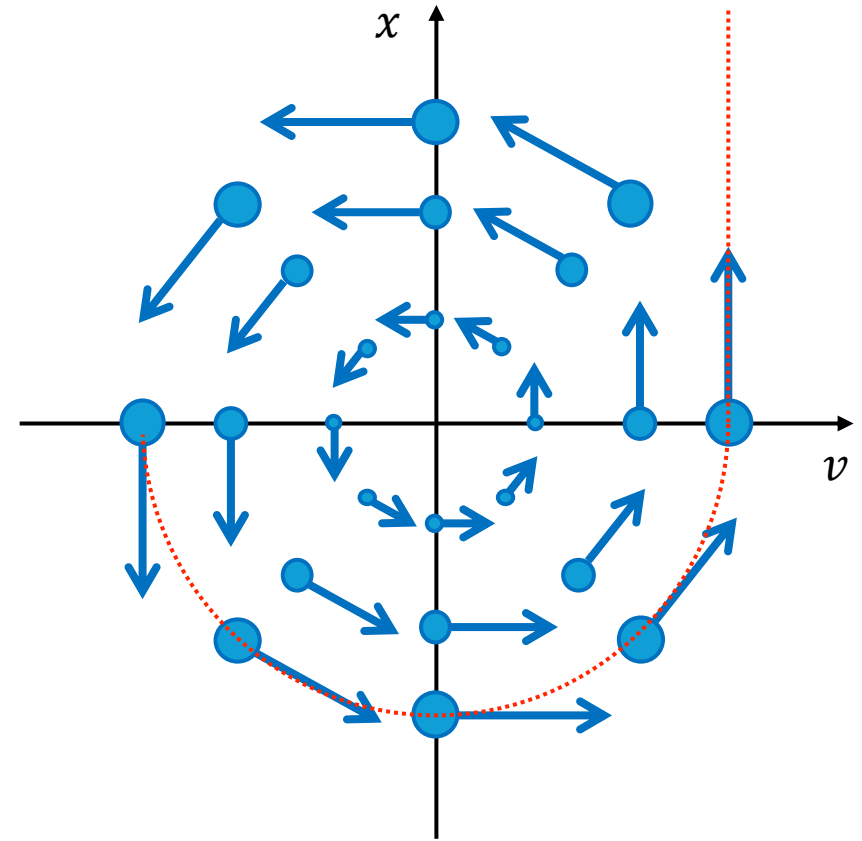
# Time Integration Algorithms

- Problem: How to solve the ODE numerically? We can only approximate infinitesimal  $dt$  with discrete  $\Delta t$
- Two types of time integration algorithms:
  1. Explicit time integration methods: Next time step can be computed entirely using values from the current time step or before
  2. Implicit time integration methods: Next time step is computed using values from the future
- How to choose the time integration algorithms?
  - Performance
  - Stability
  - Accuracy

# Stability of Time Integration Algorithms

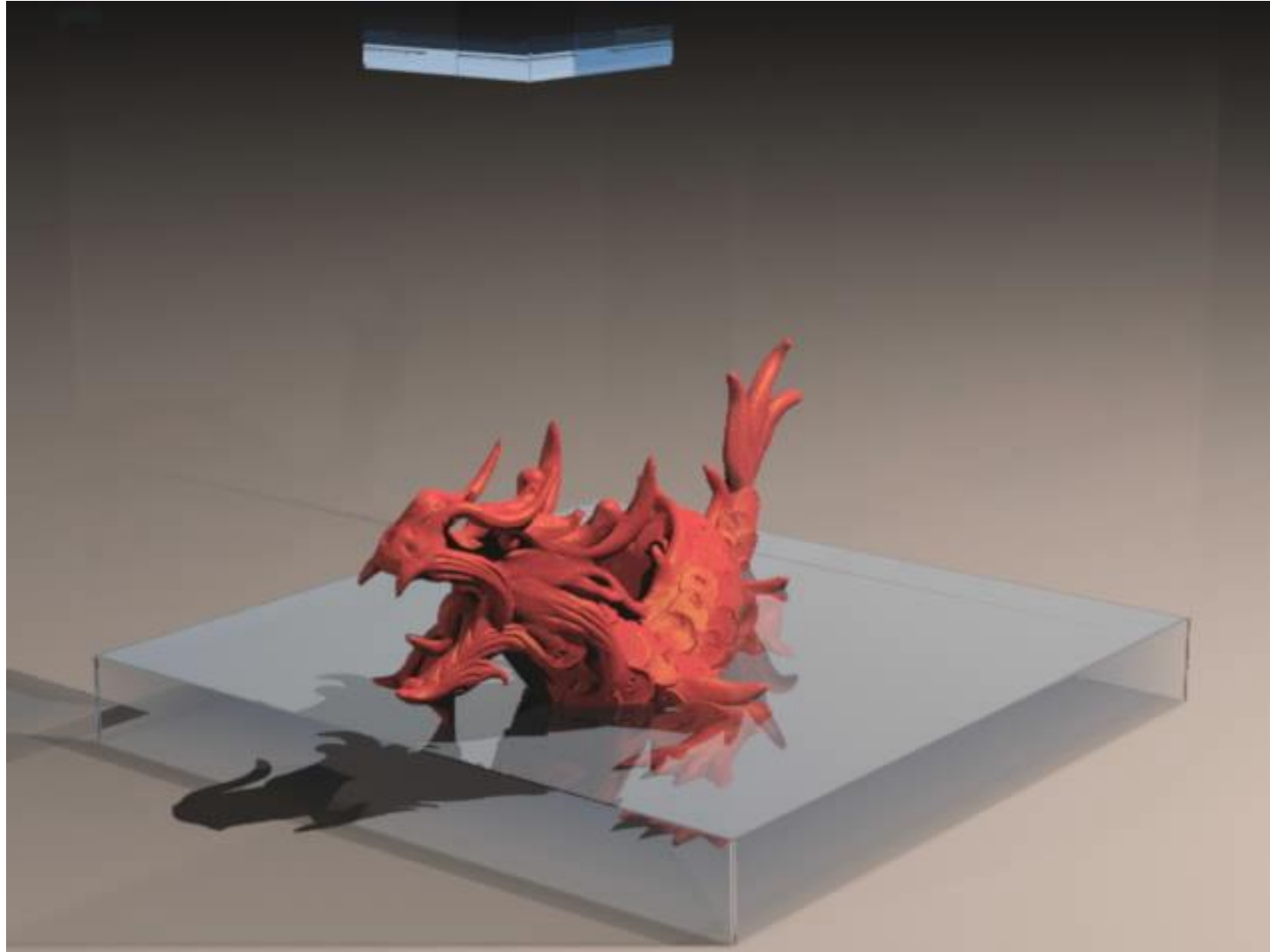


Stable: the path traced out by the numerical approximator stays the same as the analytical solution



Unstable: the path traced out by the numerical approximator diverges from the analytical solution

# Accuracy of Time Integration Algorithms



# Forward Euler Time Integration

- Our ODE equation:

$$\underbrace{\begin{pmatrix} m & 0 \\ 0 & 1 \end{pmatrix}}_A \underbrace{\frac{d}{dt} \begin{pmatrix} v \\ x \end{pmatrix}}_{\dot{y}} = \underbrace{\begin{pmatrix} 0 & -k \\ 1 & 0 \end{pmatrix}}_{f(y)} \underbrace{\begin{pmatrix} v \\ x \end{pmatrix}}_y$$

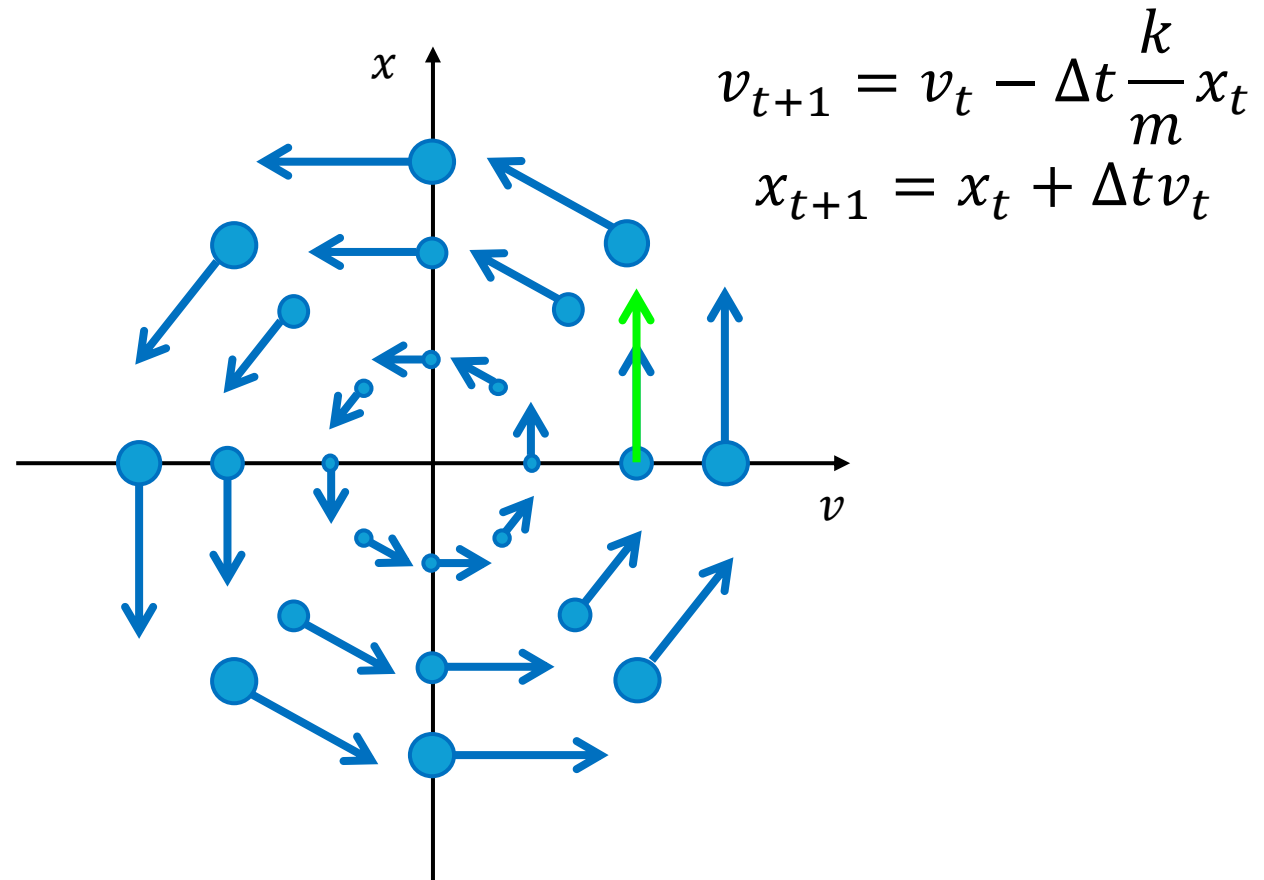
- We have:  $\dot{y} \approx \frac{1}{\Delta t} (y_{t+1} - y_t)$
- Substitute  $\dot{y}$  in the original ODE:

$$A \frac{1}{\Delta t} (y_{t+1} - y_t) = f(y_t) \Rightarrow y_{t+1} = \underbrace{\frac{\Delta t}{A} f(y_t)}_{\text{update}} + y_t$$

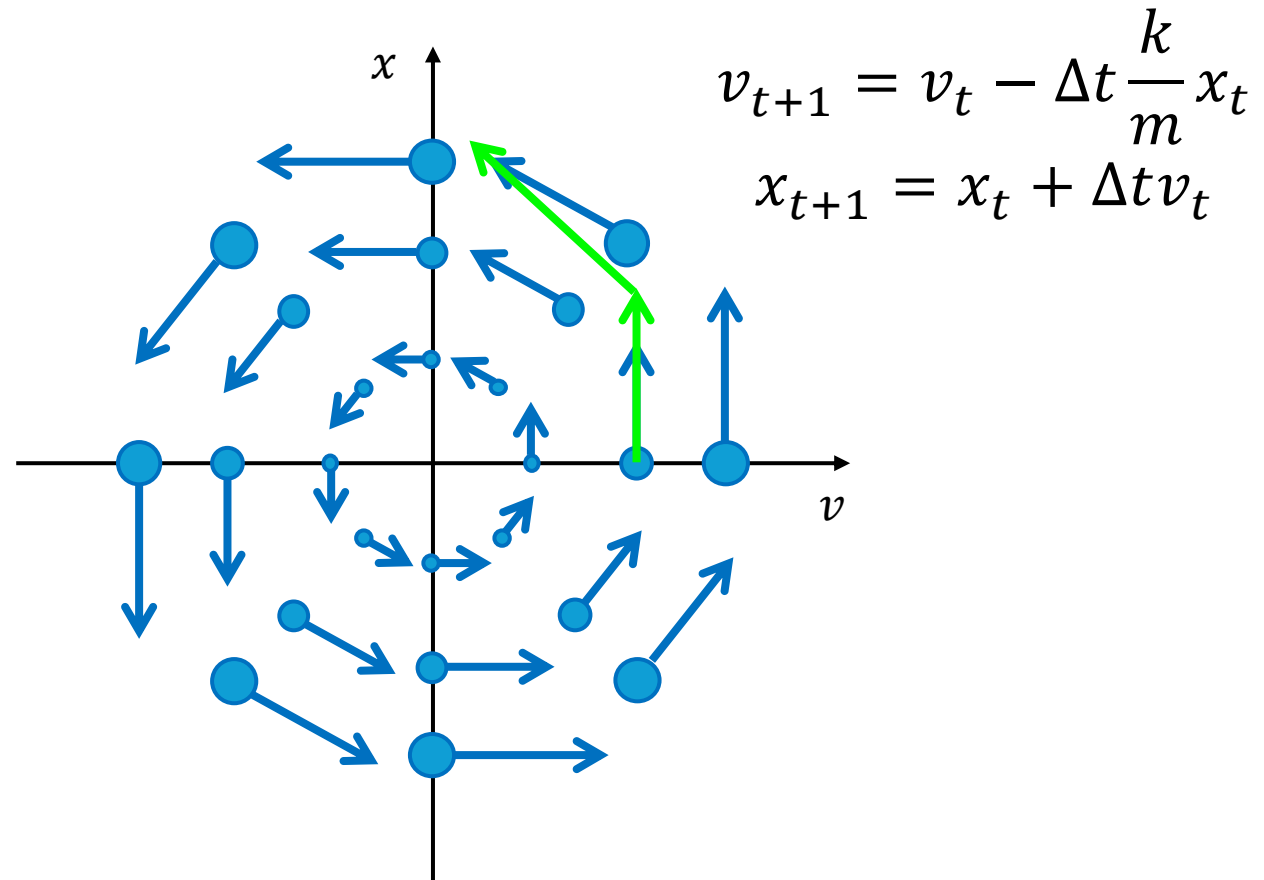
$$v_{t+1} = v_t - \Delta t \frac{k}{m} x_t$$

$$x_{t+1} = x_t + \Delta t v_t$$

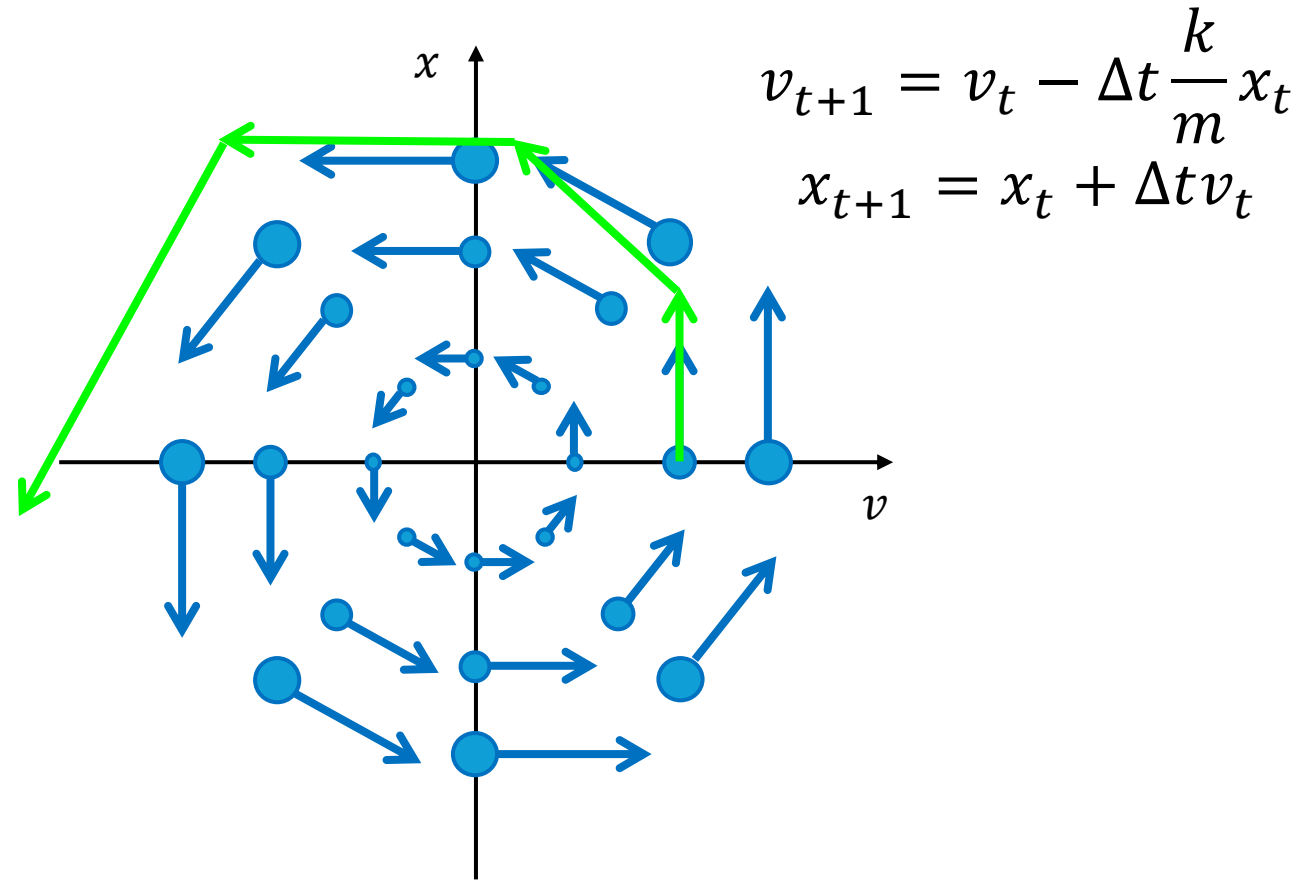
# Forward Euler Time Integration



# Forward Euler Time Integration



# Forward Euler Time Integration

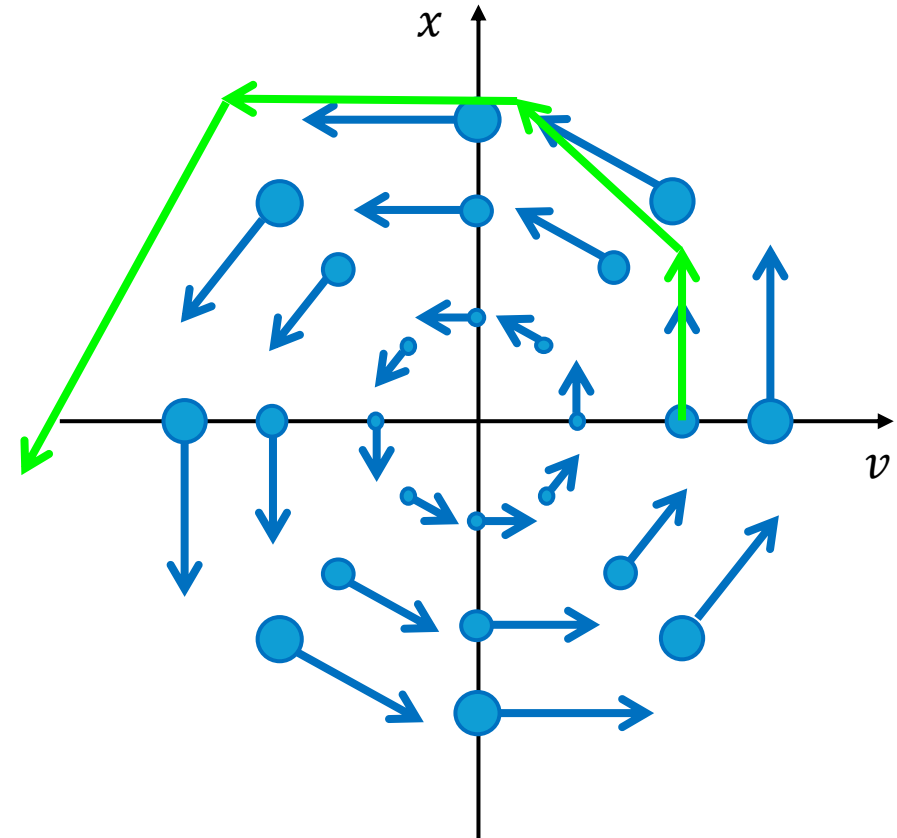


# Forward Euler Time Integration

- Forward Euler time integration updates  $y$  with “current slope”:

$$y_{t+1} = \frac{\Delta t}{A} f(y_t) + y_t$$

- Problem: the integrated values overshoot as the numerical update lags behind the analytical solution
- Idea:
  - Update  $y$  with “average slope” of the current and future slope.

