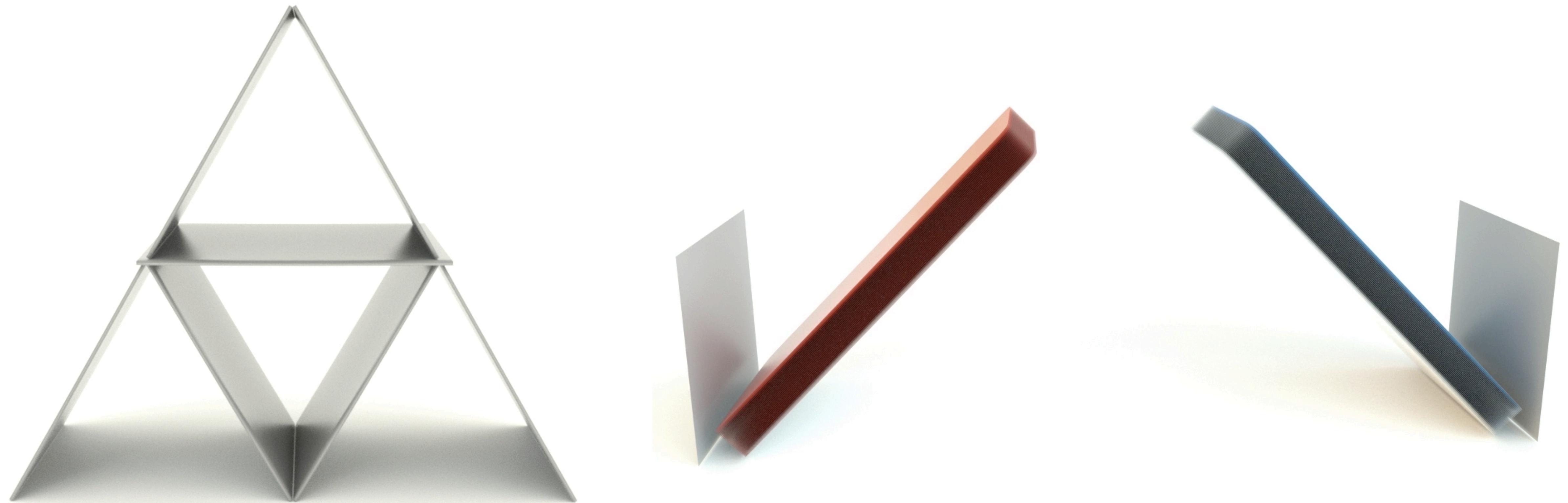


Instructor: Minchen Li



Lec 5: Friction

15-763: Physics-based Animation of Solids and Fluids (S25)

Recap: Normal Contact Force

- Inequality constraints

$$\min_x E(x) = \frac{1}{2} \|x - (x^n + hv^n)\|_M^2 + h^2 P(x).$$

Inertia term **Elasticity**

s.t. $\forall k, d_k(x) \geq 0$

e.g. for distances between any distinct points on the solid

- Barrier method: $\min_x E(x) + h^2 P_b(x)$
- Filtered line search

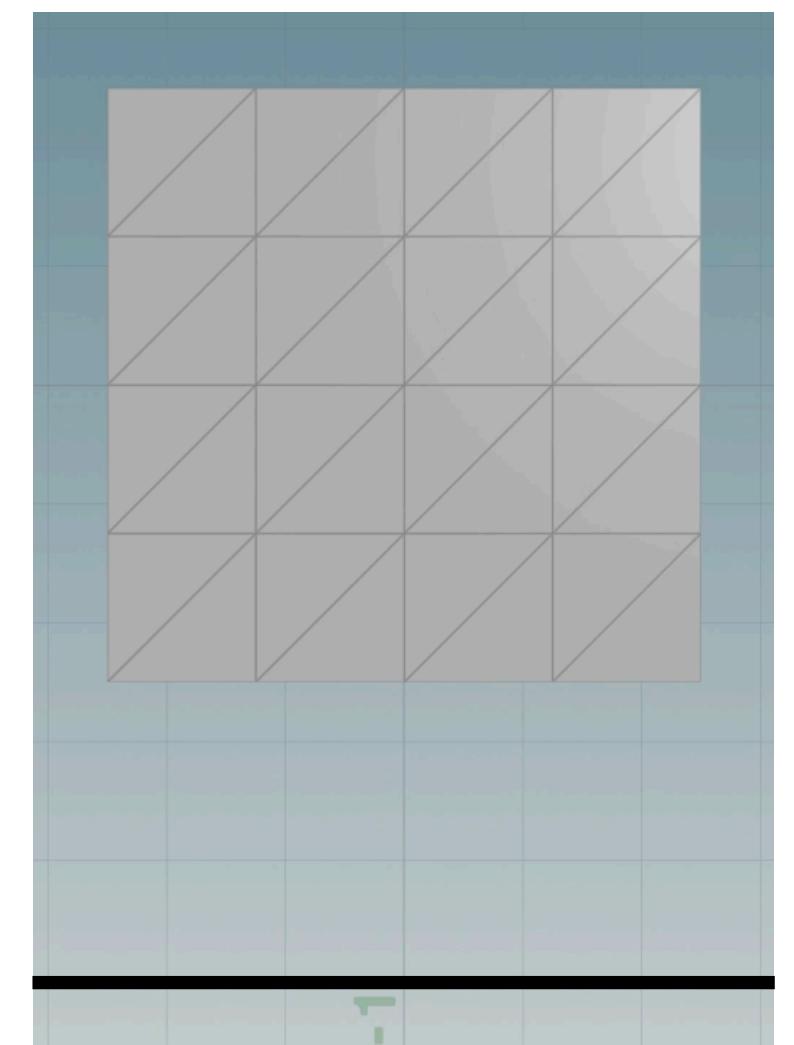
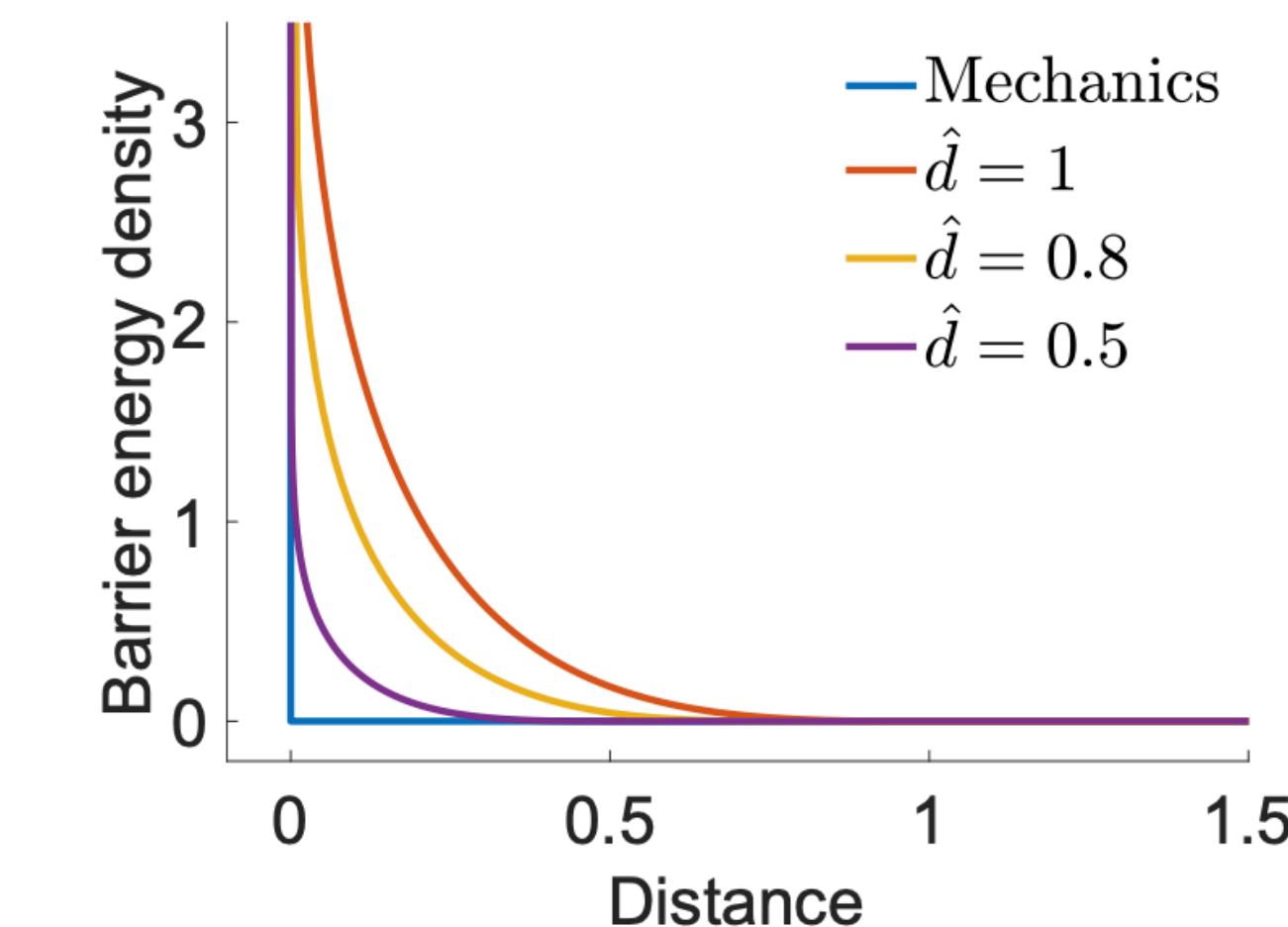
Algorithm 4: Filter Backtracking Line Search

