Simultaneous Learning of Contact and Continuous Dynamics

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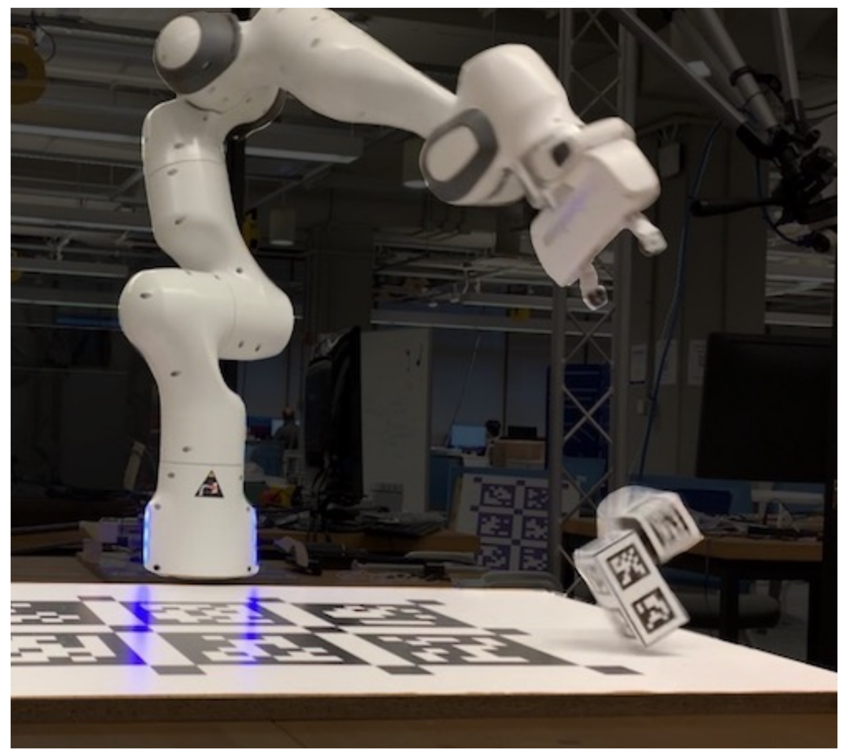
GOAL, CHALLENGES, APPROACH

- **Goal:** To capture the contact and continuous dynamics of novel objects by build useful dynamics models from scratch, from observed odometry data.
- **Challenges:**
  - Stiff and sharp contact dynamics overwhelm smooth and small continuous dynamics, making it difficult to capture both simultaneously.
  - Existing model-based physics simulators neglect some significant real effects, like complex joint friction.
  - Common learning techniques like weight regularization are ill-suited for the discontinuities of contact.
- **Our Approach:** Learn physically-meaningful dynamics parameters, encoding contact dynamics via geometry and friction, and continuous dynamics via inertial parameters augmented with a residual physics network.

EXPERIMENTS

We test across **challenging contact-rich, collision-ridden datasets** of objects falling under their autonomous dynamics and colliding with a flat ground.

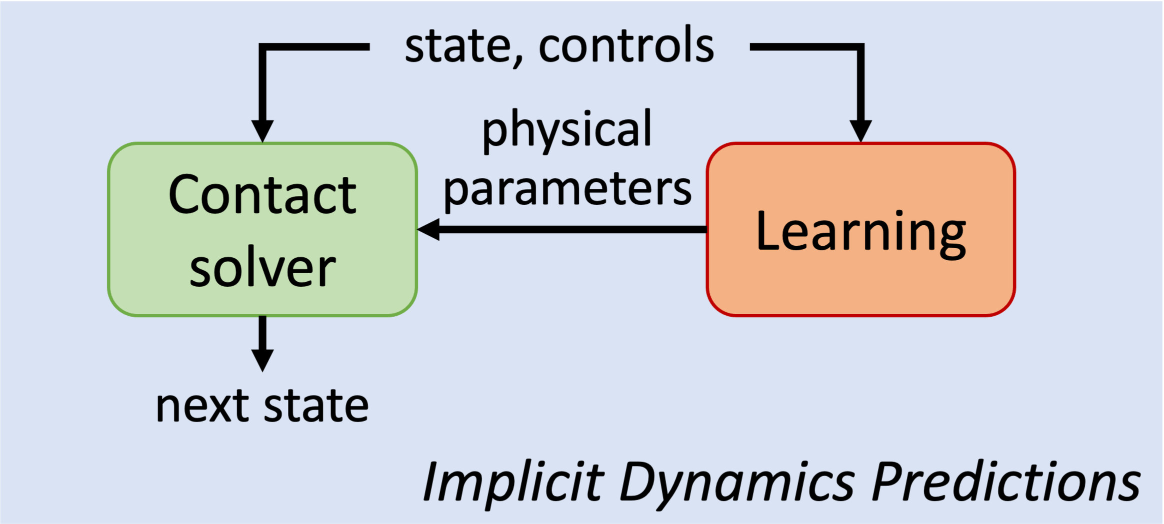
1. **New, real articulated object toss dataset** (publicly available!), automated via a Franka Panda arm.



