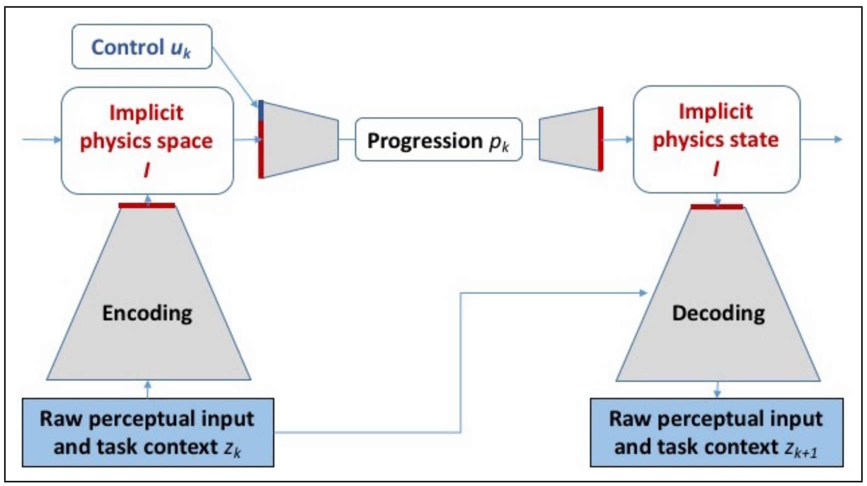
Experiential Learning for Robots: From Physics to Actions to Tasks

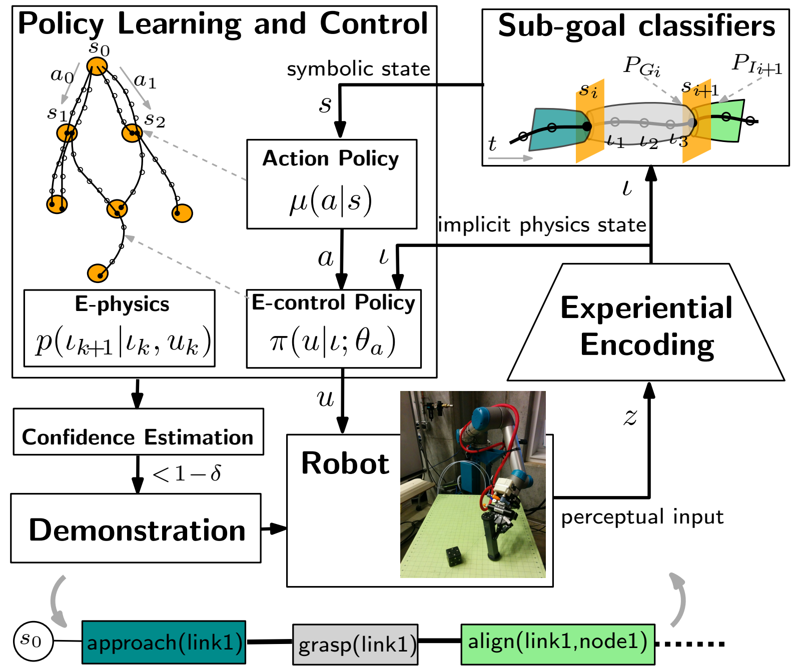
Dieter Fox, Ali Farhadi, University of Washington
Greg Hager, Marin Kobilarov, Johns Hopkins University

NSF NRI **1637949**

The High Level View

Can we learn transferrable model from robot experience, and use those models for planning and control in new contexts?





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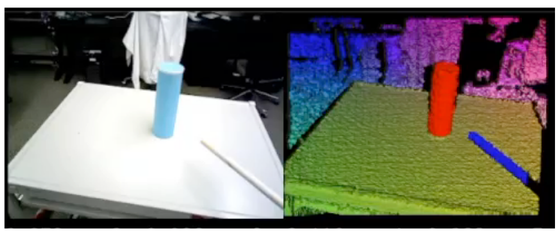
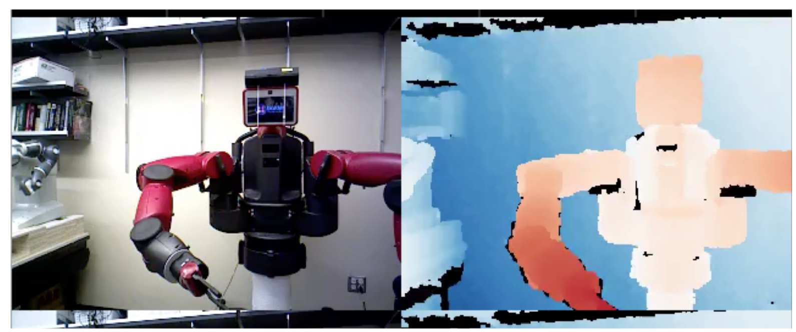
Structured Deep Visual Models For Robot Manipulation

