





### Cloth simulation has wide applications...





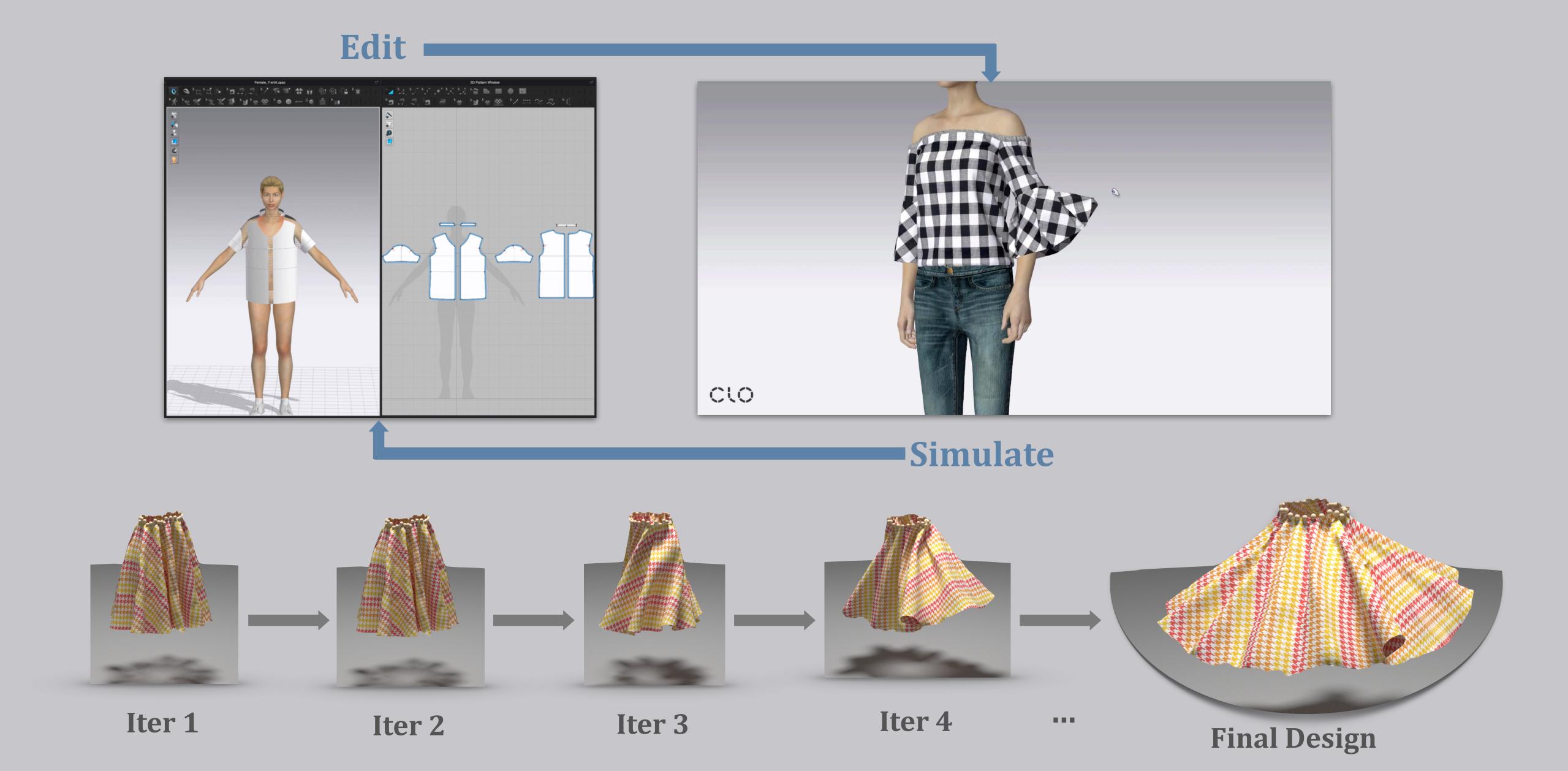






#### Slow & Tedious Manual Workflow





#### Differentiable Cloth Simulation



Goal: Optimize  $\theta$  (e.g. cloth material) to perform a task (e.g. garment design)

