Accelerating Robotic Manipulation with Data-Enhanced Contact Mechanics

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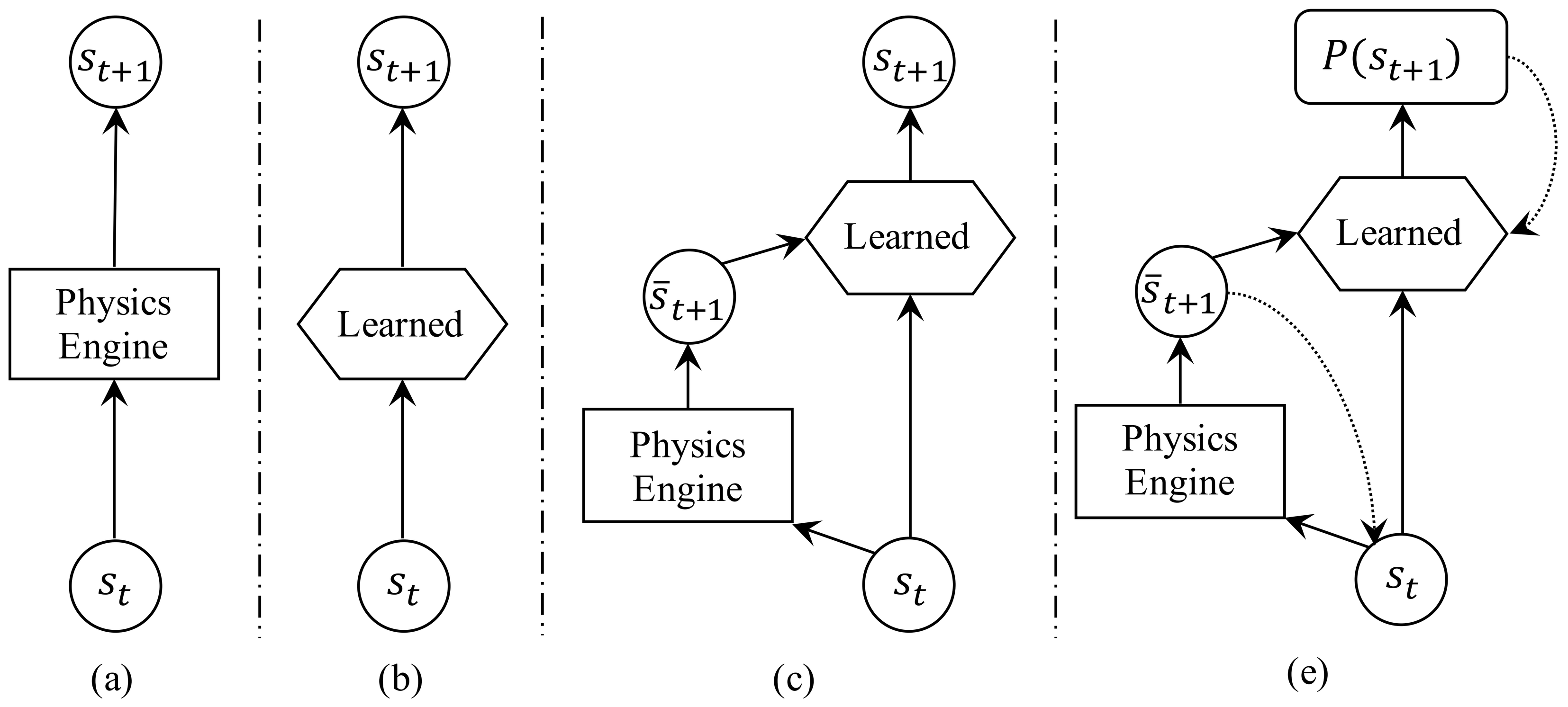
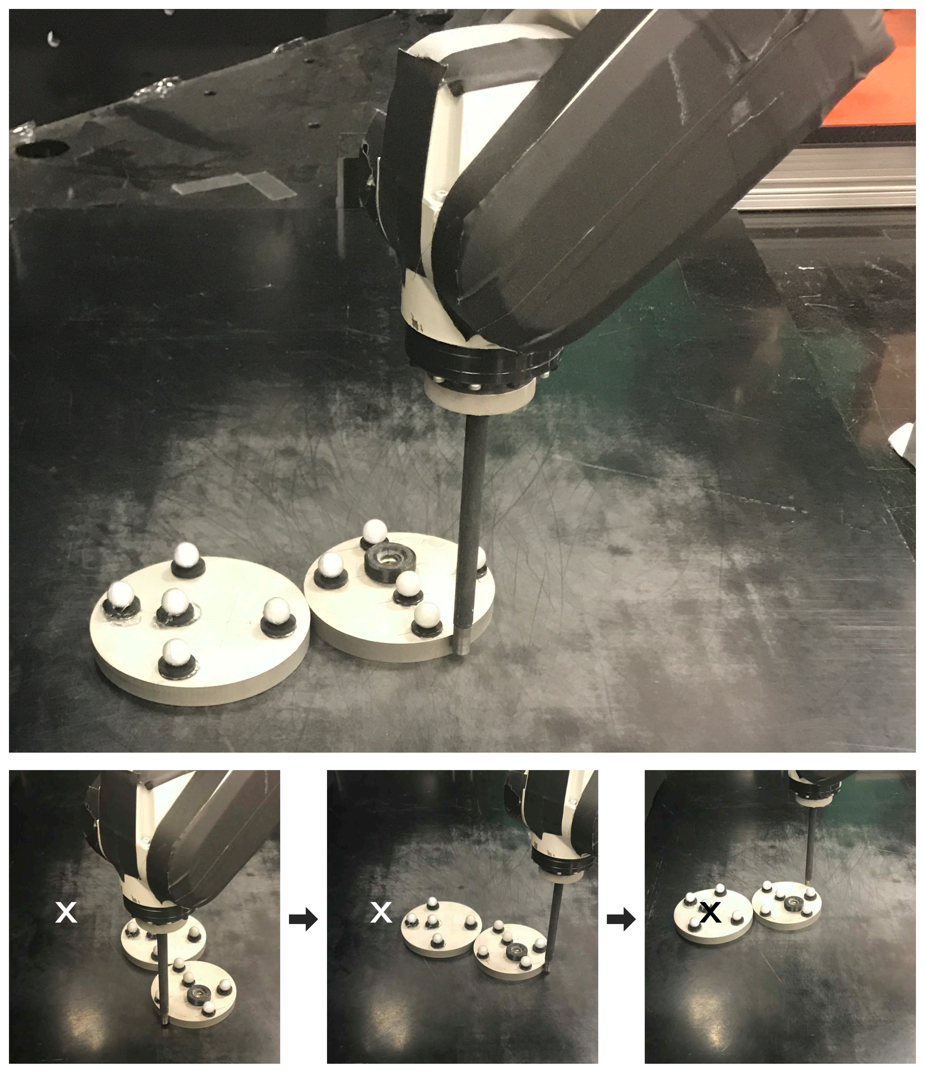
Objective: Developing principled techniques to *enhance* analytical models of contact mechanics with data for robotic manipulation. Data-efficient and high-fidelity models for planning, state-estimation, and controls.