Result: α

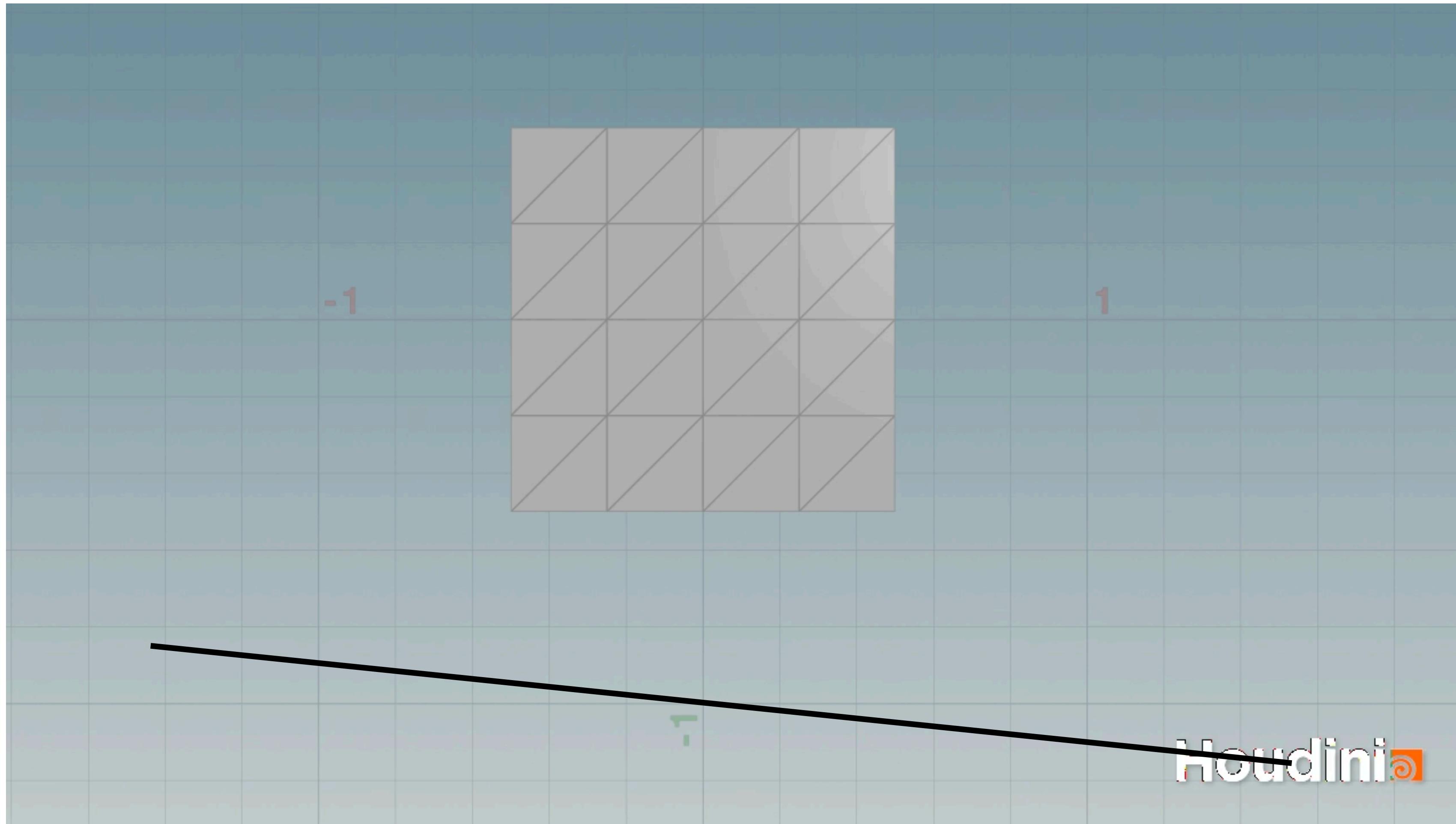
```

1  $\alpha \leftarrow \text{CCD}(x^i, p);$  // the only different line from algorithm 2
2 while  $E(x^i + \alpha p) > E(x^i)$  do
3    $\alpha \leftarrow \alpha/2;$ 

```



Simulating Tangential Contact Force – Friction



Today:

- Formulation
- Case Study: Square on Slope
- Remarks

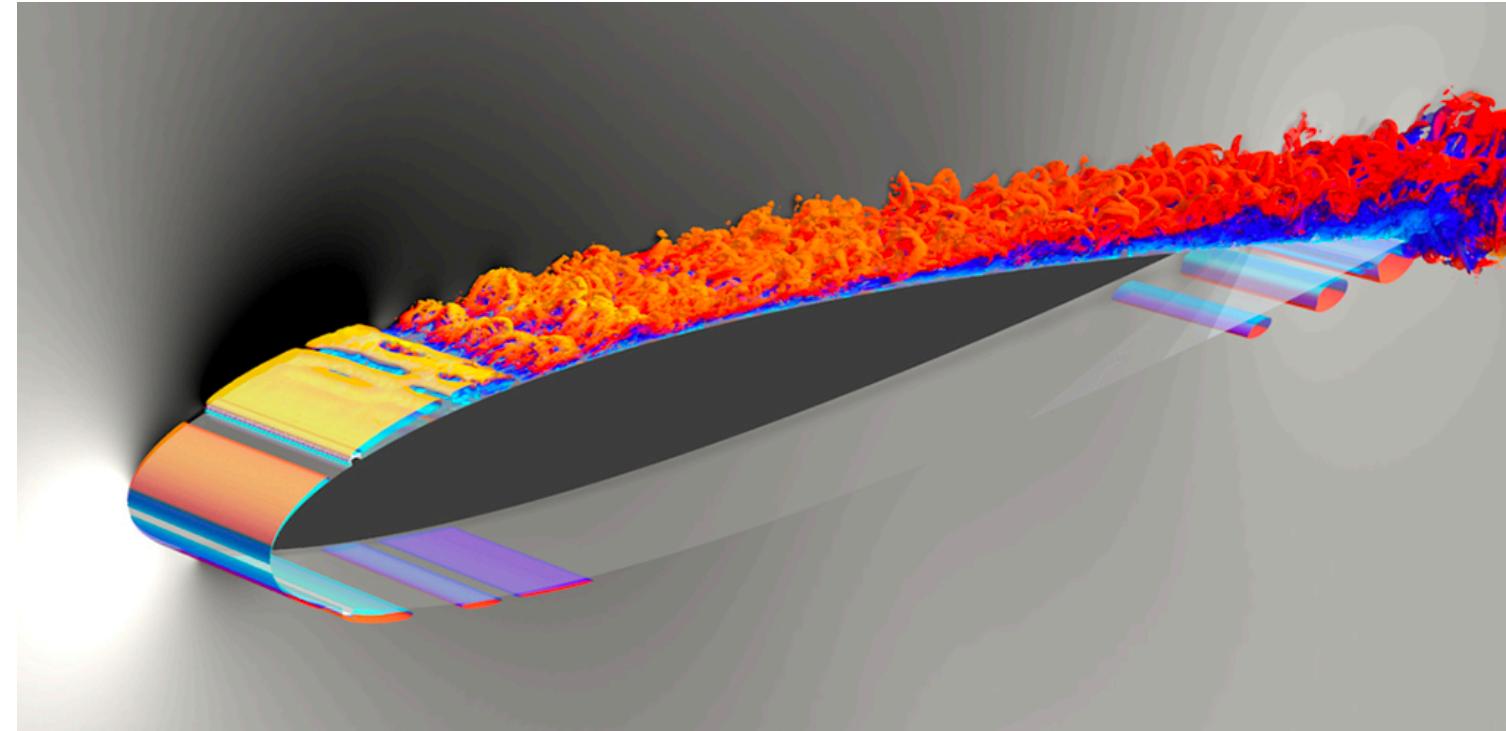
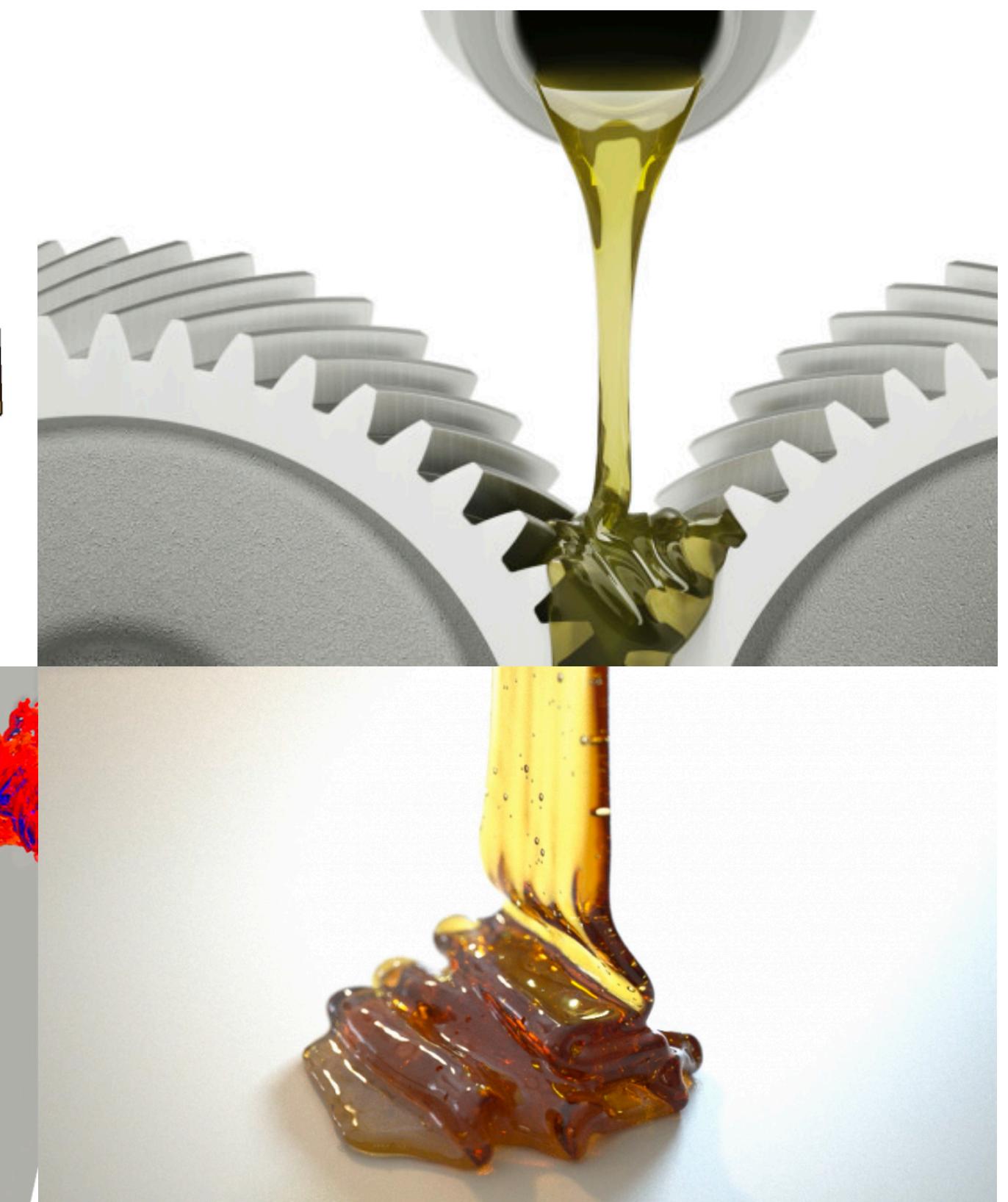
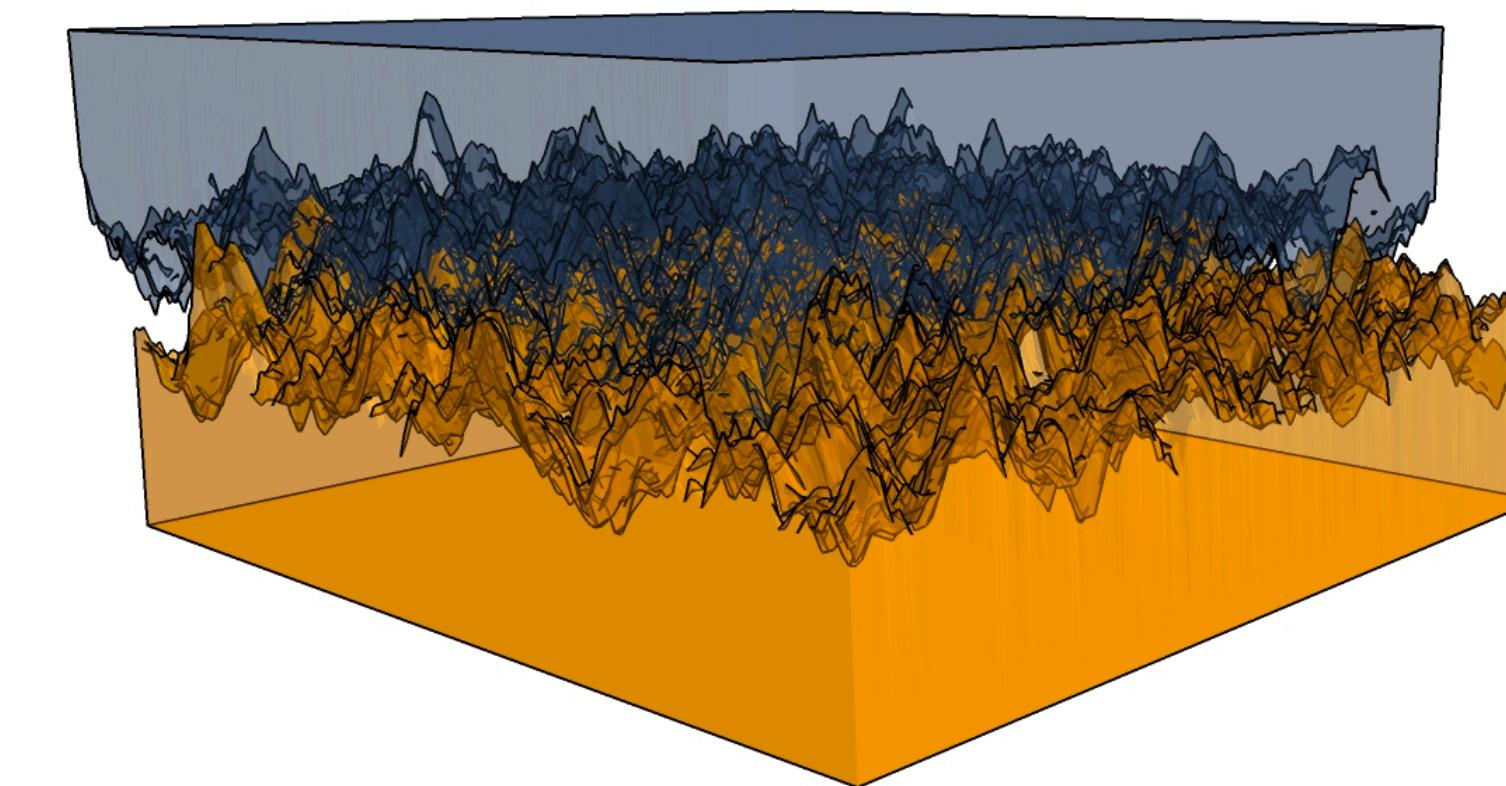
Today:

- **Formulation**
- Case Study: Square on Slope
- Remarks

Types of Friction (Macroscopic Views)

- Dry friction
 - Between rough surfaces
- Fluid friction
 - i.e. fluid viscosity
- Lubricated friction
- Skin friction
- ...

Our focus today



Properties of Dry Friction

- Non-conservative
 - Work done by friction is **path dependent**
 - Kinetic energy is always transformed to thermal energy (not backwards)
- No potential energy
 - how to incorporate it into the optimization time integration?

$$\min_x E(x) = \frac{1}{2} \|x - (x^n + h\nu^n)\|_M^2 + h^2 \sum P(x)$$

Formulation of Dry Friction

Tangential Relative Velocity

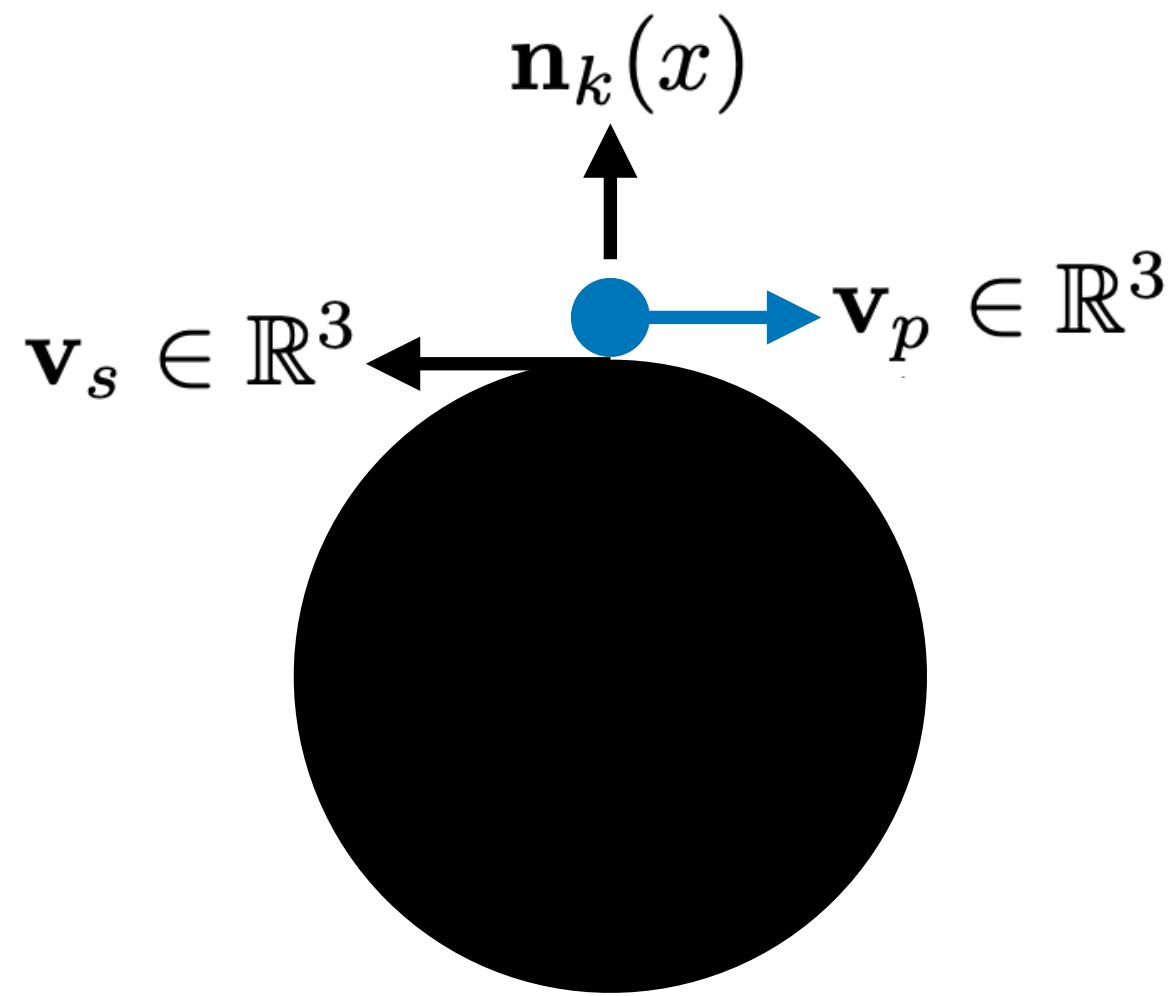
- Add friction to each contact pair k

Tangential relative velocity $\mathbf{v}_k = T_k(x)^T \mathbf{v} \in \mathbb{R}^d$

Tangent operator $T_k(x) \in \mathbb{R}^{dm \times d}$

Current configuration $\{x, v\}$

- Example:



$$\mathbf{v}_k = (\mathbf{v}_p - \mathbf{v}_s) - \mathbf{n}_k \cdot (\mathbf{v}_p - \mathbf{v}_s) \mathbf{n}_k = (\mathbf{I}_3 - \mathbf{n}_k \mathbf{n}_k^T)(\mathbf{v}_p - \mathbf{v}_s)$$

Denote $\mathbf{v} = [\mathbf{v}_p^T, \mathbf{v}_s^T]^T \in \mathbb{R}^6$ $T_k(x) = \begin{bmatrix} \mathbf{I}_3 - \mathbf{n}_k(x) \mathbf{n}_k(x)^T \\ \mathbf{n}_k(x) \mathbf{n}_k(x)^T - \mathbf{I}_3 \end{bmatrix} \in \mathbb{R}^{6 \times 3}$

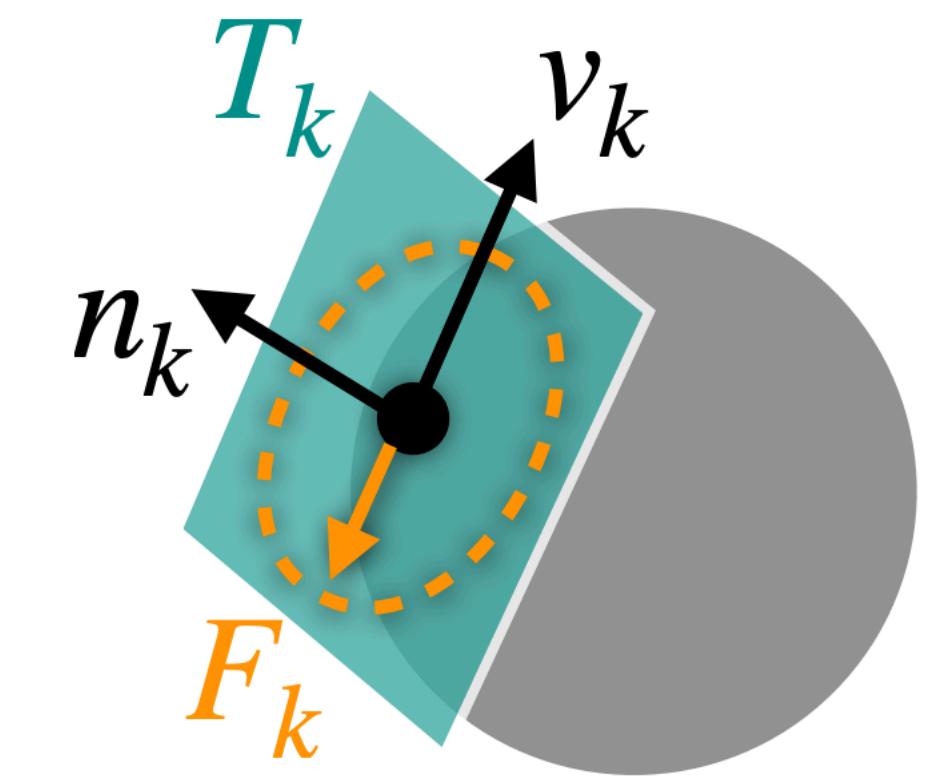
Formulation of Dry Friction

Coulomb Friction

- Add friction to each contact pair k

$$F_k(x) = T_k(x) \underset{\beta \in \mathbb{R}^d}{\operatorname{argmin}} \beta^T \mathbf{v}_k \quad \text{s.t.} \quad \|\beta\| \leq \boxed{\mu \lambda_k} \quad \text{and} \quad \beta \cdot \mathbf{n}_k = 0$$

Coefficient of friction



$\lambda_k = -w_k \frac{\partial b}{\partial d_k}$ is the contact force magnitude

contact force is $-w_k \nabla_{\mathbf{x}_k} b(d_k(x)) = -w_k \frac{\partial b}{\partial d_k} \nabla_{\mathbf{x}_k} d_k(x)$

$\lambda_k = \left\| -w_k \frac{\partial b}{\partial d_k} \nabla_{\mathbf{x}_k} d_k(x) \right\| = -w_k \frac{\partial b}{\partial d_k}$ since $\frac{\partial b}{\partial d_k} < 0$ and $\|\nabla_{\mathbf{x}_k} d_k(x)\| = 1$

$$F_k(x) = -\mu \lambda_k T_k(x) \boxed{f(\|\mathbf{v}_k\|) \mathbf{s}(\mathbf{v}_k)}$$

Non-smooth!

$$\mathbf{s}(\mathbf{v}_k) = \frac{\mathbf{v}_k}{\|\mathbf{v}_k\|} \text{ when } \|\mathbf{v}_k\| > 0$$