**Dress Design** 



#### Differentiable Cloth Simulation

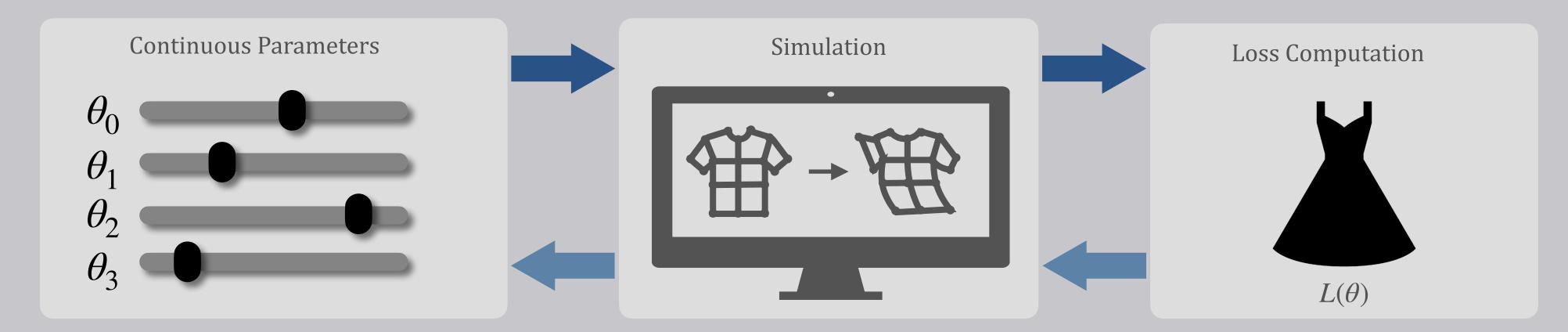


Goal: Optimize  $\theta$  (e.g. cloth material) to perform a task (e.g. garment design)

**Dress Design** 



1 Forward Simulation through time to obtain  $L(\theta)$ 



**2** Gradient Back Propagation  $\frac{\partial L}{\partial \theta} \leftarrow L$  to obtain  $\frac{\partial L}{\partial \theta}$ 

 $^{\circ}$  Use gradient-based optimizer to update  $\theta$ 

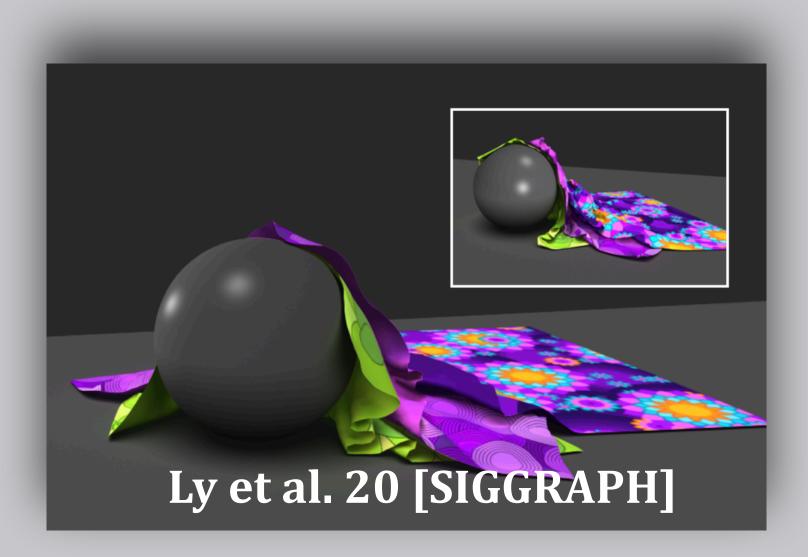
$$\theta_{new} \leftarrow \theta_{old} - \frac{\partial L}{\partial \theta} \cdot k$$