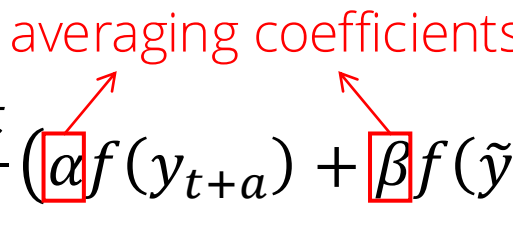


# Runge-Kutta Time Integration

- Update  $\mathbf{y}$  with “average slope” with real (current/previous) slope  $f(\mathbf{y}_{t+a})$  and estimated (future) slope  $f(\tilde{\mathbf{y}}_{t+b})$ :

$$\mathbf{y}_{t+1} = \mathbf{y}_t + \frac{\Delta t}{A} (\alpha f(\mathbf{y}_{t+a}) + \beta f(\tilde{\mathbf{y}}_{t+b}))$$

averaging coefficients



- Using Forward Euler Time Integration to estimate  $\tilde{\mathbf{y}}_{t+b}$ :

$$\tilde{\mathbf{y}}_{t+b} = \frac{b\Delta t}{A} f(\mathbf{y}_t) + \mathbf{y}_t$$

# Heun's Method: A Special Case of Runge-Kutta Time Integration

- Update  $\mathbf{y}$  with “average slope” with the current slope  $f(\mathbf{y}_t)$  and estimated future slope  $f(\tilde{\mathbf{y}}_{t+1})$  :

$$\mathbf{y}_{t+1} = \mathbf{y}_t + \frac{\Delta t}{A} \left( \frac{1}{2} f(\mathbf{y}_t) + \frac{1}{2} f(\tilde{\mathbf{y}}_{t+1}) \right)$$

- Using Forward Euler Time Integration to estimate  $\tilde{\mathbf{y}}_{t+1}$ :

$$\tilde{\mathbf{y}}_{t+1} = \frac{\Delta t}{A} f(\mathbf{y}_t) + \mathbf{y}_t$$

# Generalization of Runge-Kutta Time Integration

$$\kappa_1 = \mathbf{A}^{-1} \mathbf{f}(\mathbf{y}^t)$$

$$\kappa_2 = \mathbf{A}^{-1} \mathbf{f}(\mathbf{y}^t + \Delta t \cdot \kappa_1)$$

$$\mathbf{y}^{t+1} = \mathbf{y}^t + \frac{\Delta t}{2} (\kappa_1 + \kappa_2)$$

# Generalization of Runge-Kutta Time Integration

## Fourth-Order Runge Kutta

$$\kappa_1 = \mathbf{A}^{-1} \mathbf{f}(\mathbf{y}^t)$$

$$\kappa_2 = \mathbf{A}^{-1} \mathbf{f}\left(\mathbf{y}^t + \frac{\Delta t}{2} \cdot \kappa_1\right)$$

$$\kappa_3 = \mathbf{A}^{-1} \mathbf{f}\left(\mathbf{y}^t + \frac{\Delta t}{2} \cdot \kappa_2\right)$$

$$\kappa_4 = \mathbf{A}^{-1} \mathbf{f}(\mathbf{y}^t + \Delta t \cdot \kappa_3)$$

$$\mathbf{y}^{t+1} = \mathbf{y}^t + \frac{\Delta t}{6} (\kappa_1 + 2 \cdot \kappa_2 + 2 \cdot \kappa_3 + \kappa_4)$$



# Backward Euler Time Integration

- Our ODE equation:

$$\underbrace{\begin{pmatrix} m & 0 \\ 0 & 1 \end{pmatrix}}_A \underbrace{\frac{d}{dt} \begin{pmatrix} v \\ x \end{pmatrix}}_{\dot{y}} = \underbrace{\begin{pmatrix} 0 & -k \\ 1 & 0 \end{pmatrix}}_{f(y)} \underbrace{\begin{pmatrix} v \\ x \end{pmatrix}}_y$$

- We have:  $\dot{y} \approx \frac{1}{\Delta t} (y_{t+1} - y_t)$
- The original ODE can be re-written as:

$$A \frac{1}{\Delta t} (y_{t+1} - y_t) = f(y_{t+1})$$

Update  $y$  with future slope

# Backward Euler Time Integration

- Our ODE equation:

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- We have:  $\dot{y} \approx \frac{1}{\Delta t} (y_{t+1} - y_t)$
- The original ODE can be re-written as:

$$A \frac{1}{\Delta t} (y_{t+1} - y_t) = f(y_{t+1}) \Rightarrow y_{t+1} = \frac{\Delta t}{A} B y_{t+1} + y_t$$
$$\Rightarrow \left( I - \frac{\Delta t}{A} B \right) y_{t+1} = y_t$$

# Backward Euler Time Integration

- How to solve  $\left(I - \frac{\Delta t}{A} B\right) y_{t+1} = y_t$  ?
- We have:

$$v_{t+1} + \Delta t \frac{k}{m} x_{t+1} = v_t$$

$$x_{t+1} - \Delta t v_{t+1} = x_t$$

- Substitute  $x_{t+1}$  into the first equation, we have:

$$v_{t+1} + \Delta t \frac{k}{m} (x_t + \Delta t v_{t+1}) = v_t$$

$$\Rightarrow \left(1 + \Delta t^2 \frac{k}{m}\right) v_{t+1} = v_t - \Delta t \frac{k}{m} x_t$$

# Backward Euler Time Integration

- How to solve  $\left(I - \frac{\Delta t}{A} B\right) y_{t+1} = y_t$  ?
- We have:

$$v_{t+1} + \Delta t \frac{k}{m} x_{t+1} = v_t$$

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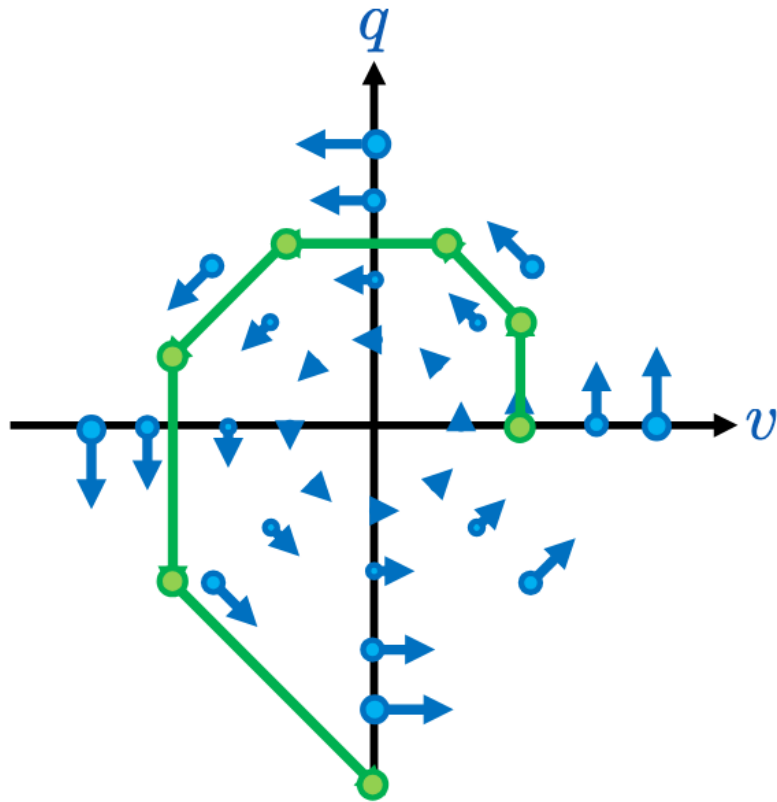
$$v_{t+1} + \Delta t \frac{k}{m} (x_t + \Delta t v_{t+1}) = v_t$$

$$\Rightarrow \left(1 + \Delta t^2 \frac{k}{m}\right) v_{t+1} = v_t - \Delta t \frac{k}{m} x_t$$

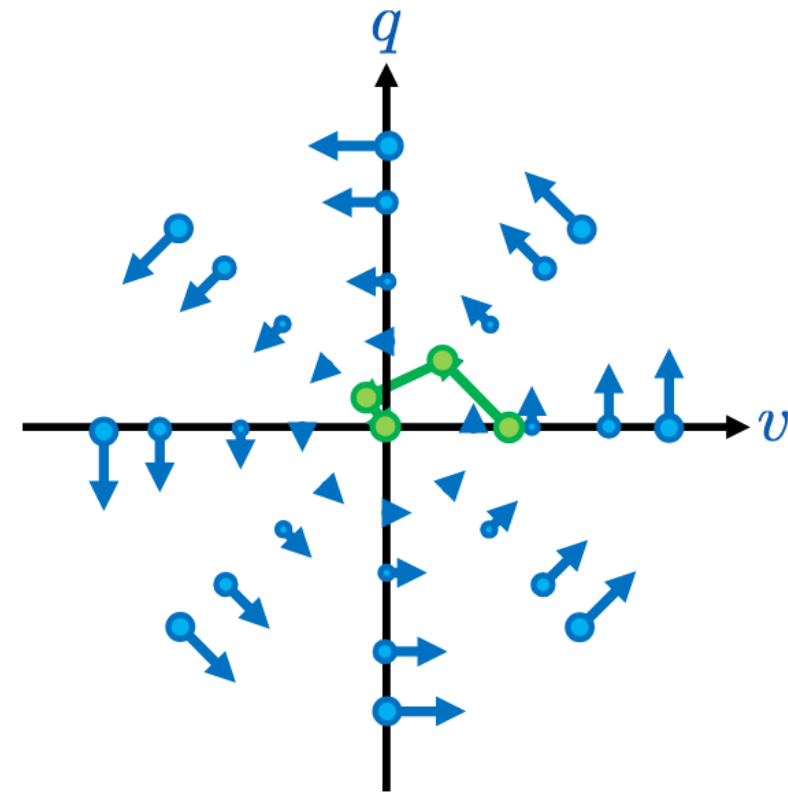
We solve the backward integration implicitly!

# Forward vs. Backward Euler Time Integration

- Can we cancel out the exploding and damping effect? Yes! Let's try to mix these two integration methods.



Explicit (exploding!!!)



Implicit (damping)

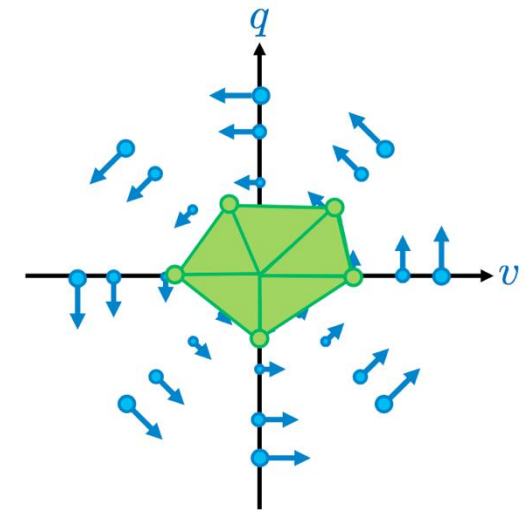
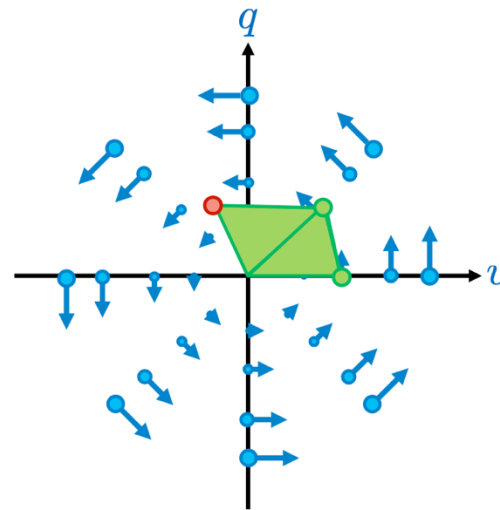
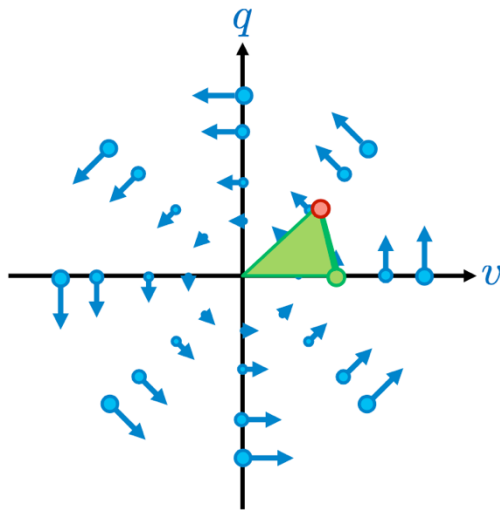
# Symplectic Euler Time Integration

- First, take an explicit step

$$v_{t+1} = v_t - \Delta t \frac{k}{m} x_t$$

- Next, take an implicit step

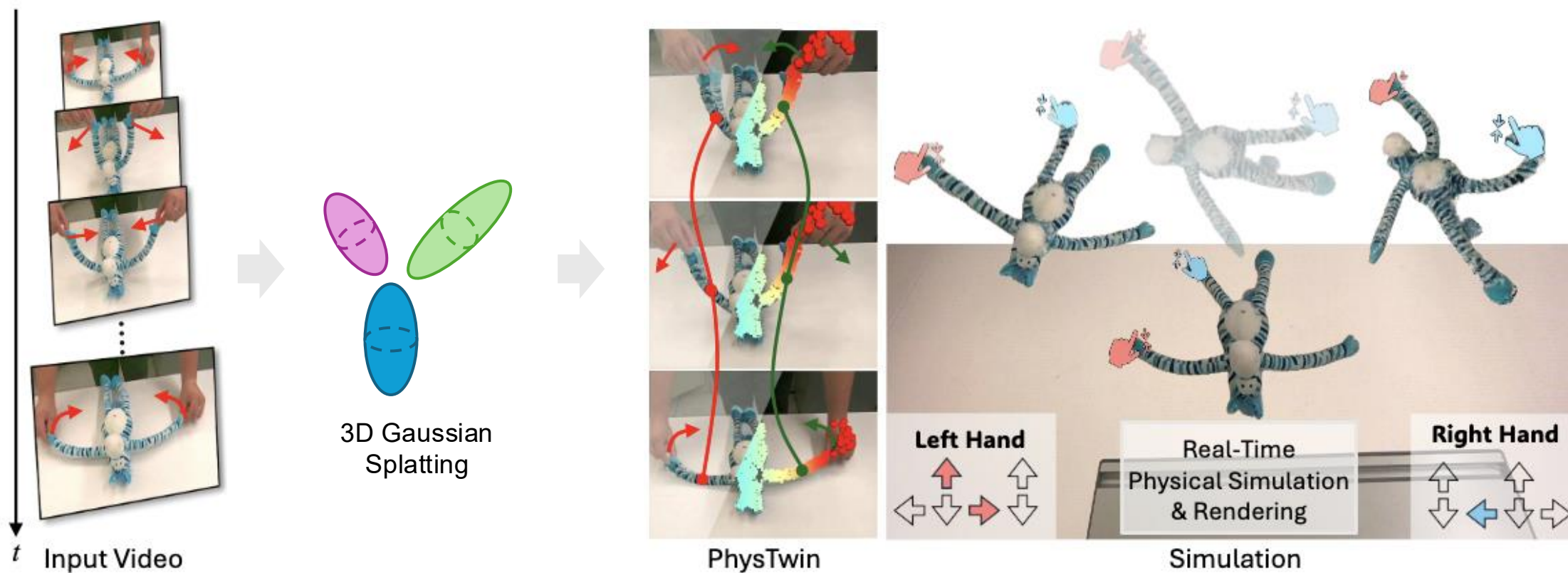
$$x_{t+1} = x_t - \Delta t v_{t+1}$$



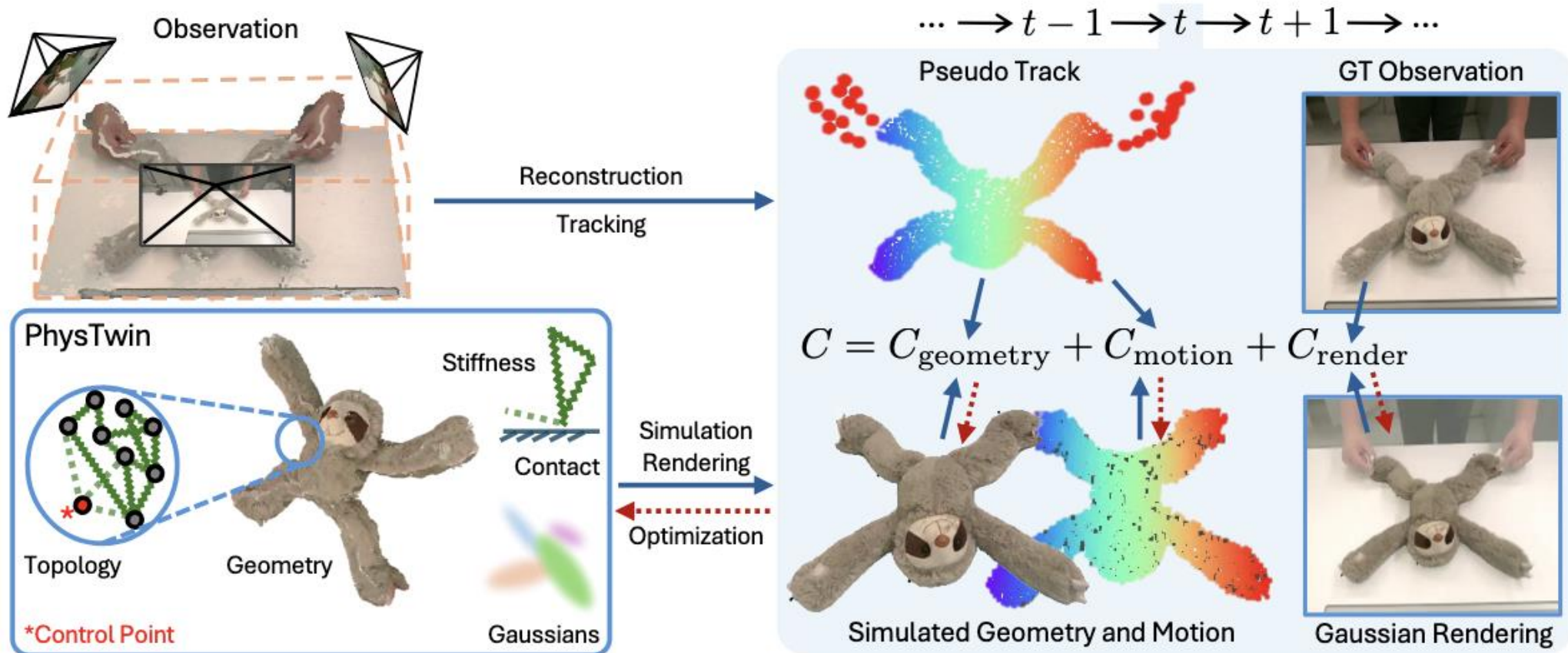
# Scene Reconstruction and Simulation with Mass-Spring System



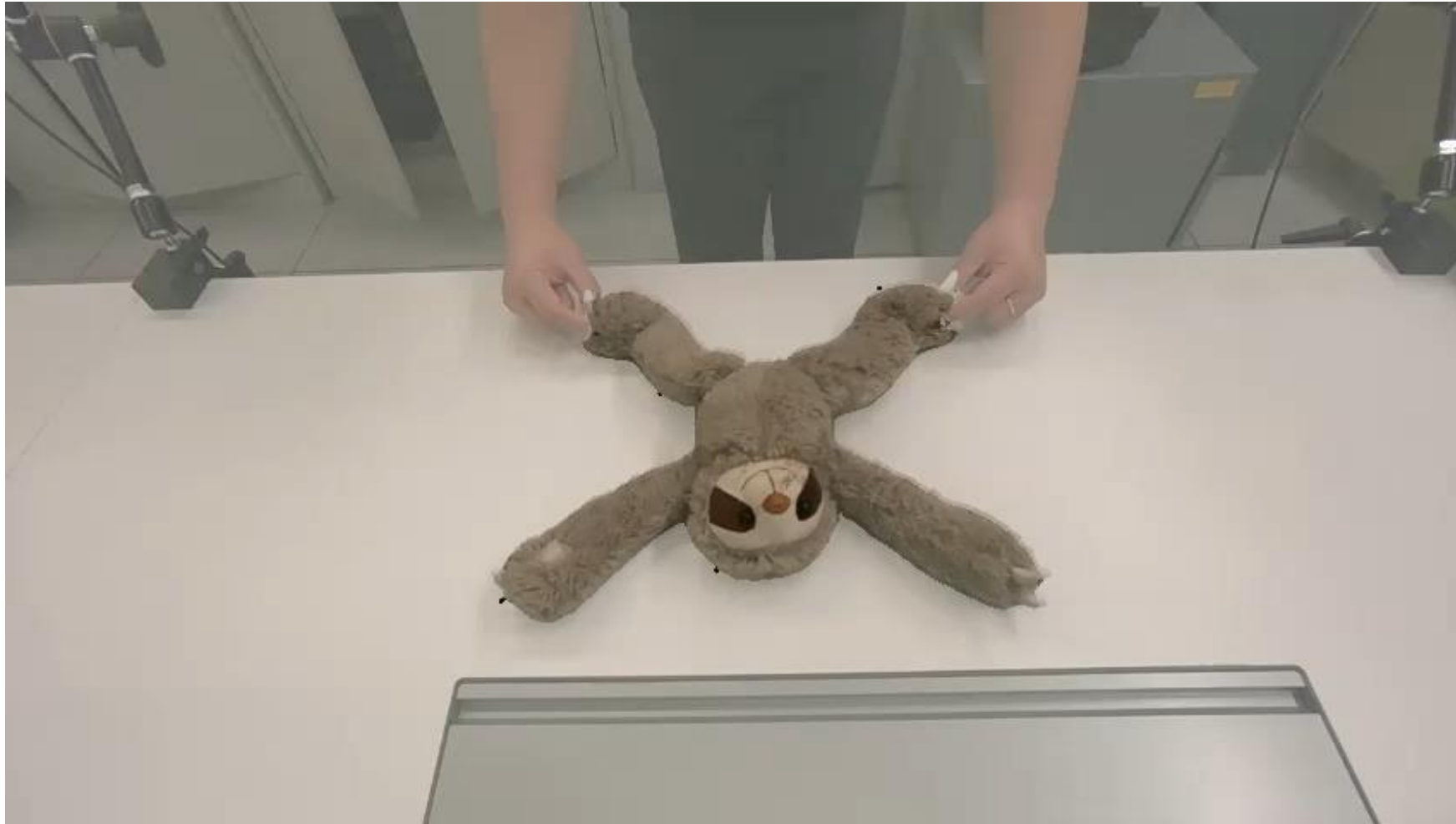
# Idea: Integrate 3D Gaussian Splatting with Mass-Spring Modeling



