SAMPLE-EFFICIENT LEARNING OF RIGID BODY DYNAMICS

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MOTIVATION

- Current robots are stuck in repetitive, predictable environments
- Want to enable dynamic interaction with objects
- Frictional contact is fundamental to robot manipulation, but difficult to model
  - Sudden changes in dynamics when making/breaking contact
  - Stick/slip transitions
  - Large regions of zero state gradients w.r.t parameters

How can we effectively learn dynamics over a stiff class of models?

MODEL REQUIREMENTS

1. True dynamics lies within class of learnable models and is optimal
2. Stiffness of underlying model does not directly determine gradients
3. Non-zero gradients exist for a large region of parameter space

PRIOR WORK

Purely learned
- Often in context of policy learning
- Slow and data inefficient
- Doesn't use existing knowledge of contact dynamics

Hybrid
- Best of both worlds

Approaches:
- Sim-to-real
- Residual physics
- **Differentiation through contact problem**

Analytical
- Only an approximation
- Doesn't fully capture real-world phenomena

METHOD

1. Formulate base contact model as fusion of Drumwright [2] and MuJoCo [3]
   Phase 1: Solver for normal forces with no friction:
$$\begin{aligned} \operatorname*{arg\,min}_{\lambda_n \geq 0} \quad & \lambda_n^T J_n M^{-1} J_n^T \lambda_n + J_n f \lambda \\ & J_n M^{-1} J_n^T \lambda_n \Delta t + (J_n f)\phi \geq 0 \end{aligned}$$
   Phase 2: Compute $\kappa = e^T \lambda_n$ from phase 1. Then solve frictional contact:
$$\begin{aligned} \operatorname*{arg\,min}_{\lambda} \quad & \lambda^T J M^{-1} J^T \lambda + J f \lambda_n + \lambda_n^T diag(exp(\phi))\lambda_n \\ & J M^{-1} J^T \lambda \Delta t + (J f)\phi \geq 0 \\ & \lambda_n \geq 0 \\ & e^T \lambda_n \leq \kappa \\ & \lambda_t \leq \mu \lambda_n \end{aligned}$$
2. Penalize deviations from measured data in subproblem
   - Incorporate L_2 **deviation penalty** in contact model objectives
   - **Soften** hard constraints in subproblems
   - Introduces a **tradeoff** between satisfying model and matching experimental observations to avoid nonexistant parameter gradients
3. Optimize model parameter set with respect to summed error over all data points:
$$\begin{aligned} \operatorname*{arg\,min}_{\theta} \quad & \sum_i (Dynamics(q_i, u_i, \lambda) - \bar{q}_i)^2 \\ s.t. \quad & \lambda = Sol(q_i, u_i) \end{aligned}$$
   Where ***Sol*** refers to the forces produced by the above subroutine. This outer optimization is performed with gradient descent, where gradients through the QP subproblems are supplied by Amos et. al. [1].

q – configuration | u – input | λ_n – normal forces | λ_t – frictional forces | J_n – normal contact Jacobian | J_t – tangential contact Jacobian | f – no contact dynamics | ϕ – gap function | μ – Coulomb friction coefficient | M - inertia matrix

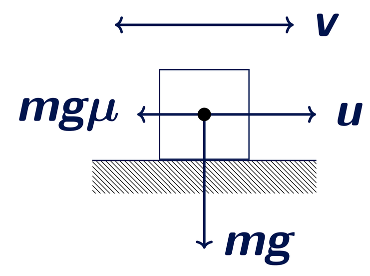
[1] Brandon Amos and J Zico Kolter. OptNet: Differentiable Optimization as a Layer in Neural Networks. 2017.

[2] Evan Drumwright and Dylan A Shell. Modeling Contact Friction and Joint Friction in Dynamic Robotic Simulation using the Principle of Maximum Dissipation.

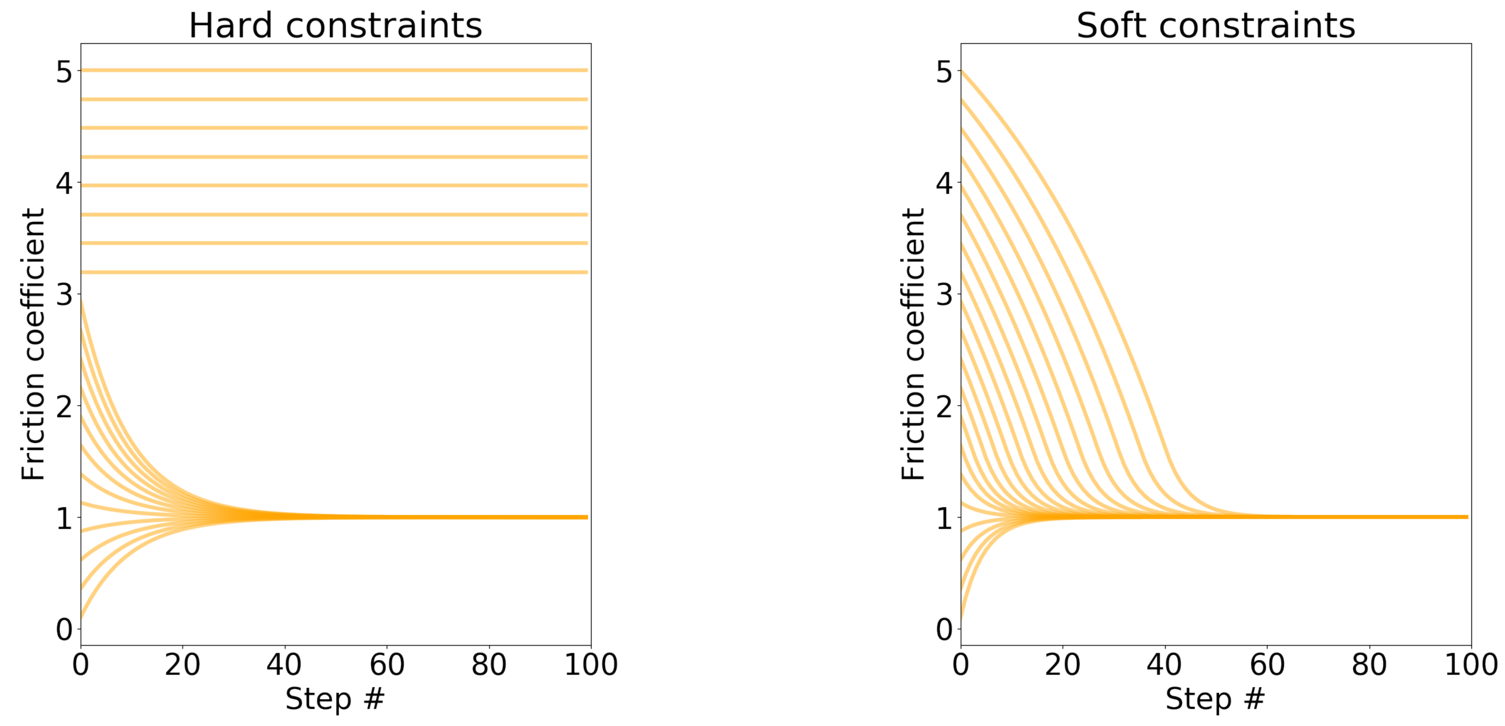
[3] Emanuel Todorov, Tom Erez, and Yuval Tassa. MuJoCo: A physics engine for model-based control.