Any unit vector $\perp n_k$ when $\|\mathbf{v}_k\| = 0$

$$f(\|\mathbf{v}_k\|) = 1 \text{ when } \|\mathbf{v}_k\| > 0$$

$f(\|\mathbf{v}_k\|) \in [0, 1]$ when $\|\mathbf{v}_k\| = 0$

Formulation of Dry Friction

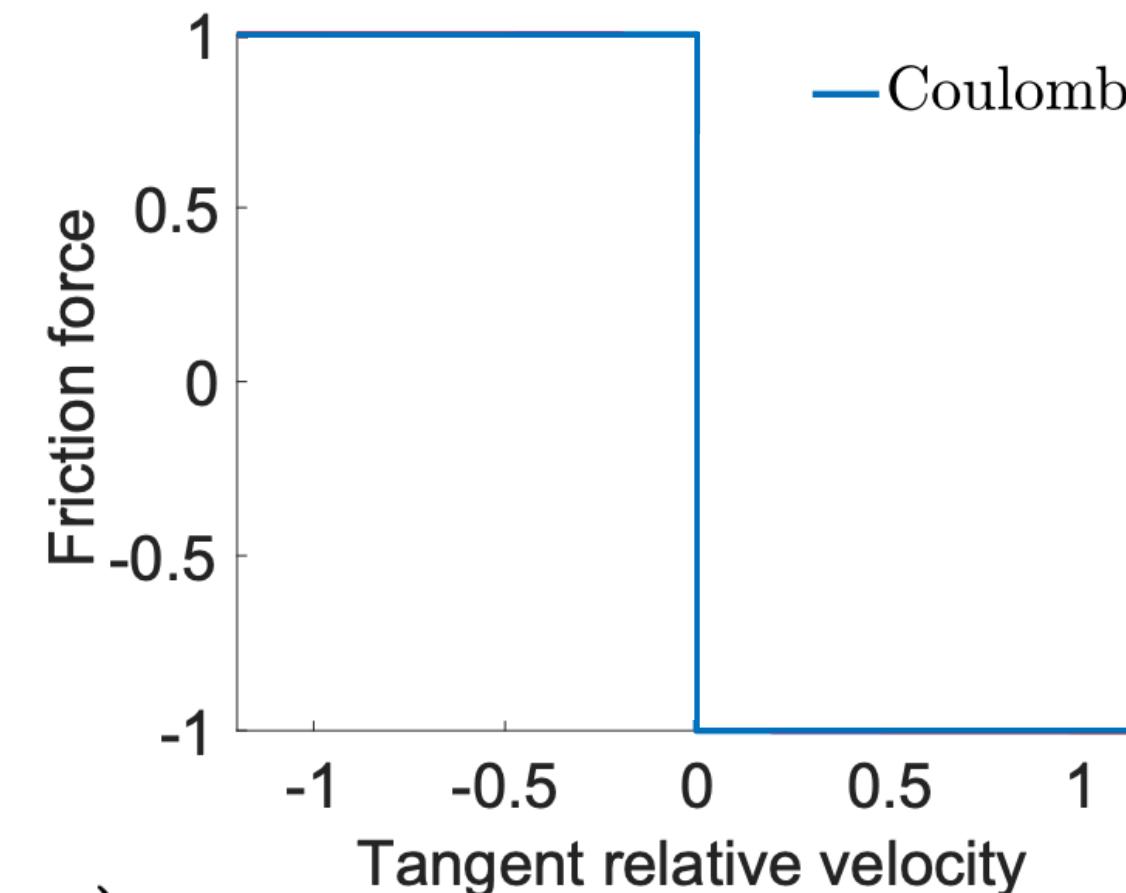
Approximation: Smooth Dynamic-Static Transition

$$F_k(x) = -\mu \lambda_k T_k(x) f(\|\mathbf{v}_k\|) \mathbf{s}(\mathbf{v}_k)$$

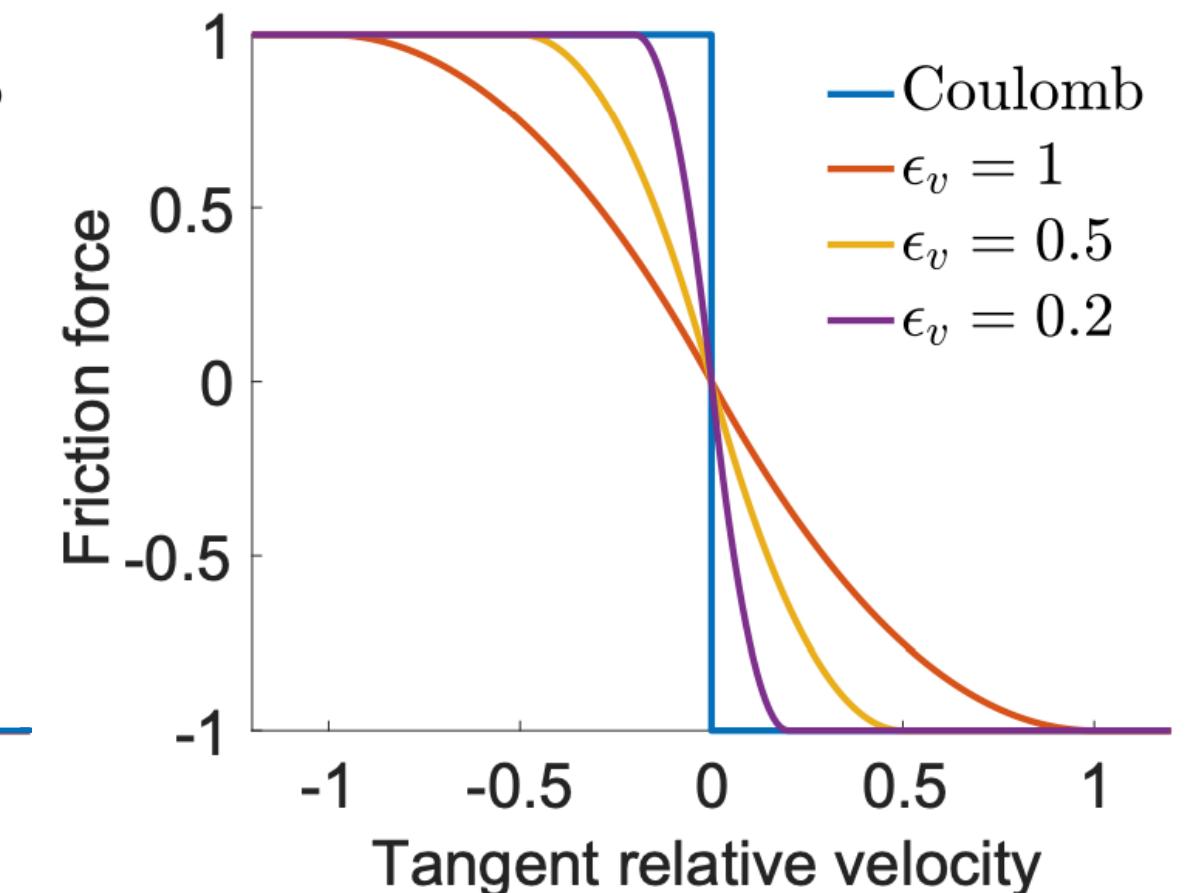
Non-smooth!

$$f(\|\mathbf{v}_k\|) = 1 \text{ when } \|\mathbf{v}_k\| > 0$$

$$f(\|\mathbf{v}_k\|) \in [0, 1] \text{ when } \|\mathbf{v}_k\| = 0$$



Approximate f with $f_1(y) = \begin{cases} -\frac{y^2}{\epsilon_v^2} + \frac{2y}{\epsilon_v}, & y \in [0, \epsilon_v) \\ 1, & y \geq \epsilon_v, \end{cases}$



What about s ?

Let $f(x)$ be a function we wish to smooth. It is C^1 continuous everywhere except at $x = a$ where it is only C^0 continuous. Applying a function $g(x)$ that is C^1 continuous everywhere with $g(a) = 0$, we have a smoothed function $f(x)g(x)$ that is C^1 continuous everywhere.

Mollification Lemma

\Rightarrow

$$F_k(x) = -\mu \lambda_k T_k(x) f_1(\|\mathbf{v}_k\|) \mathbf{s}(\mathbf{v}_k)$$

is C^1 -continuous!

Formulation of Dry Friction

Approximation: Semi-Implicit Temporal Discretization

$$F_k(x) = -\mu\lambda_k T_k(x) f_1(\|\mathbf{v}_k\|) \mathbf{s}(\mathbf{v}_k) \text{ is smooth, but, still non-conservative...}$$

Motivation: in explicit time integration, forces are constant (within a time step), thus integrable

Solution: discretize λ and T to time step n

$$F_k(x) \approx -\mu\lambda_k^n T_k^n f_1(\|\bar{\mathbf{v}}_k\|) \mathbf{s}(\bar{\mathbf{v}}_k)$$

$$P_f(x) = \sum_k \mu\lambda_k^n f_0(\|\bar{\mathbf{v}}_k \hat{h}\|)$$

\hat{h} is a constant multiple of the time step size

$$f_0(y) = \begin{cases} -\frac{y^3}{3\epsilon_v^2 \hat{h}^2} + \frac{y^2}{\epsilon_v \hat{h}} + \frac{\epsilon_v \hat{h}}{3}, & y \in [0, \epsilon_v \hat{h}] \\ y, & y \geq \epsilon_v \hat{h}, \end{cases}$$

$$f'_0(y) = f_1(y/\hat{h}) \quad \hat{h}I = (\partial v / \partial x)^{-1}$$

$$\text{where } \bar{\mathbf{v}}_k = (T_k^n)^T v \quad T^n = T(x^n) \quad \lambda^n = \lambda(x^n)$$

$$-\nabla P_f(x) = -\sum_k \mu\lambda_k^n T_k^n f_1(\|\bar{\mathbf{v}}_k\|) \mathbf{s}(\bar{\mathbf{v}}_k)$$

$$\begin{aligned} & \nabla^2 P_f(x) \\ &= \sum_k \mu\lambda_k^n T_k^n \left(\frac{f'_1(\|\bar{\mathbf{v}}_k\|) \|\bar{\mathbf{v}}_k\| - f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|^3} \bar{\mathbf{v}}_k \bar{\mathbf{v}}_k^T + \frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} \mathbf{I}_3 \right) T_k^{nT} \frac{\partial v}{\partial x} \end{aligned}$$

Formulation of Dry Friction

Fixed-Point Iteration

- How to obtain solution with **fully-implicit friction?**

Algorithm: alternate between

$$\min_x : E(x, \{\lambda, T\}) = \frac{1}{2} \|x - \tilde{x}^n\|_M^2 + \Delta t^2 (P_e(x) + P_b(x) + P_f(x, \{\lambda, T\}))$$

$$\text{s.t. } Ax = b,$$

and friction update until convergence

Fixed-point iteration on $f_m \cdot f_u$

Define

$$f_m(\{\lambda, T\}) = \operatorname{argmin}_x E(x, \{\lambda, T\})$$

$$(f_m \cdot f_u)(x) \equiv f_m(f_u(x))$$

$$f_u(x) = \text{FrictionUpdate}(x),$$

Formulation of Dry Friction

Fixed-Point Iteration (Cont.)

Definition (Fixed-Point Iterations). x is a fixed point of function $f()$ if and only if

$$x = f(x).$$

The fixed-point iterations finds the fixed-point of a function $f()$ starting from x^0 by iteratively updating the estimate

$$x^{i+1} \leftarrow f(x^i)$$

until convergence.