#### **Related Works**

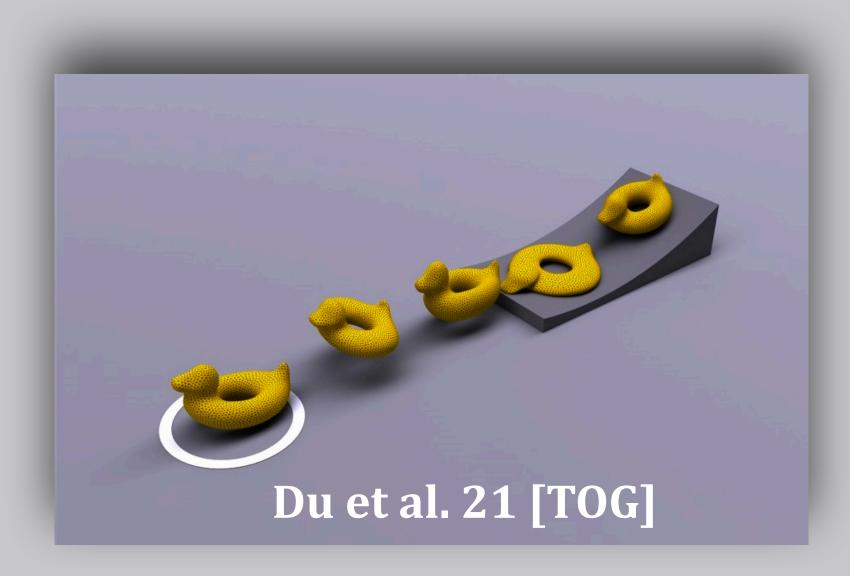




Differentiable cloth simulation for inverse problems



**Projective Dynamics with dry** frictional contact



DiffPD: Differentiable Projective Dynamics

#### **Contributions of DiffCloth**



Fast Simulation + Gradient Derivation

- Projective-Dynamics-based forward simulation
- Novel gradient computation to speed up back-propagation

Accurate Contact Modeling

Dry-frictional contact

Effective in Inverse Tasks

- Trajectory Optimization
- •Inverse Design

• Real-to-Sim

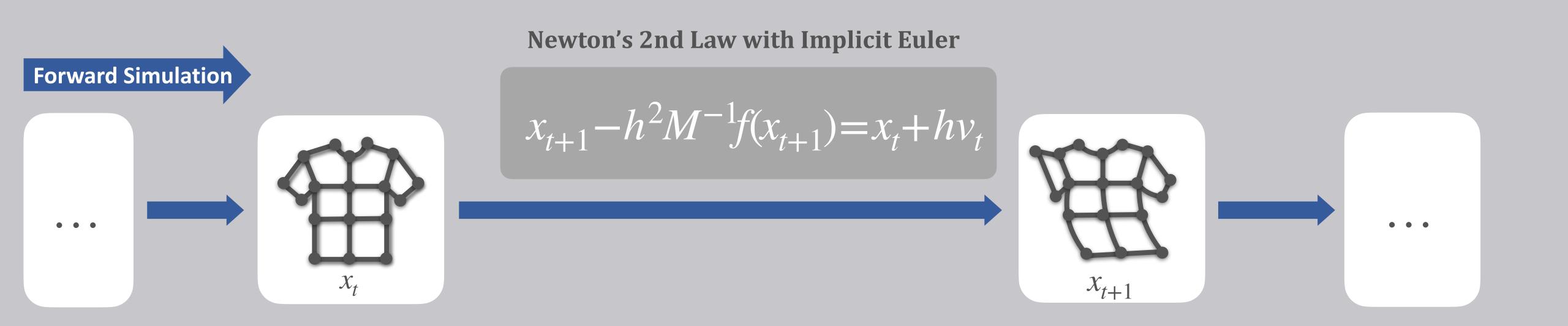
- Closed-Loop Control
- System Identification

### **Simulating Cloth Dynamics**

 $x_t, v_t$  postion, velocity



**Implicit Euler integration is robust** 



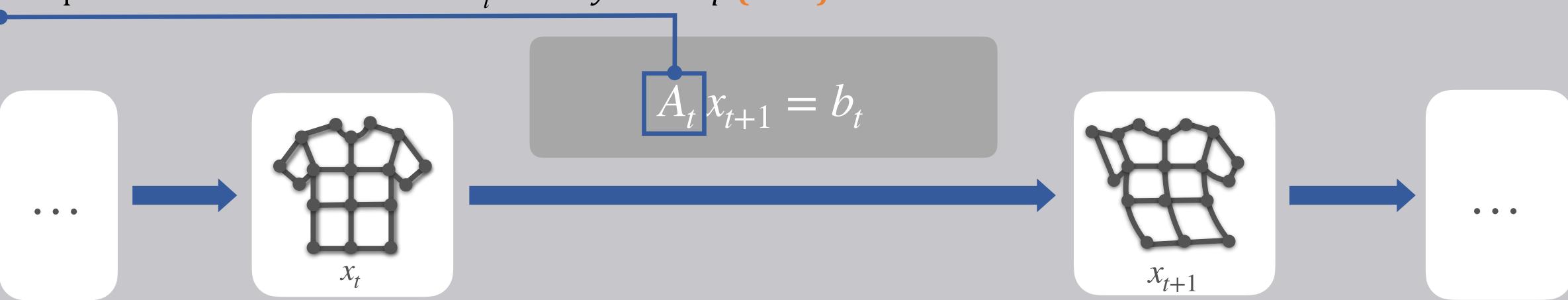
h timestep M mass matrix f force

## **Simulating Cloth Dynamics**



#### Implicit Euler integration is robust but expensive

Using Newton's method requires costly Hessian matrix computation and factorization of  $A_t$  at every timestep (slow)