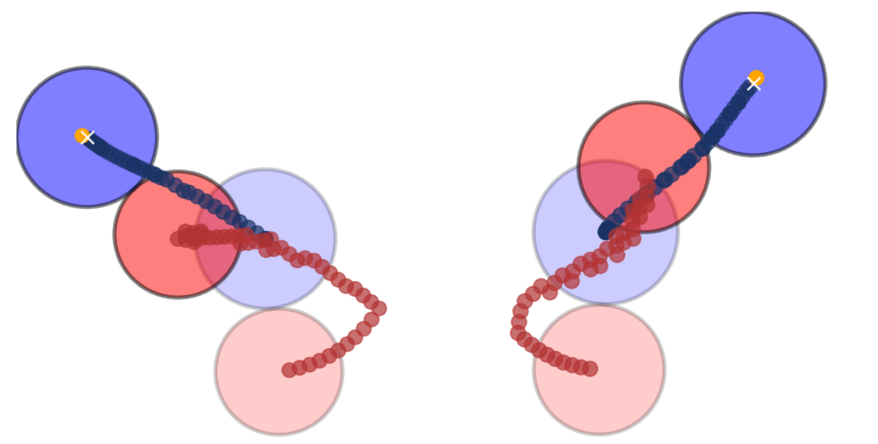
Augmenting contact models with data[1,2]: Learning high fidelity data-augmented contact models for prediction and model predictive control (MPC) -- planar manipulation.