- Class of deep networks with rigid body physics priors
- SE3-Pose-Nets: learn object masks, their SE(3) motion, and a latent pose embedding for long range control



Modeling visual dynamics

Visuomotor control



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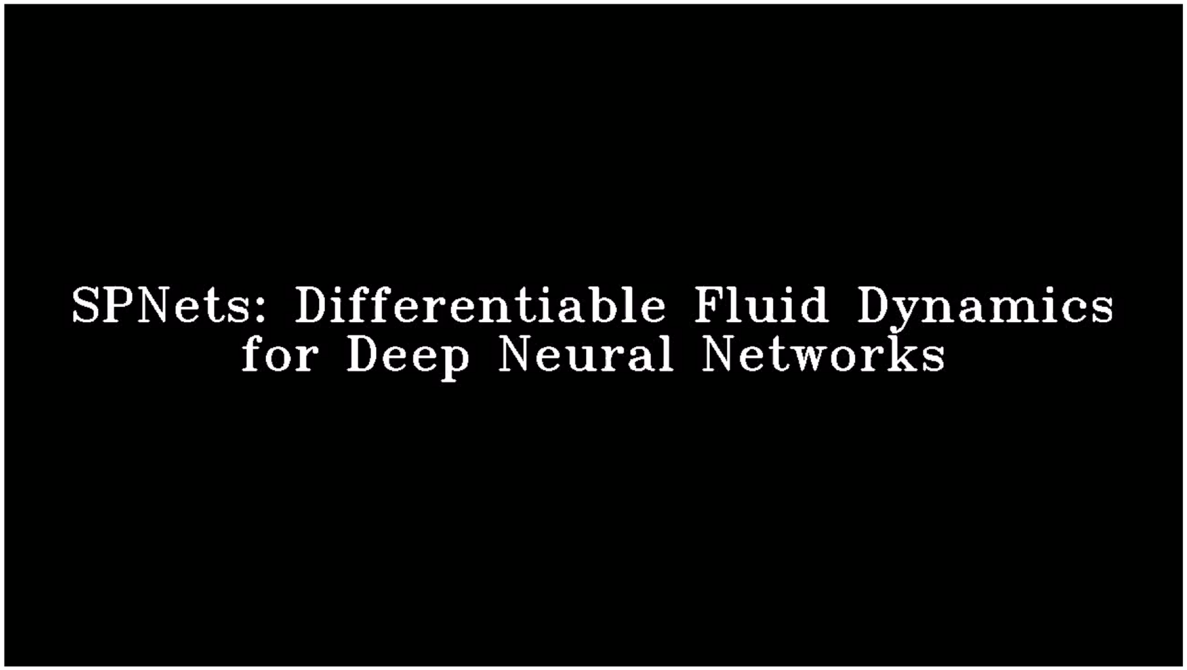
SPNets: Differentiable Fluid Dynamics for Deep Nets

Enable robots to reason about liquids in a variety of settings:

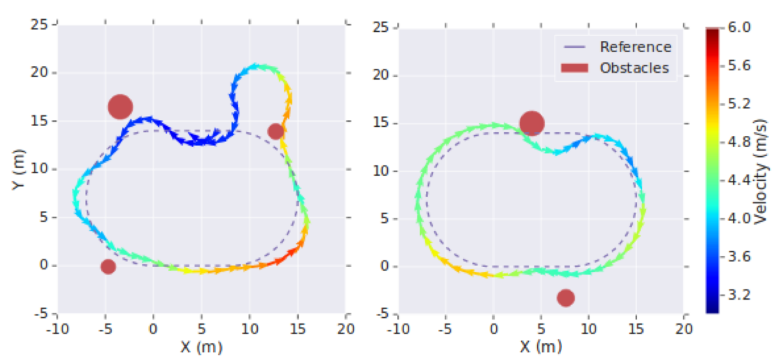
- policy learning
- optimal control
- parameter estimation
- liquid tracking



