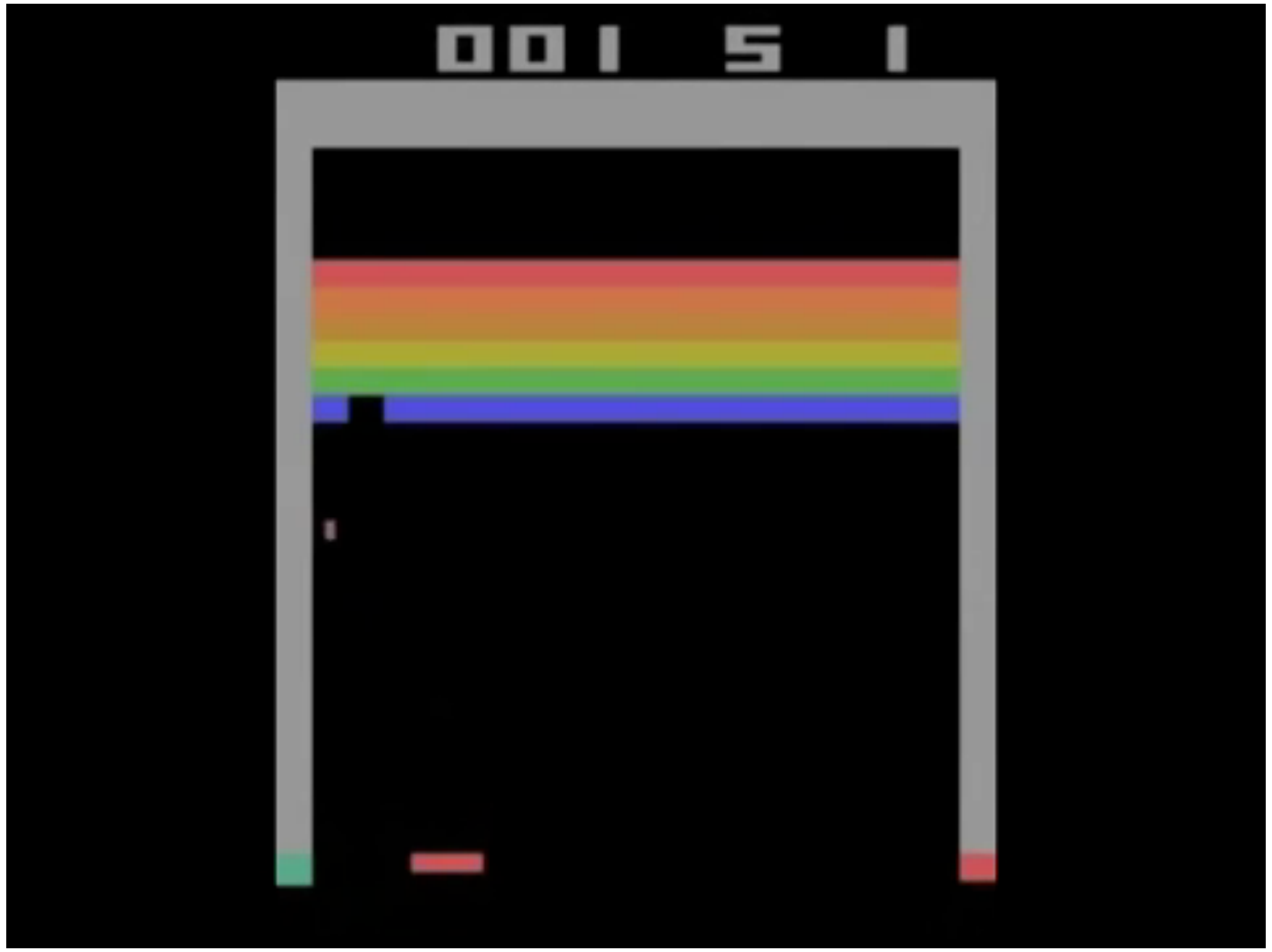
Advanced Model Learning

February 27, 2017

Chelsea Finn

Last Time: DQN with images



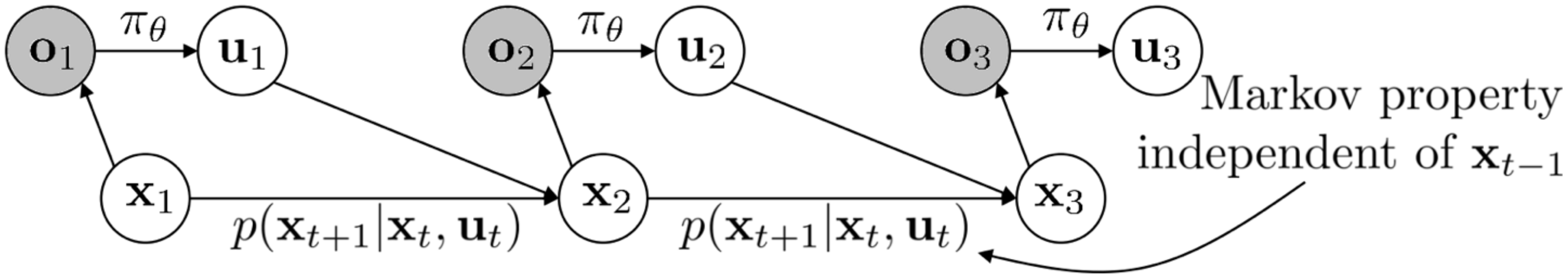
This lecture: Can we use model-based methods with images?

Recap: model-based RL

model-based reinforcement learning version 1.0:

1. run base policy $\pi_0(\mathbf{u}_t|\mathbf{x}_t)$ (e.g., random policy) to collect $\mathcal{D} = \{(\mathbf{x}, \mathbf{u}, \mathbf{x}')_i\}$
2. learn dynamics model $f(\mathbf{x}, \mathbf{u})$ to minimize $\sum_i \|f(\mathbf{x}_i, \mathbf{u}_i) - \mathbf{x}'_i\|^2$
3. backpropagate through $f(\mathbf{x}, \mathbf{u})$ to choose actions (e.g. using iLQR)
4. execute those actions and add the resulting data $\{(\mathbf{x}, \mathbf{u}, \mathbf{x}')_j\}$ to $\mathcal{D}$

What about POMDPs?



Outline

1. Models in latent space
2. Models directly in image space
3. Inverse models

Note: This is an active area of research.

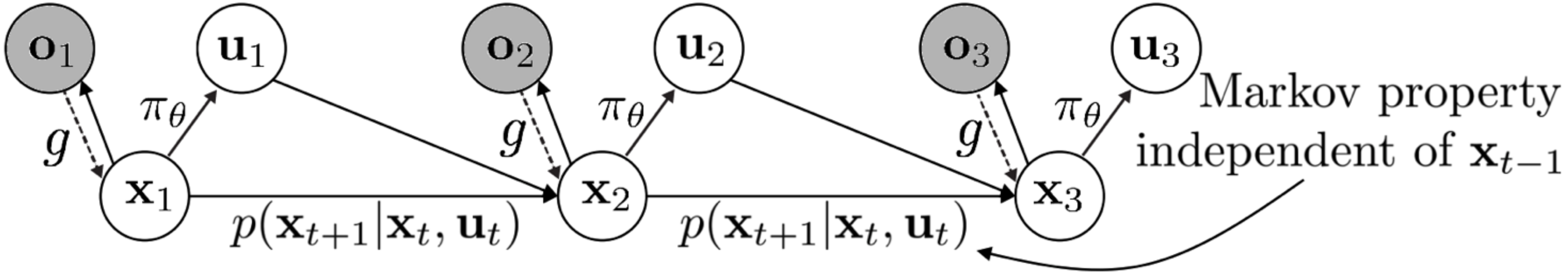
Outline

1. **Models in latent space**
2. Models directly in image space
3. Inverse models

Learning in Latent Space

Key idea: learn embedding $g(\mathbf{o}_t)$, then learn in latent space

(model-based or model-free)



What do we want g to be?

It depends on the method — we'll see.

Learning in Latent Space

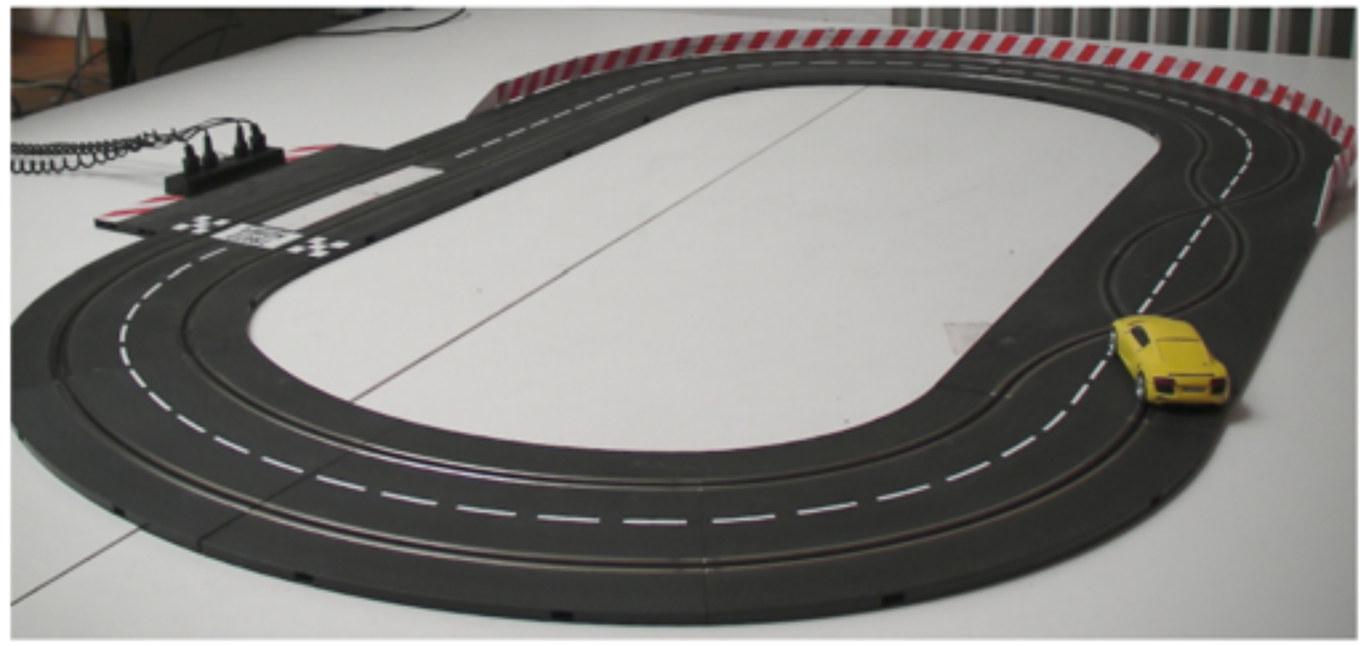
Key idea: learn embedding $g(\mathbf{o}_t) = \mathbf{x}_t$, then learn in latent space