2. Cube toss dataset from [ContactNets, CoRL 2020].
3. Two simulation examples with significant modeled-to-actual dynamics gaps.
   1. Asymmetric object toss in vortex-shaped continuous force field.
   2. Articulated object toss with artificially poor gravity initializations.

TRAINING WITH VIOLATION-BASED IMPLICIT LOSS

We learn physical parameters (standalone or as outputs of a neural network) that parameterize physics simulations during inference.



Implicit Dynamics Predictions

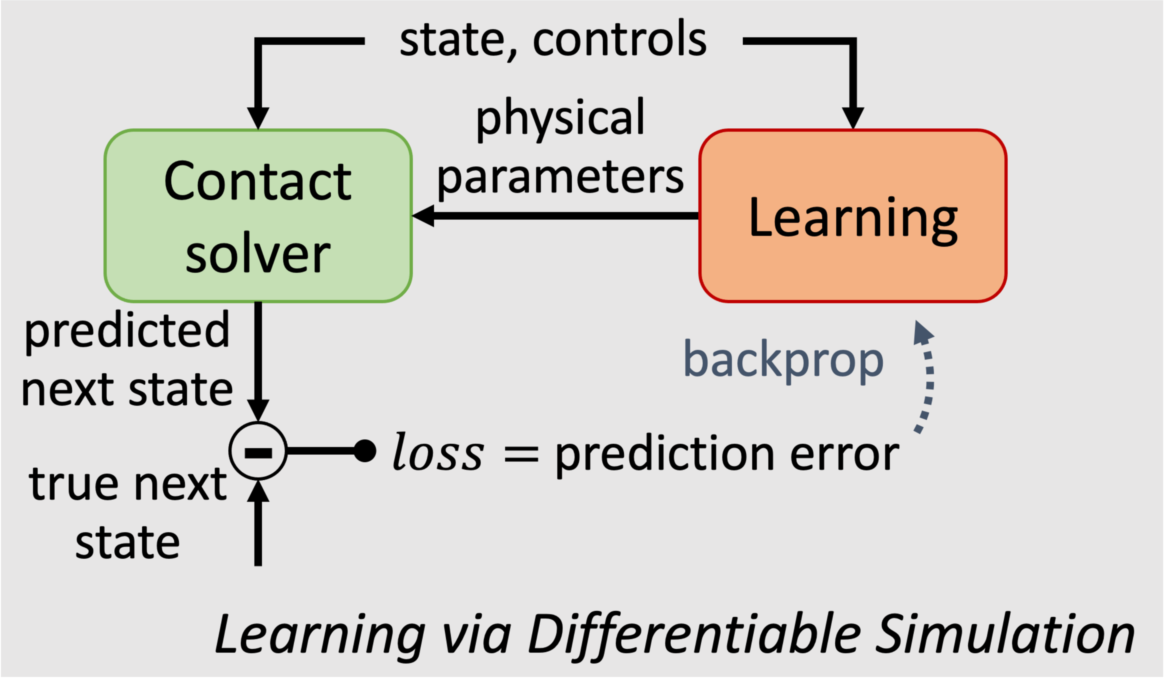
For rigid body dynamics, λ represents contact forces such that functions g, h represent dynamics and contact constraints:

$$y = g(x,\lambda), \text{ such that } \lambda = \underset{\lambda \in \Lambda}{\arg\min}\, h(x,y,\lambda)$$

Our goal is to train a dynamics model g^θ, h^θ that will get used as above.

Differentiable simulation trains these parameters by forward simulating during training, penalizing differences in predicted next states with the observed next states.