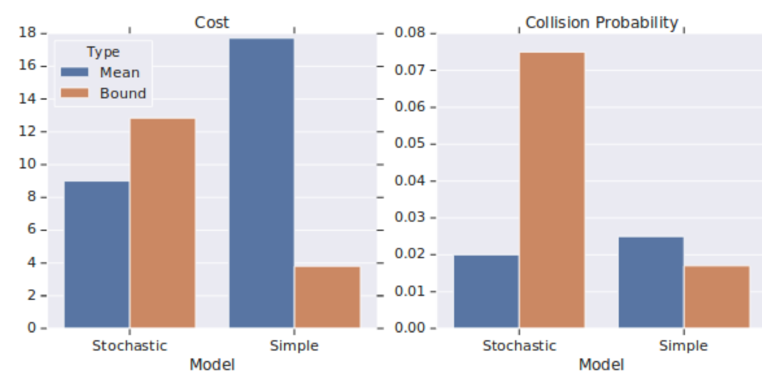
Using Data-Driven Domain Randomization to Transfer Robust Control Policies to Mobile Robots (Kobilarov, JHU)

- Learn stochastic model of vehicle using deep MLE
- Train policy in simulation and compute performance guarantees
- Transfer policy to real vehicle and show guarantees are valid

Sample Trajectory on Real Vehicle



Simple Stochastic



Model	Avg Offset	Avg Vel Error	Avg Vel	Max Vel
Simple	1.8 m	2.8 m/s	3.69 m/s	5.79 m/s
Stochastic	1.4 m	1.8 m/s	4.72 m/s	6.53 m/s

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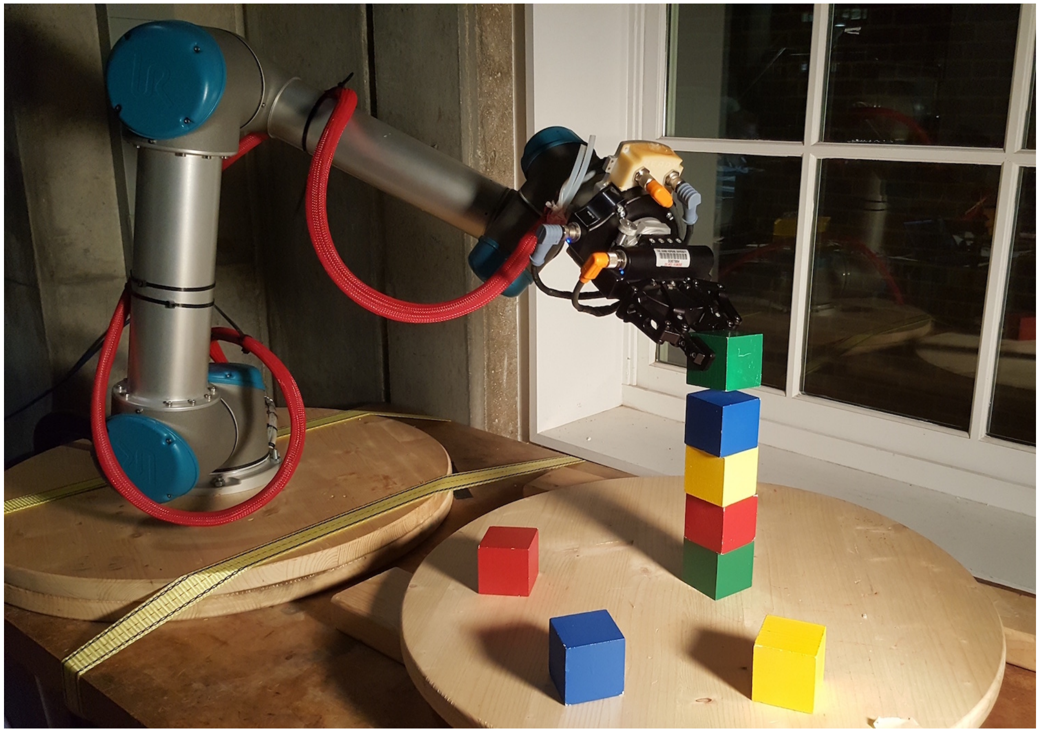
Using Data-Driven Domain Randomization to Transfer Robust Control Policies to Mobile Robots

Matthew Sheckells, Gowtham Garimella, Subhransu Mishra, Marin Kobilarov
Autonomous Systems, Control, and Optimization Lab
Johns Hopkins University