(model-based or **model-free**)

Autonomous reinforcement learning on raw visual input data in a real world application

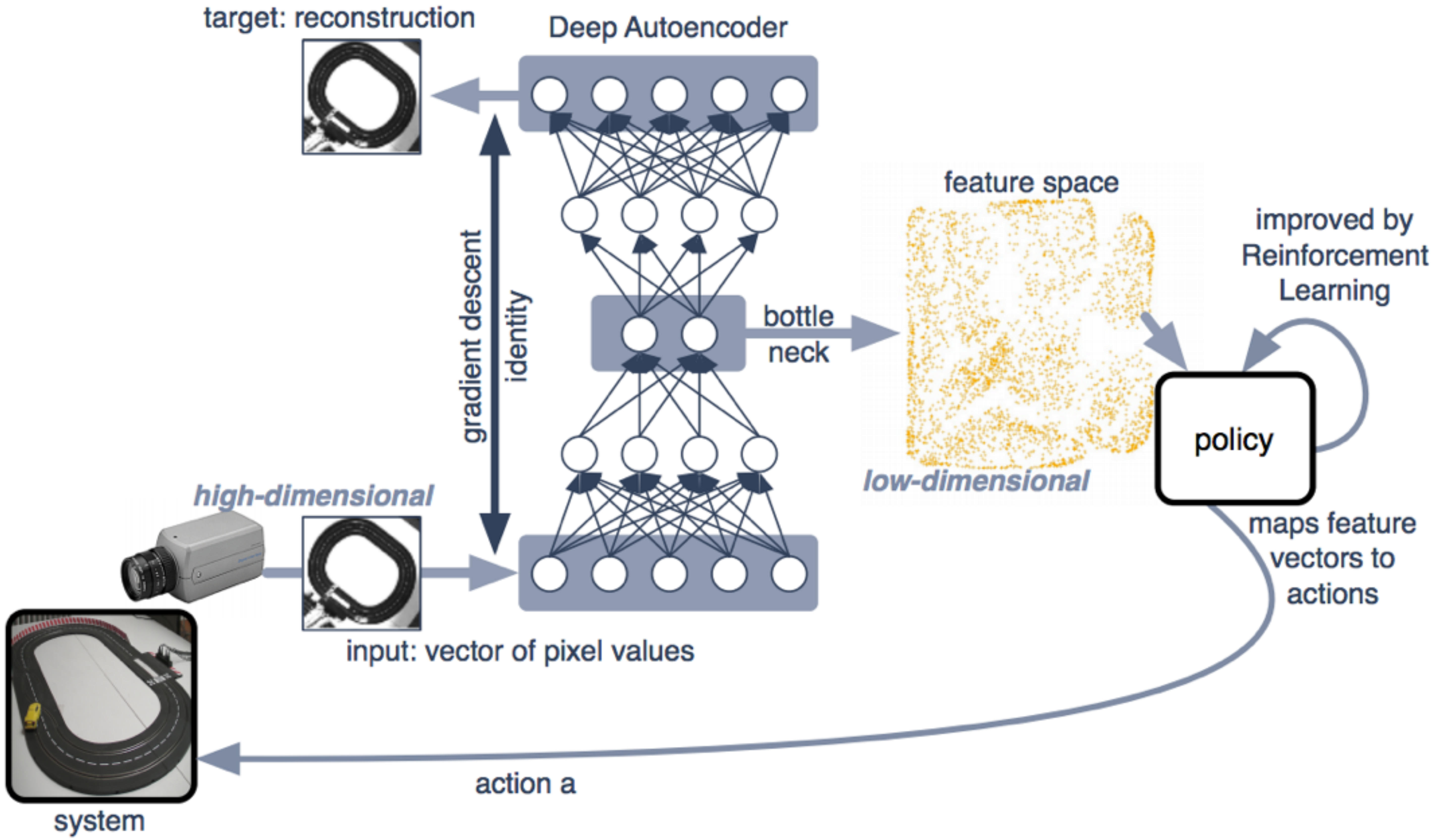
Sascha Lange, Martin Riedmiller
Department of Computer Science
Albert-Ludwigs-Universität Freiburg

Arne Voigtländer
Shoogee GmbH & Co. KG
Krögerweg 16a



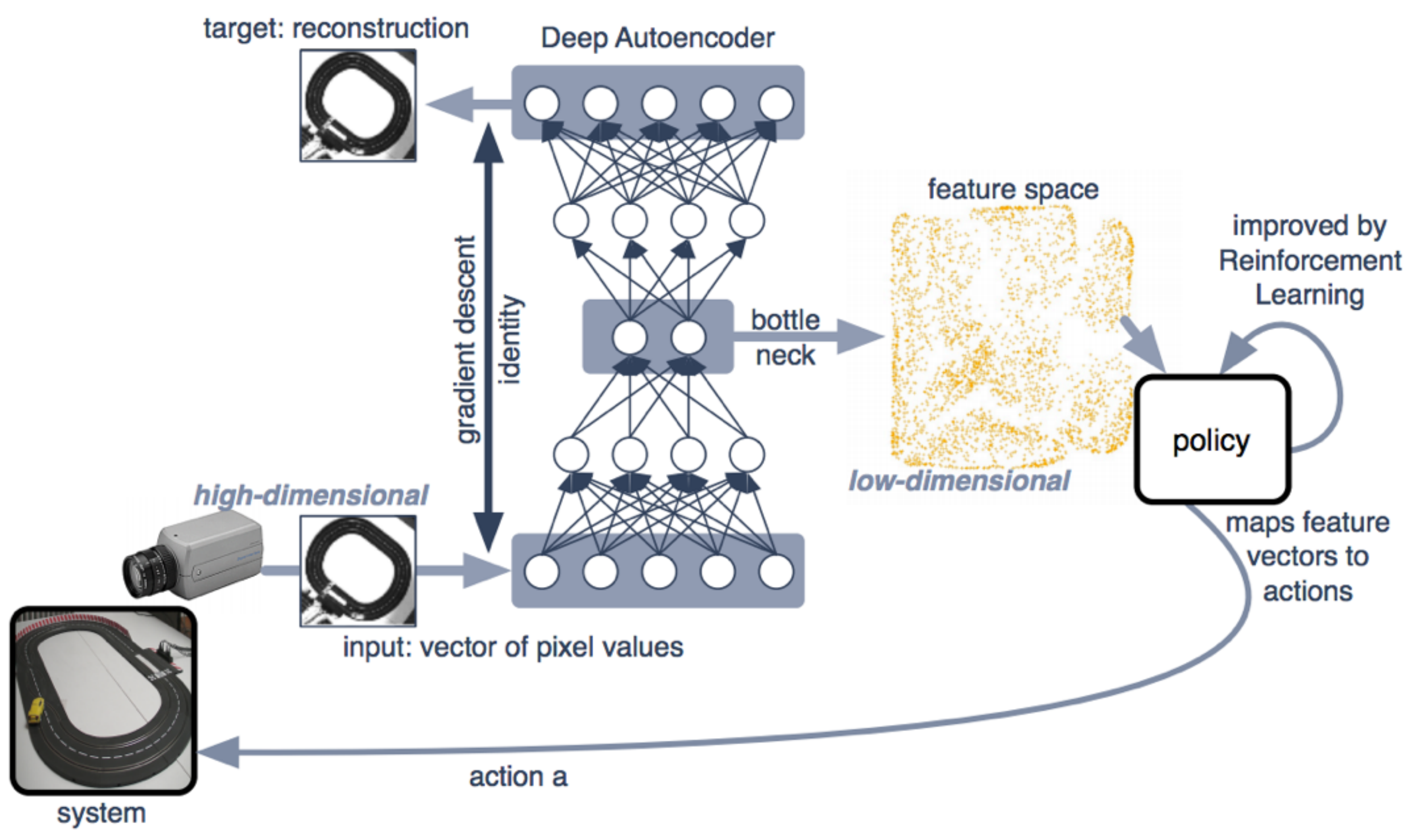
controlling a slot-car

1. collect data with exploratory policy
2. learn **low-dimensional** embedding of image (how?)
3. run q-learning with function approximation with embedding



embedding is **low-dimensional** and summarizes the image

1. collect data with exploratory policy
2. learn **low-dimensional** embedding of image (how?)
3. run q-learning with function approximation with embedding



Pros:

+ Learn visual skill very efficiently

Cons:

- Autoencoder might not recover the right representation
- Not necessarily suitable for model-based methods

Learning in Latent Space

Key idea: learn embedding $g(\mathbf{o}_t) = \mathbf{x}_t$, then learn in latent space