# PhysTwin: Physics-Informed Reconstruction and Simulation of Deformable Objects from Videos



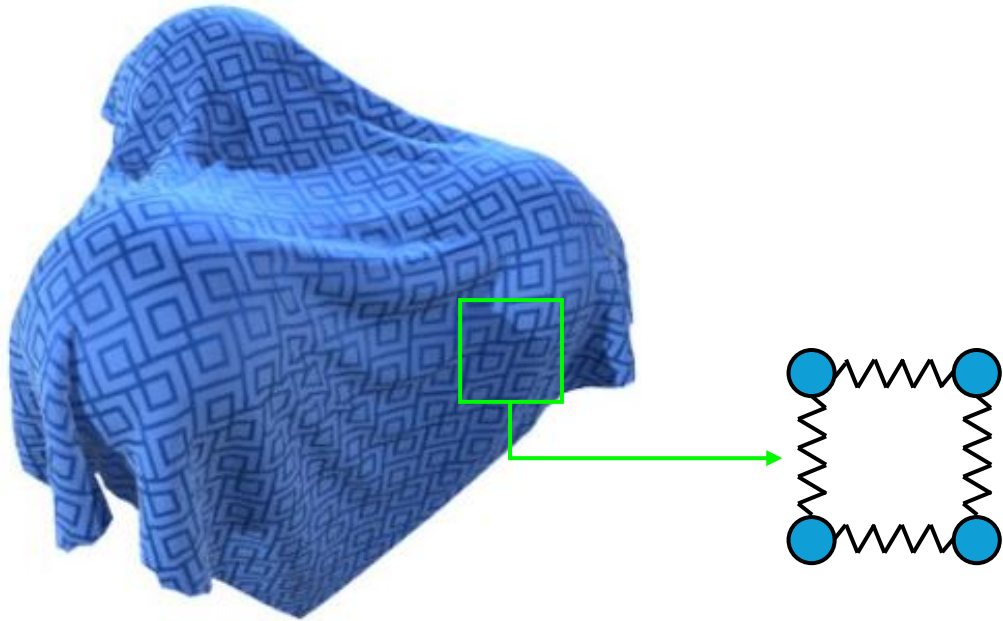
# Results: Real-to-Sim Demo



# Content

- Non-Rigid Modeling
  - Mass-spring system
  - Position-based Dynamics
  - Tetrahedral and Deformation

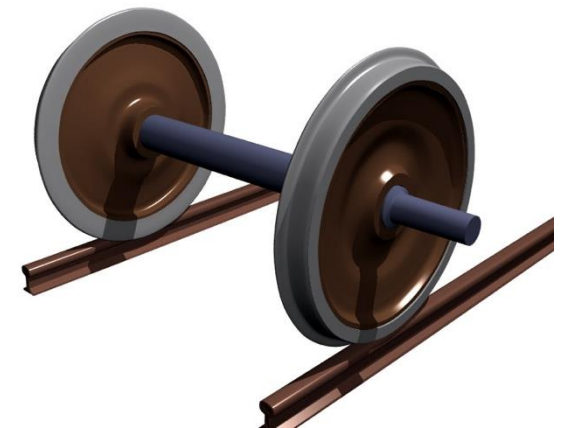
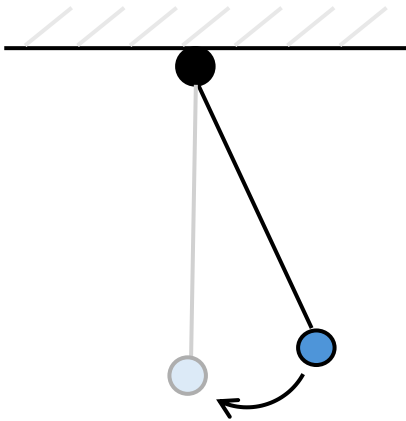
# Mass-Spring System Has Problems



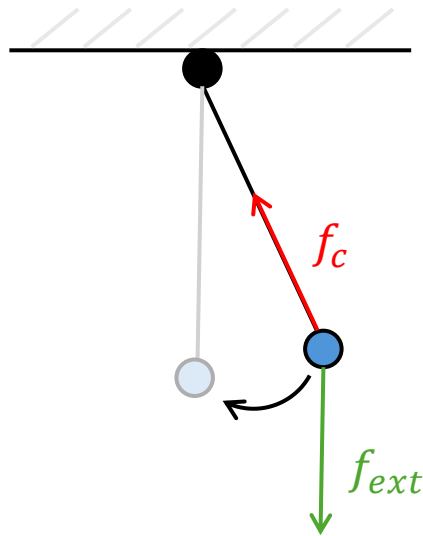
- How to describe objects of different kinetic constraints, e.g. bending, impenetrability etc?
- How to model continuum material? The empty space between spring-connected nodes has no mass and energy.

# A Dynamic System May Have Multiple Constraints

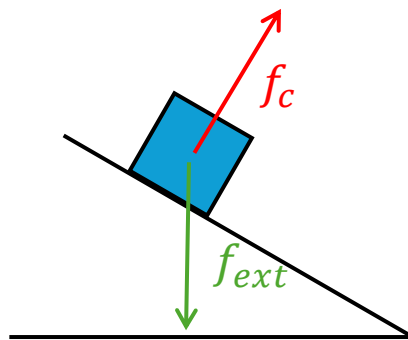
- Constraints limit the motion of objects by restricting them to follow a specific trajectory or path. For example:
  - The circular motion of a pendulum
  - The distance constraints between two objects
  - The resistance when bending an iron rod



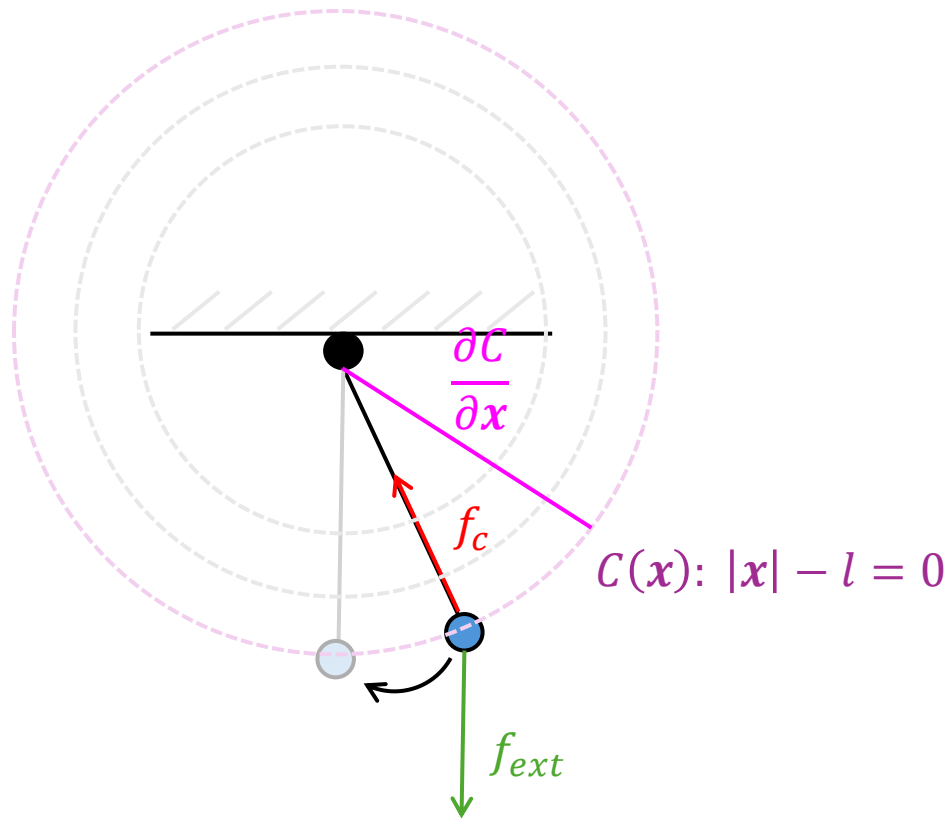
# How to Solve a Dynamic System with Constraints?



- Idea 1: Directly calculate the forces required to maintain the constraints
- The job of these constraint forces is to cancel just those parts of the applied forces that act against the constraints



# How to Solve a Dynamic System with Constraints?



- Idea 1: Directly calculate the forces required to maintain the constraints
- The job of these constraint forces is to cancel just those parts of the applied forces that act against the constraints
- For a constraint  $C$ , the corresponding constraint force is  $f_c = \lambda \frac{\partial C}{\partial \mathbf{x}}$  where  $\mathbf{x}$  denotes the spatial coordinates of the dynamic system

Check “Physically Based Modeling: Principles and Practice Constrained Dynamics by Andrew Witkin” for more details

# How to Solve a Dynamic System with Constraints?

- Idea 2: Calculate the kinetic update with Newton's law and refine the kinetic update to follow the constraints
- Problem formulation: Given a set of positions  $\mathbf{x} = [x_1, \dots, x_N]$  and constraints  $C_1(\mathbf{x}), \dots, C_M(\mathbf{x})$ , the goal is to find new positions  $\mathbf{p} = [p_1, \dots, p_N]$  such that  $C_i(\mathbf{p}) \geq 0 \forall i$

# Position Based Dynamics

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**Algorithm 1** Position-based dynamics

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```
1: for all vertices  $i$  do
2:   initialize  $\mathbf{x}_i = \mathbf{x}_i^0$ ,  $\mathbf{v}_i = \mathbf{v}_i^0$ ,  $w_i = 1/m_i$ 
3: end for
4: loop           Derive the initial kinetic update with Newton's law
5:   for all vertices  $i$  do  $\mathbf{v}_i \leftarrow \mathbf{v}_i + \Delta t w_i \mathbf{f}_{\text{ext}}(\mathbf{x}_i)$ 
6:   for all vertices  $i$  do  $\mathbf{p}_i \leftarrow \mathbf{x}_i + \Delta t \mathbf{v}_i$ 
7:   for all vertices  $i$  do  $\text{genCollConstraints}(\mathbf{x}_i \rightarrow \mathbf{p}_i)$ 
8:   loop solverIteration times
9:      $\text{projectConstraints}(C_1, \dots, C_{M+M_{\text{Coll}}}, \mathbf{p}_1, \dots, \mathbf{p}_N)$ 
10:  end loop       Modify the kinetic update based on constraints
11:  for all vertices  $i$  do
12:     $\mathbf{v}_i \leftarrow (\mathbf{p}_i - \mathbf{x}_i) / \Delta t$ 
13:     $\mathbf{x}_i \leftarrow \mathbf{p}_i$ 
14:  end for
15:   $\text{velocityUpdate}(\mathbf{v}_1, \dots, \mathbf{v}_N)$ 
16: end loop
```

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# Position Based Dynamics

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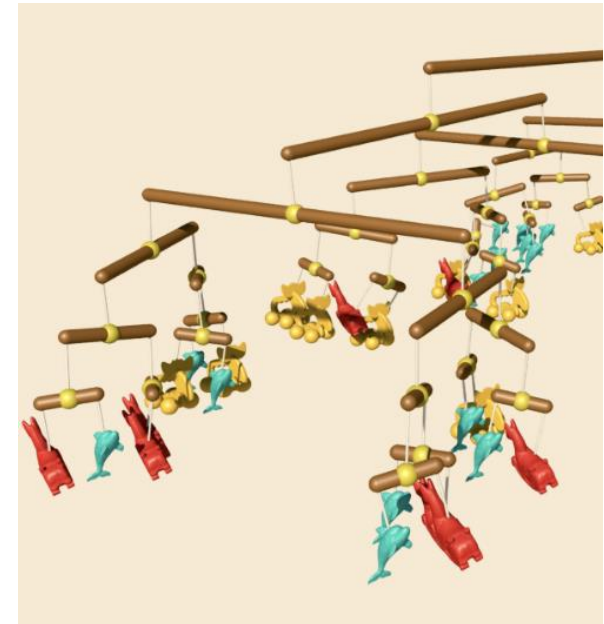
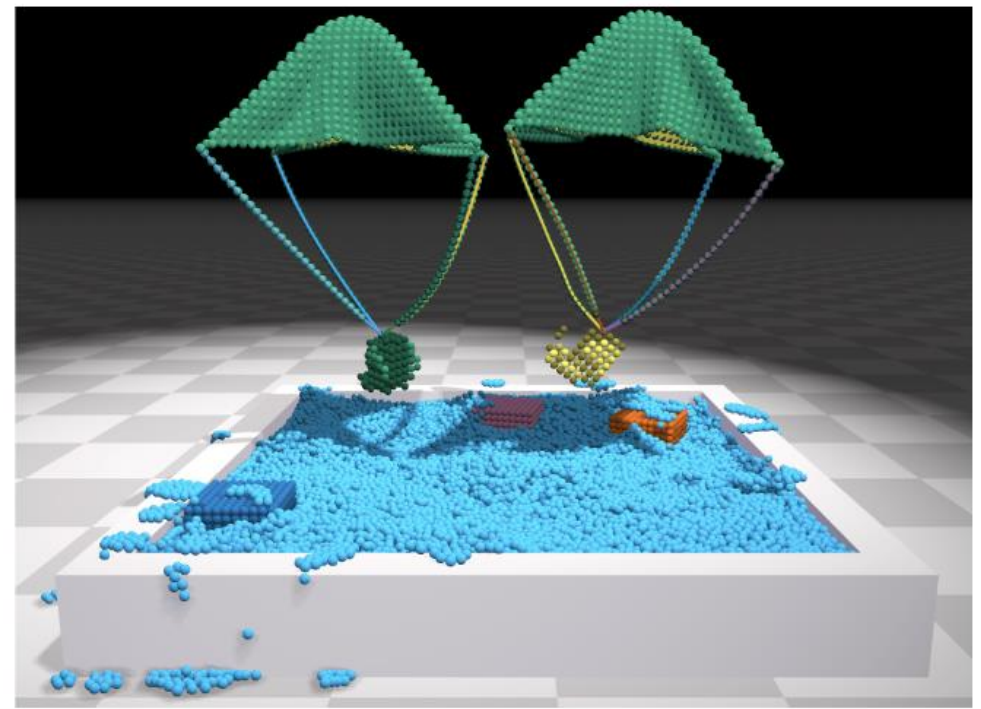
**Algorithm 1** Position-based dynamics

---