- However, this results in **poor generalizability in high-stiffness regimes characteristic of contact dynamics**.



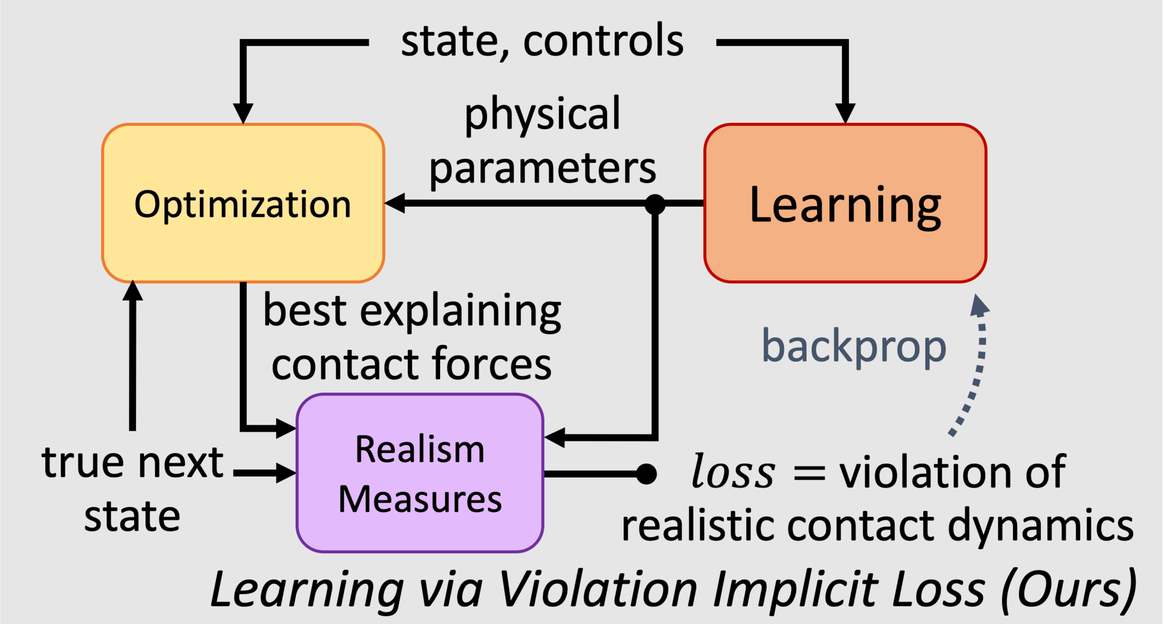
Learning via Differentiable Simulation

$$l^\theta_{\text{diffsim}}(x_i,y_i) = \left\|y_i - g^\theta(x_i,\lambda_i)\right\|^2, \text{ such that } \lambda_i = \underset{\lambda \in \Lambda}{\arg\min}\, h^\theta(x_i, g^\theta(x_i,\lambda),\lambda)$$

Ours:

Instead, we use a **physics-inspired violation-based implicit loss**, avoiding simulation and allowing contact constraint violation during training.

- Our approach boasts **better performance in contact-rich and low-data scenarios**.



Learning via Violation Implicit Loss (Ours)

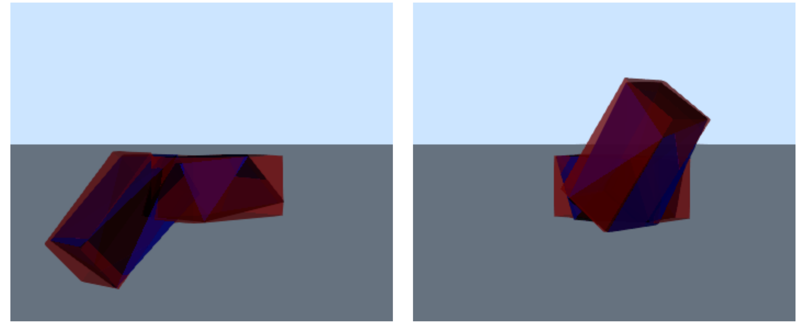
$$l^\theta_{\text{vimp}}(x_i,y_i) = \underset{\lambda \in \Lambda}{\min}\, \left\|y_i - g^\theta(x_i,\lambda)\right\|^2 + \frac{1}{\epsilon} h^\theta(x_i,y_i,\lambda)$$