(**model-based** or model-free)

Deep Spatial Autoencoders for Visuomotor Learning

Chelsea Finn, Xin Yu Tan, Yan Duan, Trevor Darrell, Sergey Levine, Pieter Abbeel

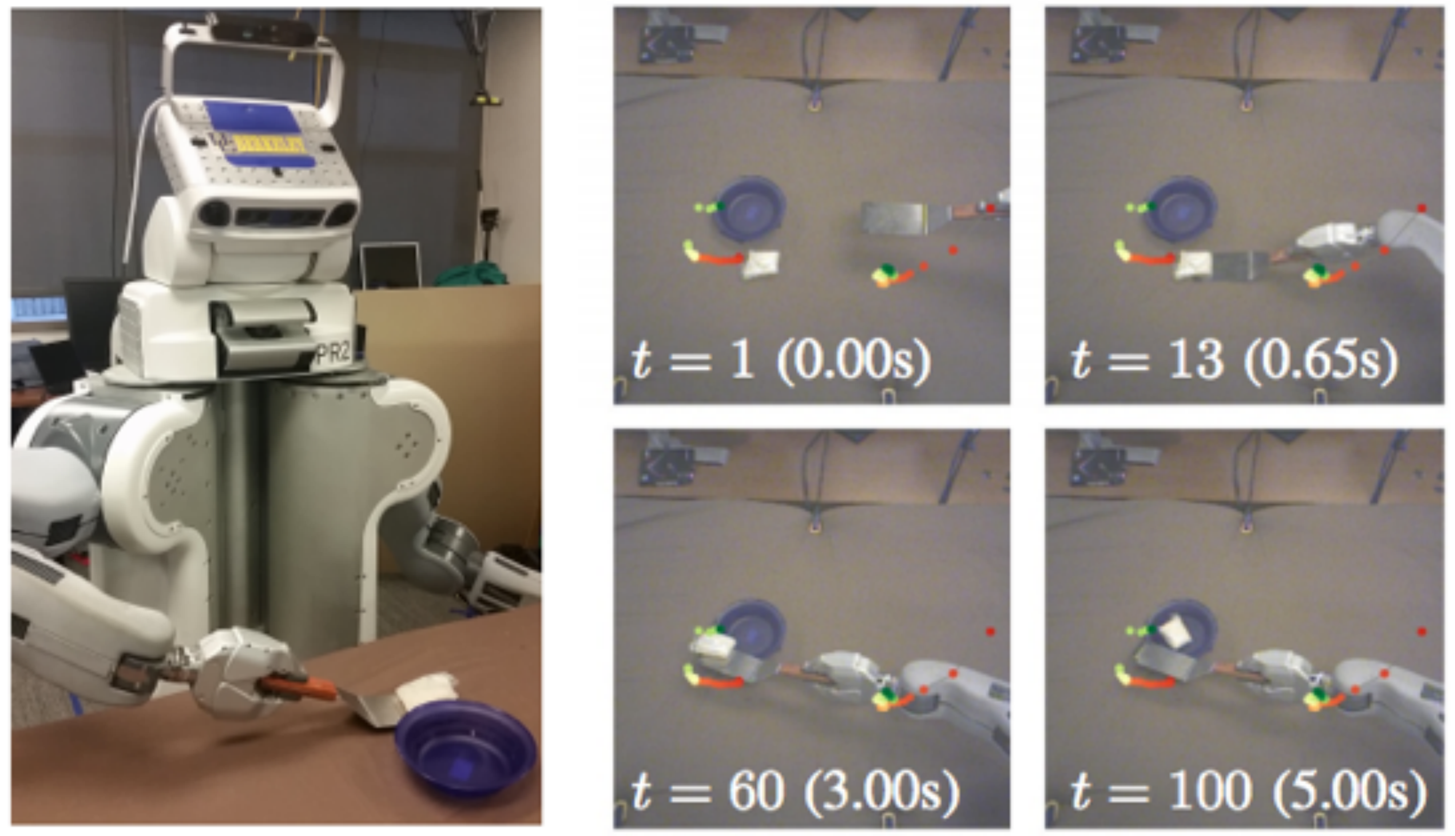
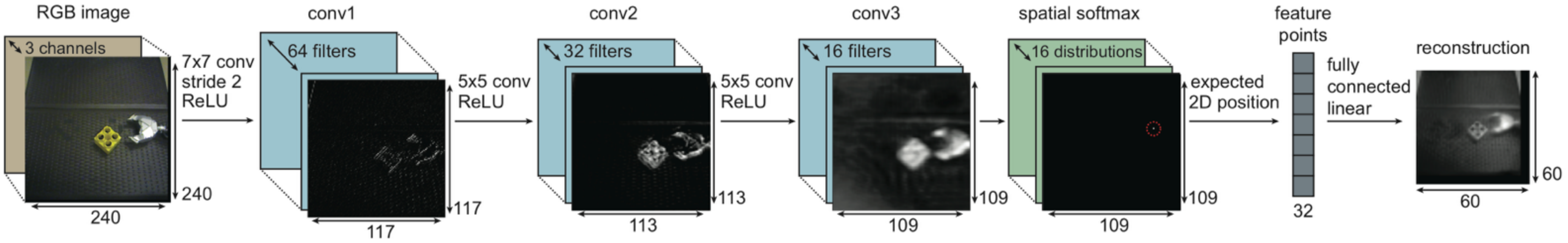
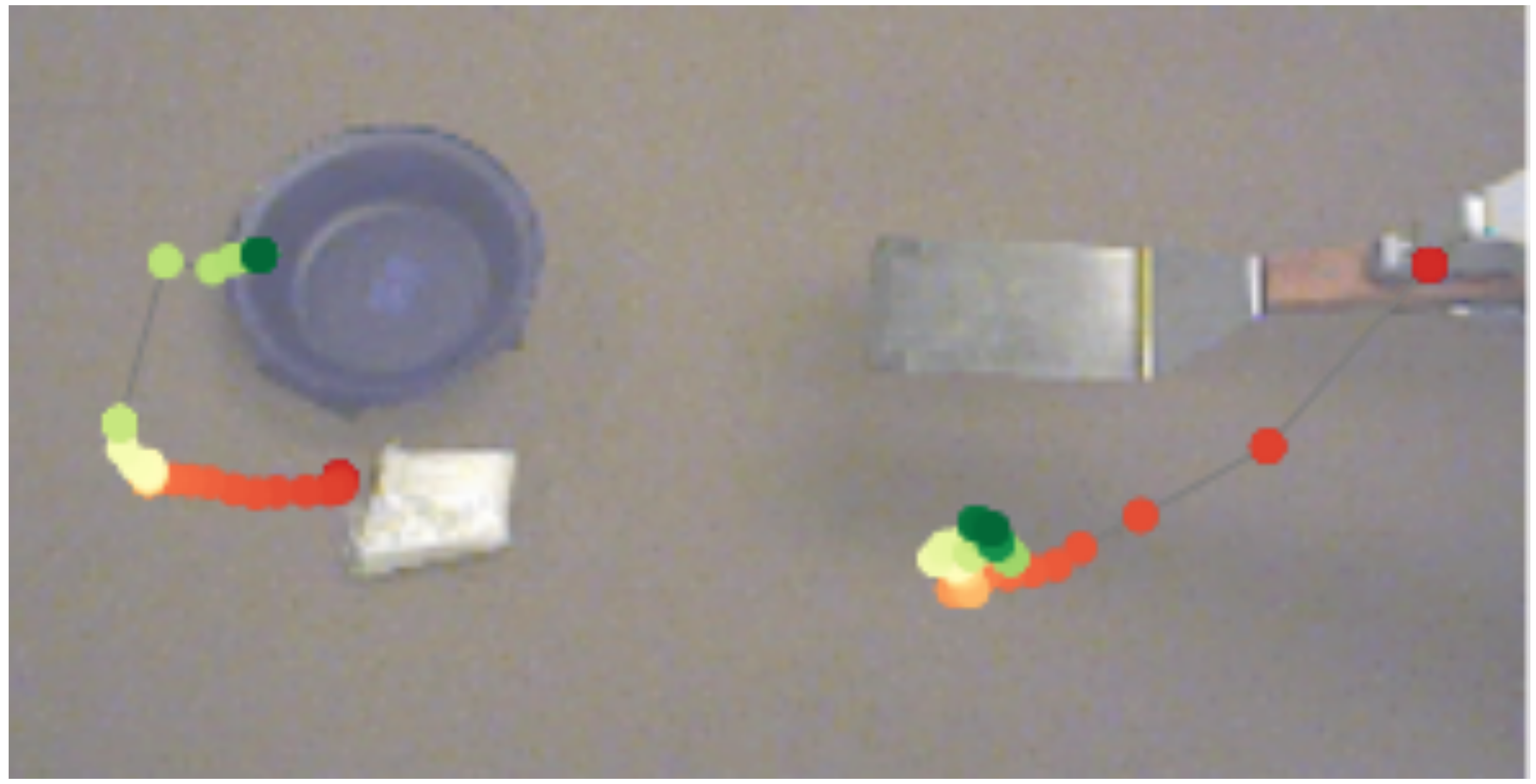


Fig. 1: PR2 learning to scoop a bag of rice into a bowl with a spatula (left) using a learned visual state representation (right).