[Li et al 2020]

Algorithm 5: Fixed-Point Iteration for Fully-Implicit Friction

Result: x^{n+1}, v^{n+1}

```
1  $x^j \leftarrow x^n;$ 
2  $\{\lambda^j, T^j\} \leftarrow \text{FrictionUpdate}(x^j);$ 
3 while  $\|((\nabla^2 E)^{-1} \nabla E)(x^j, \{\lambda^j, T^j\})\| > \epsilon$  do
4    $x^{j+1} \leftarrow \text{argmin}_x E(x, \{\lambda^j, T^j\});$ 
5    $\{\lambda^{j+1}, T^{j+1}\} \leftarrow \text{FrictionUpdate}(x^{j+1});$ 
6    $j \leftarrow j + 1$ 
```

Converges only when starting sufficiently close.

No numerical explosion issues here.

Today:

- **Formulation**
Mollification, Semi-Implicit Approx., Fixed-Point Iteration
- **Case Study: Square on Slope**
- **Remarks**

Case Study: Square on Slope

From Ground to Slope

Group: $d(\mathbf{x}) = \mathbf{x}_y - y_0, \quad \nabla d(\mathbf{x}) = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad \nabla^2 d(\mathbf{x}) = \mathbf{0}$

General half-space (including slope):

$$d(\mathbf{x}) = \mathbf{n}^T(\mathbf{x} - \mathbf{o}), \quad \nabla d(\mathbf{x}) = \mathbf{n}, \quad \text{and} \quad \nabla^2 d(\mathbf{x}) = \mathbf{0}$$

simulator.py

```
17 ground_n = np.array([0.1, 1.0])      # normal of the slope
18 ground_n /= np.linalg.norm(ground_n)    # normalize ground
     normal vector just in case
19 ground_o = np.array([0.0, -1.0])      # a point on the slope

58     pygame.draw.aaline(screen, (0, 0, 255), screen_projection
([ground_o[0] - 3.0 * ground_n[1], ground_o[1] + 3.0 *
ground_n[0]]),
                     screen_projection([ground_o[0] + 3.0 * ground_n[1],
ground_o[1] - 3.0 * ground_n[0]]))    # slope
```

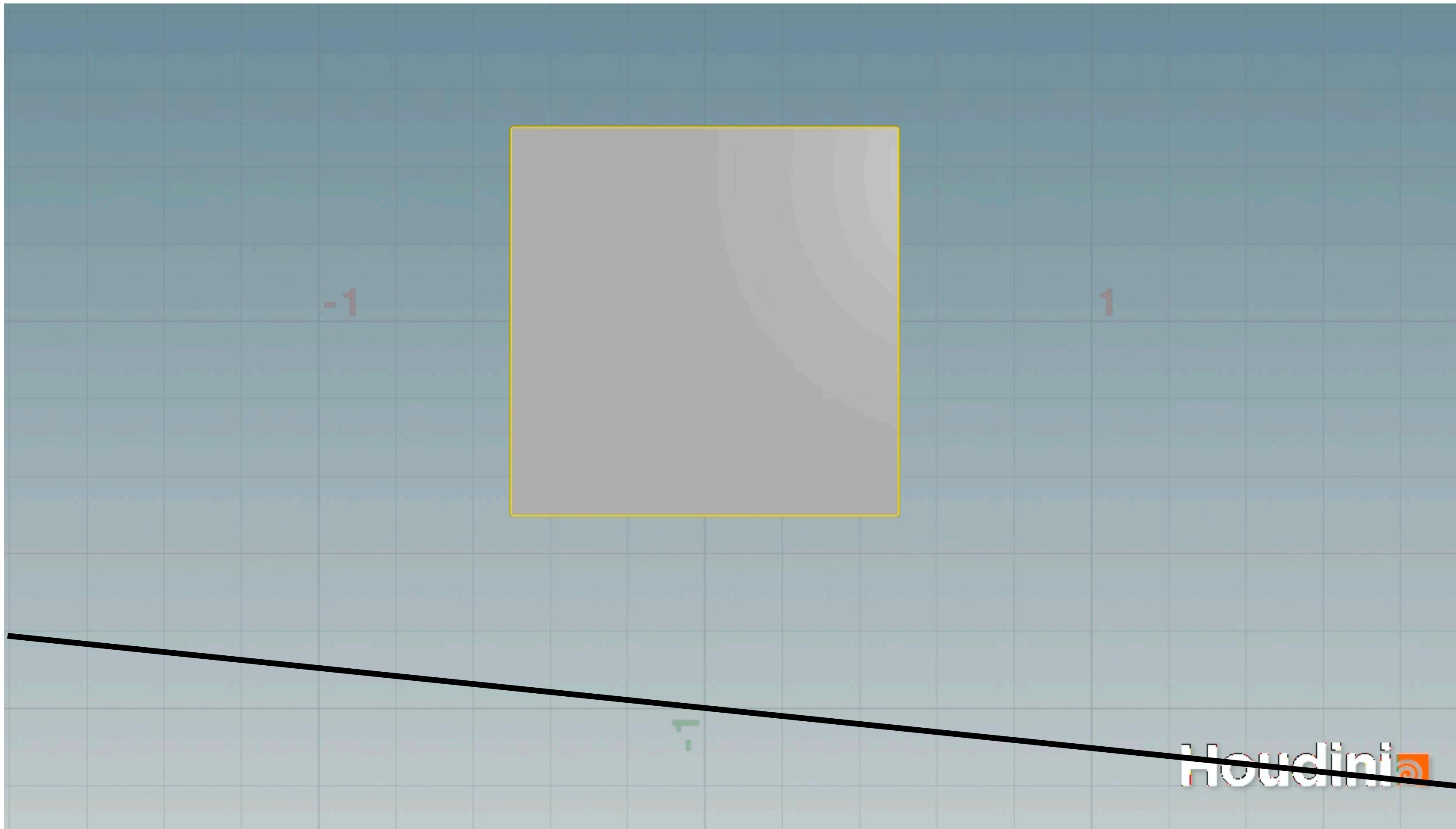
```

7 def val(x, n, o, contact_area):
8     sum = 0.0
9     for i in range(0, len(x)):
10        d = n.dot(x[i] - o)
11        if d < dhat:
12            s = d / dhat
13            sum += contact_area[i] * dhat * kappa / 2 * (s -
14) * math.log(s)
15    return sum
16
17 def grad(x, n, o, contact_area):
18    g = np.array([[0.0, 0.0]] * len(x))
19    for i in range(0, len(x)):
20        d = n.dot(x[i] - o)
21        if d < dhat:
22            s = d / dhat
23            g[i] = contact_area[i] * dhat * (kappa / 2 * (math
24) .log(s) / dhat + (s - 1) / d) * n
25    return g
26
27 def hess(x, n, o, contact_area):
28    IJV = [[0] * 0, [0] * 0, np.array([0.0] * 0)]
29    for i in range(0, len(x)):
30        d = n.dot(x[i] - o)
31        if d < dhat:
32            local_hess = contact_area[i] * dhat * kappa / (2 *
33) d * d * dhat) * (d + dhat) * np.outer(n, n)
34            for c in range(0, 2):
35
36    def init_step_size(x, n, o, p):
37        alpha = 1
38        for i in range(0, len(x)):
39            p_n = p[i].dot(n)
40            if p_n < 0:
41                alpha = min(alpha, 0.9 * n.dot(x[i] - o) / -p_n)
42        return alpha
43
44

```

Case Study: Square on Slope

Without Friction



Case Study: Square on Slope

Friction Implementation

$$-\nabla P_{f,k}(x) = -\mu \lambda_k^n T_k^n \frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} \bar{\mathbf{v}}_k$$

$$\frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} = \begin{cases} -\frac{\|\bar{\mathbf{v}}_k\|}{\epsilon_v^2} + \frac{2}{\epsilon_v}, & \|\bar{\mathbf{v}}_k\| \in [0, \epsilon_v) \\ 1/\|\bar{\mathbf{v}}_k\|, & \|\bar{\mathbf{v}}_k\| \geq \epsilon_v, \end{cases}$$

$$-\nabla P_{f,k}(x) = -\mu \lambda_k^n T_k^n \frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} \bar{\mathbf{v}}_k = 0 \quad \text{when} \quad \|\bar{\mathbf{v}}_k\| = 0$$

$$\begin{aligned} & \nabla^2 P_f(x) \\ &= \sum_k \mu \lambda_k^n T_k^n \left(\frac{f'_1(\|\bar{\mathbf{v}}_k\|) \|\bar{\mathbf{v}}_k\| - f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|^3} \bar{\mathbf{v}}_k \bar{\mathbf{v}}_k^T + \frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} \mathbf{I}_3 \right) T_k^{nT} \frac{\partial v}{\partial x} \end{aligned}$$

$$\frac{f'_1(\|\bar{\mathbf{v}}_k\|) \|\bar{\mathbf{v}}_k\| - f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|^2} = \begin{cases} -1/\epsilon_v^2, & \|\bar{\mathbf{v}}_k\| \in [0, \epsilon_v) \\ -1/\|\bar{\mathbf{v}}_k\|^2, & \|\bar{\mathbf{v}}_k\| \geq \epsilon_v, \end{cases}$$

$$\nabla^2 P_{f,k}(x) = \mu \lambda_k^n T_k^n \left(\frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} \mathbf{I}_3 \right) T_k^{nT} \frac{\partial v}{\partial x} \quad \text{when} \quad \|\bar{\mathbf{v}}_k\| = 0$$

FrictionEnergy.py

```

1 import numpy as np
2 import utils
3
4 epsv = 1e-3
5
6 def f0(vbarnorm, epsv, hhat):
7     if vbarnorm >= epsv:
8         return vbarnorm * hhat
9     else:
10        vbarnormhhat = vbarnorm * hhat
11        epsvhhat = epsv * hhat
12        return vbarnormhhat * vbarnormhhat * (-vbarnormhhat /
13            3.0 + epsvhhat) / (epsvhhat * epsvhhat) + epsvhhat / 3.0
14
15 def f1_div_vbarnorm(vbarnorm, epsv):
16     if vbarnorm >= epsv:
17         return 1.0 / vbarnorm
18     else:
19         return (-vbarnorm + 2.0 * epsv) / (epsv * epsv)
20
21 def f_hess_term(vbarnorm, epsv):
22     if vbarnorm >= epsv:
23         return -1.0 / (vbarnorm * vbarnorm)
24     else:
25         return -1.0 / (epsv * epsv)

```

Case Study: Square on Slope

Friction Implementation (Cont.)