Idea: Rather than learning a full physics model end-to-end, use pre-existing physical models and only learn the residual error. Learning an error is more sample efficient and yields better generalization properties when compared to learning from scratch.



Experimental Setup: Planar Pushing.



Experiments: (Left) Control under nominal conditions. (Right) Control for novel radii.

Simulation: Success rate.

Models	Easy Push	Hard Push
IN	100%	88%
SAIN (ours)	100%	100%

Experimental: Success rate.

Model	Data	Easy Push	Hard Push
SAIN	Sim	100%	68%
SAIN	Sim + Real	100%	96%

Models	Fine-tuning	Object 1			Object 2		
		trans (%)	pos (mm)	rot (deg)	trans (%)	pos (mm)	rot (deg)
Physics	N/A	0.87	3.06	**0.32**	1.91	6.41	**0.17**
IN	No	0.86	2.96	0.96	1.84	5.75	0.32
SAIN (ours)	No	0.69	2.38	0.43	1.06	3.52	0.18
IN	Yes	0.63	2.23	0.41	0.61	2.05	0.19
SAIN (ours)	Yes	**0.42**	**1.50**	0.34	**0.43**	**1.52**	**0.17**

Fidelity on real data: Predictive performance comparison.

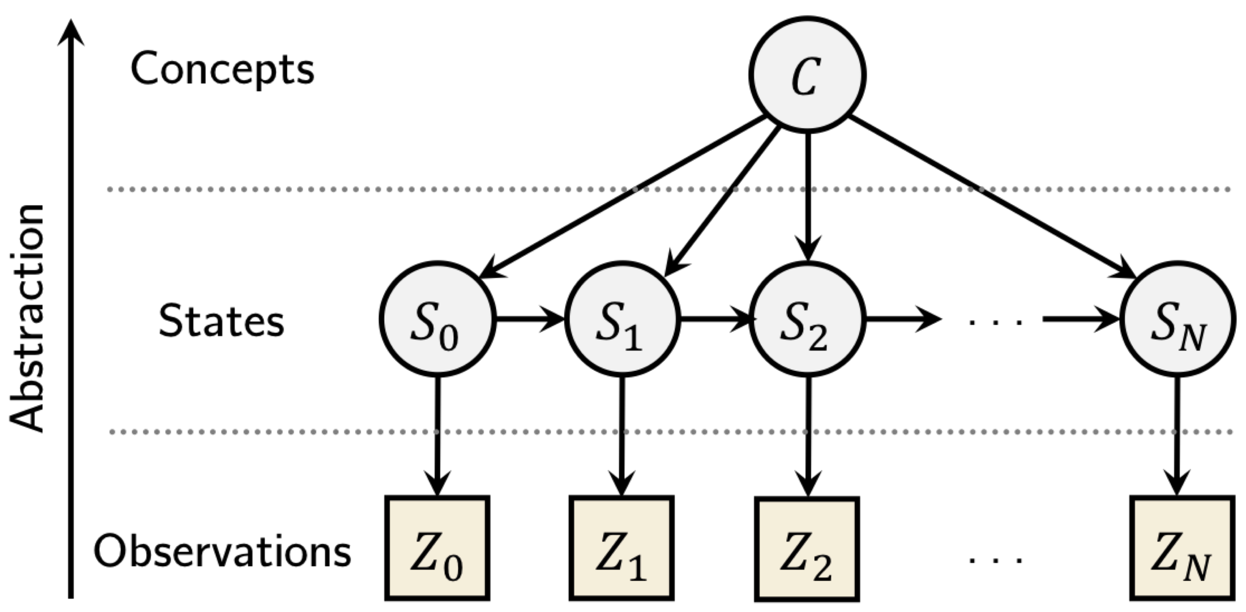
[1] "Augmenting Physical Simulators with Stochastic Neural Networks: Case Study of Planar Pushing and Bouncing," A. Ajay, J. Wu, N. Fazeli, M. Bauza, L. P. Kaelbling, J. B. Tenenbaum, A. Rodriguez, *International Conference of Intelligent Robots and Systems (IROS)*, 2018
[2] "Combining Physical Simulators and Object-Based Networks for Control," A. Ajay, M. Bauza, J. Wu, N. Fazeli, J. B. Tenenbaum, A. Rodriguez, L. P. Kaelbling, *International Conference on Robotics and Automation (ICRA)*, 2019

Learning Complex Manipulation Skills with Causal Structure and Multi-Sensory Fusion[3]: Using rich physics-based with abstractions for learning, inference, and controls.