1. collect data with exploratory policy
2. learn **smooth, structured** embedding of image
3. learn local-linear model with embedding
4. run iLQG to learn to reach image of goal & goal gripper pose

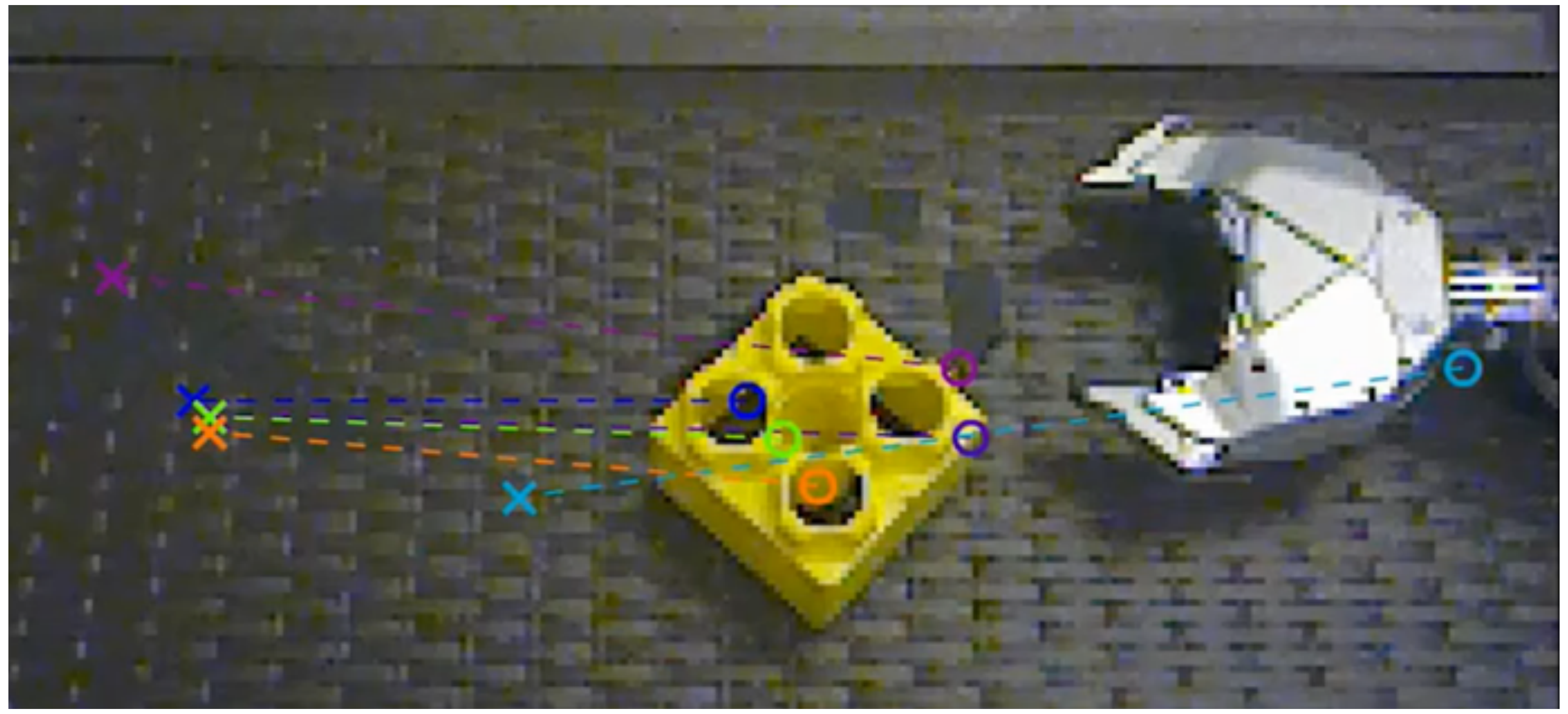


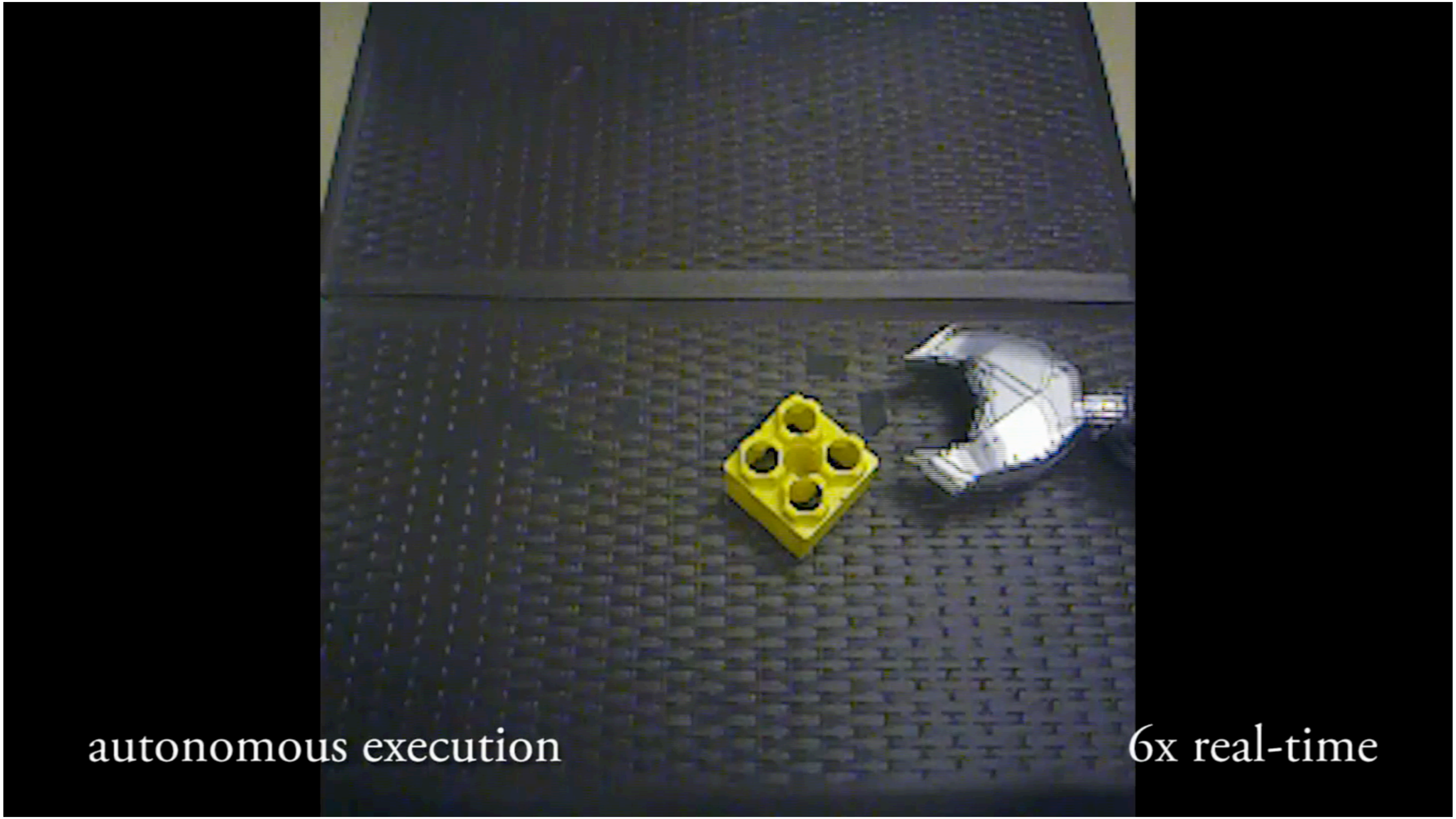


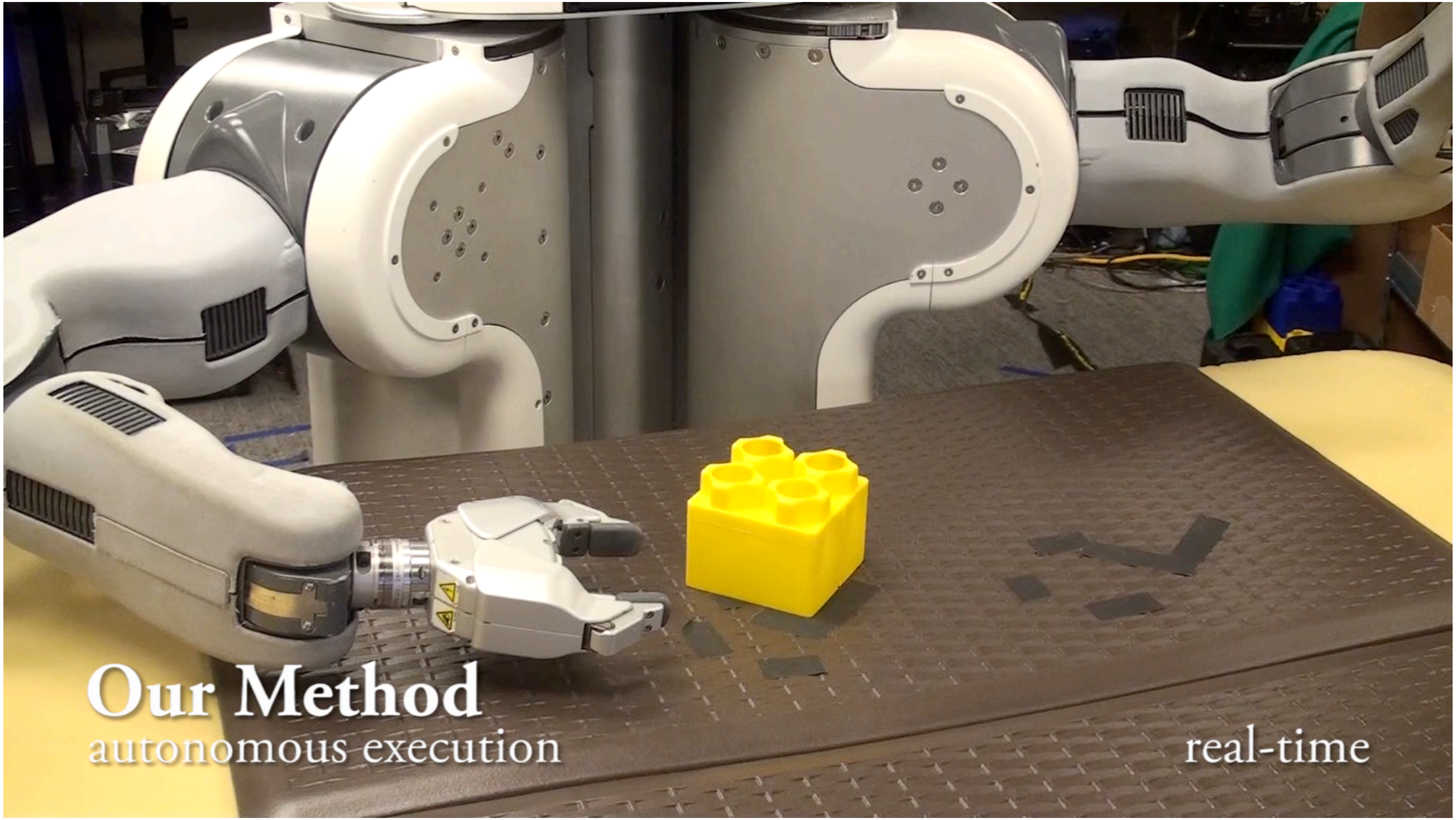
embedding is **smooth and structured**