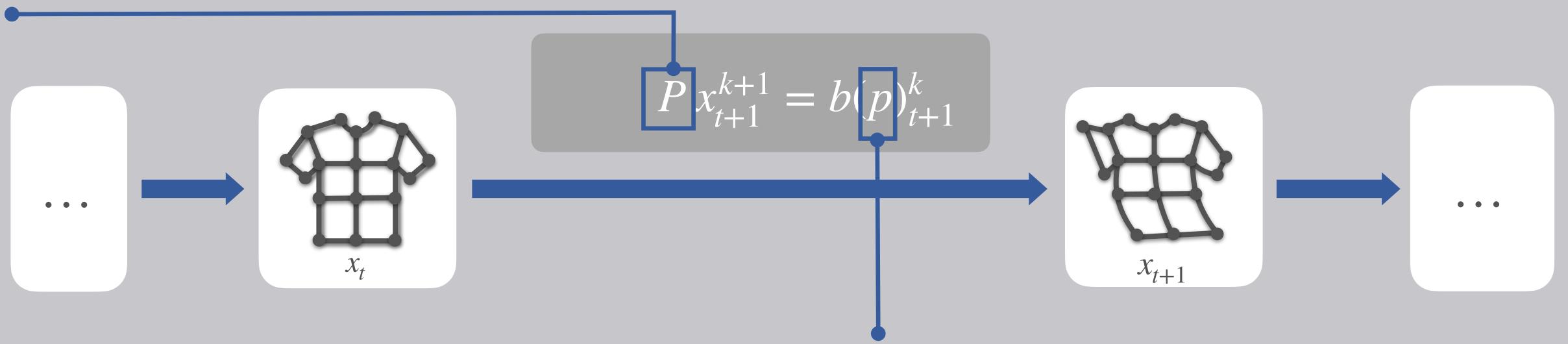


#### Fast Simulation with Projective Dynamics

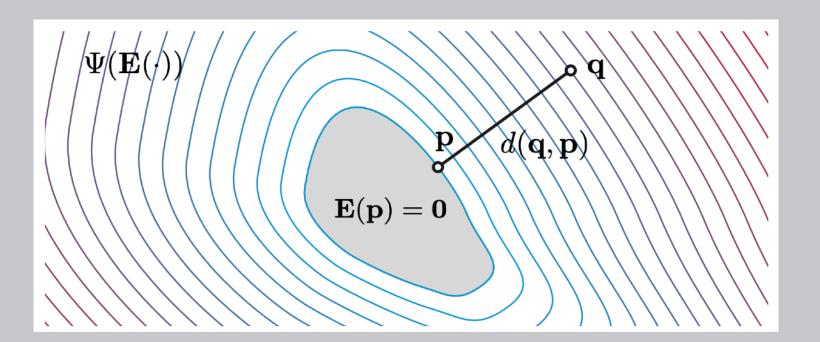


local/global iterative scheme [Bouaziz et al. 14]

Global: Same system matrix P at every timestep



**Local**: parallel local projections *p* 



## PD with Dry Frictional Contact [Ly et al. 20]



enforce vertex-vertex frictional contact semi-implicitly to satisfy Signorine-Coulomb condition

$$P v^{k+1} = b(p)^k$$

$$:= f(p)^k + r^k$$
impulse contact impulse

#### PD with Dry Frictional Contact [Ly et al. 20]

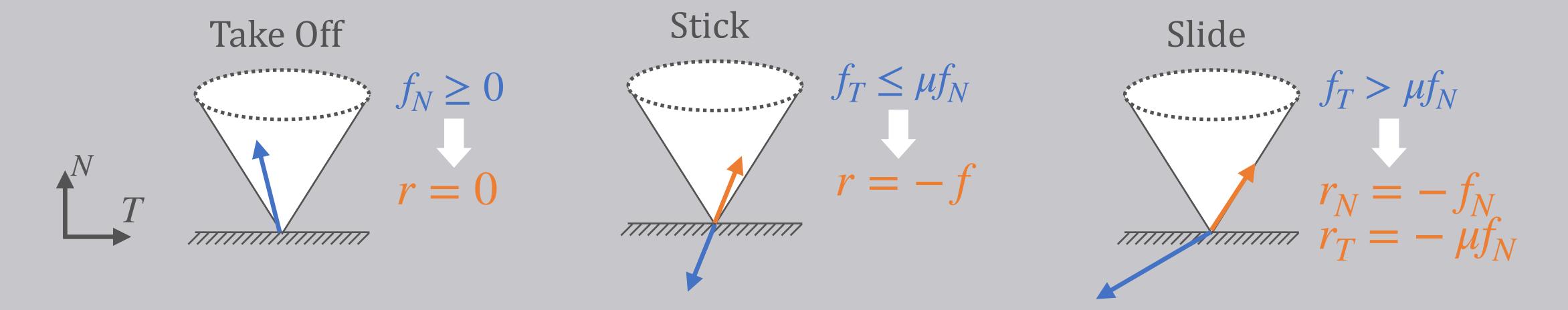


 $||r_T|| = \mu r_N, v_N = 0, r_T ||v_T, r_T \cdot u_t \le 0$ 

enforce vertex-vertex frictional contact semi-implicitly to satisfy Signorine-Coulomb condition