Visual Task Planning (Hager, Paxton)

- Learn to understand what effects our actions will have on the world
- Build models from data, rather than hand-coded rules
- Perform more challenging, complex tasks based on perception



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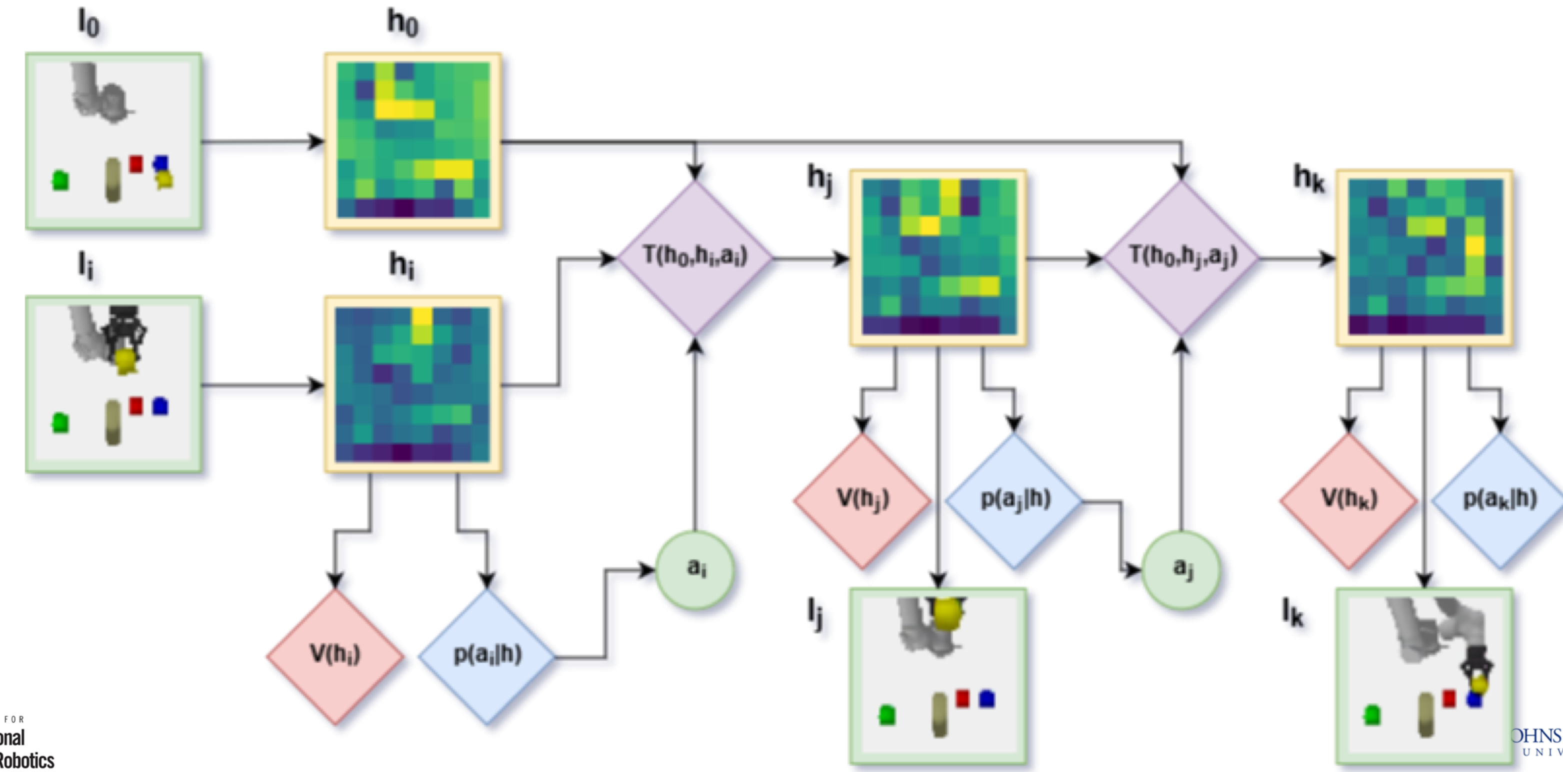
Model Architecture: Predictor Network