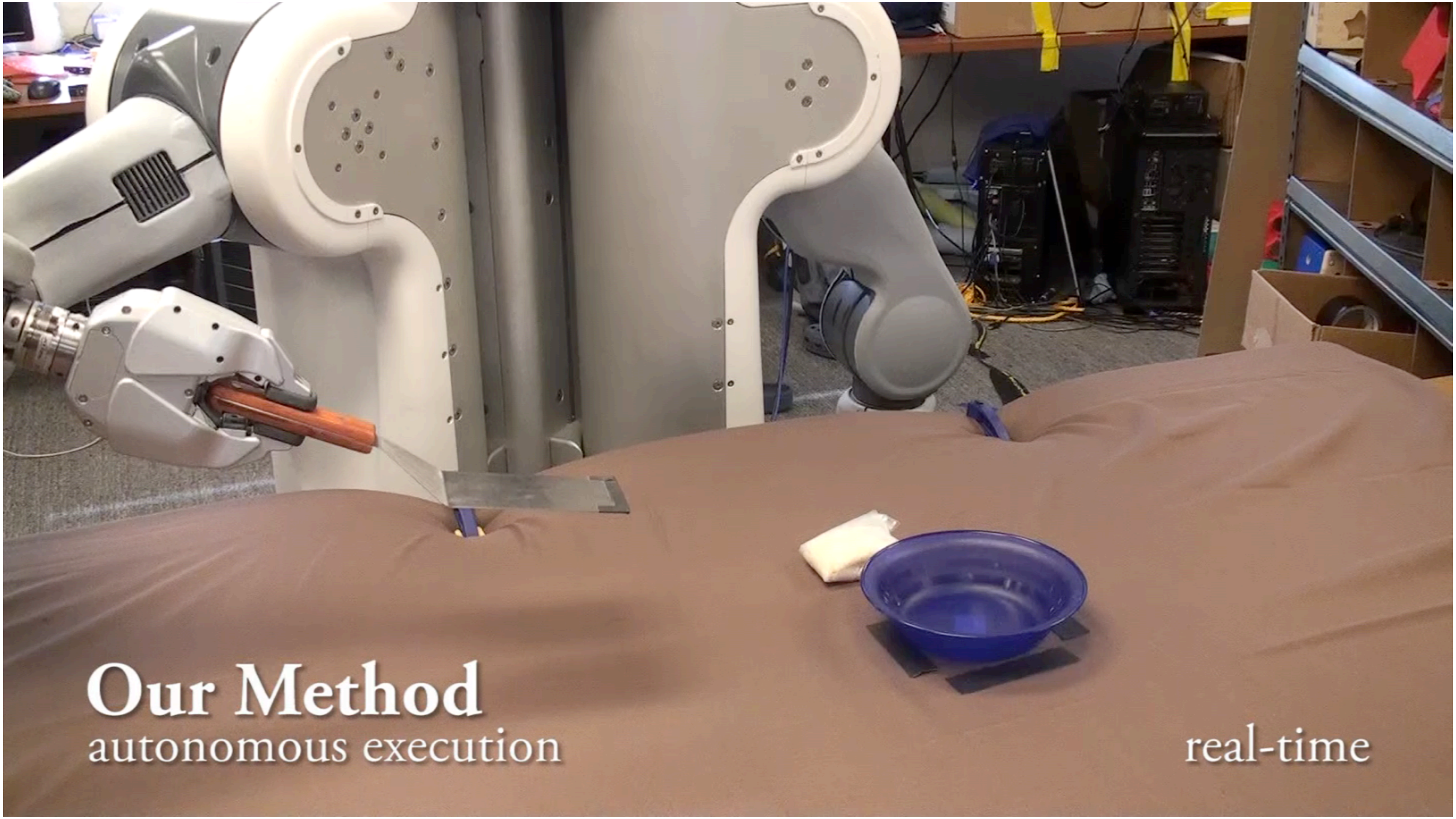
1. collect data with exploratory policy
2. learn **smooth, structured** embedding of image
3. learn local-linear model with embedding
4. run iLQG to learn to reach **image of goal** & goal gripper pose

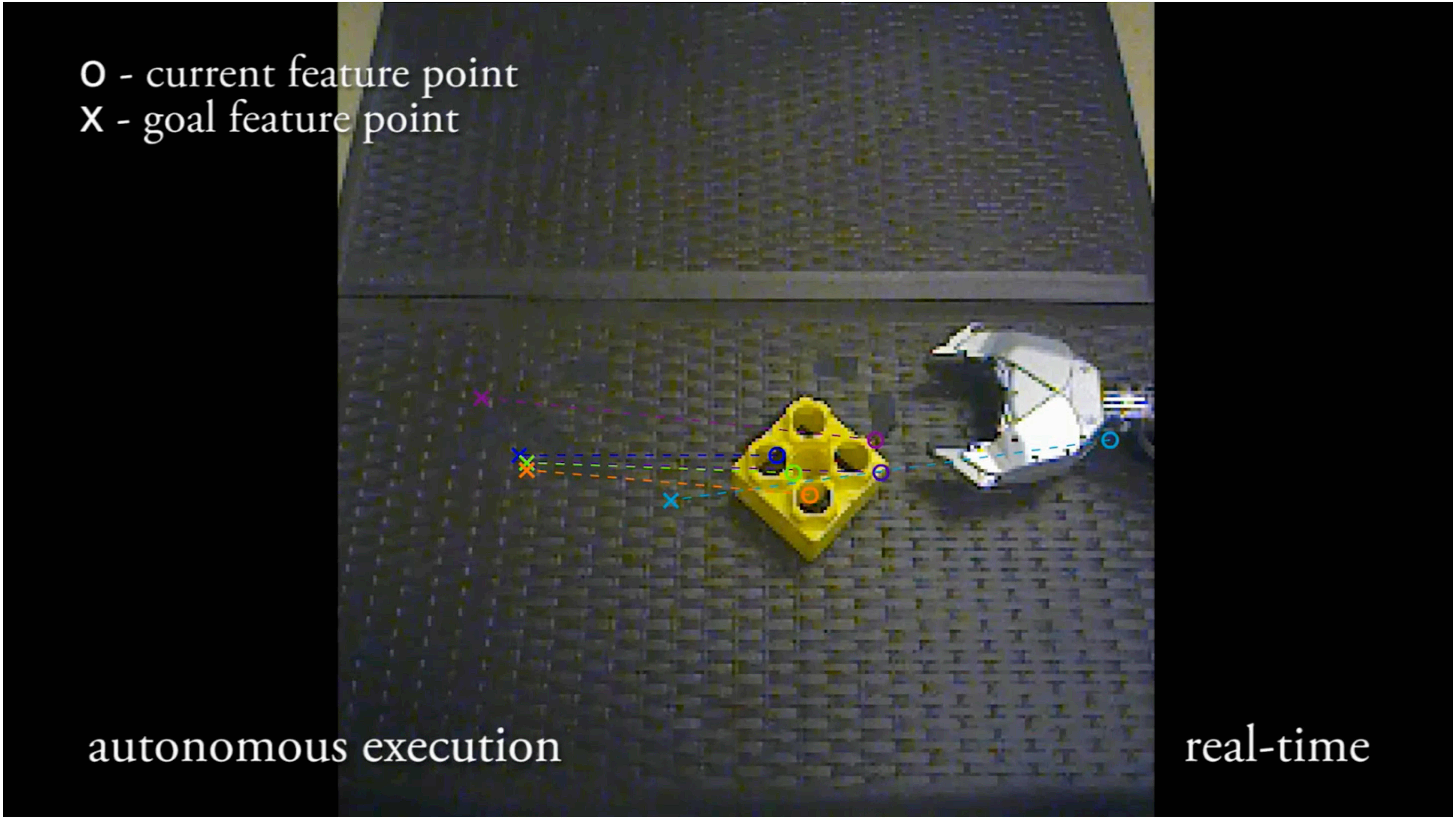
Because we aren't using states, we need a reward.