FrictionEnergy.py

$$-\nabla P_{f,k}(x) = -\mu \lambda_k^n T_k^n \frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} \bar{\mathbf{v}}_k$$

$$\frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} = \begin{cases} -\frac{\|\bar{\mathbf{v}}_k\|}{\epsilon_v^2} + \frac{2}{\epsilon_v}, & \|\bar{\mathbf{v}}_k\| \in [0, \epsilon_v) \\ 1/\|\bar{\mathbf{v}}_k\|, & \|\bar{\mathbf{v}}_k\| \geq \epsilon_v, \end{cases}$$

$$-\nabla P_{f,k}(x) = -\mu \lambda_k^n T_k^n \frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} \bar{\mathbf{v}}_k = 0 \quad \text{when} \quad \|\bar{\mathbf{v}}_k\| = 0$$

$$\begin{aligned} & \nabla^2 P_f(x) \\ &= \sum_k \mu \lambda_k^n T_k^n \left(\frac{f'_1(\|\bar{\mathbf{v}}_k\|) \|\bar{\mathbf{v}}_k\| - f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|^3} \bar{\mathbf{v}}_k \bar{\mathbf{v}}_k^T + \frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} \mathbf{I}_3 \right) T_k^{nT} \frac{\partial v}{\partial x} \end{aligned}$$

$$\frac{f'_1(\|\bar{\mathbf{v}}_k\|) \|\bar{\mathbf{v}}_k\| - f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|^2} = \begin{cases} -1/\epsilon_v^2, & \|\bar{\mathbf{v}}_k\| \in [0, \epsilon_v) \\ -1/\|\bar{\mathbf{v}}_k\|^2, & \|\bar{\mathbf{v}}_k\| \geq \epsilon_v, \end{cases}$$

$$\nabla^2 P_{f,k}(x) = \mu \lambda_k^n T_k^n \left(\frac{f_1(\|\bar{\mathbf{v}}_k\|)}{\|\bar{\mathbf{v}}_k\|} \mathbf{I}_3 \right) T_k^{nT} \frac{\partial v}{\partial x} \quad \text{when} \quad \|\bar{\mathbf{v}}_k\| = 0$$

```

26 def val(v, mu_lambda, hhat, n):
27     sum = 0.0
28     T = np.identity(2) - np.outer(n, n) # tangent of slope is
29     constant
30     for i in range(0, len(v)):
31         if mu_lambda[i] > 0:
32             vbar = np.transpose(T).dot(v[i])
33             sum += mu_lambda[i] * f0(np.linalg.norm(vbar),
34             epsv, hhat)
35     return sum
36
37 def grad(v, mu_lambda, hhat, n):
38     g = np.array([[0.0, 0.0]] * len(v))
39     T = np.identity(2) - np.outer(n, n) # tangent of slope is
40     constant
41     for i in range(0, len(v)):
42         if mu_lambda[i] > 0:
43             vbar = np.transpose(T).dot(v[i])
44             g[i] = mu_lambda[i] * f1_div_vbarnorm(np.linalg.
45             norm(vbar), epsv) * T.dot(vbar)
46     return g
47
48 def hess(v, mu_lambda, hhat, n):
49     IJV = [[0] * 0, [0] * 0, np.array([0.0] * 0)]
50     T = np.identity(2) - np.outer(n, n) # tangent of slope is
51     constant
52     for i in range(0, len(v)):
53         if mu_lambda[i] > 0:
54             vbar = np.transpose(T).dot(v[i])
55             vbarnorm = np.linalg.norm(vbar)
56             inner_term = f1_div_vbarnorm(vbarnorm, epsv) * np.
57             identity(2)
58             if vbarnorm != 0:
59                 inner_term += f_hess_term(vbarnorm, epsv) /
60                 vbarnorm * np.outer(vbar, vbar)
61                 local_hess = mu_lambda[i] * T.dot(utils.make_PD(
62                 inner_term)).dot(np.transpose(T)) / hhat
63                 for c in range(0, 2):
64                     for r in range(0, 2):
65                         IJV[0].append(i * 2 + r)
66                         IJV[1].append(i * 2 + c)
67                         IJV[2] = np.append(IJV[2], local_hess[r, c]
68                         )
69     return IJV

```

Case Study: Square on Slope

Calculating Normal Force Magnitude

$\lambda_k = -w_k \frac{\partial b}{\partial d_k}$ is the contact force magnitude

```
46 def compute_mu_lambda(x, n, o, contact_area, mu):
47     mu_lambda = np.array([0.0] * len(x))
48     for i in range(0, len(x)):
49         d = n.dot(x[i] - o)
50         if d < dhat:
51             s = d / dhat
52             mu_lambda[i] = mu * -contact_area[i] * dhat * (
53                 kappa / 2 * (math.log(s) / dhat + (s - 1) / d))
54     return mu_lambda
```

BarrierEnergy.py

```
15 def step_forward(x, e, v, m, l2, k, n, o, contact_area, mu,
16     is_DBC, h, tol):
17     x_tilde = x + v * h      # implicit Euler predictive
18     position
19     x_n = copy.deepcopy(x)
20     mu_lambda = BarrierEnergy.compute_mu_lambda(x, n, o,
21         contact_area, mu) # compute mu * lambda for each node
22         using x^n
23
24     # Newton loop
```

time_integrator.py

Demo!

Code: github.com/phys-sim-book/solid-sim-tutorial

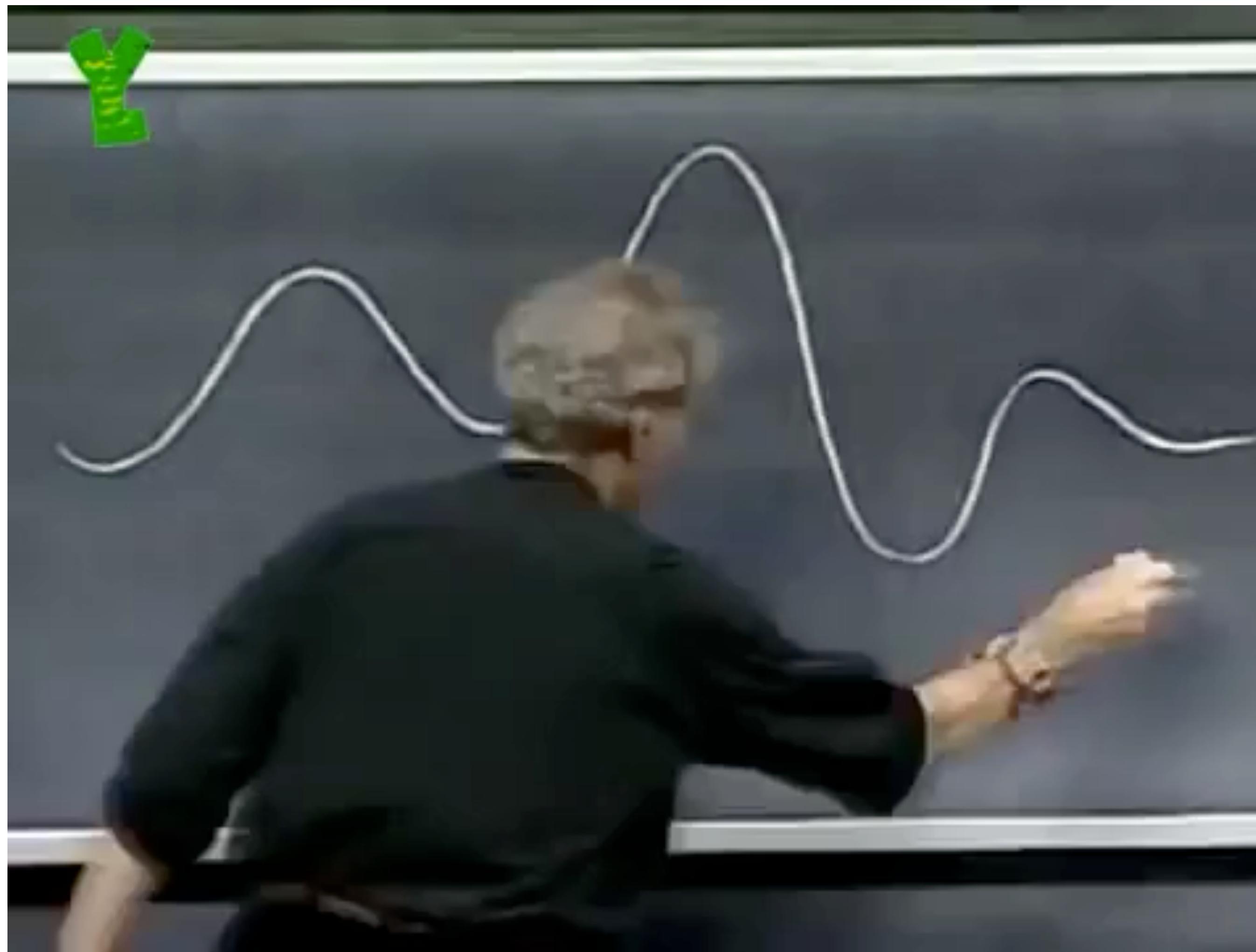
GPU Version: github.com/phys-sim-book/solid-sim-tutorial-gpu

Online Book: phys-sim-book.github.io

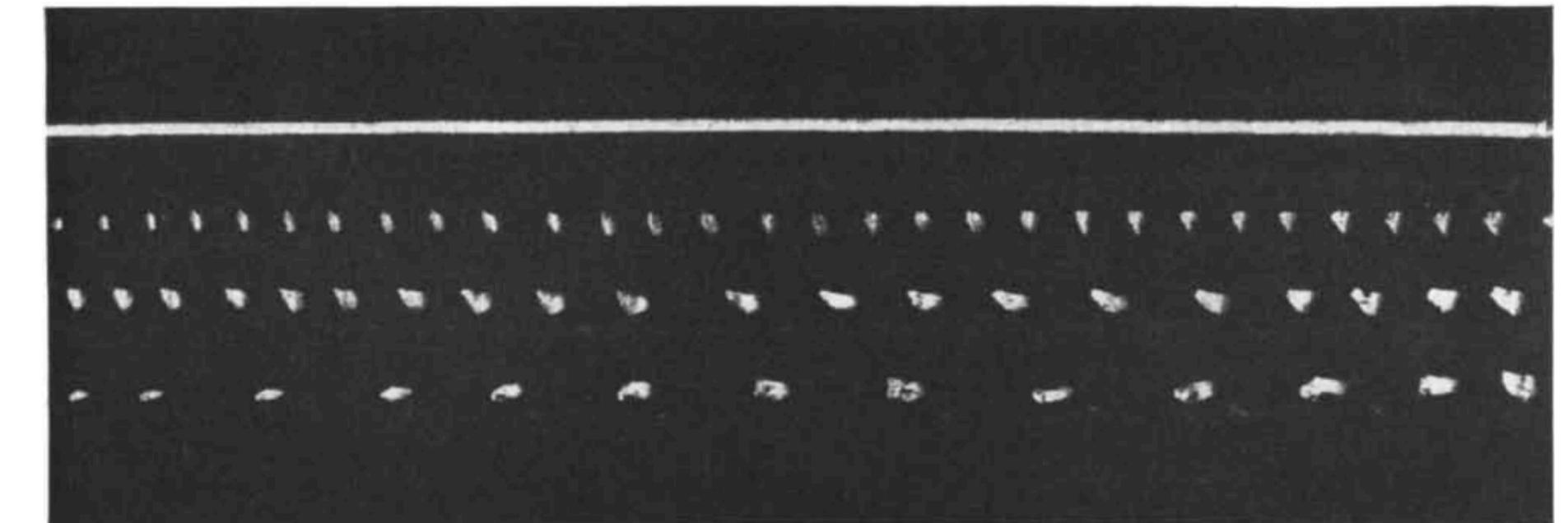
Today:

- **Formulation**
Mollification, Semi-Implicit Approx., Fixed-Point Iteration
- **Case Study: Square on Slope**
Avoid Numerical Issues
- **Remarks**

Remarks – Stick-Slip Instability Effect



Rabinowicz, Ernest. "Stick and slip." *Scientific American* 194, no. 5 (1956): 109-119.



CHALK MARKS on a blackboard demonstrate stick-slip. The top mark was made by a piece of chalk held at an acute angle to the direction of motion; the marks below it, by pieces of chalk held

at an obtuse angle to this direction. In the latter marks the chalk stuck to the blackboard, then slipped, then stuck again and so on. The more tightly the chalk is held, the smaller the distance of slip.