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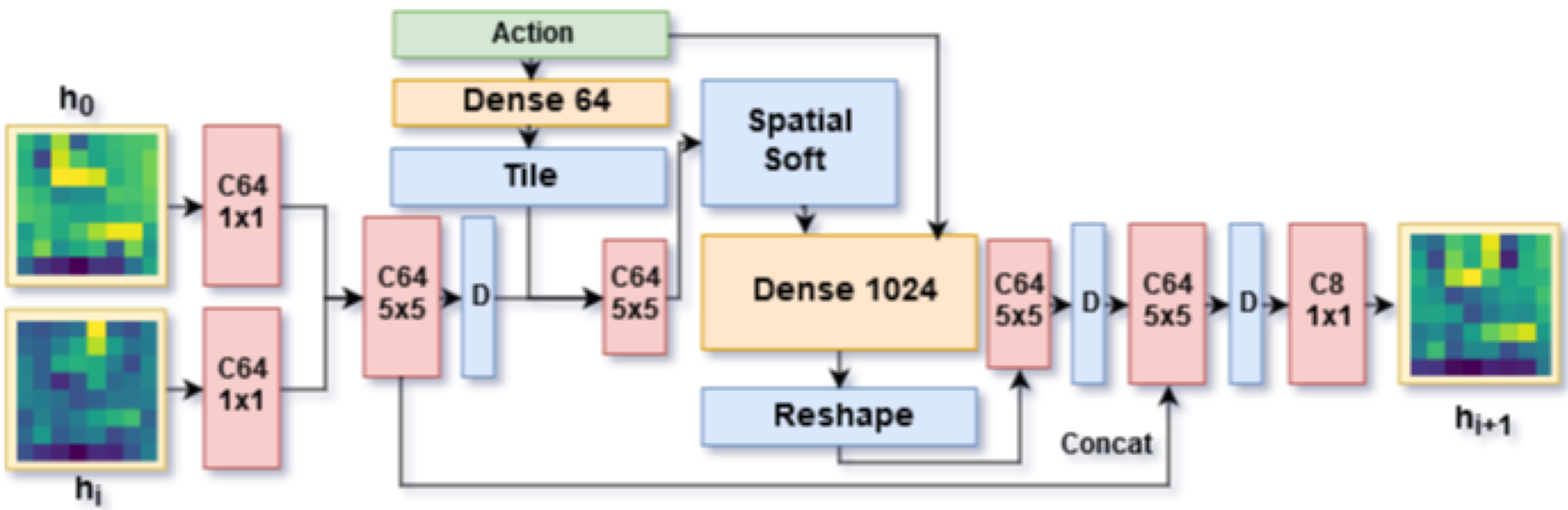