Signorini Condition  $r = 0, v_N > 0$ 

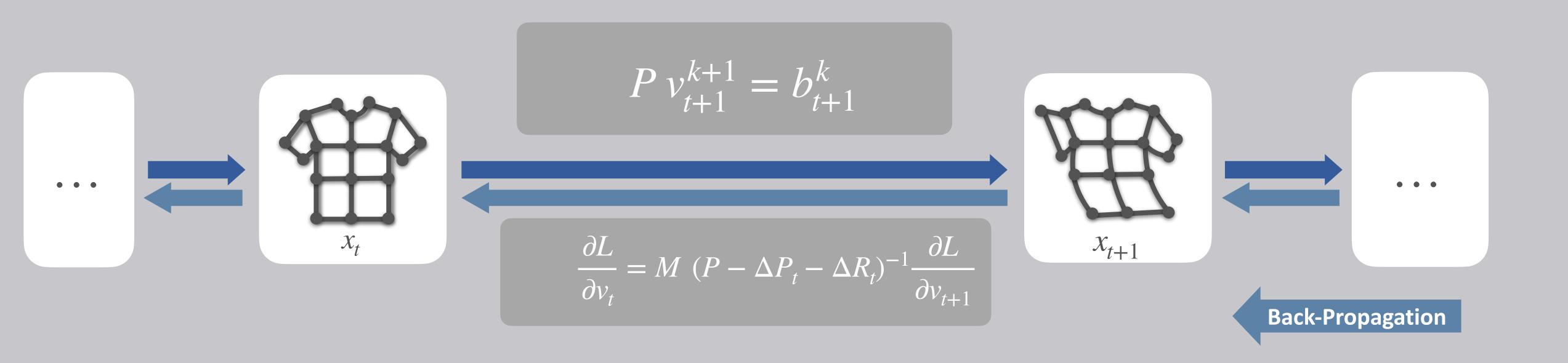
$$P \, v^{k+1} = b(p)^k$$
 
$$:= f(p)^k + r^k$$
 impulse contact impulse



 $||r_T|| < \mu r_N, v = 0$ 

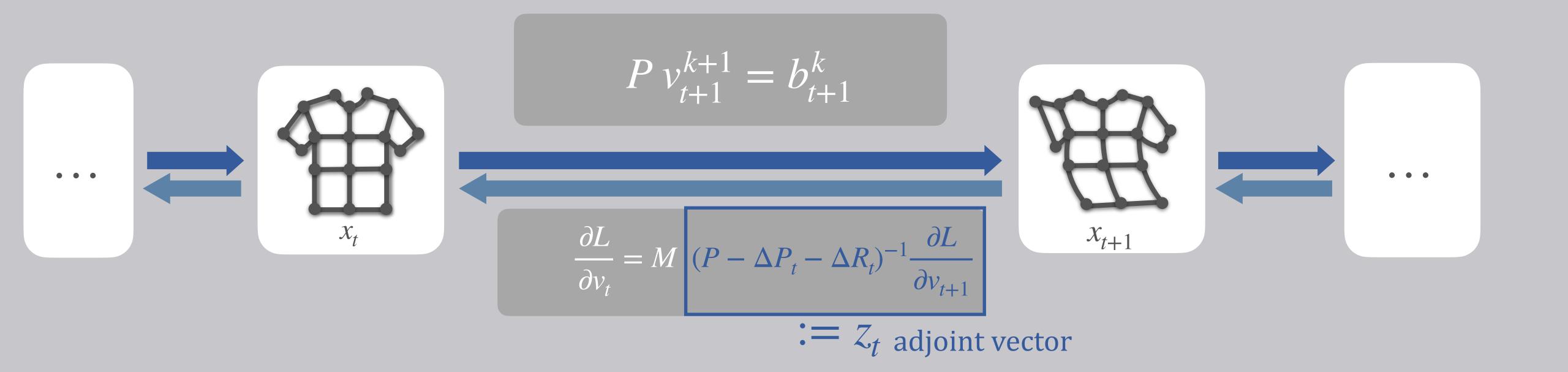


gradient computation via adjoint method

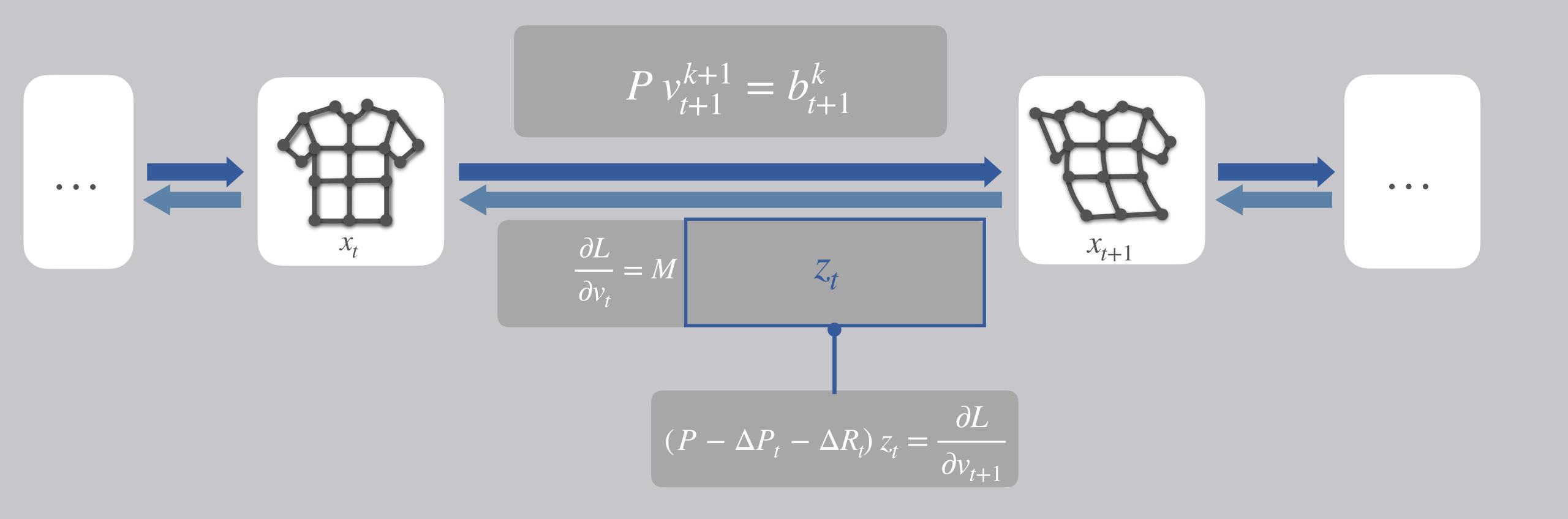


 $\Delta P$  Gradient for the projection vector p $\Delta R$  Gradient for the contact impulse response vector r