APPLICATION: 1D FRICTIONAL BLOCK

A simple example of a sliding point-mass with stick-slip friction. If the initial estimate for the friction coefficient μ is much higher than the actual μ, local changes of μ will be unable to reward the optimizer (block stays sticking no matter what). Introducing tradeoffs into the subproblem helps create gradients.

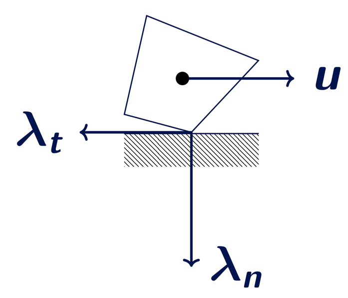


Modification of subproblem produces learnable gradients

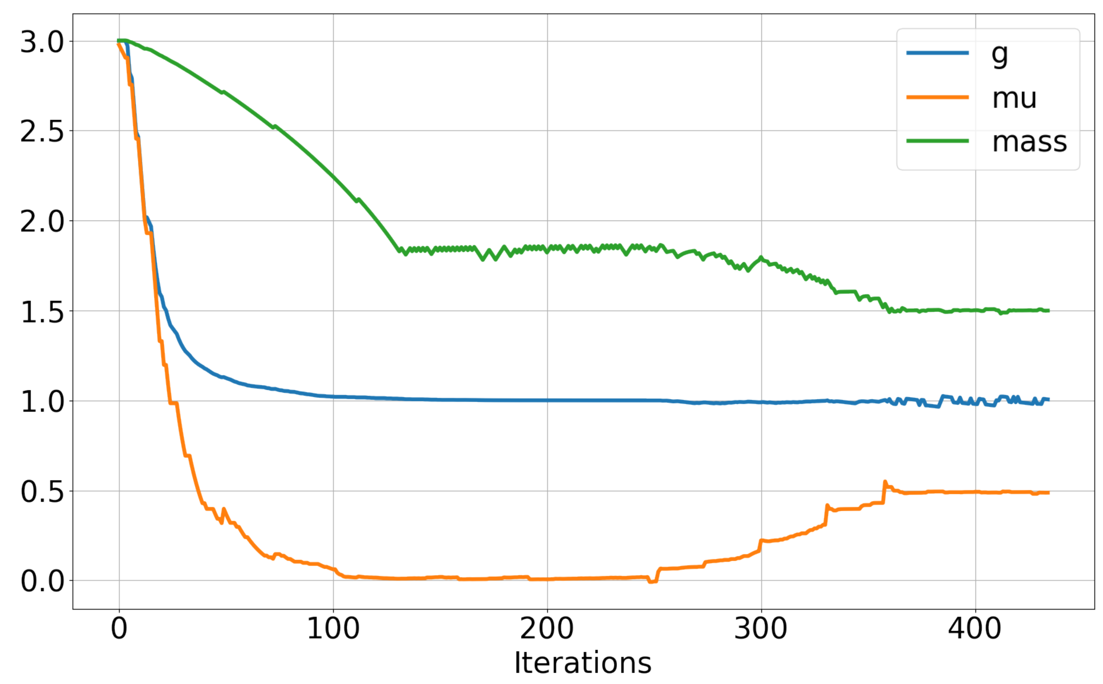


APPLICATION: 2D POLYGON

A planar polygon tumbling on a static surface. The forward dynamics can be solved using a variety of different methods; for learning, we used the combined Drumwright / MuJoCo model on the left due to its convenient convex form. Optimization was performed using stochastic gradient descent.



Simultaneous optimization of multiple parameters



SUMMARY

Contributions
- Convex time-stepping contact model that addresses weaknesses of MuJoCo and Drumwright
- Bilevel optimization formulation of contact dynamics learning
- Expanded regions of nonzero gradients

Ongoing Work
- Introducing learning of nonphysical quantities
- Experimenting with different normal force softening methods
- Testing with real Kuka arm