```
1: for all vertices  $i$  do
2:   initialize  $\mathbf{x}_i = \mathbf{x}_i^0, \mathbf{v}_i = \mathbf{v}_i^0, w_i = 1/m_i$ 
3: end for
4: loop           Derive the initial kinetic update with Newton's law
5:   for all vertices  $i$  do  $\mathbf{v}_i \leftarrow \mathbf{v}_i + \Delta t w_i \mathbf{f}_{\text{ext}}(\mathbf{x}_i)$ 
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15:  velocityUpdate( $\mathbf{v}_1, \dots, \mathbf{v}_N$ )
16: end loop
```

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The idea is applicable to both particles and rigid bodies



# Constraint Projection

- Let  $\mathbf{p} = \mathbf{x} + \Delta\mathbf{x}$ . The problem becomes to find the correction  $\Delta\mathbf{x}$  such that  $C(\mathbf{x} + \Delta\mathbf{x}) > 0$ .
- We can first approximate the constraint equation with Taylor expansion:

$$C(\mathbf{x} + \Delta\mathbf{x}) \approx C(\mathbf{x}) + \nabla C(\mathbf{x}) \cdot \Delta\mathbf{x} > 0 \quad \nabla = \left( \frac{\partial}{\partial x_1}, \dots, \frac{\partial}{\partial x_N} \right)$$

- A possibly good solution is to restrict  $\Delta\mathbf{x}$  to be in the direction of  $\nabla C(\mathbf{x})$ .  
Let  $M = \text{diag}(m_1, \dots, m_N)$  be the diagonal matrix of point masses

$$\Delta\mathbf{x} = \lambda M^{-1} \nabla C(\mathbf{x})^\top$$

Why this is a possibly good solution?

# Constraint Projection

- We can first approximate the constraint equation with Taylor expansion:

$$C(\mathbf{x} + \Delta\mathbf{x}) \approx C(\mathbf{x}) + \nabla C(\mathbf{x}) \cdot \Delta\mathbf{x} > 0$$

- A possibly good solution is to restrict  $\Delta\mathbf{x}$  to be in the direction of  $\nabla C(\mathbf{x})$ .  
Let  $M = \text{diag}(m_1, \dots, m_N)$  be the diagonal matrix of point masses

$$\Delta\mathbf{x} = \lambda M^{-1} \nabla C(\mathbf{x})^\top$$

1. Linear / angular momentum is conserved: No position / velocity change along the constrained motion direction
2. The value of  $C(\mathbf{x} + \Delta\mathbf{x})$  will increase

# Constraint Projection

- A possibly good solution is to restrict  $\Delta \mathbf{x}$  to be in the direction of  $\nabla C(\mathbf{x})$ .  
Let  $M = \text{diag}(m_1, \dots, m_N)$  be the diagonal matrix of point masses

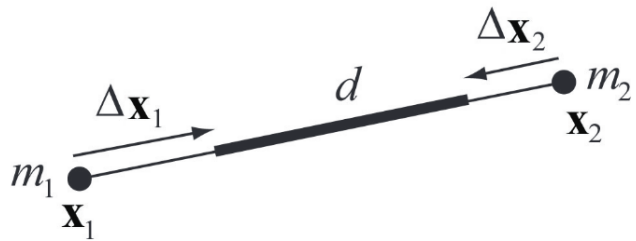
$$\Delta \mathbf{x} = \lambda M^{-1} \nabla C(\mathbf{x})^\top$$

- Let's consider the case where  $C(\mathbf{x} + \Delta \mathbf{x}) \approx C(\mathbf{x}) + \nabla C(\mathbf{x}) \cdot \Delta \mathbf{x} = 0$ , we obtain the solution of  $\lambda$ :

$$\lambda = -\frac{C(\mathbf{x})}{\nabla C(\mathbf{x}) M^{-1} \nabla C(\mathbf{x})^\top}$$

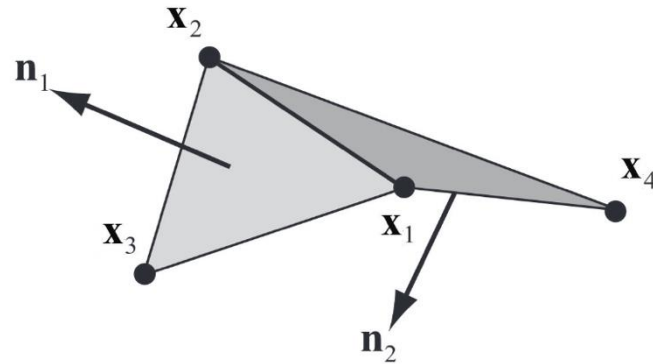
# Different Types of Constraints

Stretching



$$C(x_1, x_2) = |x_1 - x_2| - d$$

Bending



$$C_{bend}(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4) = \arccos \left( \frac{\mathbf{x}_{2,1} \times \mathbf{x}_{3,1}}{|\mathbf{x}_{2,1} \times \mathbf{x}_{3,1}|} \cdot \frac{\mathbf{x}_{2,1} \times \mathbf{x}_{4,1}}{|\mathbf{x}_{2,1} \times \mathbf{x}_{4,1}|} \right) - \varphi_0$$

where  $x_{i,j} = x_i - x_j$  and  $\varphi_0$  is the initial dihedral angle between the two triangles

Collision



$$C(\mathbf{q}, \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3) = (\mathbf{q} - \mathbf{x}_1) \cdot \frac{\mathbf{x}_{2,1} \times \mathbf{x}_{3,1}}{|\mathbf{x}_{2,1} \times \mathbf{x}_{3,1}|} - h,$$

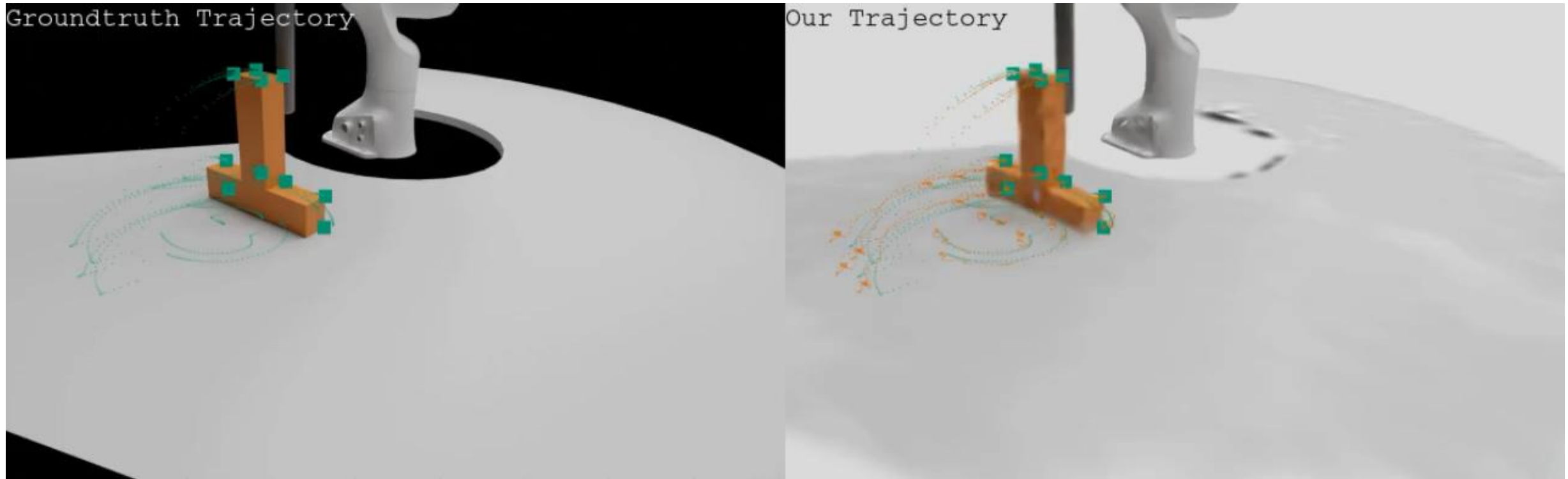
or

$$C(\mathbf{q}, \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3) = (\mathbf{q} - \mathbf{x}_1) \cdot \frac{\mathbf{x}_{3,1} \times \mathbf{x}_{2,1}}{|\mathbf{x}_{3,1} \times \mathbf{x}_{2,1}|} - h.$$

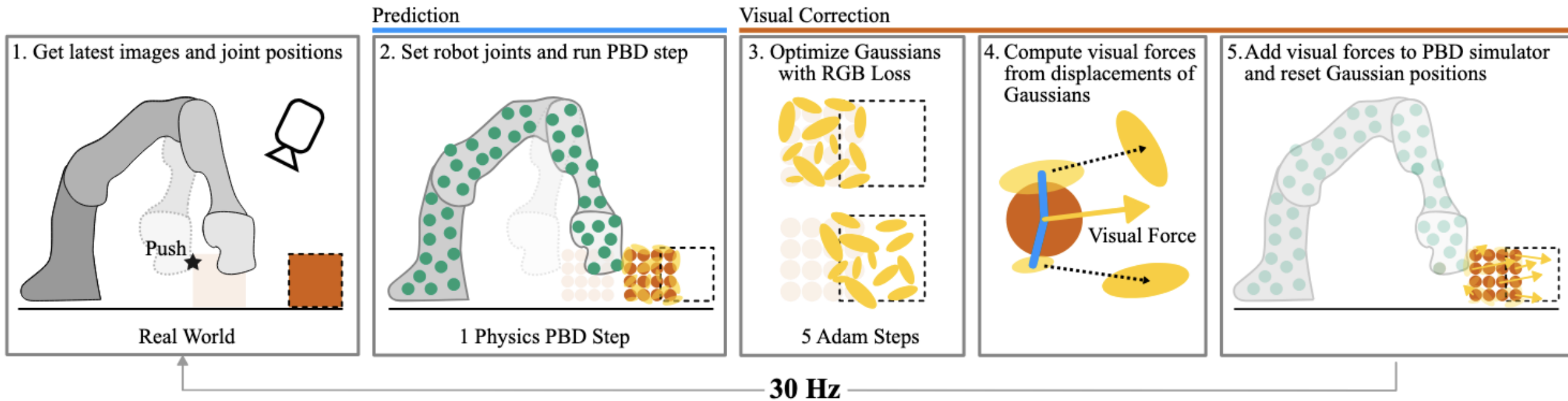