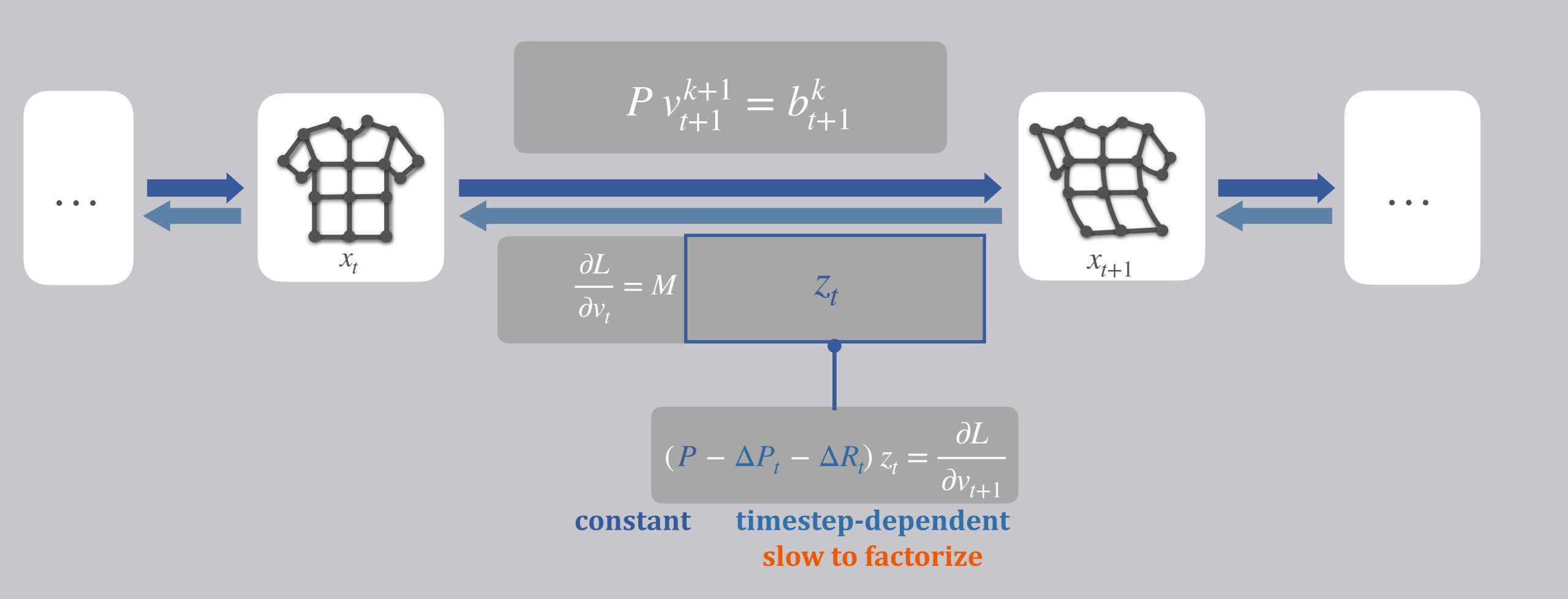








Can we exploit the source of efficiency in forward solve for backward solve?



#### **Fast Gradient Computation**





**Direct Solve** 

**Iterative Solve: Good convergence in practice** 

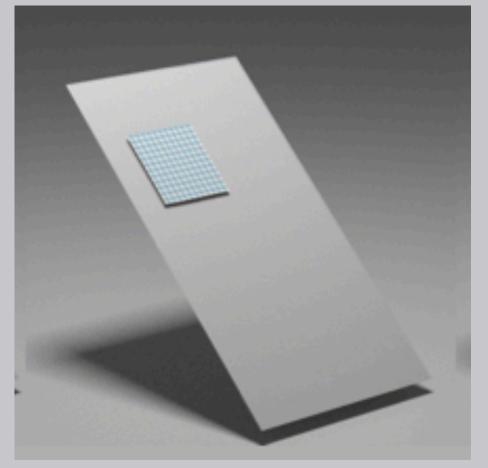