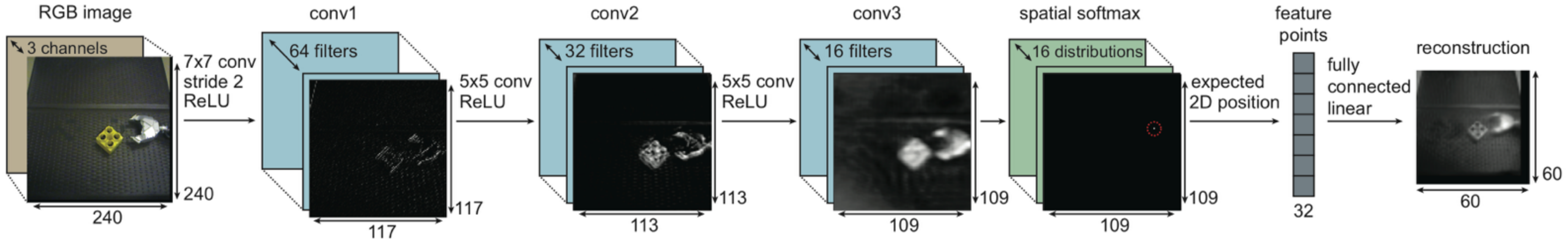

autonomous execution
6x real-time


Our Method
autonomous execution
real-time


Our Method
autonomous execution
real-time


O - current feature point
X - goal feature point
autonomous execution
real-time

1. collect data with exploratory policy
2. learn **smooth, structured** embedding of image
3. learn local-linear model with embedding
4. run iLQG to learn to reach image of goal & goal gripper pose



Pros:

+ Learn complex visual skill very efficiently

+ Structured representation enables effective learning

Cons:

- Autoencoder might not recover the right representation

Learning in Latent Space

Key idea: learn embedding $g(\mathbf{o}_t) = \mathbf{x}_t$, then learn in latent space

(**model-based** or model-free)

Embed to Control: A Locally Linear Latent Dynamics Model for Control from Raw Images

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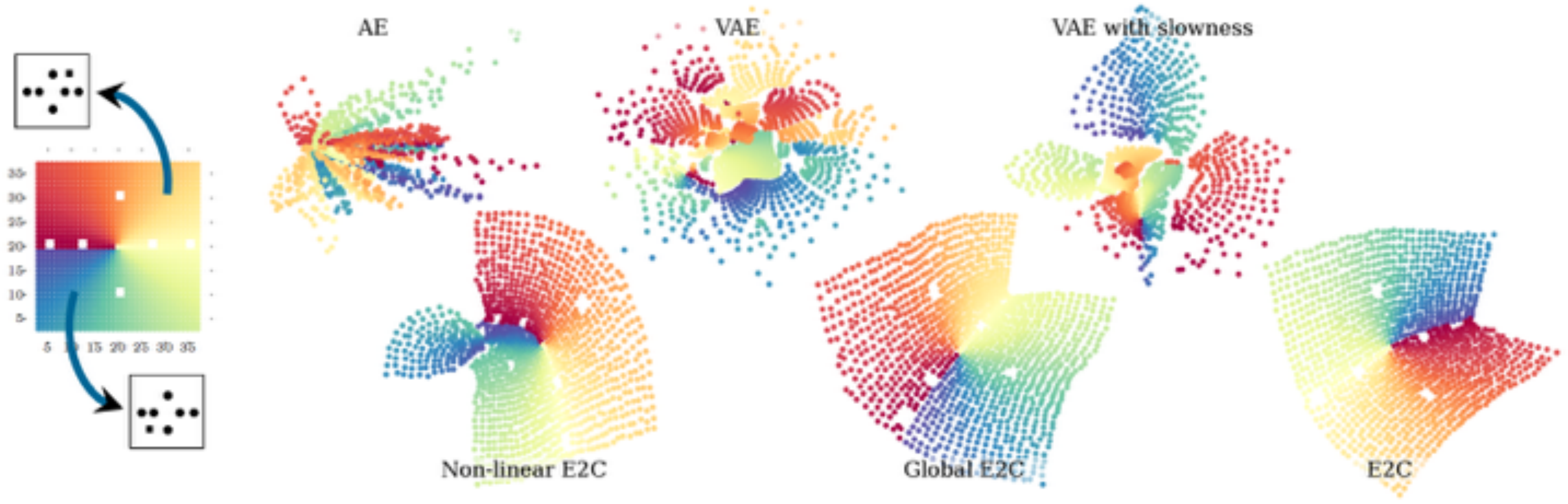
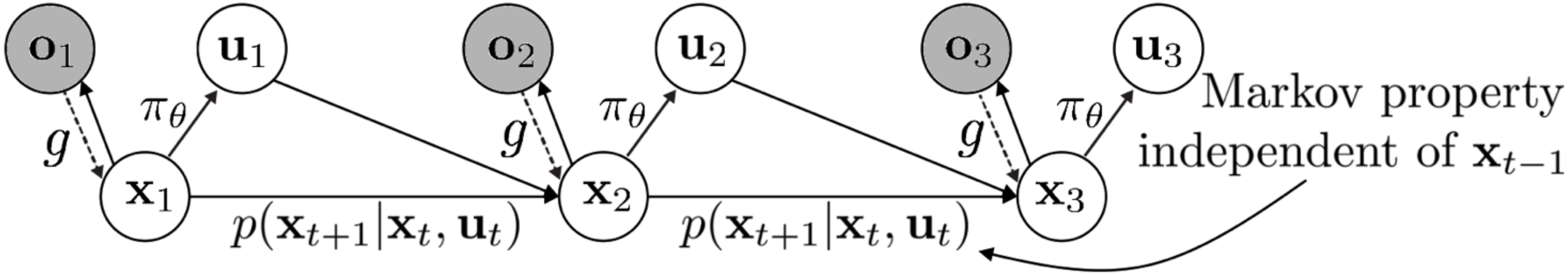


1. collect data
2. learn embedding of image & dynamics model (**jointly**)
3. run iLQG to learn to reach image of goal



embedding that can be **modeled**

Swing-up with the E2C algorithm

Thought exercise:

Why reconstruct the image?

Why not just learn embedding and model on embedding?

Outline

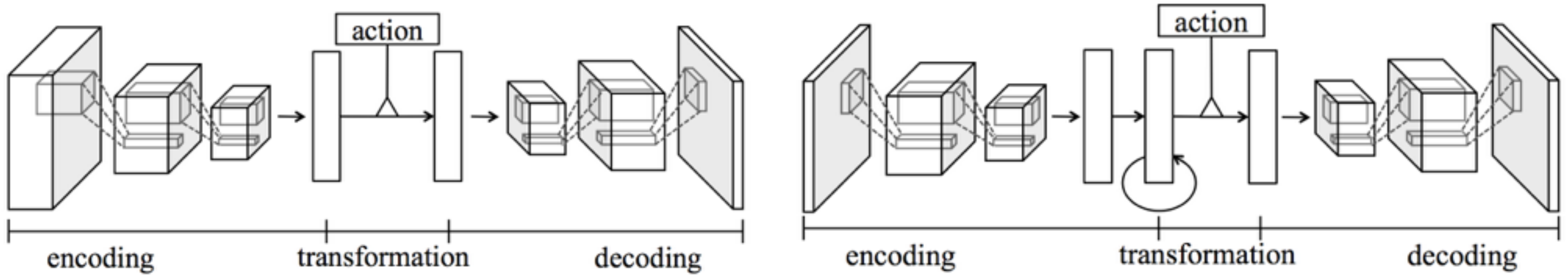
1. Models in latent space
2. **Models directly in image space**
3. Inverse models

Models with Images

Action-conditioned video prediction $f(\mathbf{o}_t, \mathbf{u}_t) = \mathbf{o}_{t+1}$

Action-Conditional Video Prediction using Deep Networks in Atari Games

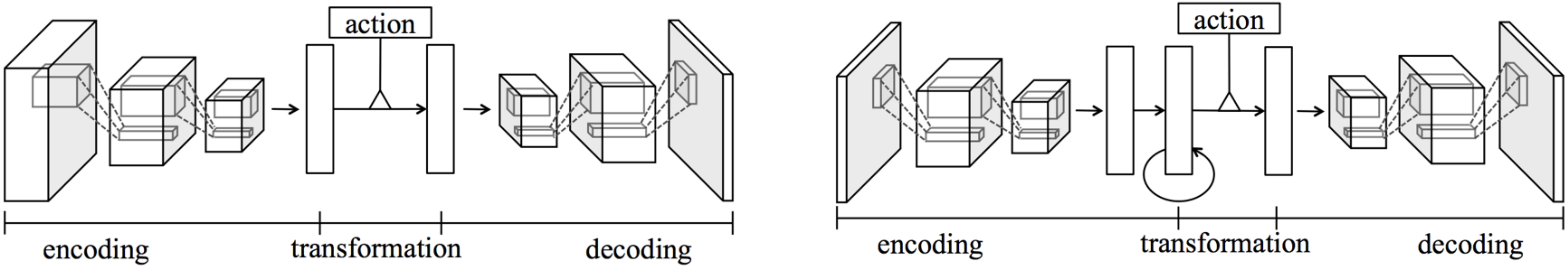
Junhyuk Oh **Xiaoxiao Guo** **Honglak Lee** **Richard Lewis** **Satinder Singh**
University of Michigan, Ann Arbor, MI 48109, USA



(a) Feedforward encoding (b) Recurrent encoding

Models with Images

Action-conditioned video prediction $f(\mathbf{o}_t, \mathbf{u}_t) = \mathbf{o}_{t+1}$