# Physical Modeling with Position Based Dynamics



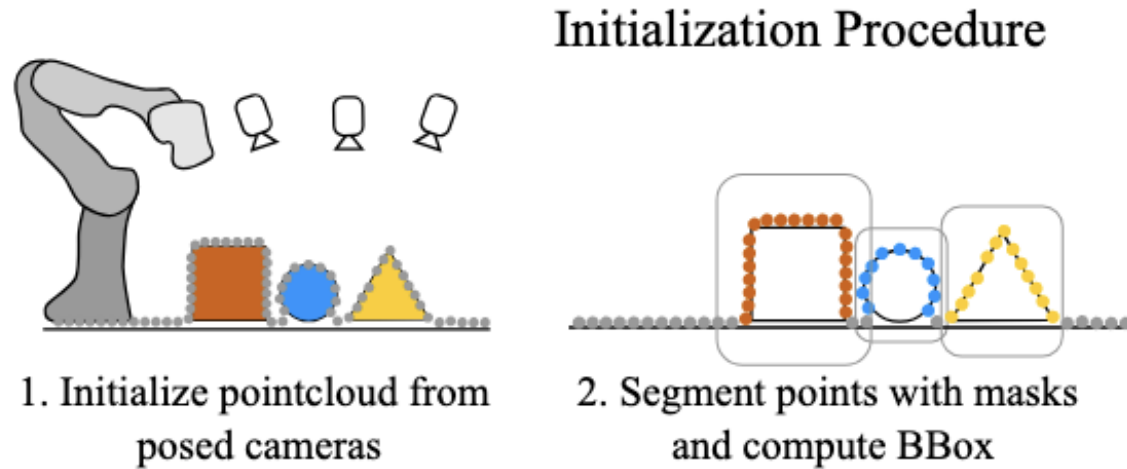
# Scene Reconstruction and Simulation with Position-Based Dynamics



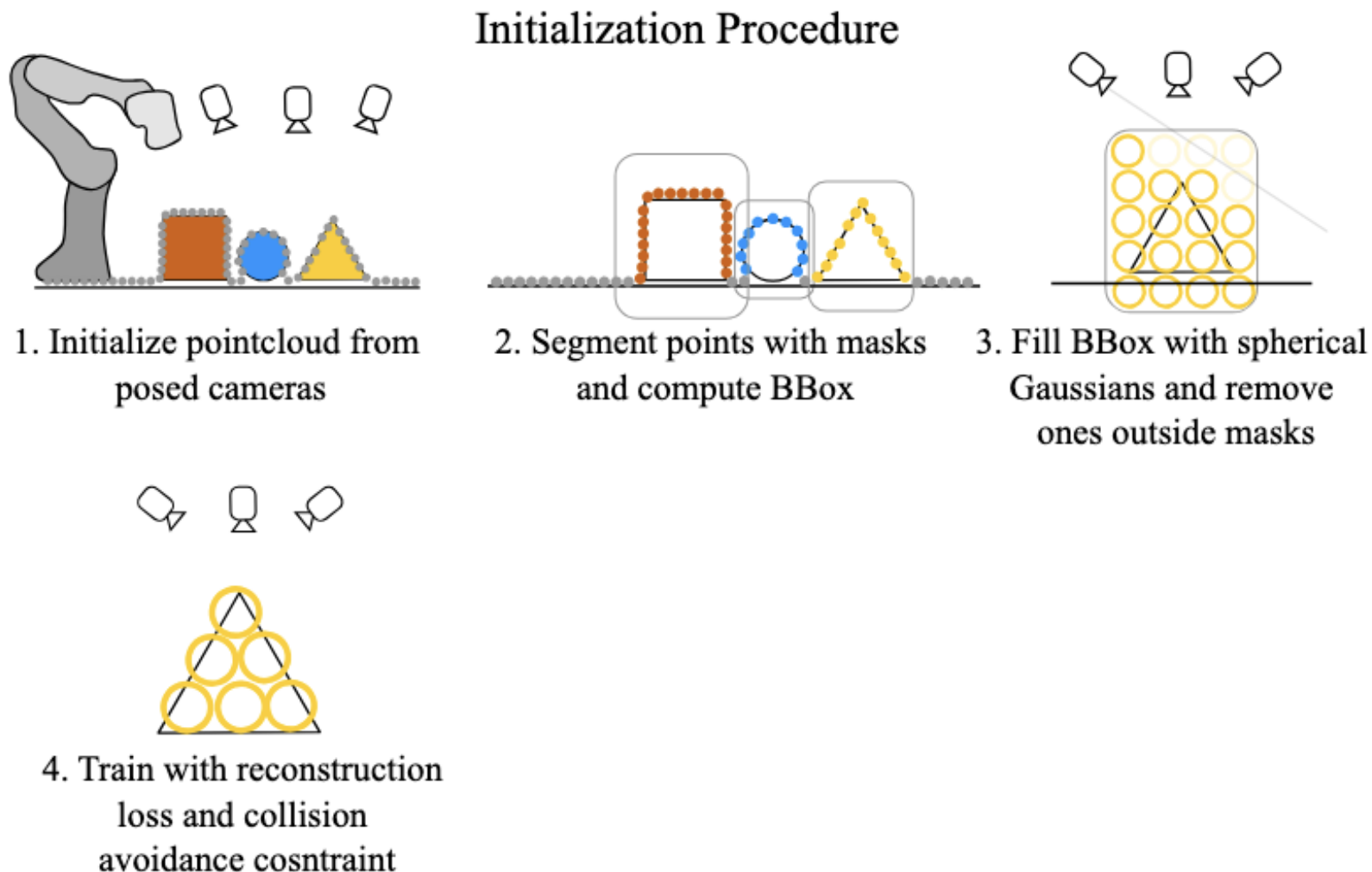
# Idea: Integrate 3D Gaussian Splatting with PBD System and Correct Simulation with Visual Input



# Problem: How to Couple 3D Gaussian Splatting with Particle Presentations of PBD System?

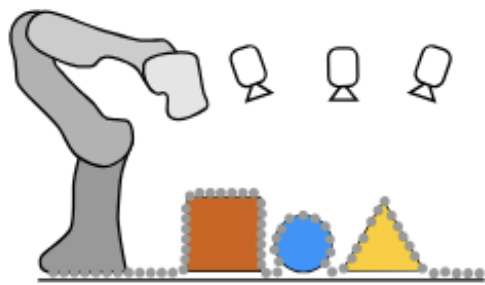


# Problem: How to Couple 3D Gaussian Splatting with Particle Presentations of PBD System?

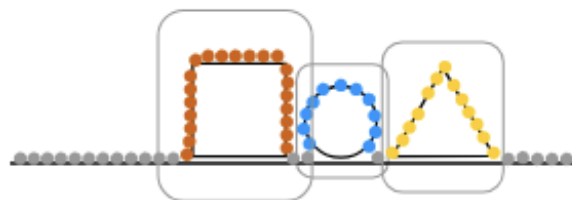


# Problem: How to Couple 3D Gaussian Splatting with Particle Presentations of PBD System?

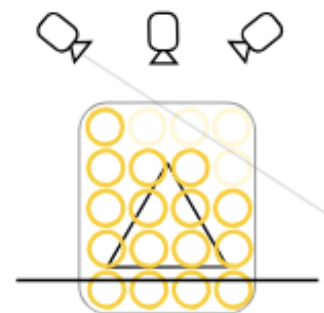
## Initialization Procedure



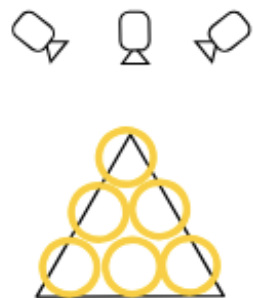
1. Initialize pointcloud from posed cameras



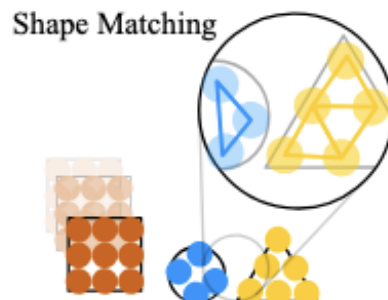
2. Segment points with masks and compute BBox



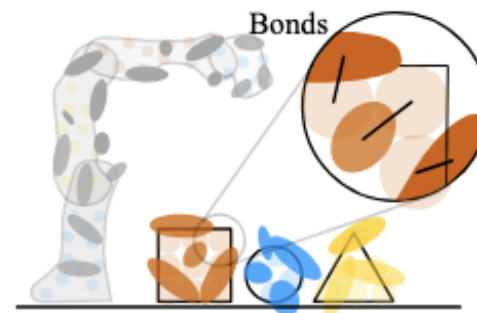
3. Fill BBox with spherical Gaussians and remove ones outside masks



4. Train with reconstruction loss and collision avoidance constraint

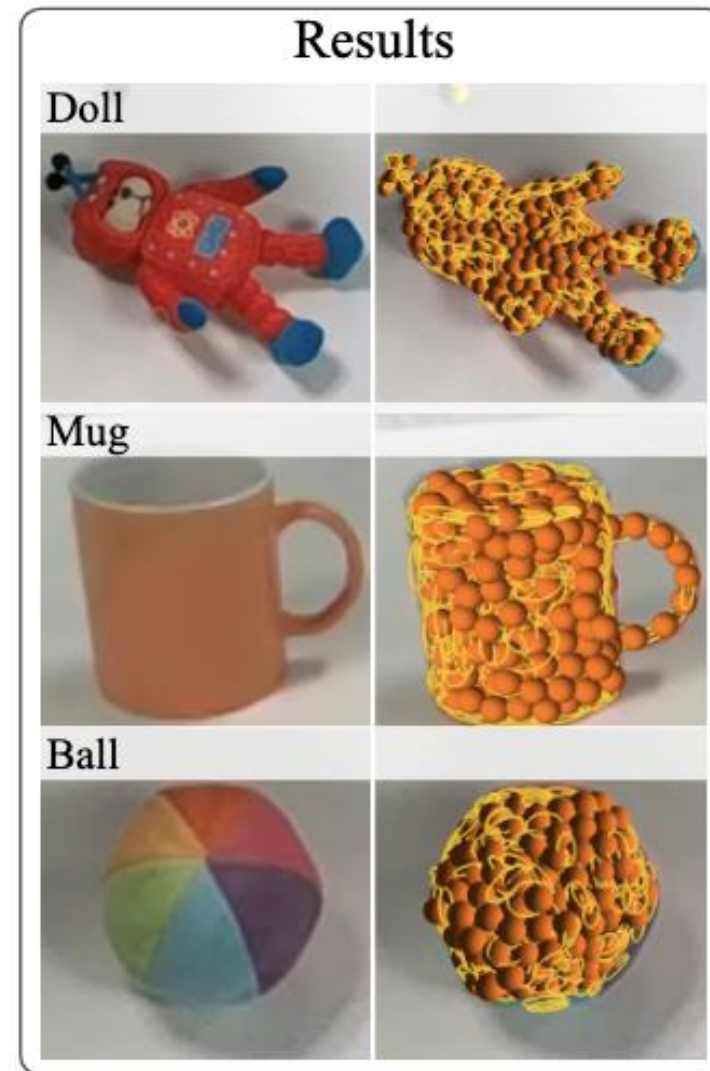
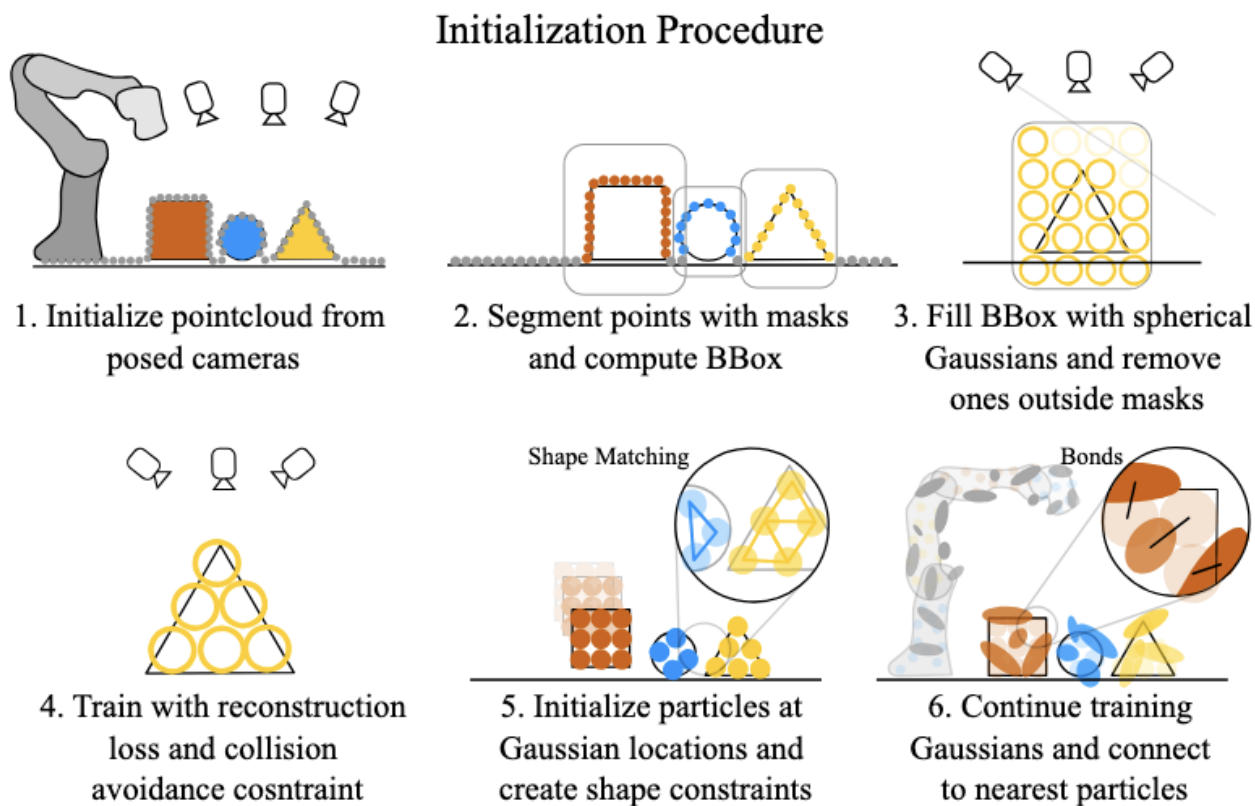


5. Initialize particles at Gaussian locations and create shape constraints



6. Continue training Gaussians and connect to nearest particles

# Problem: How to Couple 3D Gaussian Splatting with Particle Presentations of PBD System?



# PBD Constraints

- PBD acts on oriented particles. Each particle  $i$  has position  $\mathbf{p}_i \in \mathbb{R}^3$ , velocity  $\mathbf{v}_i \in \mathbb{R}^3$ , orientation  $\mathbf{q}_i \in \mathbb{S}^3$ , angular velocity  $\boldsymbol{\omega}_i \in \mathbb{R}^3$ , external force  $\mathbf{f}_i \in \mathbb{R}^3$ , radius  $r_i \in \mathbb{R}^+$ , and mass  $m_i \in \mathbb{R}^+$ . A particle may belong to a shape  $\mathcal{S}_i$  and thus has its resting position  $\bar{\mathbf{p}}_i$ .
- Ground constraint: Prevent particles from penetrating the ground plane given by  $(\mathbf{n}, d)$

$$\Delta \mathbf{p}_i^{\text{ground}} = C_{\text{ground}}(\mathbf{p}_i; \mathbf{n}, d) \cdot \mathbf{n}, \quad C_{\text{ground}}(\mathbf{p}_i; \mathbf{n}, d) = \min(\mathbf{n}^T \mathbf{p}_i + d - r_i, 0)$$

# PBD Constraints

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- Particle collision constraint: Operate on a pair of particles  $i$  and  $j$  is used to model collisions

$$\Delta \mathbf{p}_i^{\text{col}} = \frac{w_i}{w_i + w_j} \frac{\mathbf{p}_i - \mathbf{p}_j}{\|\mathbf{p}_i - \mathbf{p}_j\|} C_{\text{col}}(\mathbf{p}_i, \mathbf{p}_j), \quad C_{\text{col}}(\mathbf{p}_i, \mathbf{p}_j) = \min(\|\mathbf{p}_i - \mathbf{p}_j\| - r_i - r_j, 0)$$

# PBD Constraints

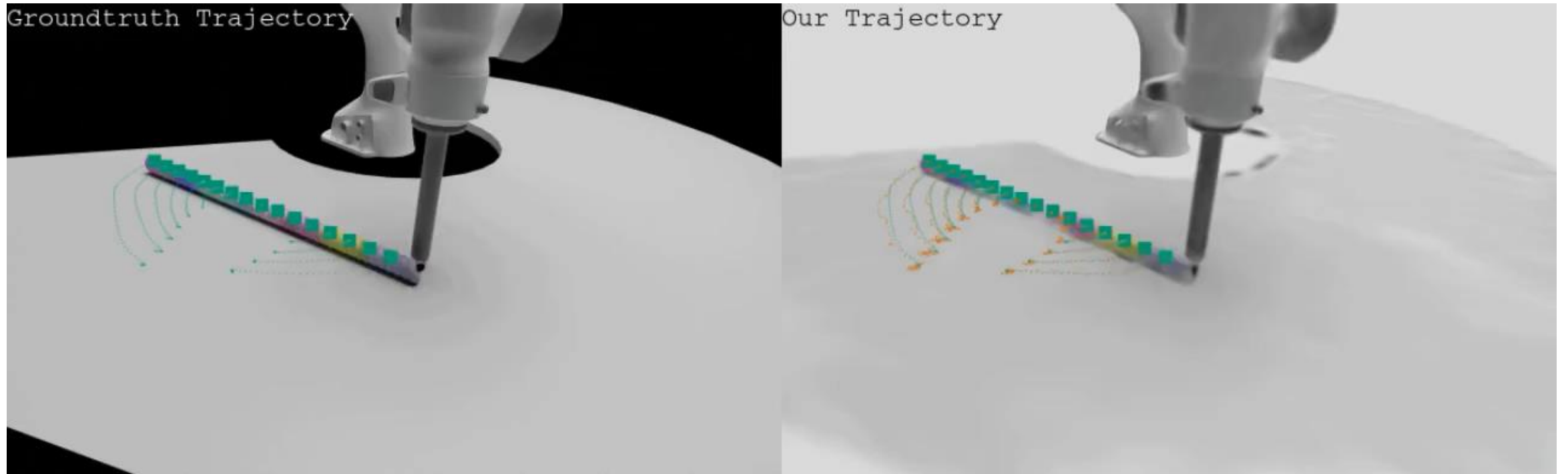
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- Shape matching constraint: Ensure a group of particles belonging to a particular object (either deformable or rigid) maintain their structure throughout the simulation

$$\boxed{\mathbf{A}_S} = \sum_{i \in S} \frac{1}{5} m_i \mathbf{R}_i + \mathbf{p}_i \bar{\mathbf{p}}_i^T - M \mathbf{c}_S \bar{\mathbf{c}}_S^T, \quad \mathbf{c}_S = \frac{\sum_{i \in S} m_i \mathbf{p}_i}{M}, \quad \bar{\mathbf{c}}_S = \frac{\sum_{i \in S} m_i \bar{\mathbf{p}}_i}{M}, \quad M = \sum_{i \in S} m_i$$

$\mathbf{A}_S = \mathbf{R}_S \mathbf{S}$  can be decomposed into a rotation matrix  $\mathbf{R}_S$  and a symmetrical matrix  $\mathbf{S}$

$$\Delta \mathbf{p}_i^{\text{shape}} = k_S [\mathbf{R}_S (\bar{\mathbf{p}}_i - \bar{\mathbf{c}}_S) + \mathbf{c} - \mathbf{p}_i]$$

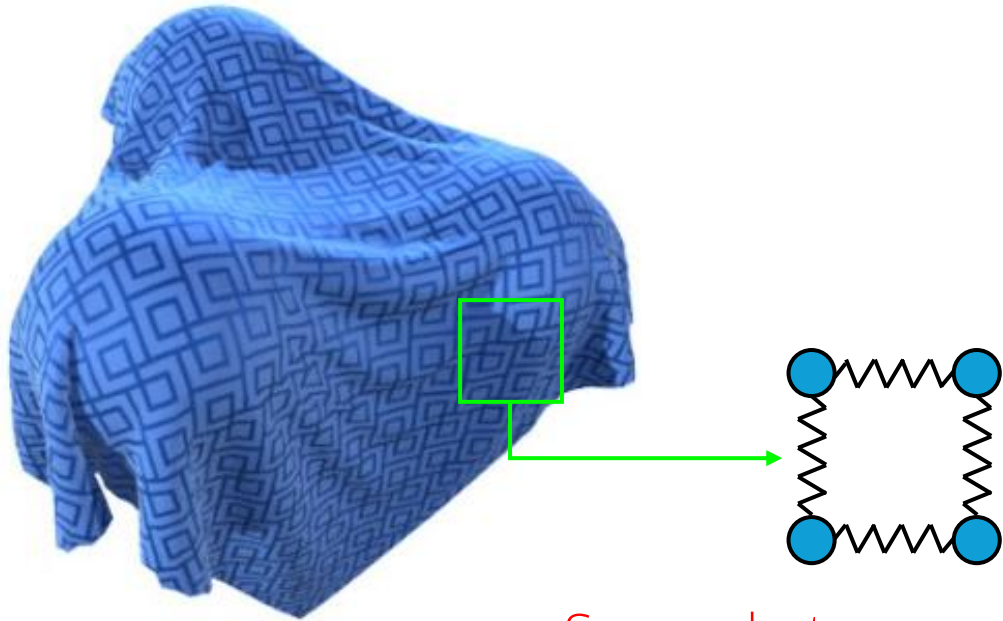
# Results: Real-to-Sim Demo



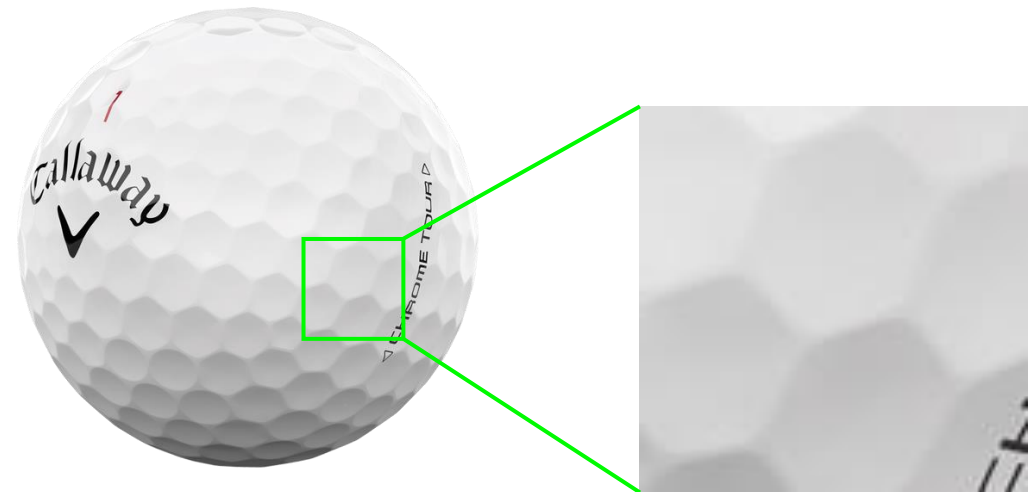
# Content

- Non-Rigid Modeling
  - Mass-spring system
  - Position-based Dynamics