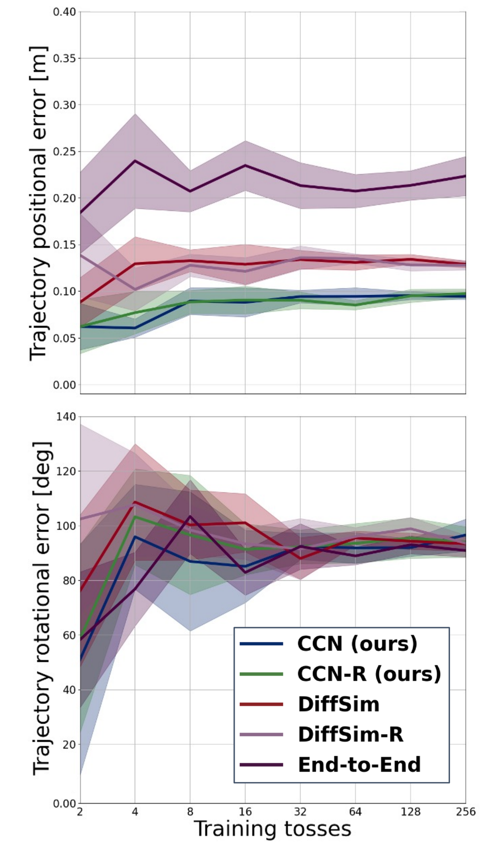
ARTICULATED OBJECT RESULTS

Our approaches match or outperform differentiable simulation and end-to-end alternatives across all performance metrics.

Our approach does significantly better for positional (right, top) and geometric accuracy (below).

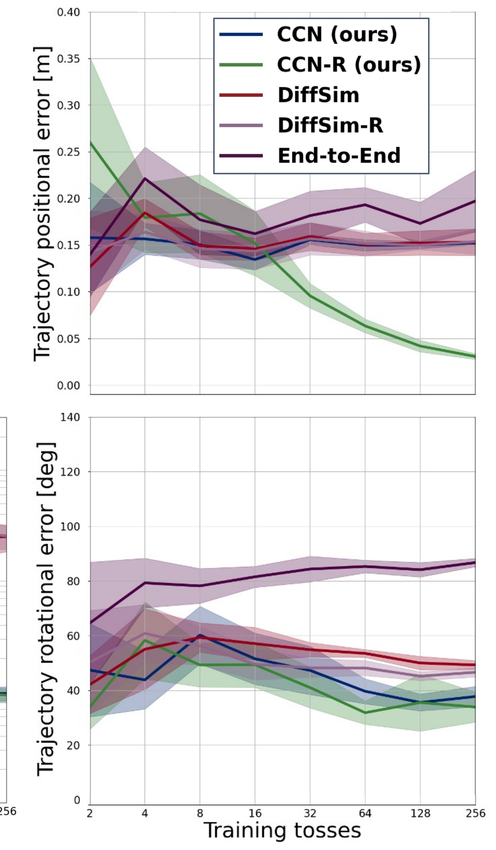
No approach successfully captured the rotational component of the articulated object's dynamics (right, bottom).

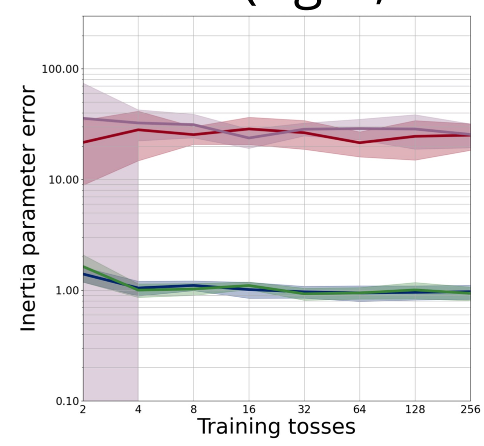




VORTEX SIMULATION RESULTS

In the vortex simulation with a complicated continuous force field, only our approach recovers inertia (below) and predicts position (with residual physics) (right, top) and rotation (right, bottom) accurately.





CONCLUSION, FUTURE WORK

- Our approaches built the most dynamically and physically accurate system models.
- Residual physics helped in simulation but not on real data.
- The community is welcome to contribute their own approaches towards learning a more accurate dynamics model of the articulated object using our dataset.

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