(a) Feedforward encoding

(b) Recurrent encoding

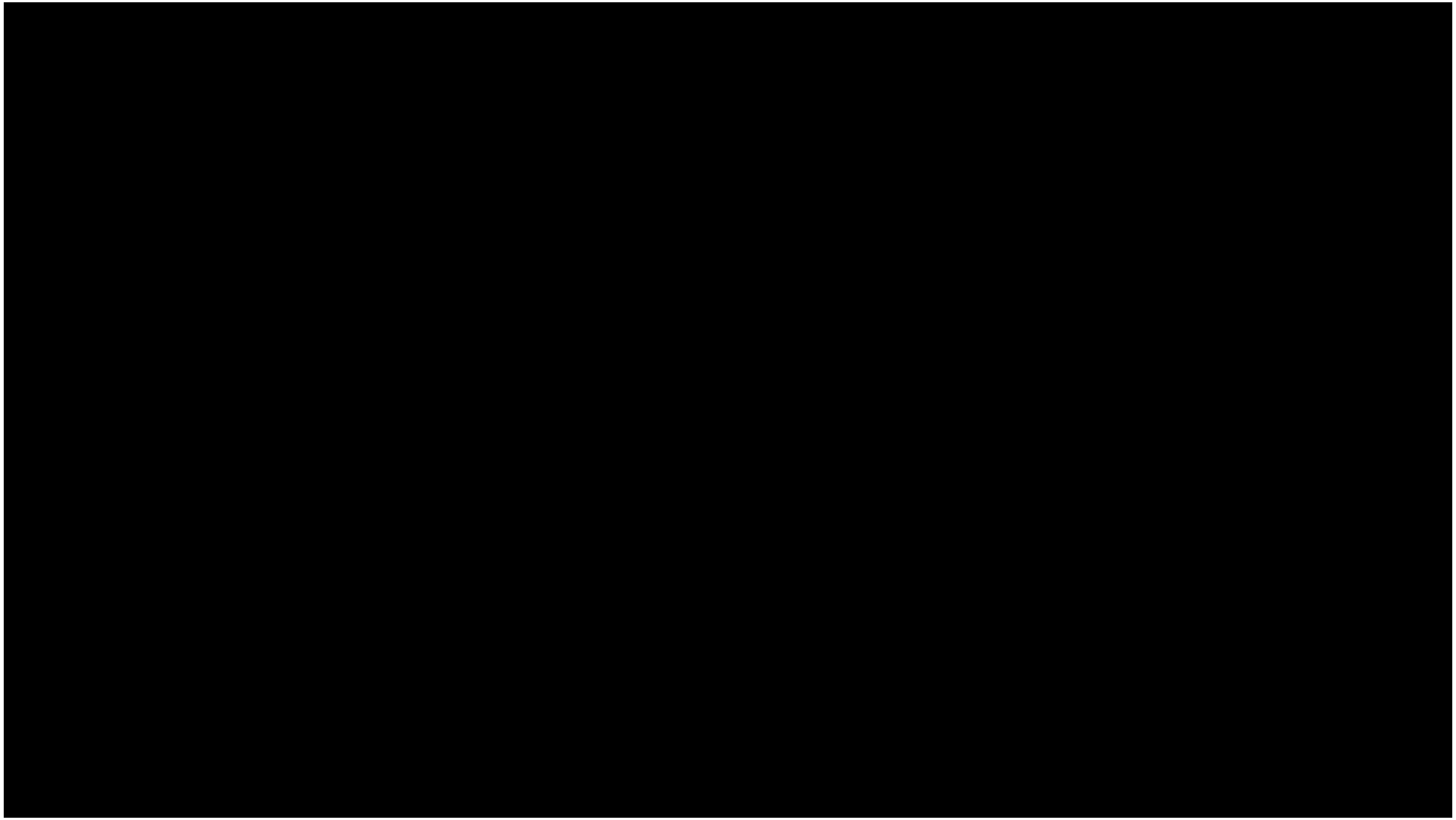
Key components:

multi-step prediction $f(\mathbf{o}_t, \mathbf{u}_{t:T-1}) = \mathbf{o}_{t+1:T}$

curriculum learning and/or scheduled sampling

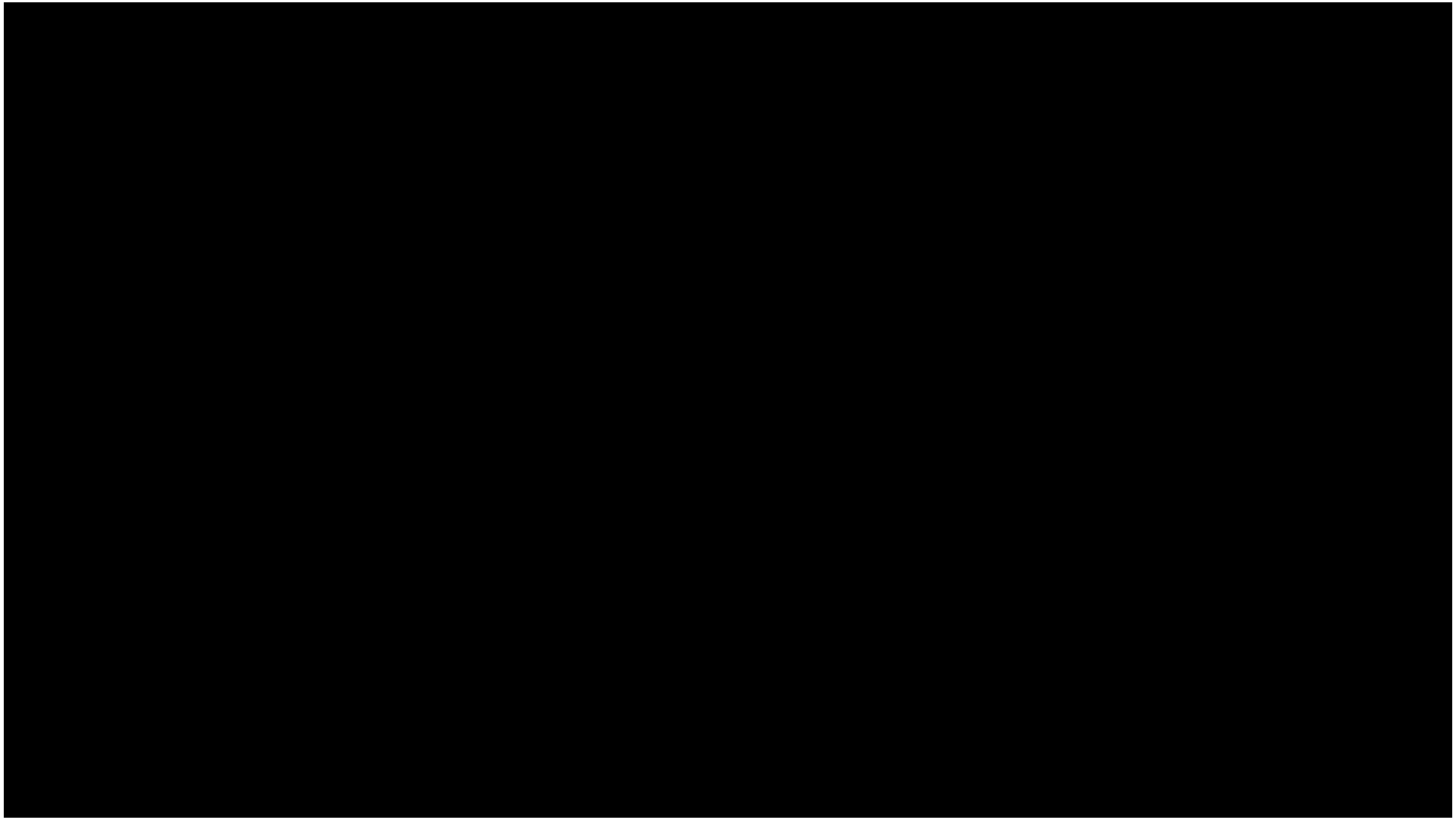
Does it work?

Yes!



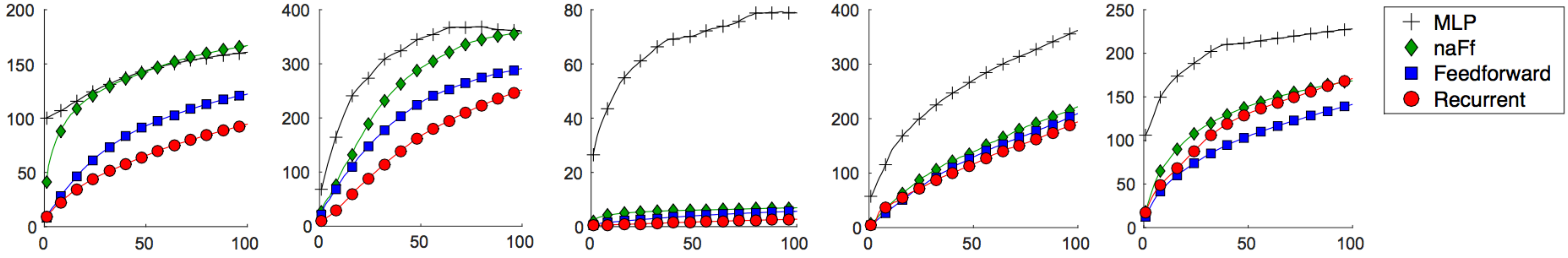
can make 100-step predictions

Does it work? Maybe not.



fails to model a critical part of the game

Does it work?