  - Tetrahedral and Deformation

# Mass-Spring System and Particle-based PBD Do Not Model Continuum Mechanics

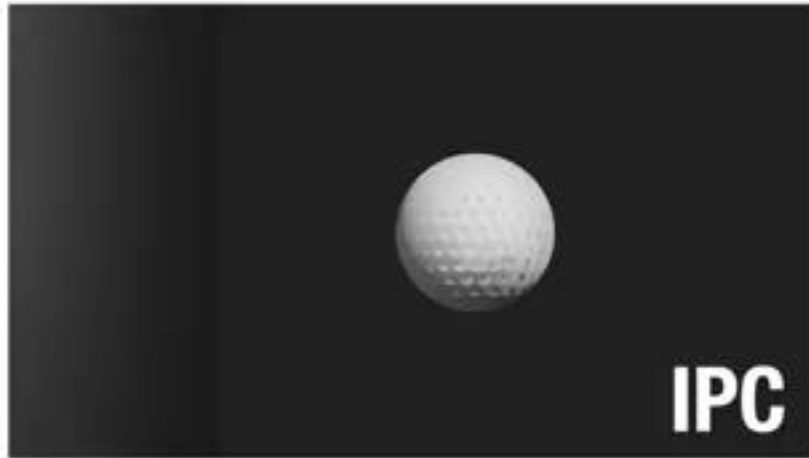


Spaces between nodes are empty: no mass and energy



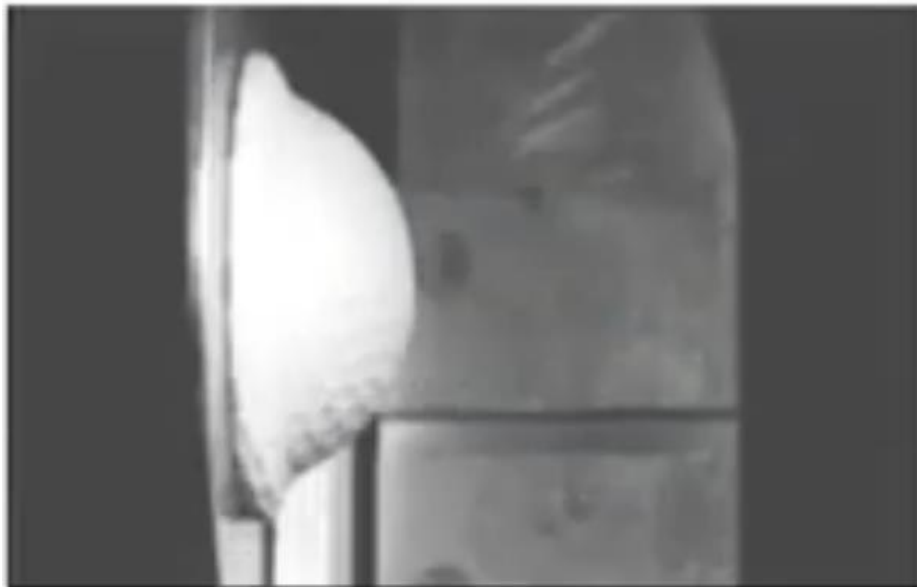
Spaces are continuously filled

# Common Objects are Elastic, Even Though They Look Like Rigid Bodies



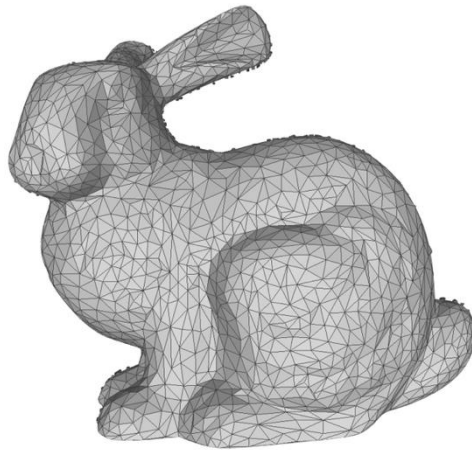
# Continuum Mechanics

- How did every point in the object change shape?
- How to represent a continuum object?

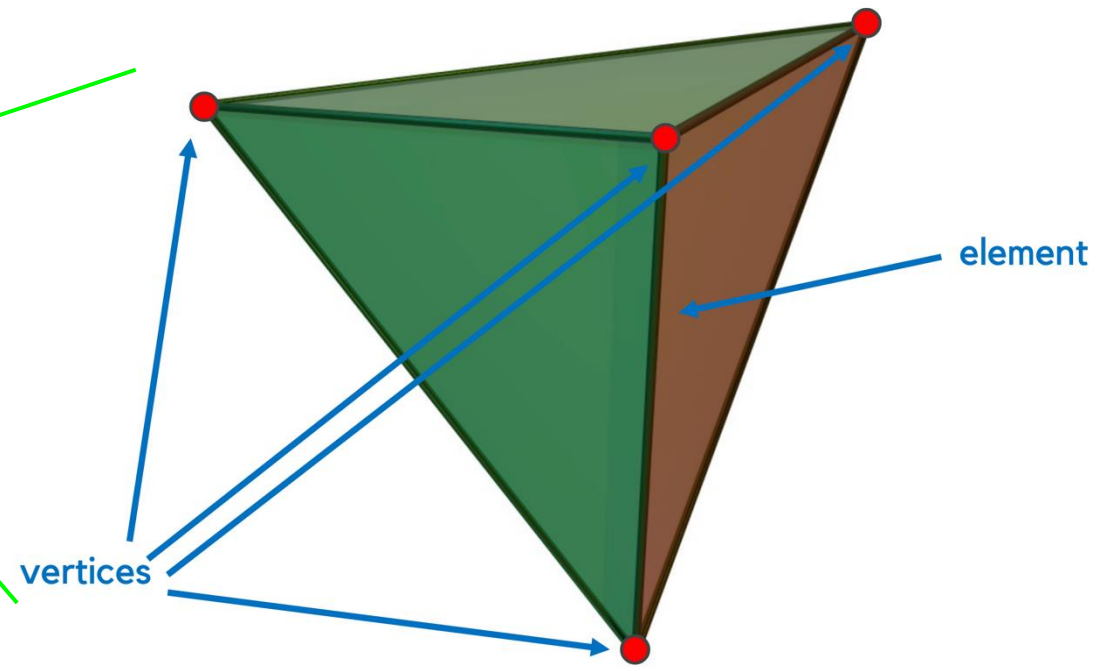
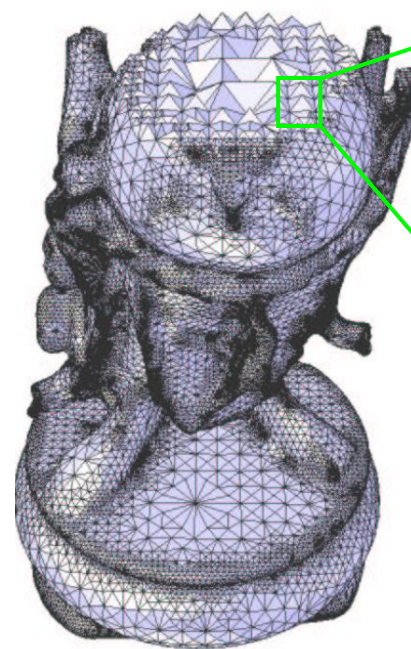


# Tetrahedral Finite Elements

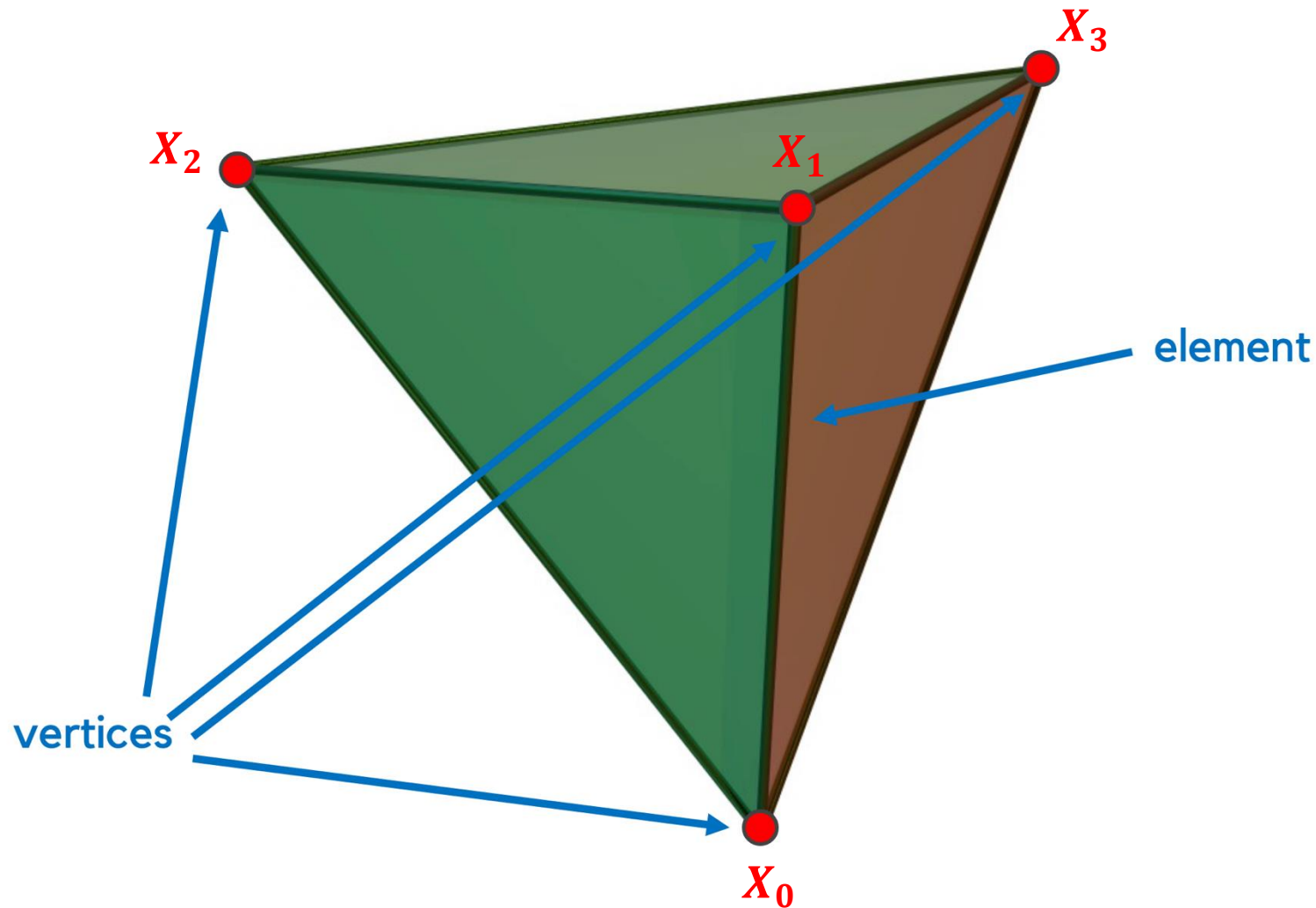
Mesh



Tetrahedral Mesh



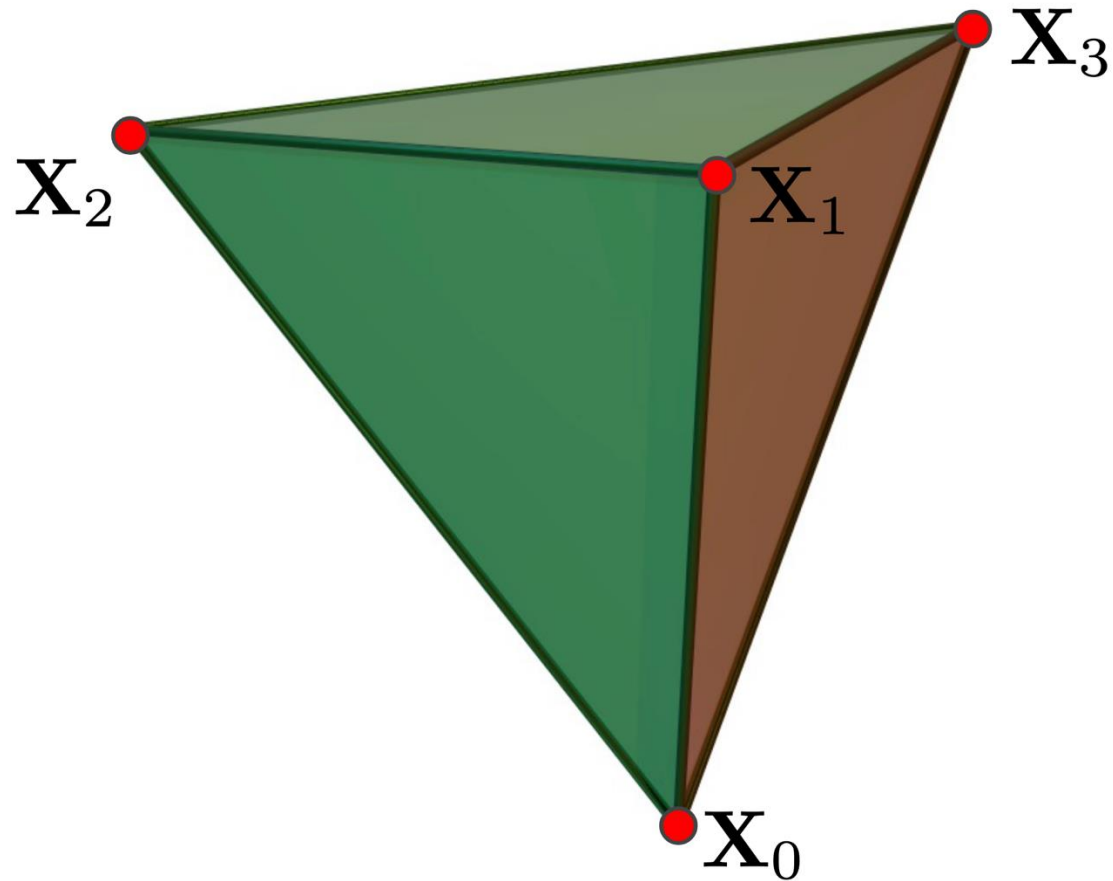
# Tetrahedral Finite Elements



$$\mathbf{q} = \begin{pmatrix} X_0 \\ X_1 \\ X_2 \\ X_3 \end{pmatrix}$$

$$\dot{\mathbf{q}} = \begin{pmatrix} \dot{X}_0 \\ \dot{X}_1 \\ \dot{X}_2 \\ \dot{X}_3 \end{pmatrix}$$

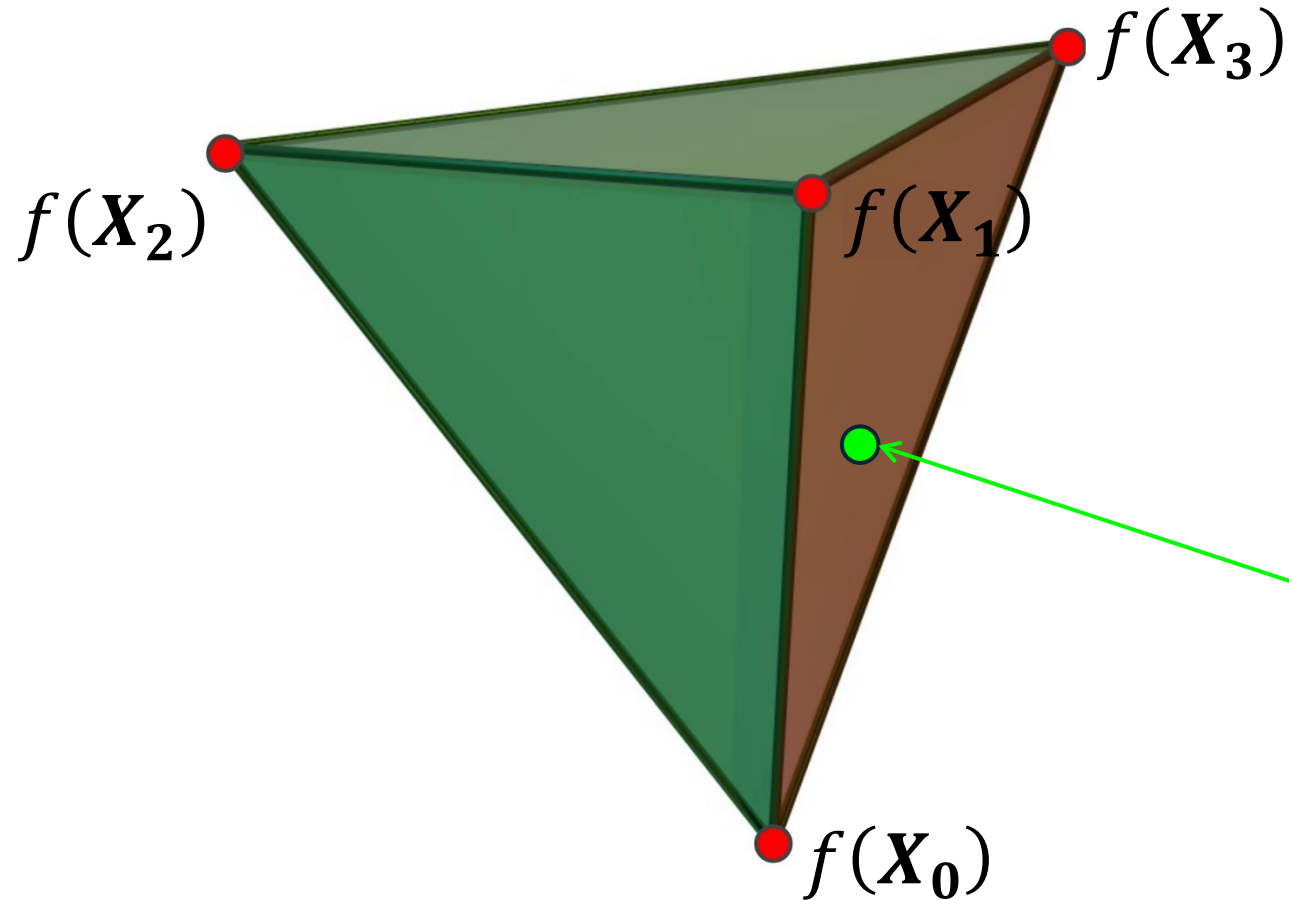
# Generalized Coordinates for Tetrahedra Finite Elements



- $X$  can be a set of parameters that specify the configuration of a physical system at each point in time (e.g. rotational angle in a pendulum system)

$$\mathbf{q} = \begin{pmatrix} \mathbf{X}_0 \\ \mathbf{X}_1 \\ \mathbf{X}_2 \\ \mathbf{X}_3 \end{pmatrix} \quad \dot{\mathbf{q}} = \begin{pmatrix} \dot{\mathbf{X}}_0 \\ \dot{\mathbf{X}}_1 \\ \dot{\mathbf{X}}_2 \\ \dot{\mathbf{X}}_3 \end{pmatrix}$$

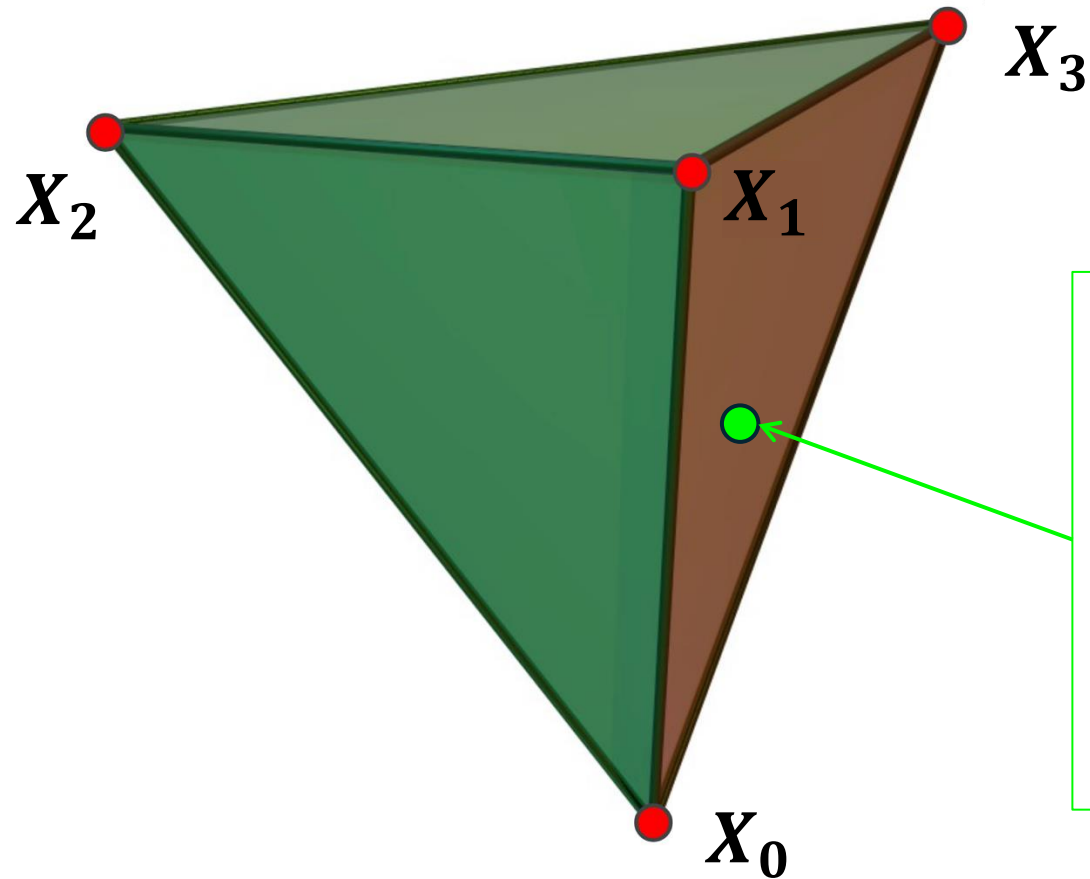
# Why Do We Need Such a Representation?



- The value of any point in a tetrahedra can be linearly interpolated
- We don't need to keep track of the deformation of every point but few vertices

$$f(\mathbf{X}) = \sum_{i=0}^3 f(\mathbf{X}_i) \phi_i(\mathbf{X})$$

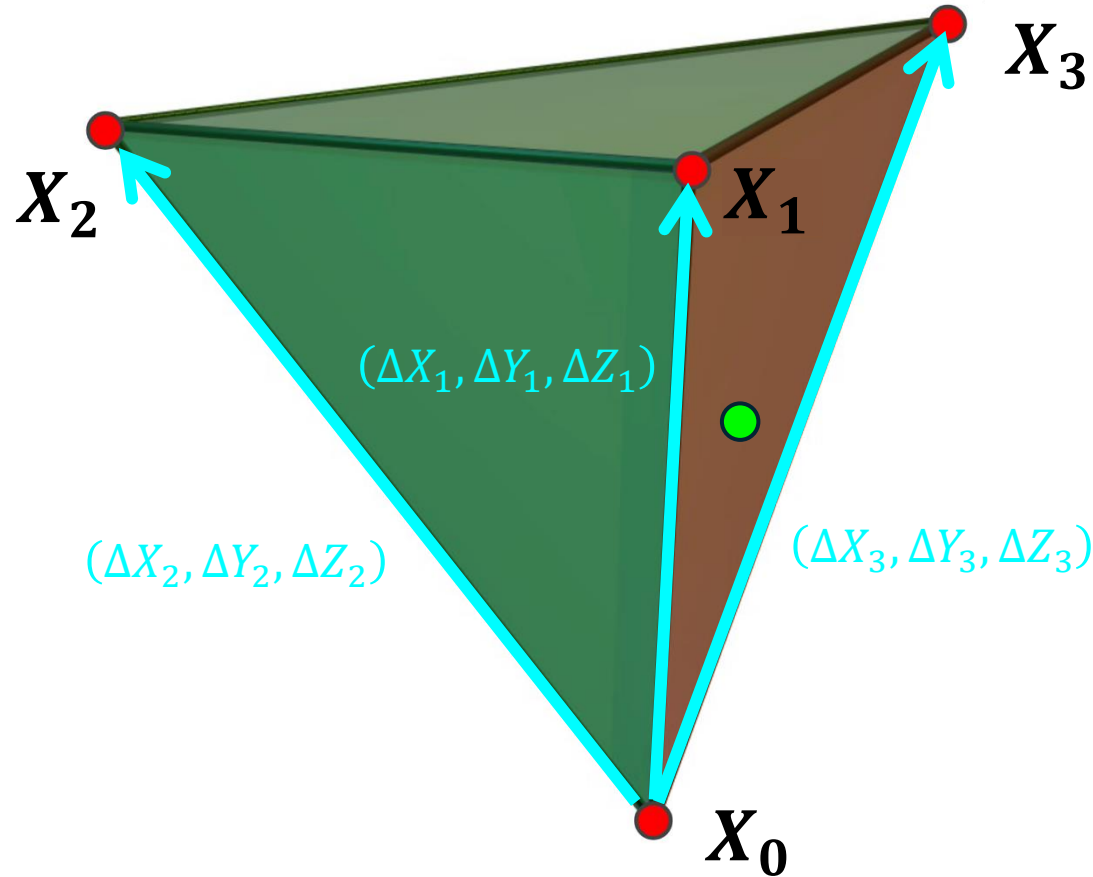
# Why Do We Need Such a Representation?



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$$\mathbf{X} = \sum_{i=0}^3 \mathbf{X}_i \phi_i(\mathbf{X})$$
$$\Rightarrow \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} X_0 & X_1 & X_2 & X_3 \\ Y_0 & Y_1 & Y_2 & Y_3 \\ Z_0 & Z_1 & Z_2 & Z_3 \end{pmatrix} \begin{pmatrix} \phi_0(\mathbf{X}) \\ \phi_1(\mathbf{X}) \\ \phi_2(\mathbf{X}) \\ \phi_3(\mathbf{X}) \end{pmatrix}$$

# Why Do We Need Such a Representation?

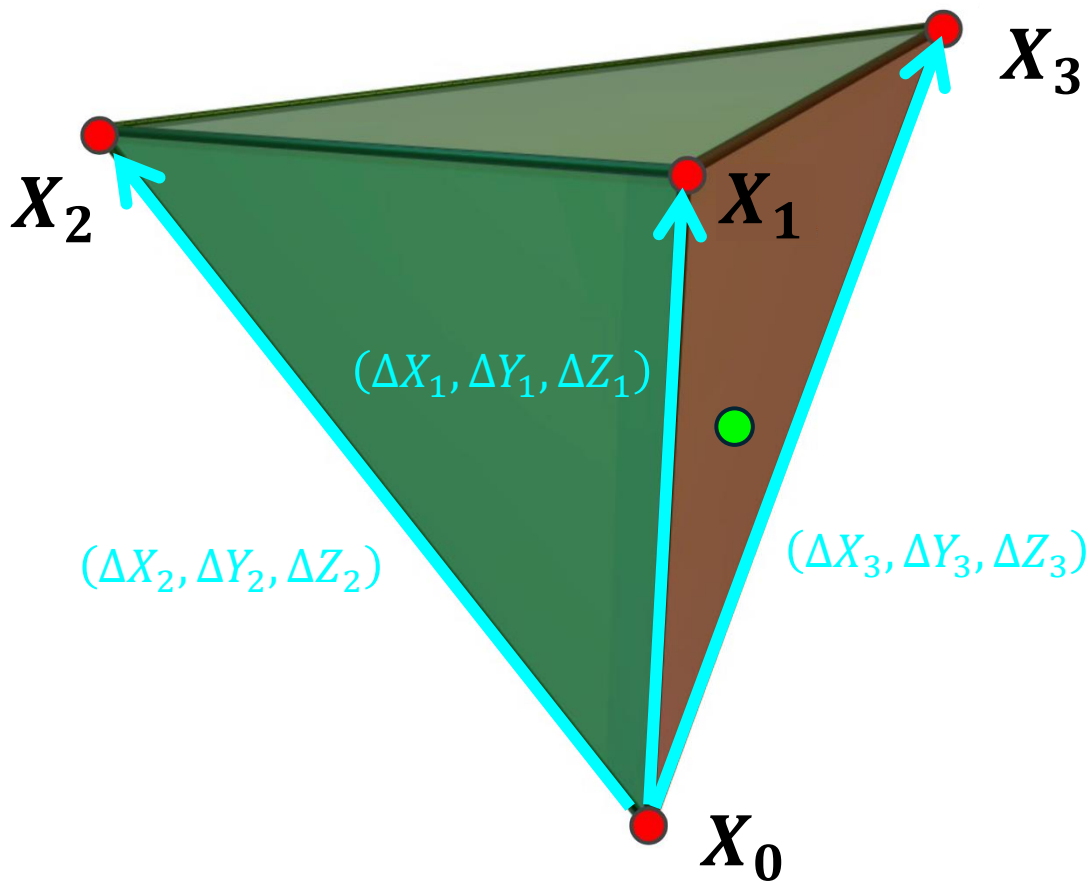


$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} X_0 & X_1 & X_2 & X_3 \\ Y_0 & Y_1 & Y_2 & Y_3 \\ Z_0 & Z_1 & Z_2 & Z_3 \end{pmatrix} \begin{pmatrix} \phi_0(\mathbf{X}) \\ \phi_1(\mathbf{X}) \\ \phi_2(\mathbf{X}) \\ \phi_3(\mathbf{X}) \end{pmatrix}$$

Let  $\phi_0(\mathbf{X}) = 1 - \phi_1(\mathbf{X}) - \phi_2(\mathbf{X}) - \phi_3(\mathbf{X})$

$$\Rightarrow \begin{pmatrix} X - X_0 \\ Y - Y_0 \\ Z - Z_0 \end{pmatrix} = \begin{pmatrix} \Delta X_1 & \Delta X_2 & \Delta X_3 \\ \Delta Y_1 & \Delta Y_2 & \Delta Y_3 \\ \Delta Z_1 & \Delta Z_2 & \Delta Z_3 \end{pmatrix} \begin{pmatrix} \phi_1(\mathbf{X}) \\ \phi_2(\mathbf{X}) \\ \phi_3(\mathbf{X}) \end{pmatrix}$$

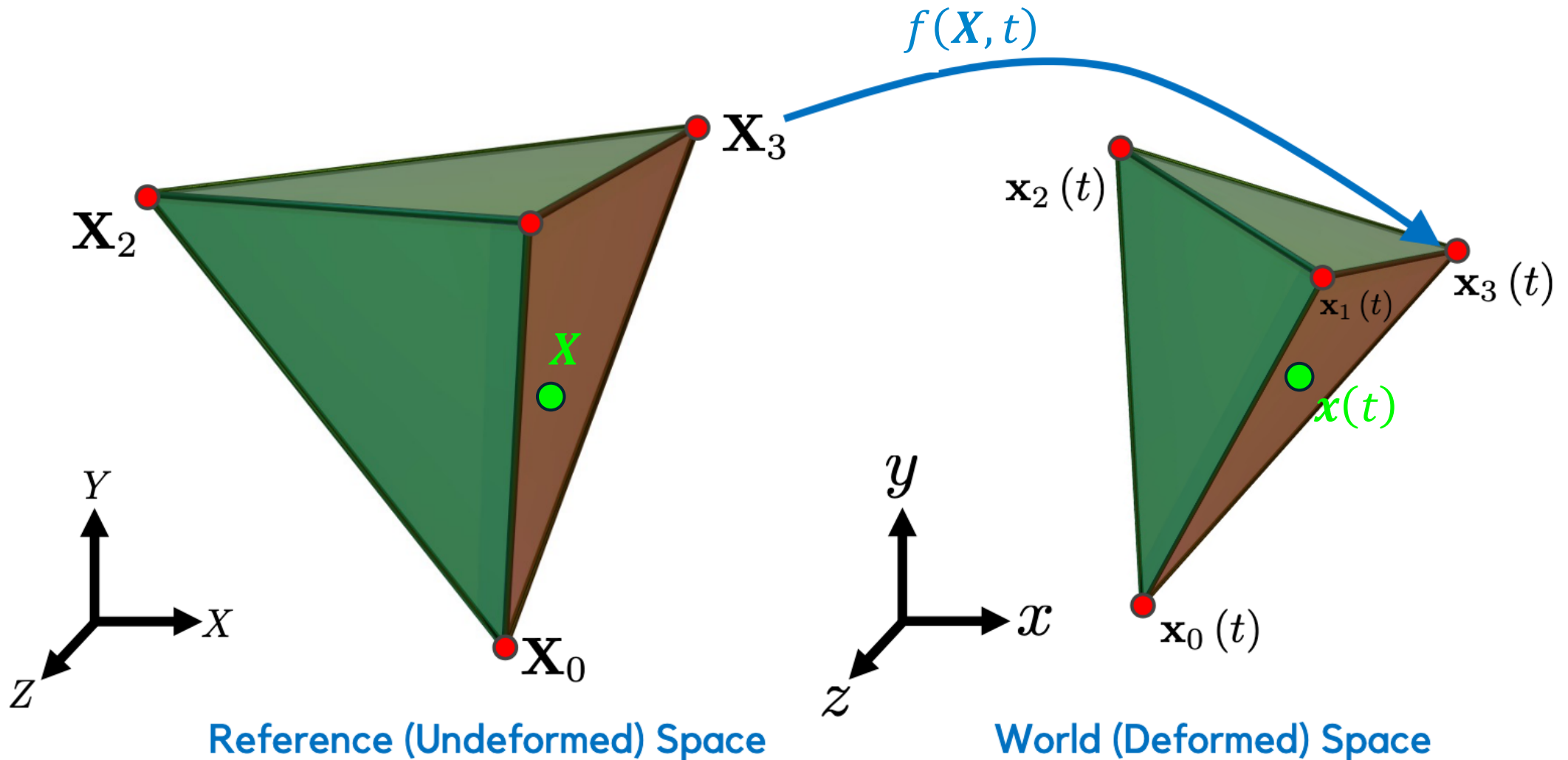
# Barycentric Coordinates



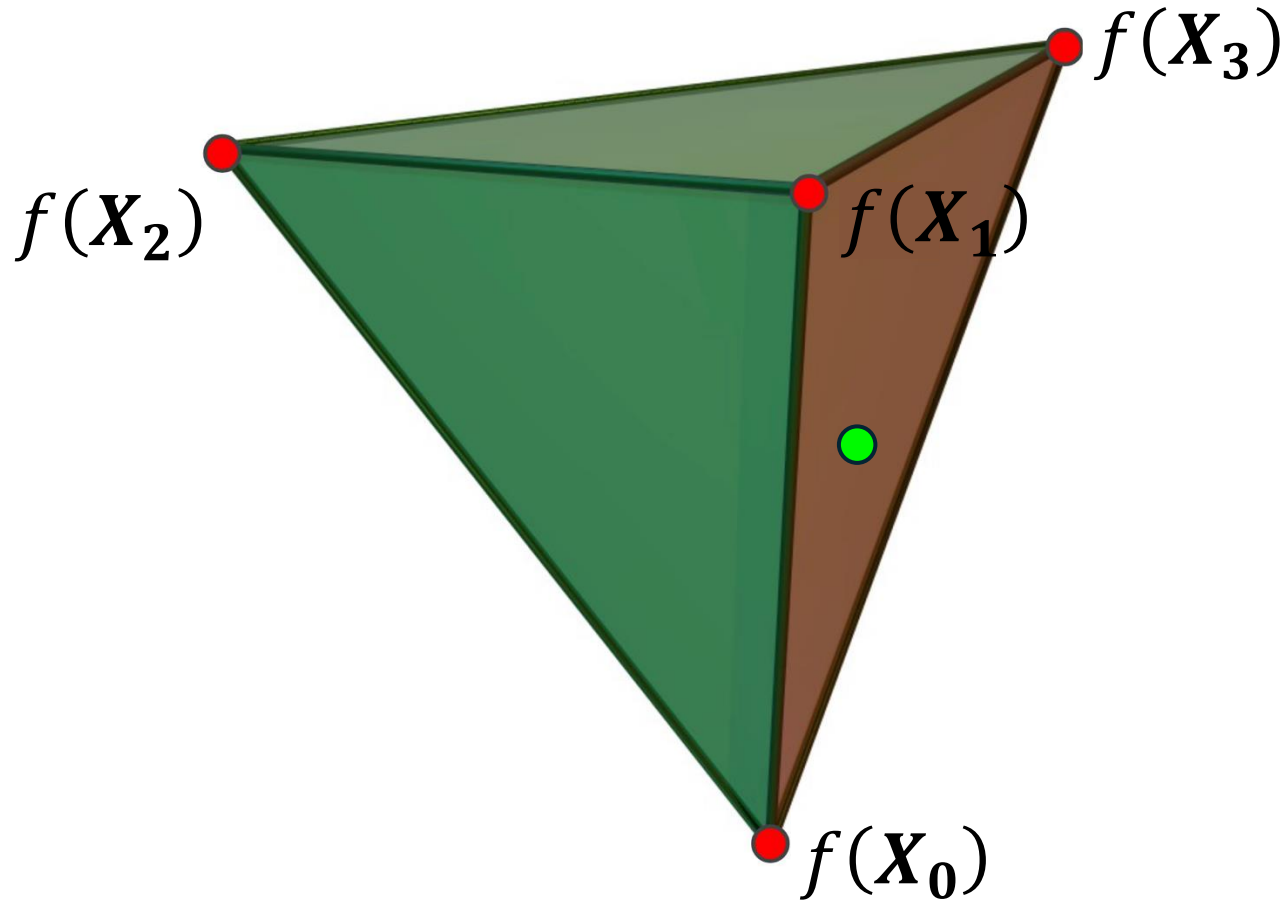
$$\begin{pmatrix} X - X_0 \\ Y - Y_0 \\ Z - Z_0 \end{pmatrix} = \begin{pmatrix} \Delta X_1 & \Delta X_2 & \Delta X_3 \\ \Delta Y_1 & \Delta Y_2 & \Delta Y_3 \\ \Delta Z_1 & \Delta Z_2 & \Delta Z_3 \end{pmatrix} \begin{pmatrix} \phi_1(\mathbf{X}) \\ \phi_2(\mathbf{X}) \\ \phi_3(\mathbf{X}) \end{pmatrix}$$
$$\Rightarrow \begin{pmatrix} \phi_1(\mathbf{X}) \\ \phi_2(\mathbf{X}) \\ \phi_3(\mathbf{X}) \end{pmatrix} = \begin{pmatrix} \Delta X_1 & \Delta X_2 & \Delta X_3 \\ \Delta Y_1 & \Delta Y_2 & \Delta Y_3 \\ \Delta Z_1 & \Delta Z_2 & \Delta Z_3 \end{pmatrix}^{-1} \begin{pmatrix} X - X_0 \\ Y - Y_0 \\ Z - Z_0 \end{pmatrix}$$