## Fast Differentiable Cloth Simulation (Backward)



Iterative Solver Speedup (convergence  $\epsilon = 1\text{e-4}$ ): 3x - 12x



Wind: minimal contact



**Slope:** maximal contact

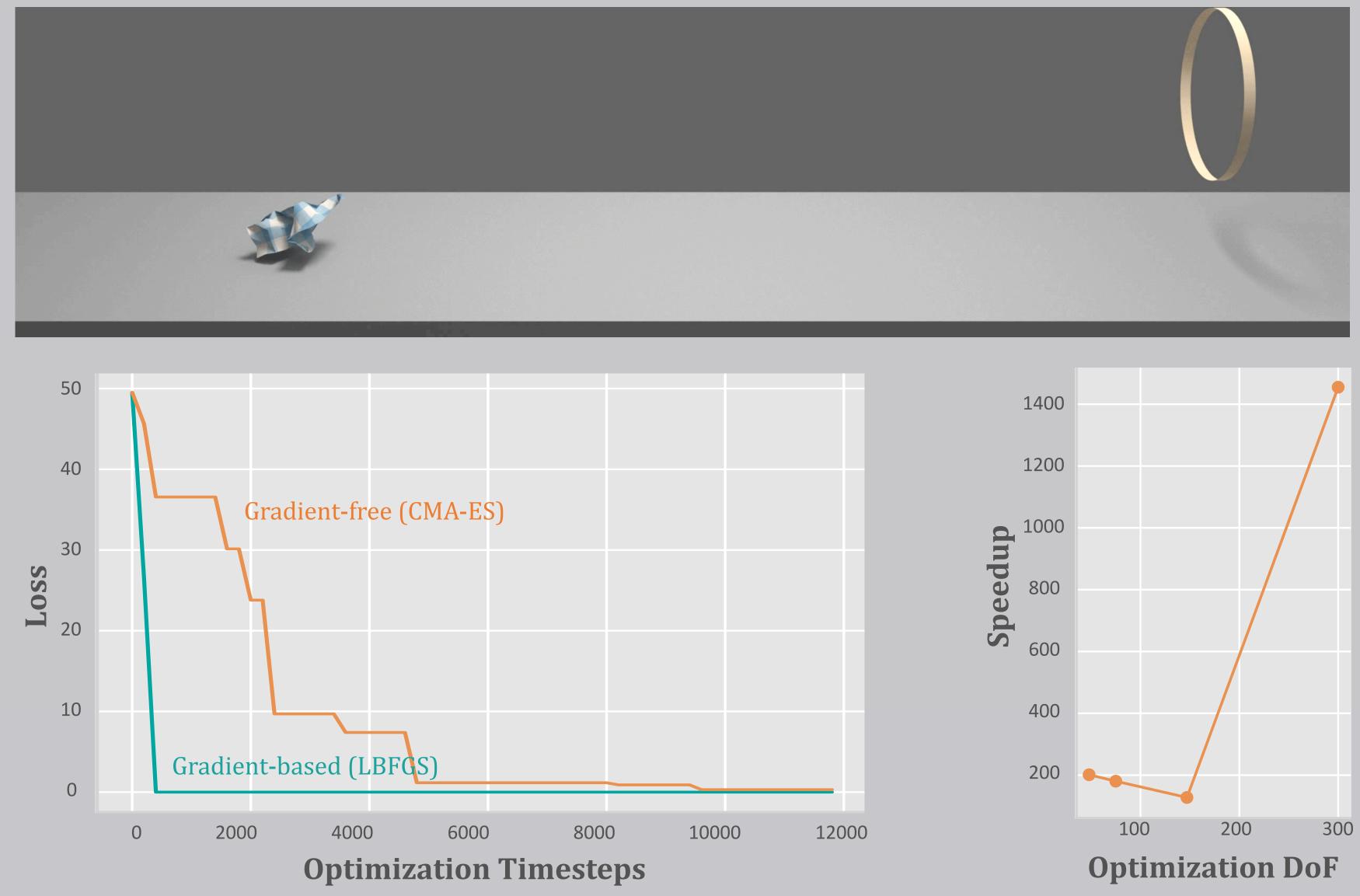
	Cloth Grid Resolution		
	12x12	24x24	48x48
Wind	2.9x	5.7x	10.6x
Slope	3.1x	6.8x	12.0x