Zoom View

0.25X

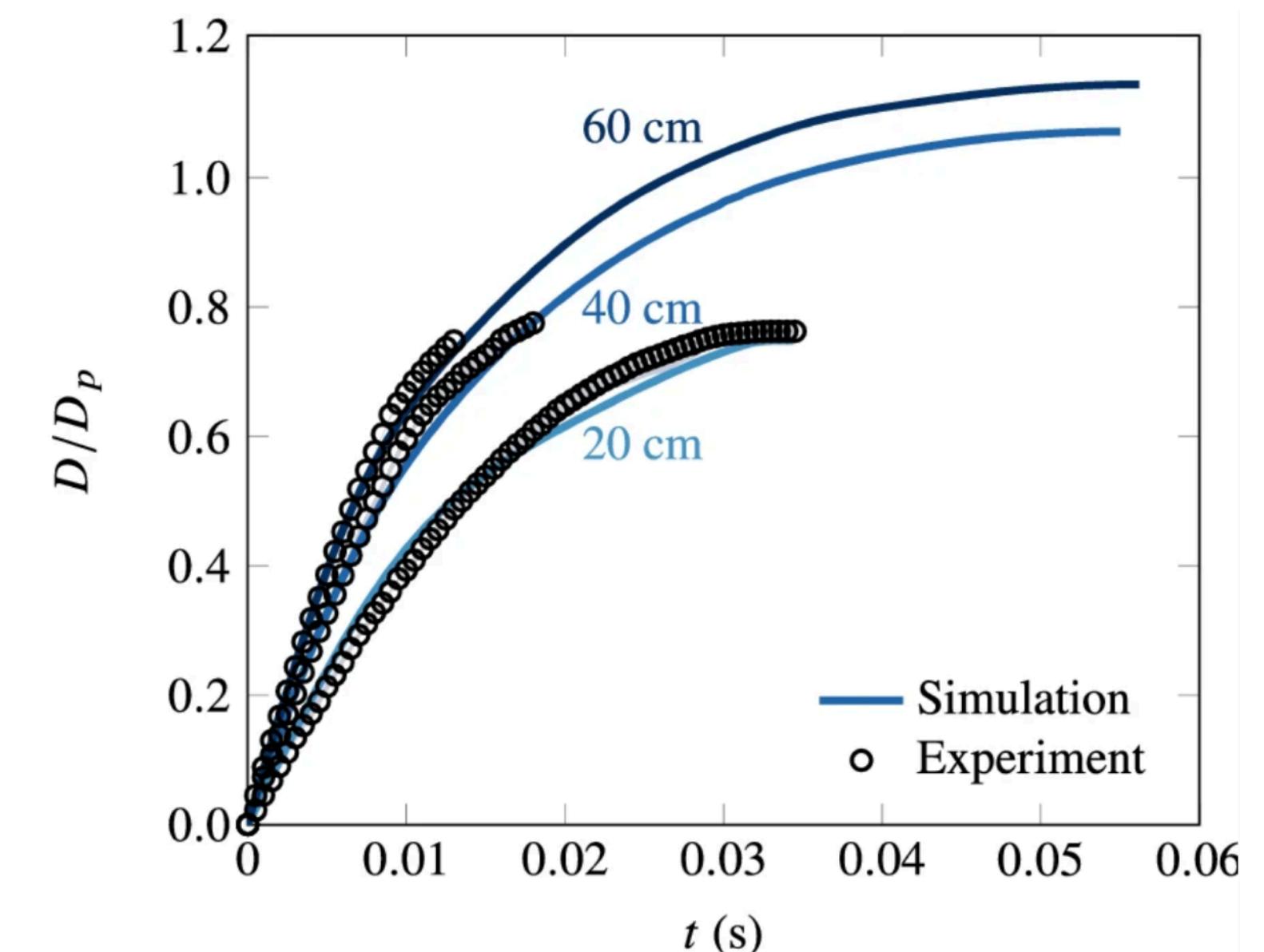
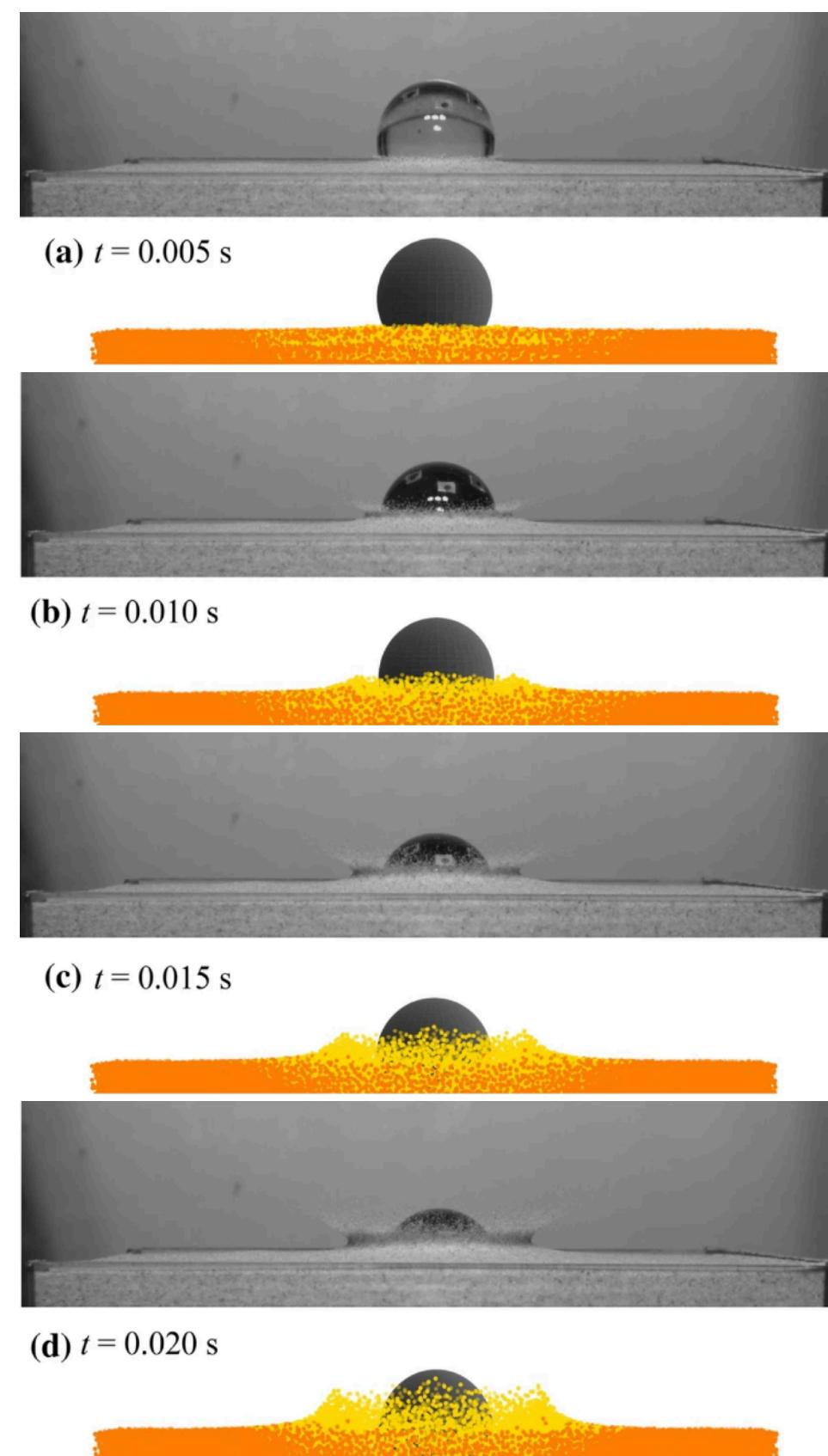
tetrahedra: 2K
contacts per step (max): 16
dt: 0.001
 μ : 0.35



Remarks – Applications

Computational Mechanics

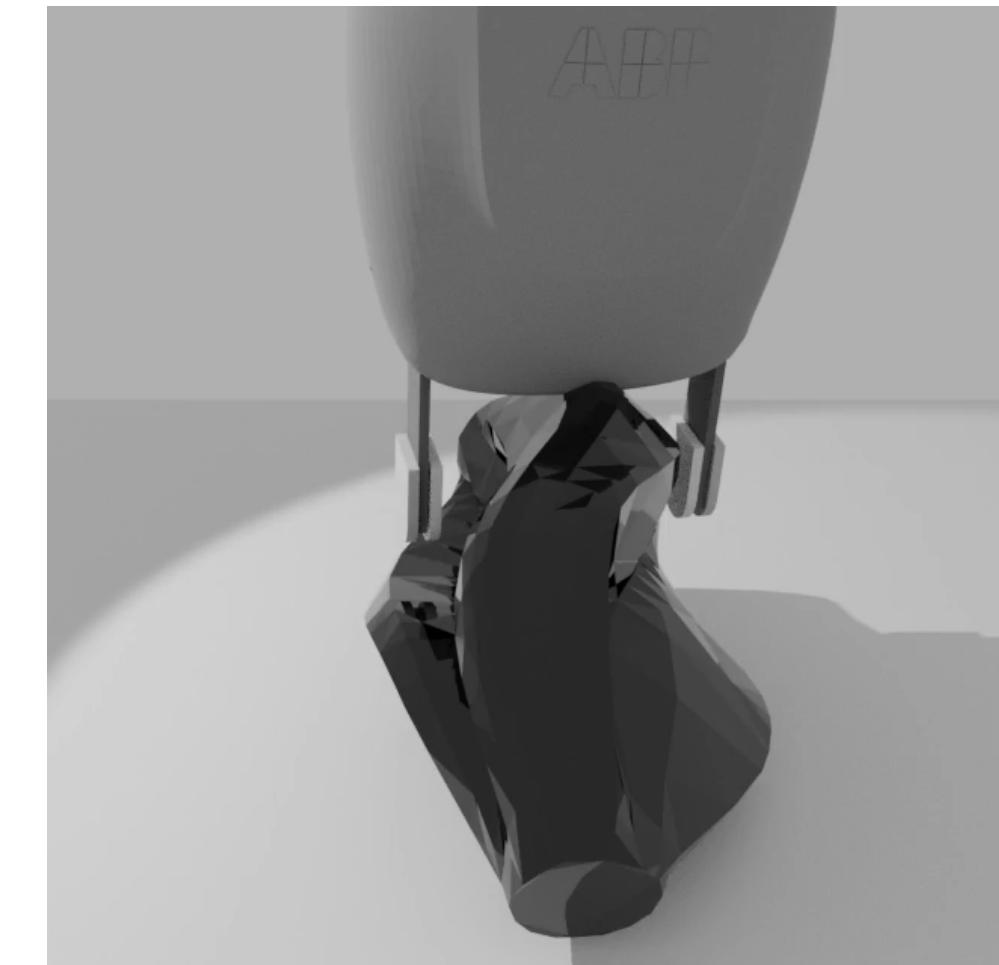
- Jiang et al. [2022]
 - Uses IPC to couple discrete element method (DEM) and material point method (MPM)
 - ...