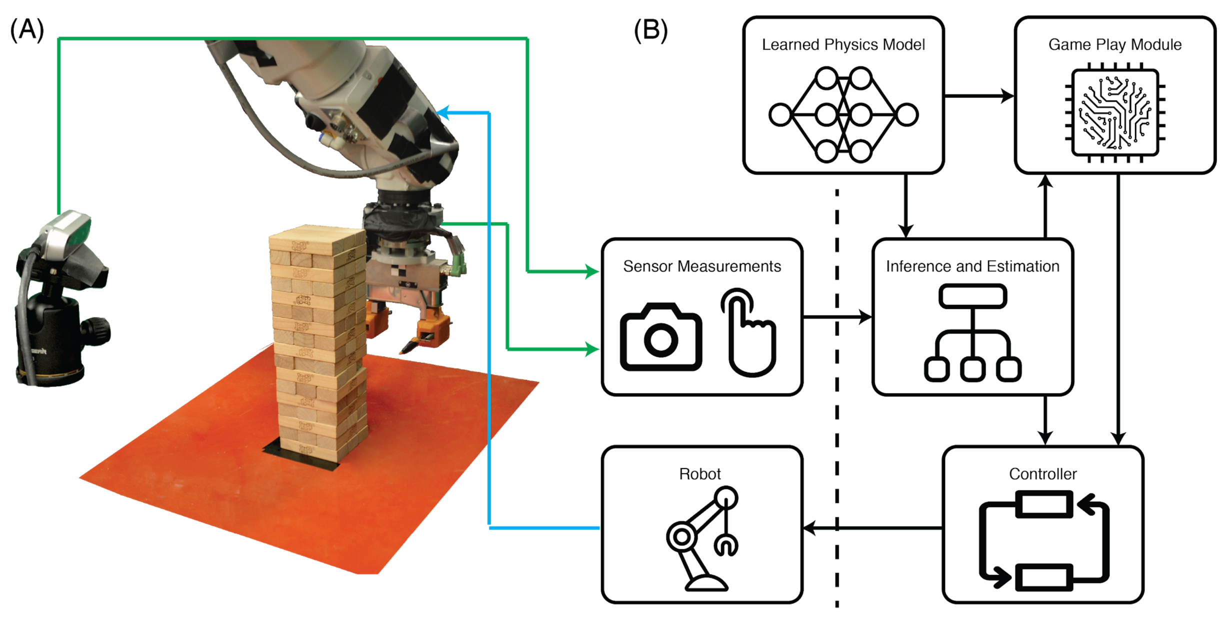
Theme 1: *Tactile* and *visual* stimuli both play an important role in manipulation. *State-estimation* and *control* that operate in the tactile and visual domain are valuable tools for manipulation.

Theme 2: Causal structure and abstractions can improve learning sample efficiency, yield rich physics-based models that are interpretable and amenable to controls and state-estimation.