We can infer the interpolation weights from an undeformed tetrahedron

# Material Deformation



# Material Deformation

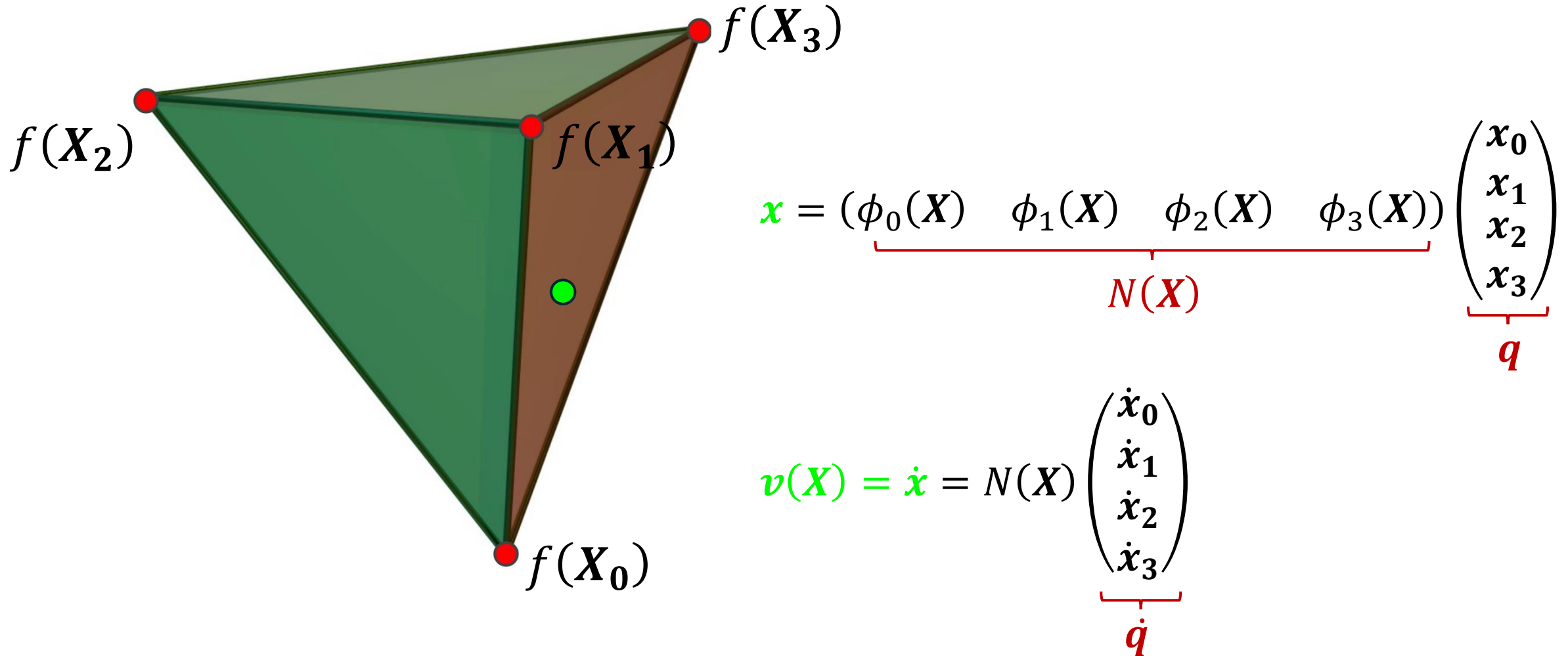


- The value of any point in a tetrahedra can be linearly interpolated
- We don't need to keep track of the deformation of every point but few vertices

$$\mathbf{x}(t) = \sum_{i=0}^3 \mathbf{x}_i(t) \phi_i(\mathbf{X})$$

↓  
Deformed vertex position

# Material Deformation



# In the Next Lecture, We'll Introduce a More General Framework to Derive Equations of Motion

- The Lagrangian:

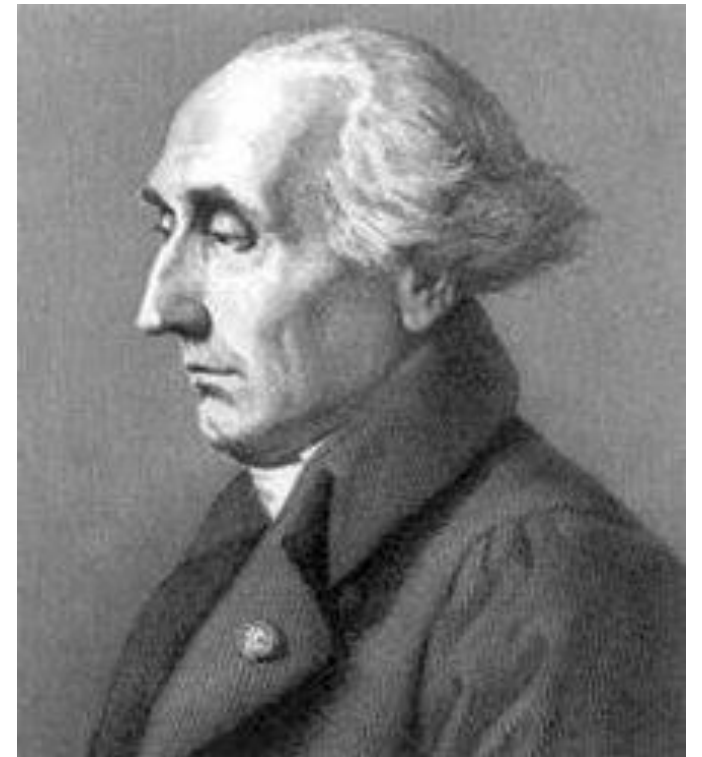
Potential energy

$$L = T - V$$

Kinetic energy

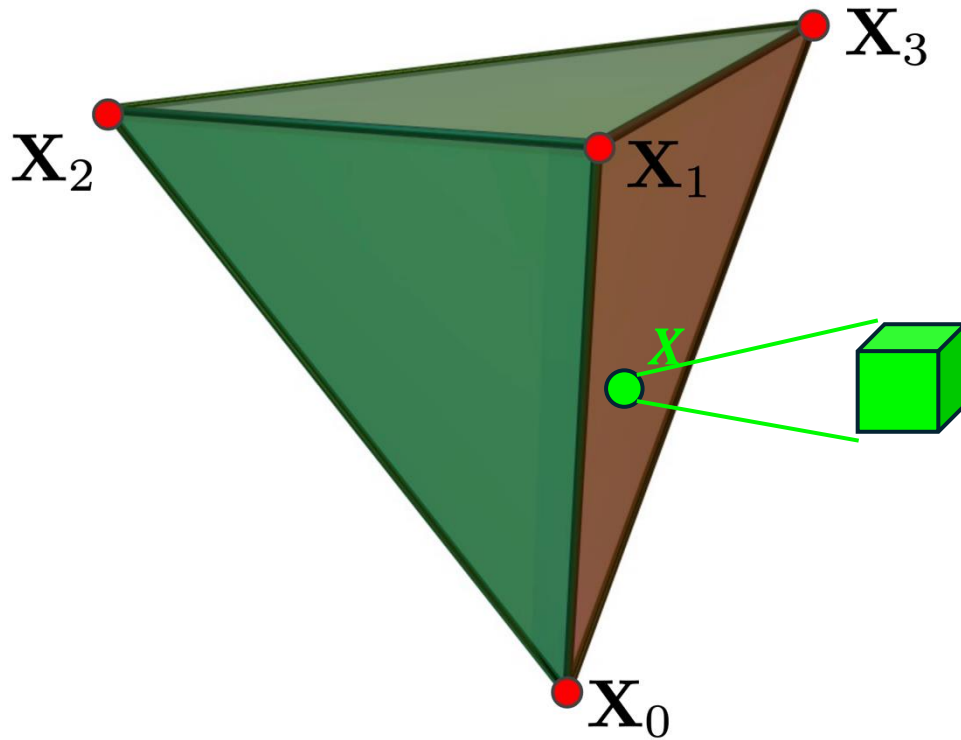
- Euler-Lagrange Equation:

$$\frac{d}{dt} \frac{\partial L}{\partial \dot{\mathbf{q}}} = - \frac{\partial L}{\partial \mathbf{q}}$$



Joseph-Louis Lagrange

# Kinetic Energy of a Deformed Material



- Kinetic energy at  $\mathbf{X}$ :

$$\frac{1}{2} \rho \|v(\mathbf{X})\|_2^2 d\Omega$$

↑ infinitesimal volume

↘ unit density

- Kinetic energy of the tetrahedral

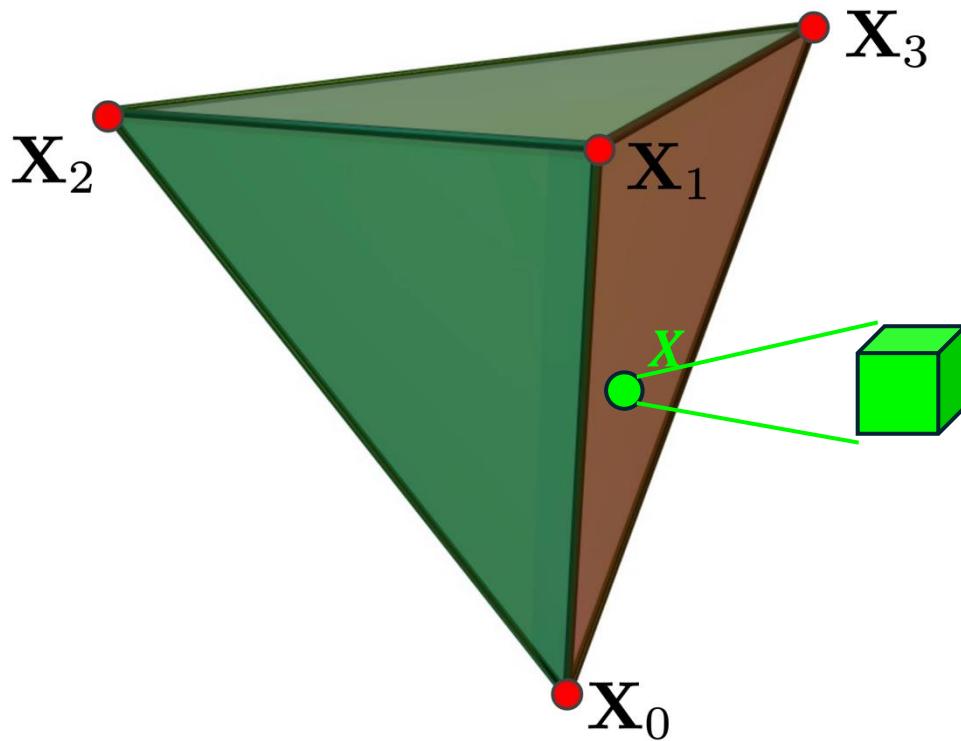
$$\int_{\Omega} \frac{1}{2} \rho \|v(\mathbf{X})\|_2^2 d\Omega$$

↘ Tetrahedra domain

$$\Rightarrow \frac{1}{2} \int_{\Omega} \rho (N(\mathbf{X}) \dot{\mathbf{q}})^T N(\mathbf{X}) \dot{\mathbf{q}} d\Omega$$

$$\Rightarrow \frac{1}{2} \dot{\mathbf{q}}^T \left( \int_{\Omega} \rho N(\mathbf{X})^T N(\mathbf{X}) d\Omega \right) \dot{\mathbf{q}}$$

# Kinetic Energy of a Deformed Material



- Kinetic energy of the tetrahedral

$$\frac{1}{2} \dot{\mathbf{q}}^T \left( \int_{\Omega} \rho \mathbf{N}(\mathbf{X})^T \mathbf{N}(\mathbf{X}) d\Omega \right) \dot{\mathbf{q}}$$

↓

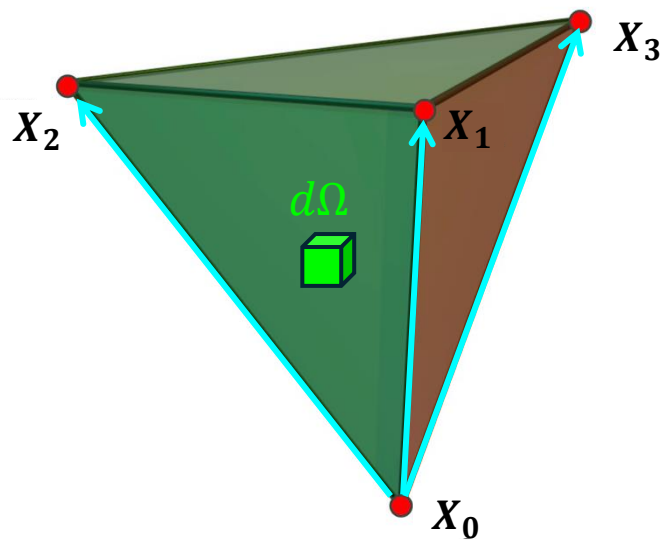
$$\int_{\Omega} \rho \begin{pmatrix} \phi_0 \phi_0 I & \phi_0 \phi_1 I & \phi_0 \phi_2 I & \phi_0 \phi_3 I \\ \phi_1 \phi_0 I & \phi_1 \phi_1 I & \phi_1 \phi_2 I & \phi_1 \phi_3 I \\ \phi_2 \phi_0 I & \phi_2 \phi_1 I & \phi_2 \phi_2 I & \phi_2 \phi_3 I \\ \phi_3 \phi_0 I & \phi_3 \phi_1 I & \phi_3 \phi_2 I & \phi_3 \phi_3 I \end{pmatrix} d\Omega$$

- Evaluate at each term separately:

$$\int_{\Omega} \rho \phi_r \phi_s I d\Omega$$

# The Differential Volume Element

- Integral over the tetrahedral domain  $\Omega$ :  $\int_{\Omega} \rho \phi_r \phi_s I d\Omega$
- The integral is difficult to calculate using the Cartesian coordinates
- Idea: Transform the Cartesian coordinates into Barycentric coordinates



We have  $\phi_0(\mathbf{X}) = 1 - \phi_1(\mathbf{X}) - \phi_2(\mathbf{X}) - \phi_3(\mathbf{X})$

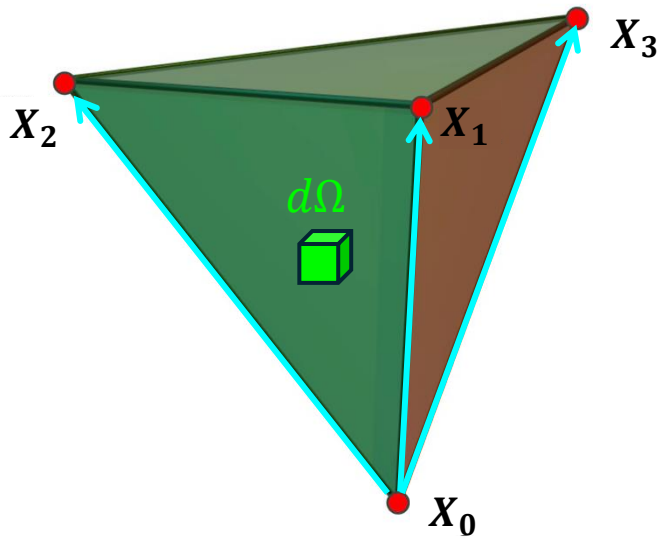
$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} X_0 & X_1 & X_2 & X_3 \\ Y_0 & Y_1 & Y_2 & Y_3 \\ Z_0 & Z_1 & Z_2 & Z_3 \end{pmatrix} \begin{pmatrix} \phi_0(\mathbf{X}) \\ \phi_1(\mathbf{X}) \\ \phi_2(\mathbf{X}) \\ \phi_3(\mathbf{X}) \end{pmatrix}$$

Cartesian coordinates

Barycentric coordinates

# The Differential Volume Element

- Integral over the tetrahedral domain  $\Omega$ :  $\int_{\Omega} \rho \phi_r \phi_s I d\Omega$
- The integral is difficult to calculate using the Cartesian coordinates
- Idea: Transform the Cartesian coordinates into Barycentric coordinates



$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} X_0 & (X_1 - X_0)\phi_1 & (X_2 - X_0)\phi_2 & (X_3 - X_0)\phi_3 \\ Y_0 & (Y_1 - Y_0)\phi_1 & (Y_2 - Y_0)\phi_2 & (Y_3 - Y_0)\phi_3 \\ Z_0 & (Z_1 - Z_0)\phi_1 & (Z_2 - Z_0)\phi_2 & (Z_3 - Z_0)\phi_3 \end{pmatrix}$$

# Remember that We Transformed Two Coordinate System with Jacobian $J_{\mathbf{u}_k}$

- Projection is not affine mapping

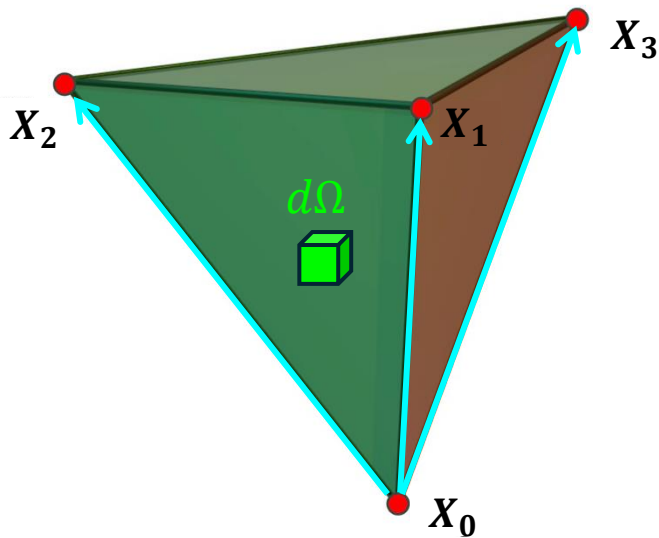
$$\begin{pmatrix} x_0 \\ x_1 \\ x_2 \end{pmatrix} = m(\mathbf{u}) = \begin{pmatrix} u_0/u_2 \\ u_1/u_2 \\ \|\mathbf{u}\| \end{pmatrix}$$