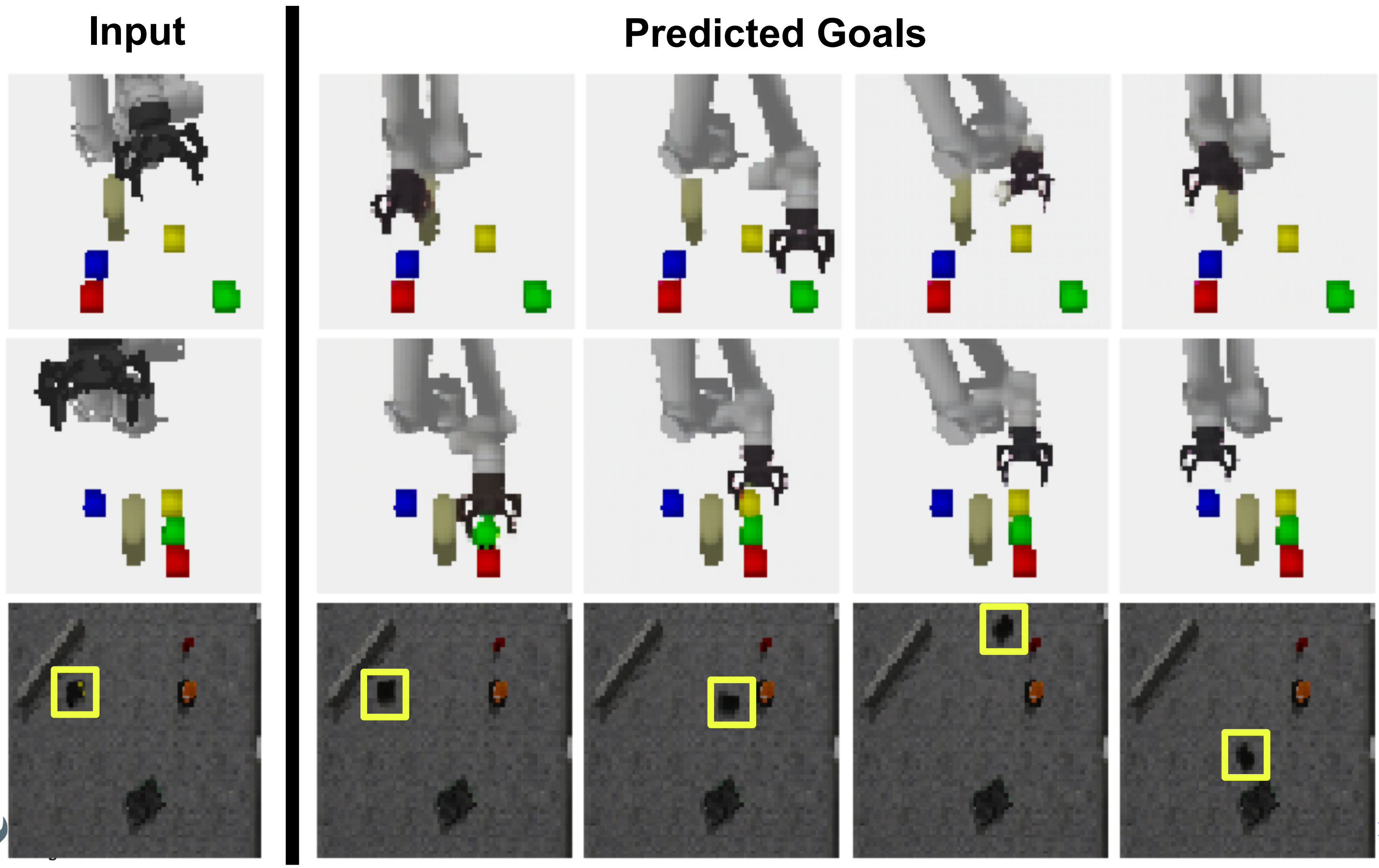
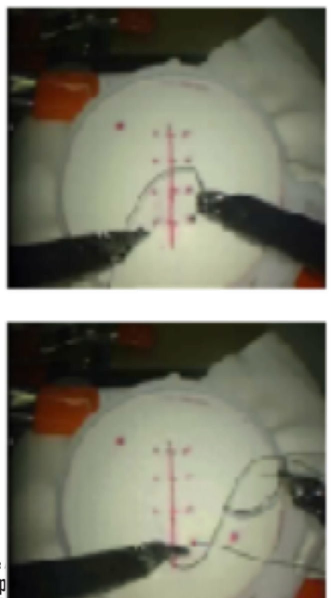
Model Architecture: Transform Network