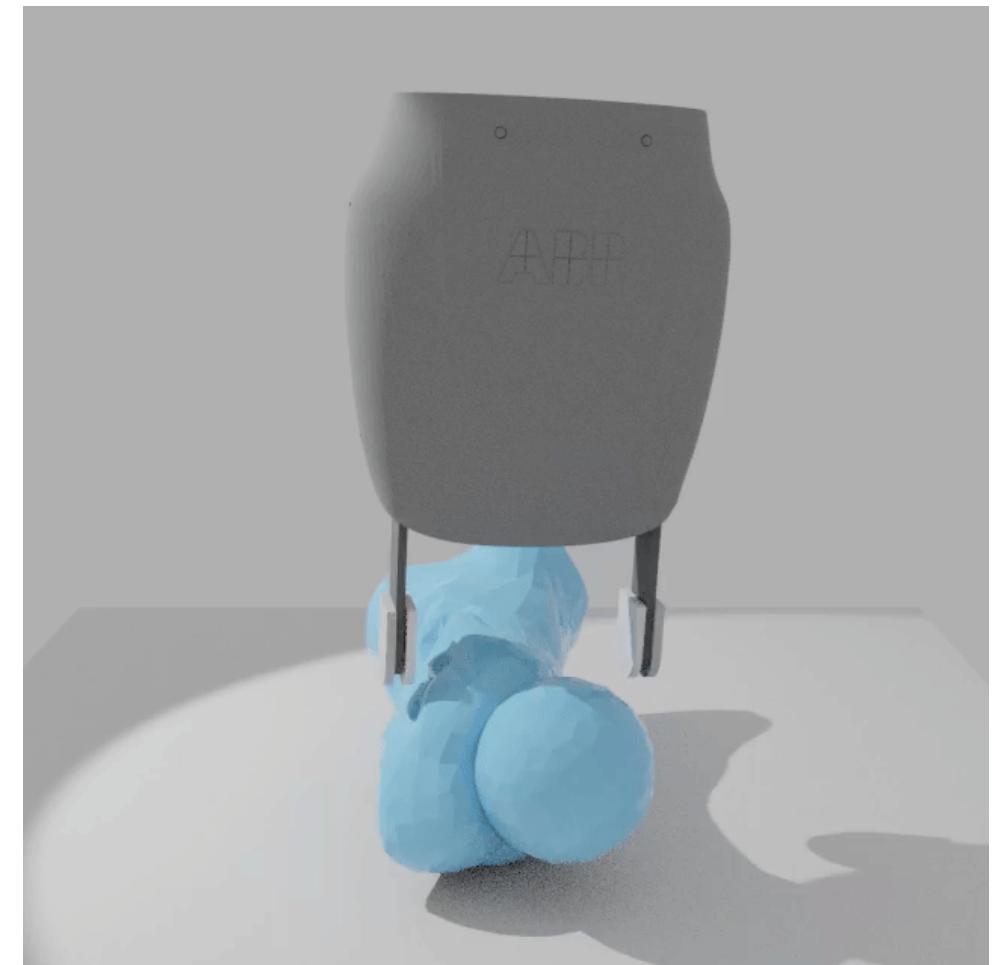
Remarks – Applications

Robotics

- IPC-GraspSim [Kim et al. 2022]
 - Compares grasping results between IPC simulations and experiments
 - ...



Successful Grasp: Vase



Failed Grasp: Pawn

Grasp sets (5 trials/grasp)	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
IPC-GraspSim	0.0	0.0	1.0	0.0	0.0	1.0	0.4	0.8	1.0	1.0	1.0	1.0	1.0	1.0	0.6	0.0	0.0	0.0	0.4	0.0	0.0	1.0	1.0	0.0	0.0
Physical Experiments	0.0	1.0	1.0	0.0	0.0	1.0	0.8	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.2	0.0	0.0	0.4	1.0	0.8	0.0	0.0

Today:

- **Formulation**
Mollification, Semi-Implicit Approx., Fixed-Point Iteration
- **Case Study: Square on Slope**
Avoid Numerical Issues
- **Remarks**
Stick-Slip Instability, Applications

Next Lecture: Moving Boundary Conditions

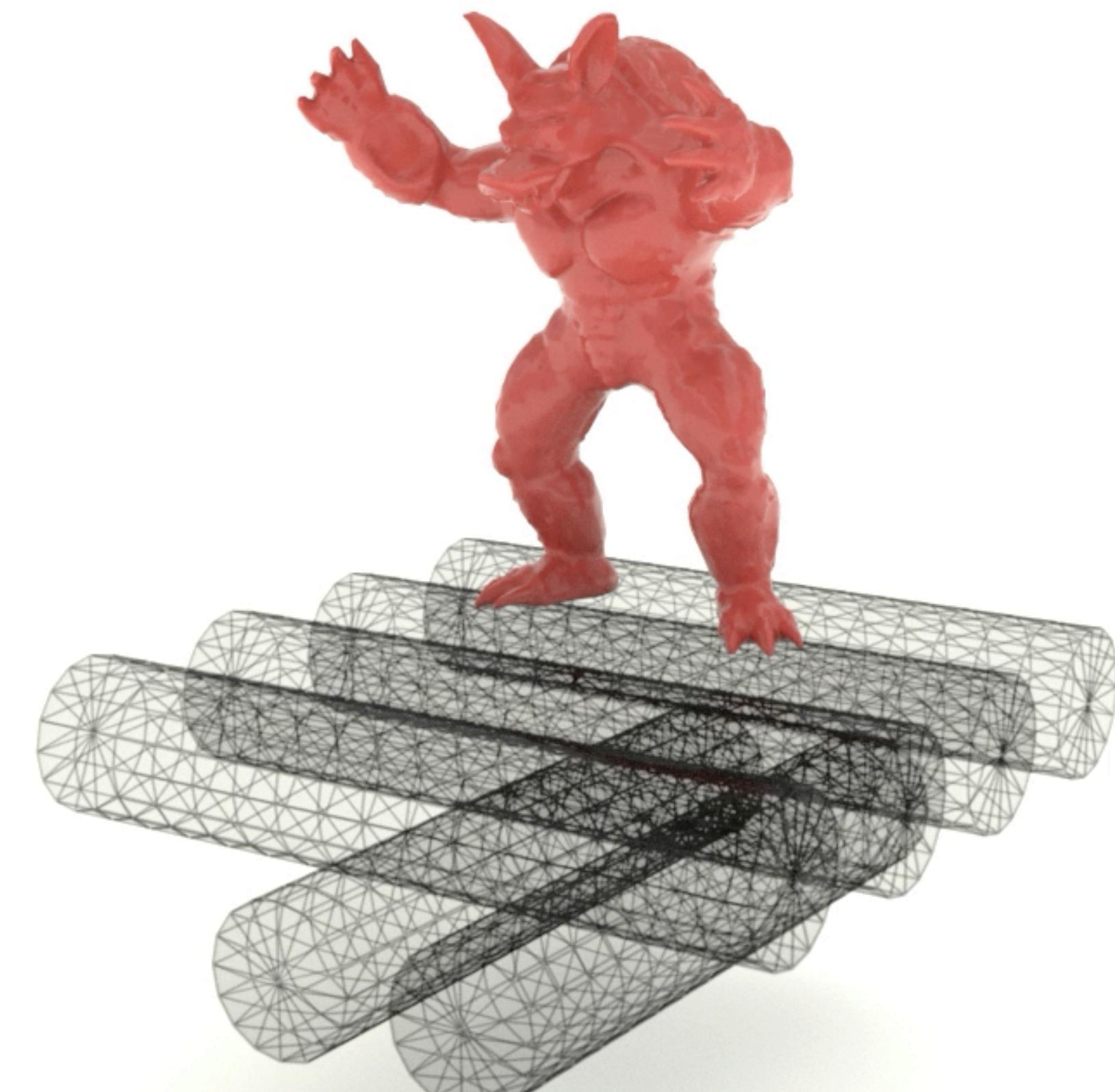
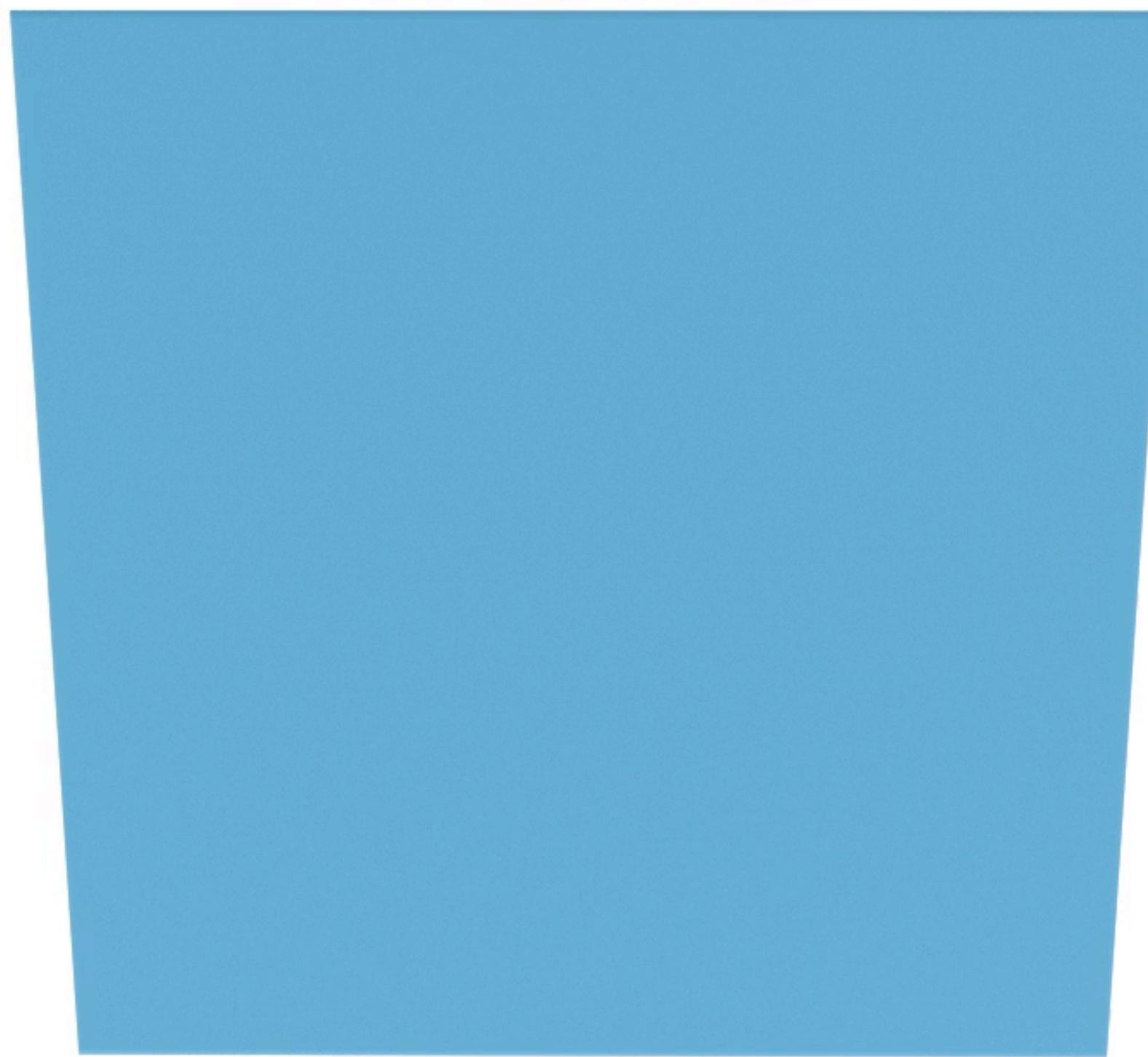


Image Sources

- <https://nacho.blogs.uv.es/2017/11/20/conformation-constraints-for-efficient-viscoelastic-fluid-simulation/>
- <https://www.gauss-centre.eu/results/computational-and-scientific-engineering/dns-of-airfoil-acoustics>
- <https://iselinc.com/explore-many-benefits-lubrication/>
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