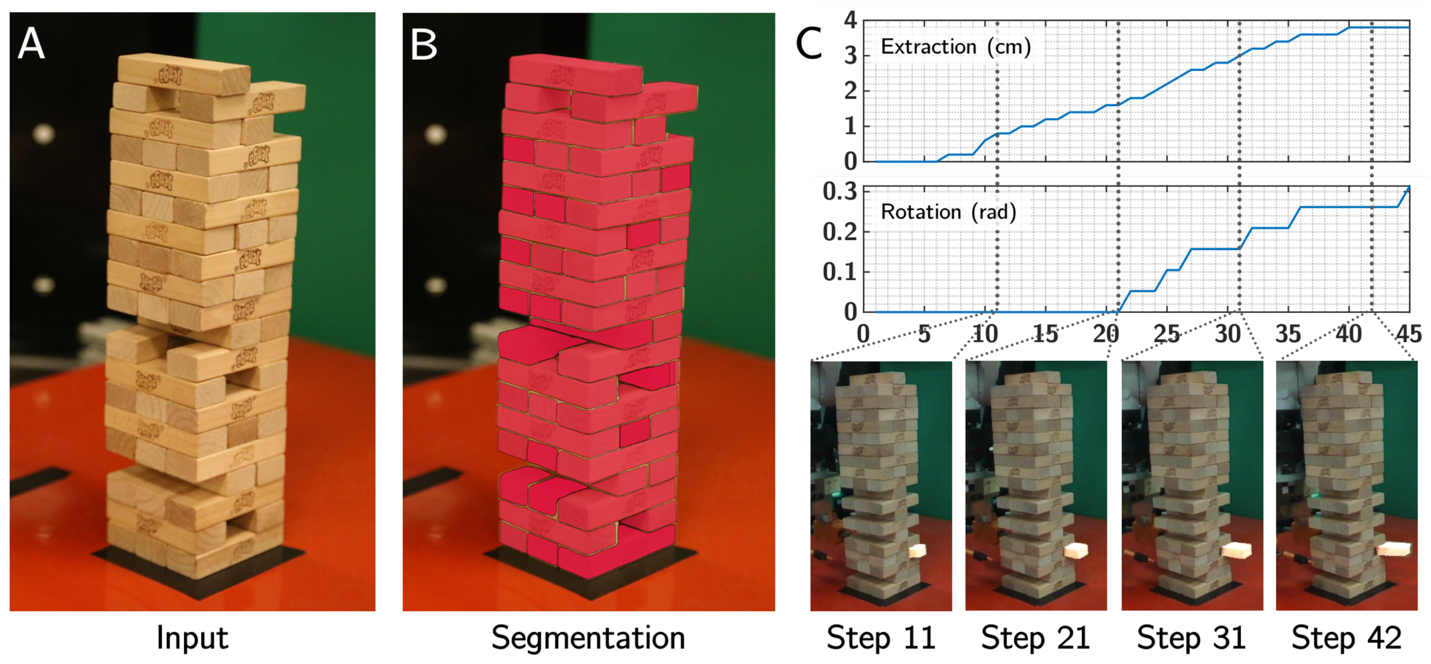
Idea: Use hierarchical Bayesian networks for structure and abstractions to learn rich physics-based models. Combine *tactile* and *visual* stimuli within the predictive physics of the network.



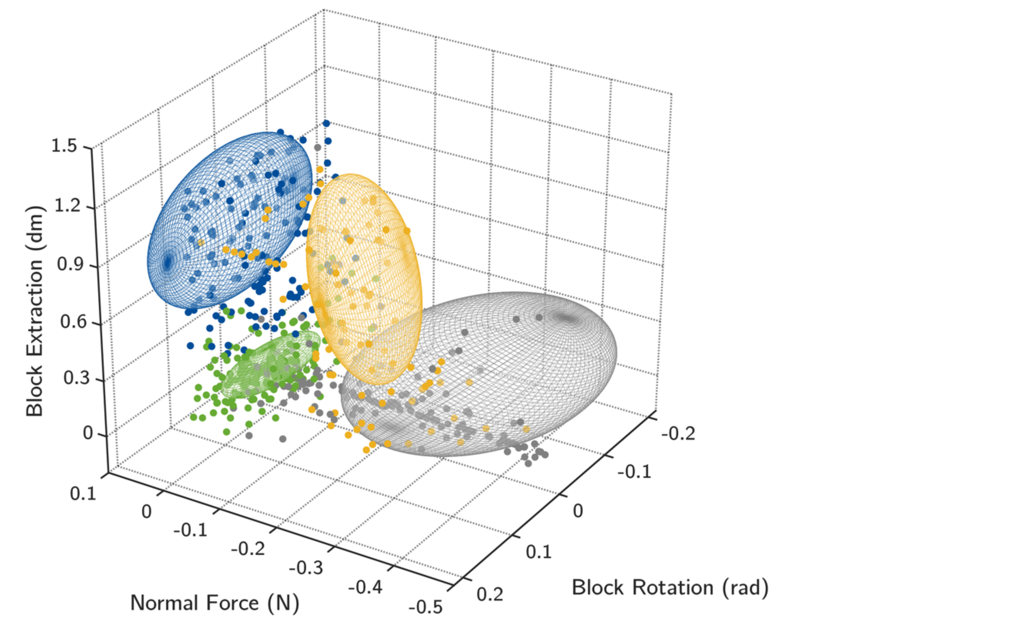
Physics Model: Hierarchical Bayesian networks for causal structure and multi-sensory fusion.