- We can approximate with 1<sup>st</sup> order Taylor Expansion at mean  $\mathbf{u}_k$  and  $\mathbf{x}_k$  of two spaces as:

$$m_{\mathbf{u}_k}(\mathbf{u}) = \mathbf{x}_k + J_{\mathbf{u}_k} \cdot (\mathbf{u} - \mathbf{u}_k), \quad \text{where } J_{\mathbf{u}_k} = \frac{\partial m}{\partial \mathbf{u}}(\mathbf{u}_k)$$

# The Differential Volume Element

- Integral over the tetrahedral domain  $\Omega$ :  $\int_{\Omega} \rho \phi_r \phi_s I d\Omega$
- The integral is difficult to calculate using the Cartesian coordinates
- Idea: Transform the Cartesian coordinates into Barycentric coordinates



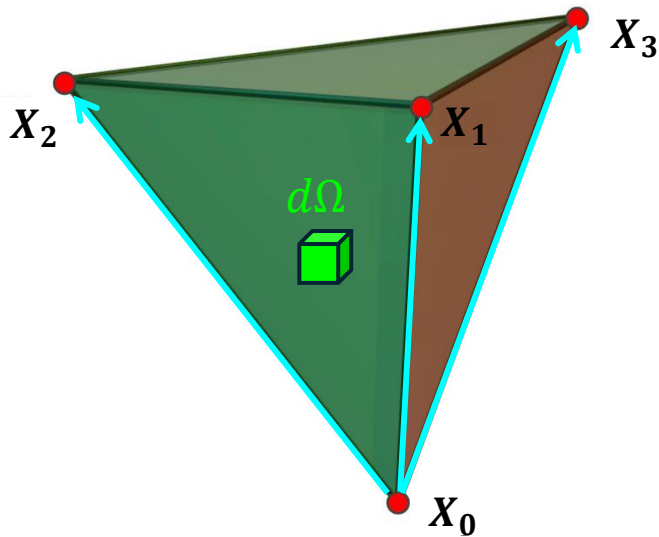
$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} X_0 & (X_1 - X_0)\phi_1 & (X_2 - X_0)\phi_2 & (X_3 - X_0)\phi_3 \\ Y_0 & (Y_1 - Y_0)\phi_1 & (Y_2 - Y_0)\phi_2 & (Y_3 - Y_0)\phi_3 \\ Z_0 & (Z_1 - Z_0)\phi_1 & (Z_2 - Z_0)\phi_2 & (Z_3 - Z_0)\phi_3 \end{pmatrix}$$

$$\Rightarrow \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} X_0 \\ Y_0 \\ Z_0 \end{pmatrix} + J \begin{pmatrix} \phi_1 \\ \phi_2 \\ \phi_3 \end{pmatrix}$$

$\phi_1 = \phi_2 = \phi_3 = 0$  evaluated at  $X_0$

# The Differential Volume Element

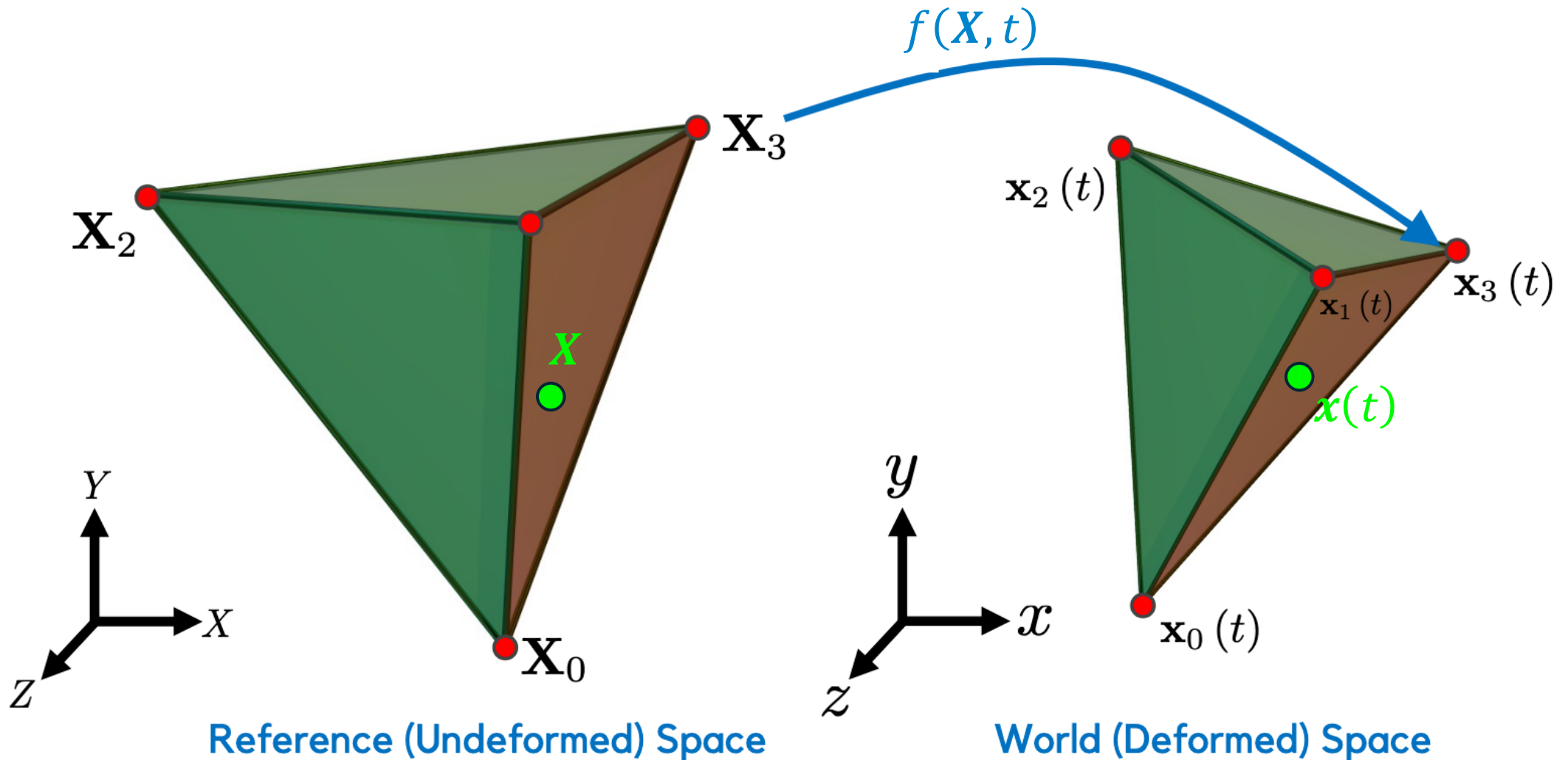
- Integral over the tetrahedral domain  $\Omega$ :  $\int_{\Omega} \rho \phi_r \phi_s I d\Omega$
- The integral is difficult to calculate using the Cartesian coordinates
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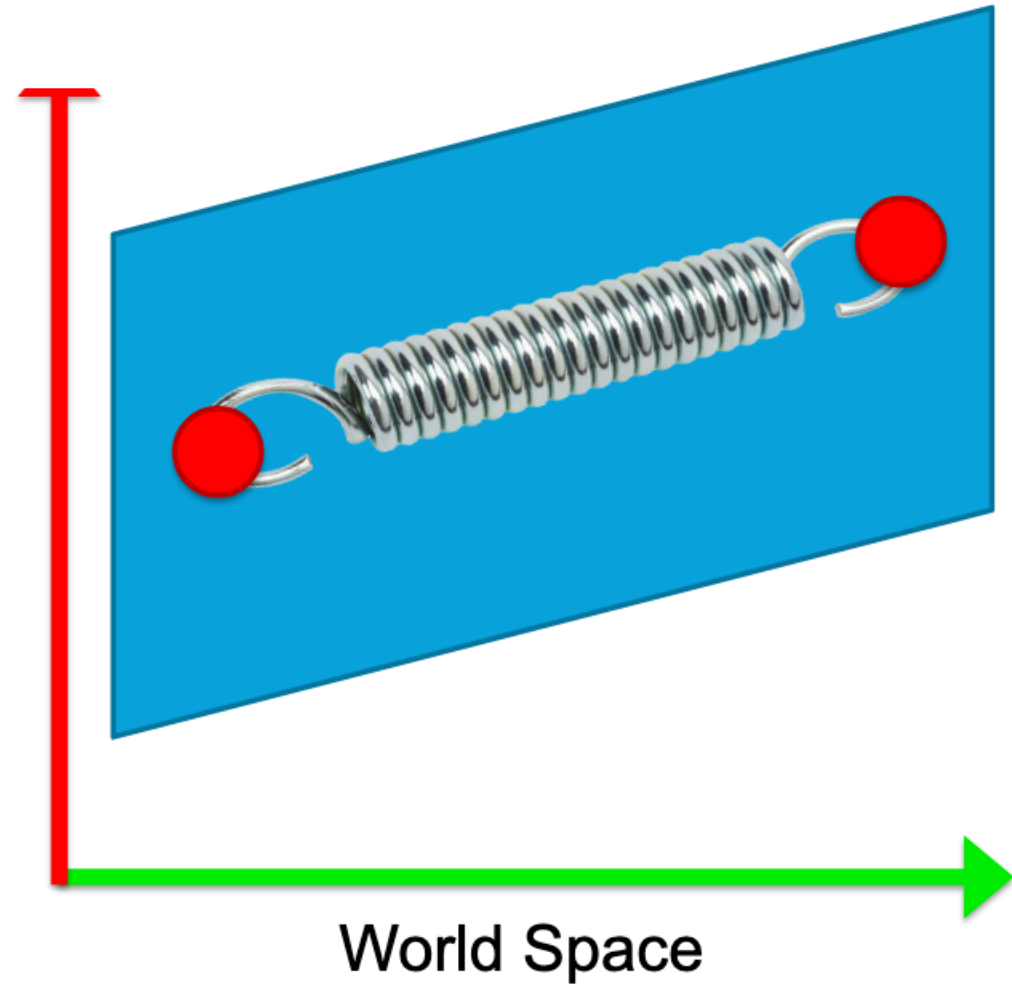
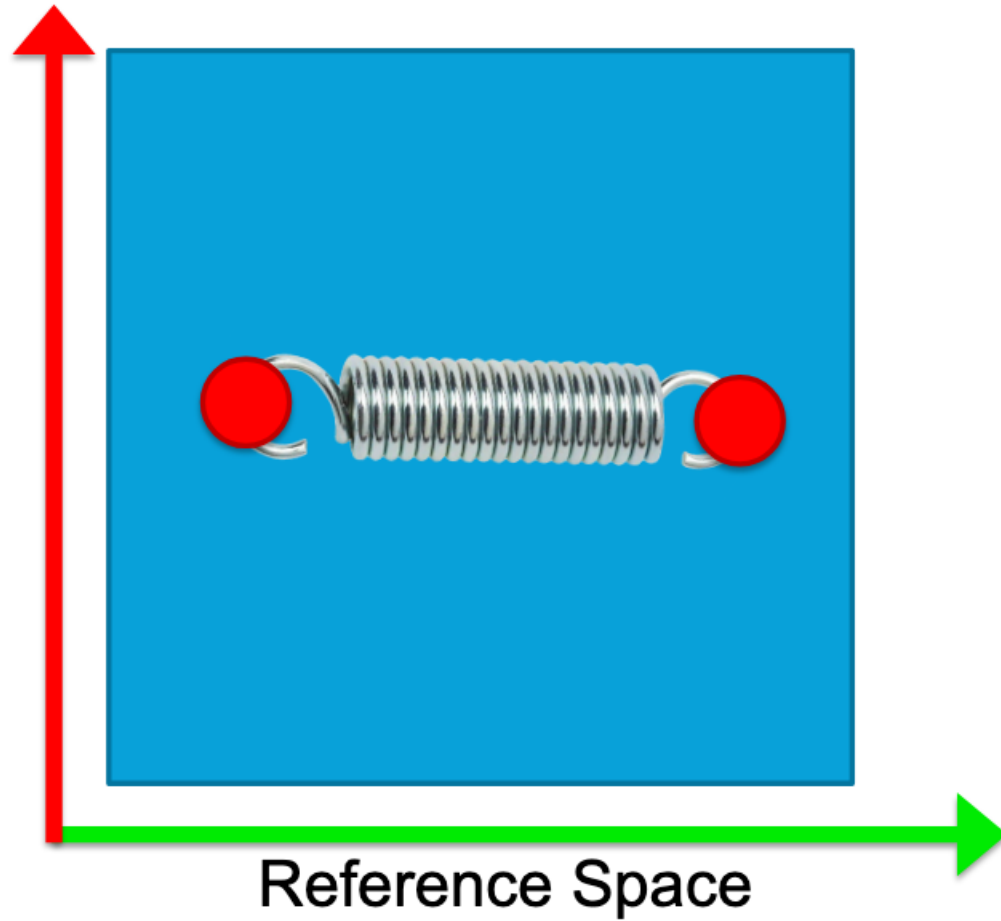
- Let  $V$  denotes the tetrahedron's volume, we have:  
$$dV = |\det \mathbf{J}| d\phi_1 d\phi_2 d\phi_3 = 6V d\phi_1 d\phi_2 d\phi_3$$
- We can calculate the integral:

$$\int_{\Omega} \rho \phi_r \phi_s I d\Omega = 6\rho V \int_0^1 \int_0^{1-\phi_1} \int_0^{1-\phi_1-\phi_2} (\phi_r \phi_s) d\phi_1 d\phi_2 d\phi_3$$

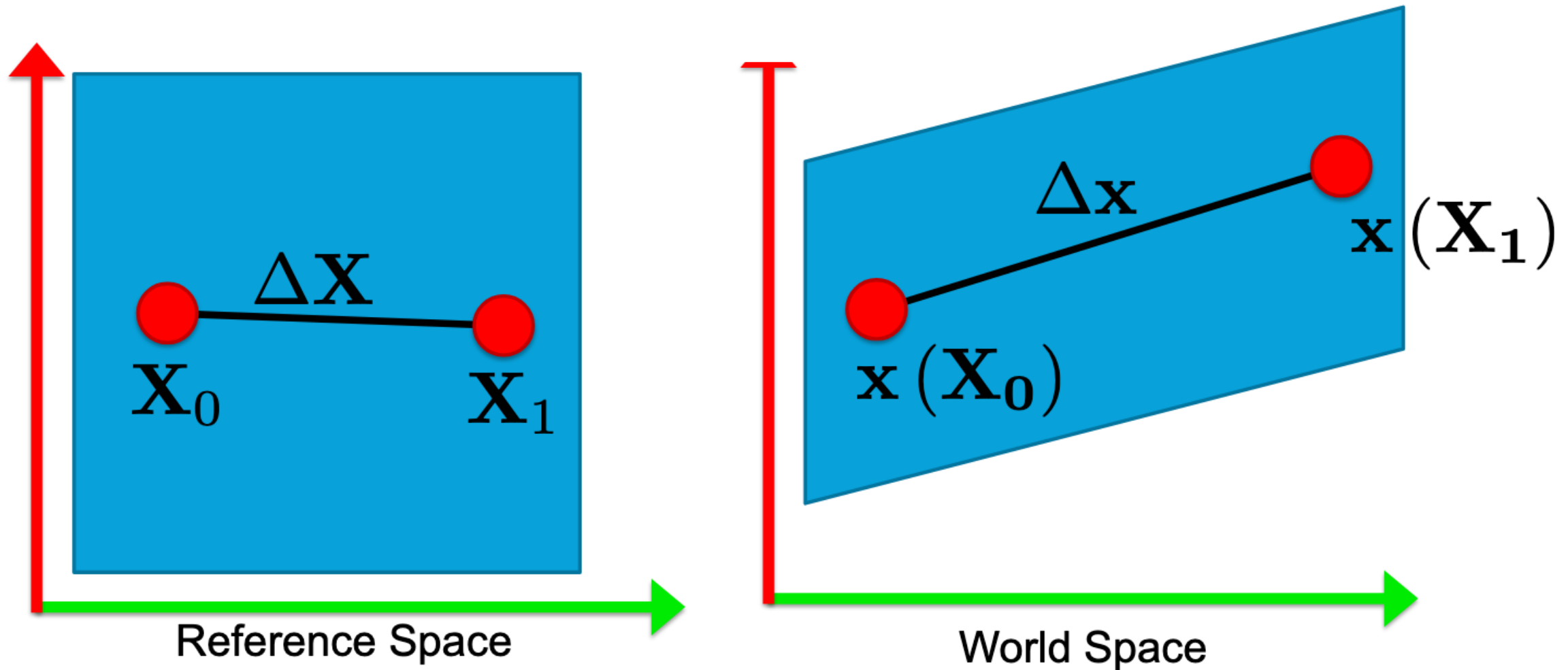
# Potential Energy of Material Deformation



# A Closer Look at Deformation

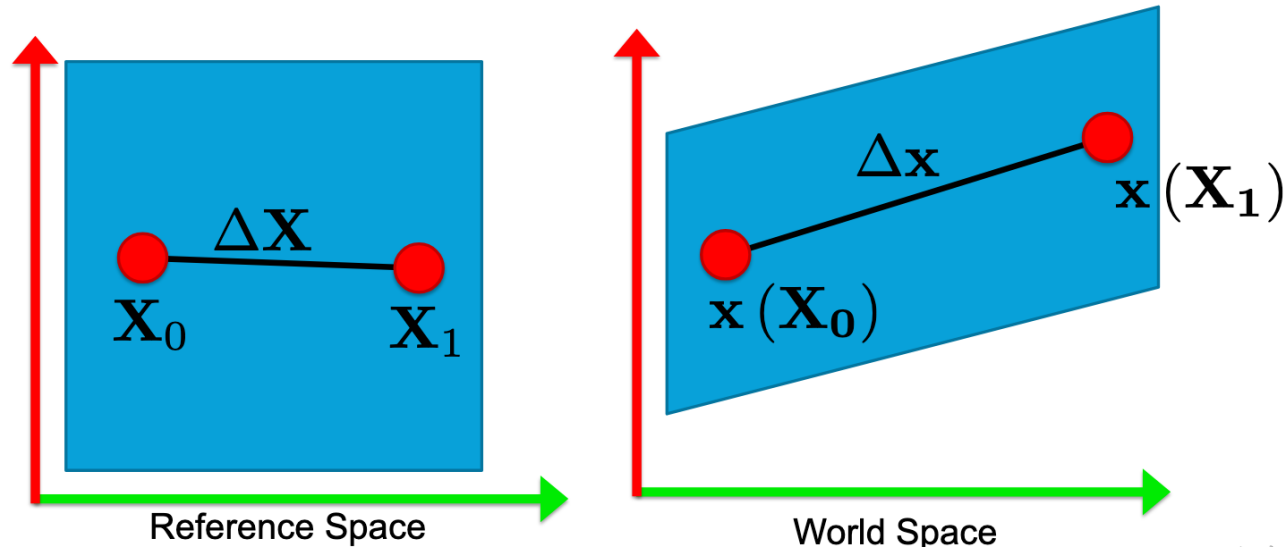


# A Closer Look at Deformation



$$\Delta \mathbf{x} = \mathbf{x}(\mathbf{X}_1) - \mathbf{x}(\mathbf{X}_0)$$

# A Closer Look at Deformation



$$\begin{aligned} \Delta \mathbf{x} &= f(\mathbf{X}_1) - f(\mathbf{X}_0) \\ \Rightarrow \Delta \mathbf{x} &= f(\mathbf{X}_0 + \Delta \mathbf{X}) - f(\mathbf{X}_0) \\ \Rightarrow \Delta \mathbf{x} &\approx \underbrace{f(\mathbf{X}_0)} + \frac{\partial f}{\partial \mathbf{X}} \Delta \mathbf{X} - \underbrace{f(\mathbf{X}_0)} \end{aligned}$$

Deformation gradient  $F$

- Deformed length squared:

$$l^2 = \Delta \mathbf{x}^\top \Delta \mathbf{x}$$

- Rest length squared:

$$l_0^2 = \Delta \mathbf{X}^\top \Delta \mathbf{X}$$

- Strain:

$$\begin{aligned} l^2 - l_0^2 &= \Delta \mathbf{x}^\top \Delta \mathbf{x} - \Delta \mathbf{X}^\top \Delta \mathbf{X} \\ &= \Delta \mathbf{X}^\top \mathbf{F}^\top \mathbf{F} \Delta \mathbf{X} - \Delta \mathbf{X}^\top \Delta \mathbf{X} \\ &= \Delta \mathbf{X}^\top (\mathbf{F}^\top \mathbf{F} - \mathbf{I}) \Delta \mathbf{X} \end{aligned}$$

- Unit potential energy resulted from strain:  $\Psi(\mathbf{F}(\mathbf{X}))$

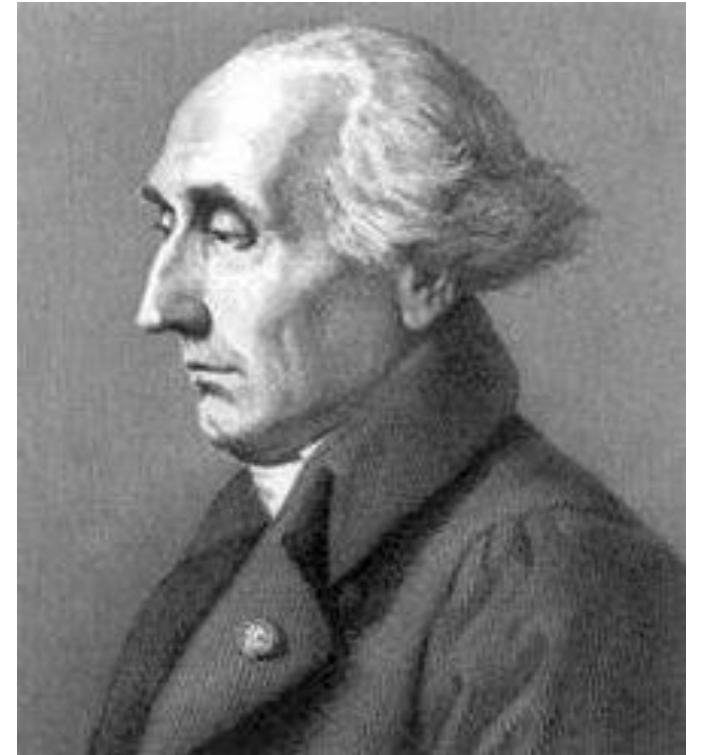
# In the Next Lecture, We'll Introduce a More General Framework to Derive Equations of Motion

- The Lagrangian:

$$L = T - V$$

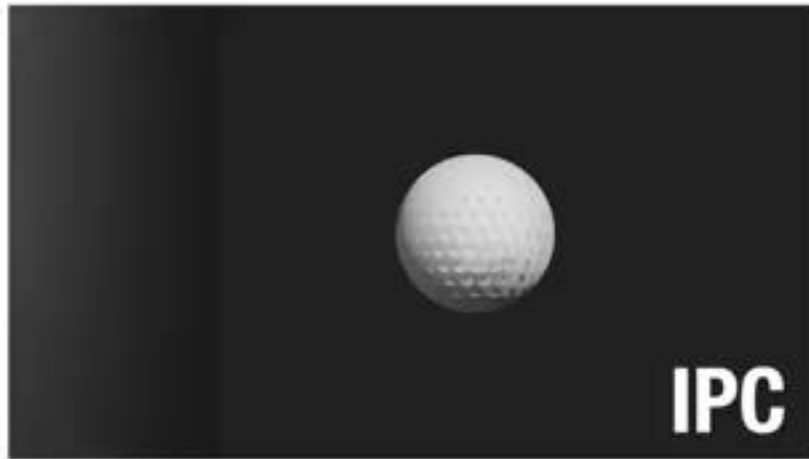
$$T = \frac{1}{2} \dot{\mathbf{q}}^T \left( \int_{\Omega} \rho \mathbf{N}(\mathbf{X})^T \mathbf{N}(\mathbf{X}) d\Omega \right) \dot{\mathbf{q}}$$

$$V = \sum_{j=0}^{m-1} vol_j \cdot \Psi(F_j(q_j))$$



Joseph-Louis Lagrange

# Why Do We Need Continuum Mechanics?



# What We Will Cover the Next Week

- Physical modeling
  - Lagrangian Mechanics
  - Contact Modeling
  - Material Point Methods