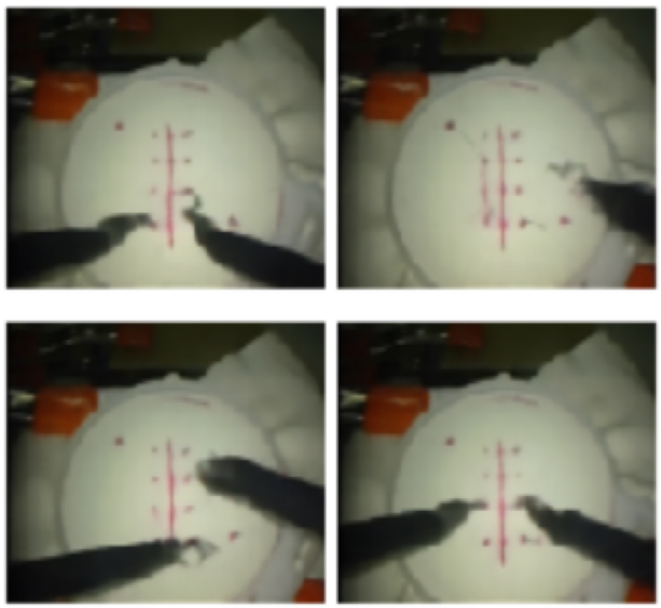

Input
Predicted Goals

Real-World Results: Suturing

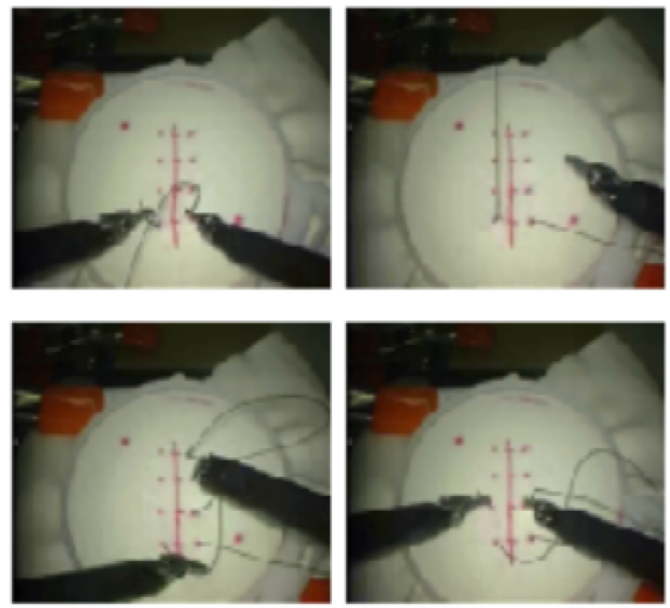
Input



Predicted Goals



Observed Goals



Simulating Many Possible Futures

- Key advantage: Now we can simulate many different futures, and have the robot “imagine” what it thinks will happen.

- What this means: robots that can learn how to solve problems in new environments, and justify their solutions to humans.

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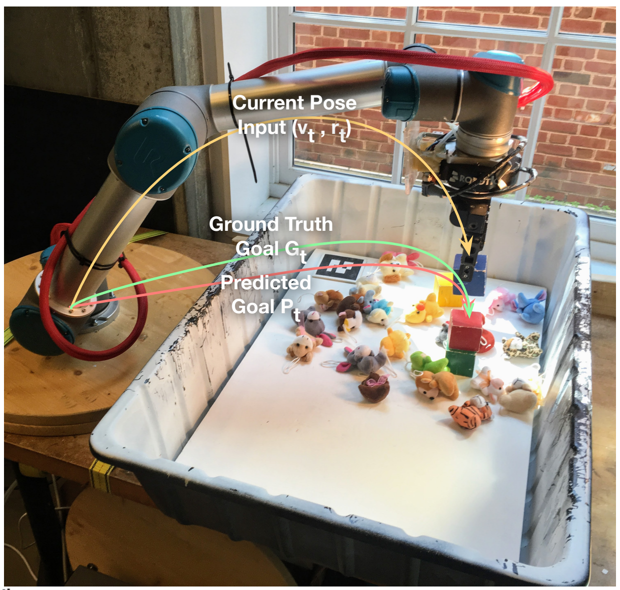
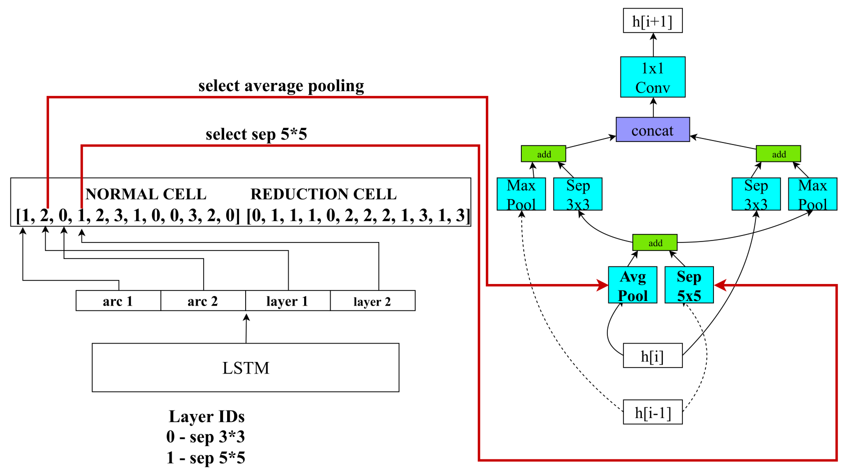
Our Poster: New Data and Architecture Search

CoSTAR Block Stacking Dataset

The CoSTAR Block Stacking Dataset includes a real robot trying to stack colored children's blocks more than 10,000 times. It is designed to benchmark neural network based algorithms.



Poster 28 in this afternoon's session!



Layer IDs
0 - sep 3*3
1 - sep 5*5
2 - average_pooling
3 - max_pooling
4 - identity

rENAS is an extension of ENAS, see paper for details

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