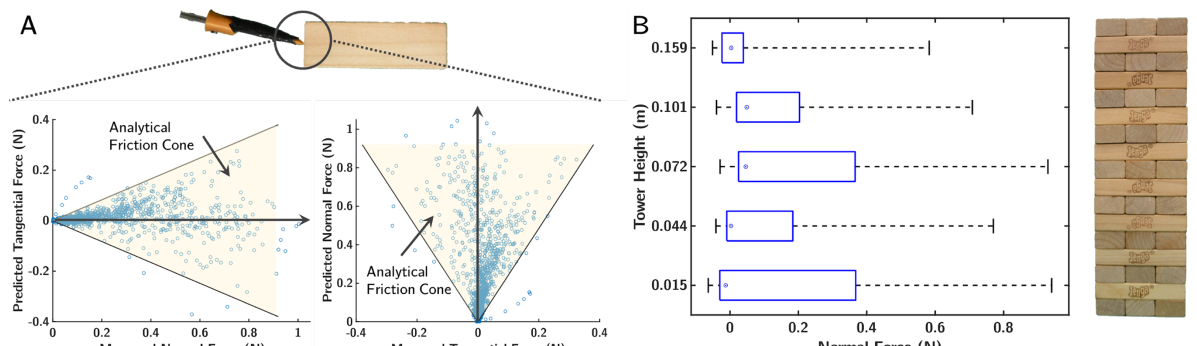
Experimental demonstration: System architecture with physics model, inference, and controls modules. The robot first executes an exploration phase to interact with the tower and collect data. The model is then learned and the game is on.



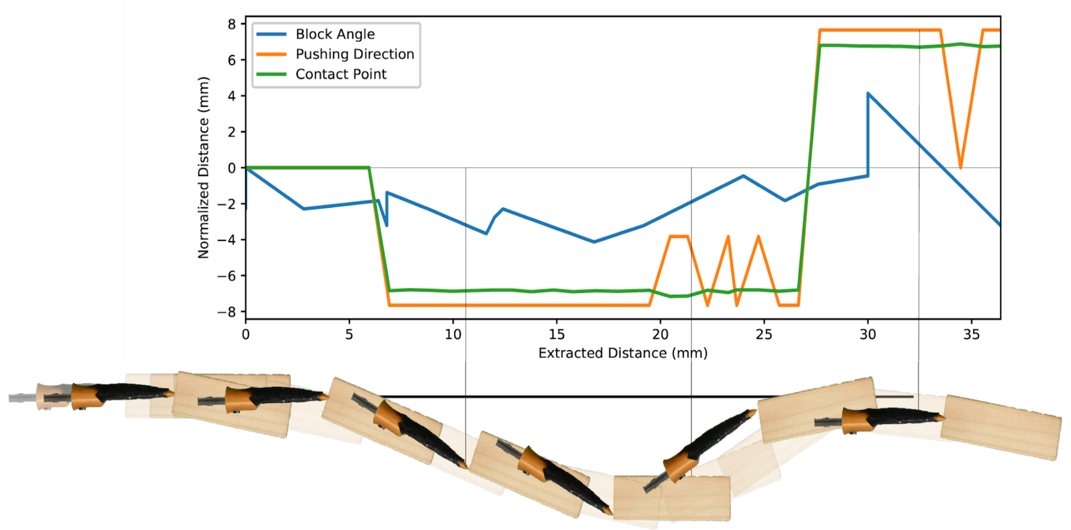
Vision System: Mask-RCNN for tracking of blocks and tower state.



Concepts learned: Unsupervised learning of concepts post-exploration.



Intuitive Physics: Friction cone and tower height vs force learned from exploration.



Controls: Sample-based MPC for block control.

[3] "See, Feel, Act: See, Feel, Act: Learning Complex Manipulation Skills with Causal Structure and Multi-sensory Fusion," N. Fazeli, J. Wu, M. Oller, Z. Wu, J. B. Tenenbaum, A. Rodriguez, *Science Robotics (In Submission)*, 2018