**Iterative Solver Speedup** 

## Inverse Task Comparison with Gradient-Free Methods @



Benchmark Test: Optimize force field on the cloth to reach the ring



Task: Identify wind model and material parameters to match target trajectory



4300 DoF  $\mid$  250 Timesteps  $\mid$   $\Delta t$  = 1/90s 6 Design Parameters: cloth stretching stiffness and sinusoidal wind model parameters

# Trajectory Optimization

Task: Optimize manipulator end effector trajectories to pull a sock on the foot model



1700 DoF | 400 Timesteps |  $\Delta t$  = 1/100s 36 Design Parameters: Tangents and endpoints of the 4 Hermite Splines

## Inverse Design

Task: Optimize dress material parameters so that the spinning angle of the dress is 50 degrees

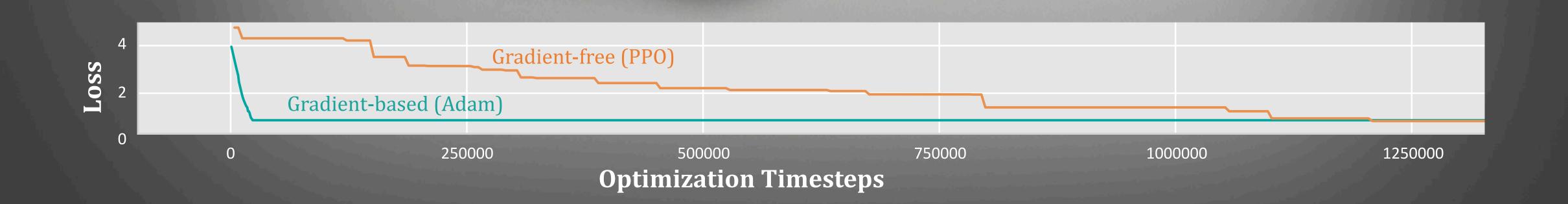


**Initial Guess** 

Optimized

19000 DoF | 125 Timesteps |  $\Delta t = 1/120s$ 2 Design Parameters: density and bending stiffness Task: A generalizable NN controller that puts hat onto the head from any initial positions around the upper hemisphere

1700 DoF | 400 Timesteps |  $\Delta t$  = 1/100s 117000 Design Parameters: Network parameters of the 2-layer MLP 85x more sampling efficient compare with Reinforcement Learning baseline



### Summary & Takeaway



A differentiable cloth simulator with dry frictional contact

Fast simulation with Projective Dynamics & fast back-propagation with iterative solver

More sampling efficient than gradient-free methods

Effective in a wide range of inverse tasks