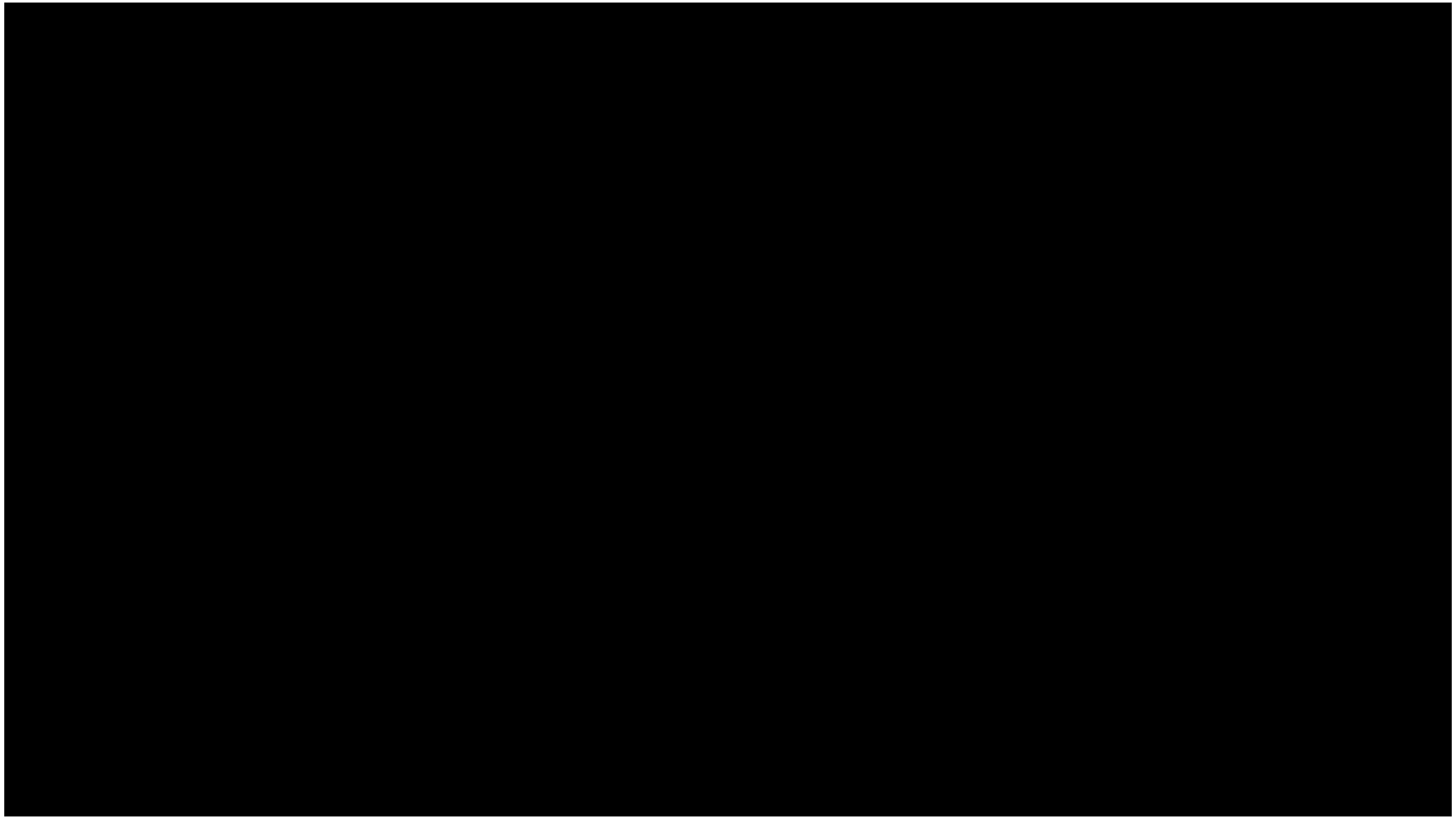


(a) Seaquest (b) Space Invaders (c) Freeway (d) QBert (e) Ms Pacman

Figure 3: Mean squared error over 100-step predictions

Is it useful?

Using model for informed exploration



Using model for informed exploration:

1. Store most recent d frames
2. For every valid action, predict 1 frame ahead
3. Take action corresponding to future frame least like the previous d frames

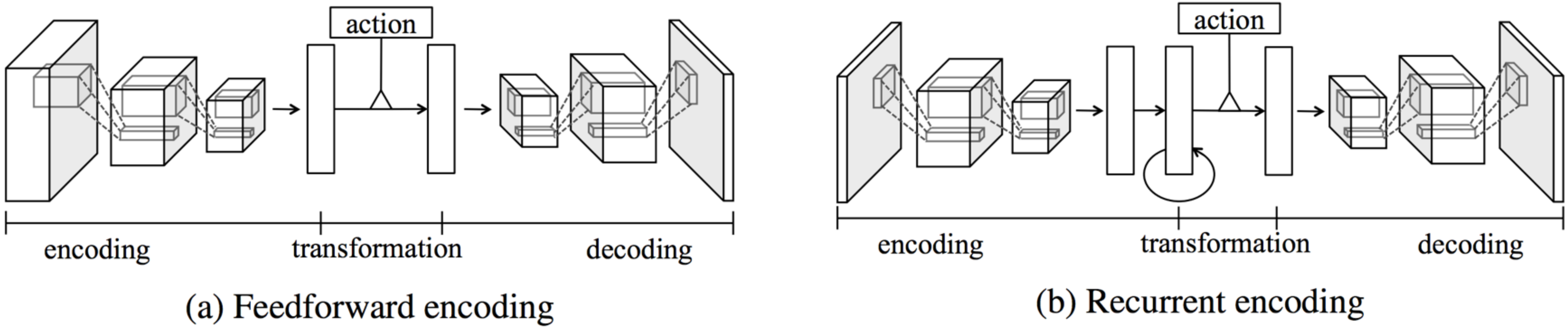
Use Gaussian kernel similarity metric on images:

$$n_D(\mathbf{x}^{(a)}) = \sum_{i=1}^{d} k(\mathbf{x}^{(a)}, \mathbf{x}^{(i)}); \quad k(\mathbf{x}, \mathbf{y}) = \exp(-\sum_j \min(\max((x_j - y_j)^2 - \delta, 0), 1)/\sigma)$$

***caveat:** prediction model was trained with data from DQN agent

more on exploration later in this course!

Action-conditioned video prediction $f(\mathbf{o}_t, \mathbf{u}_t) = \mathbf{o}_{t+1}$



Pros:

+ Stability through multi-step prediction
+ Useful for control

Cons:

- Synthetic images are easier to generate
- Not immediately clear how to plan with it

What about real images?

Unsupervised Learning for Physical Interaction through Video Prediction

Chelsea Finn* UC Berkeley

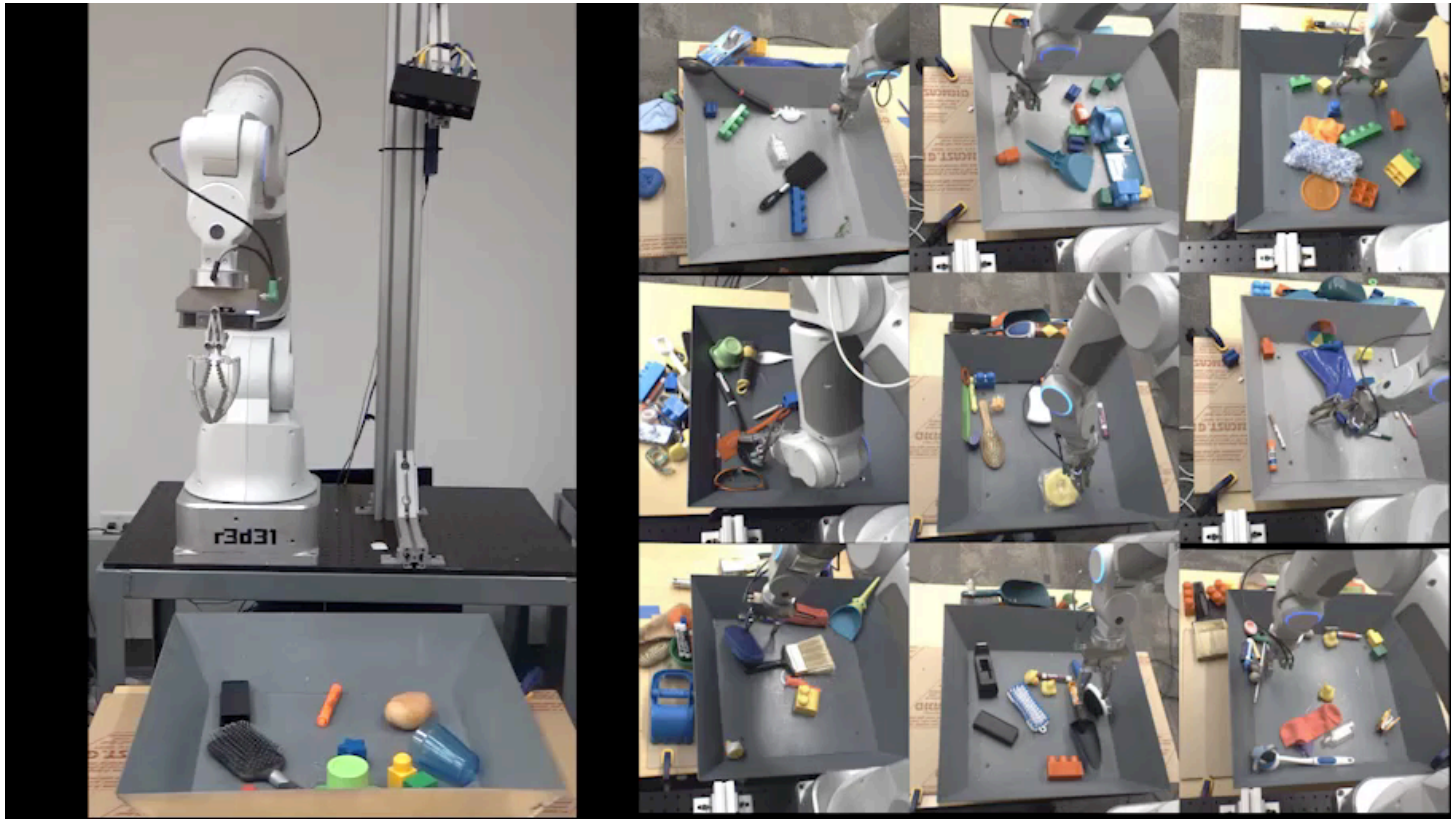
Ian Goodfellow OpenAI

Sergey Levine Google Brain

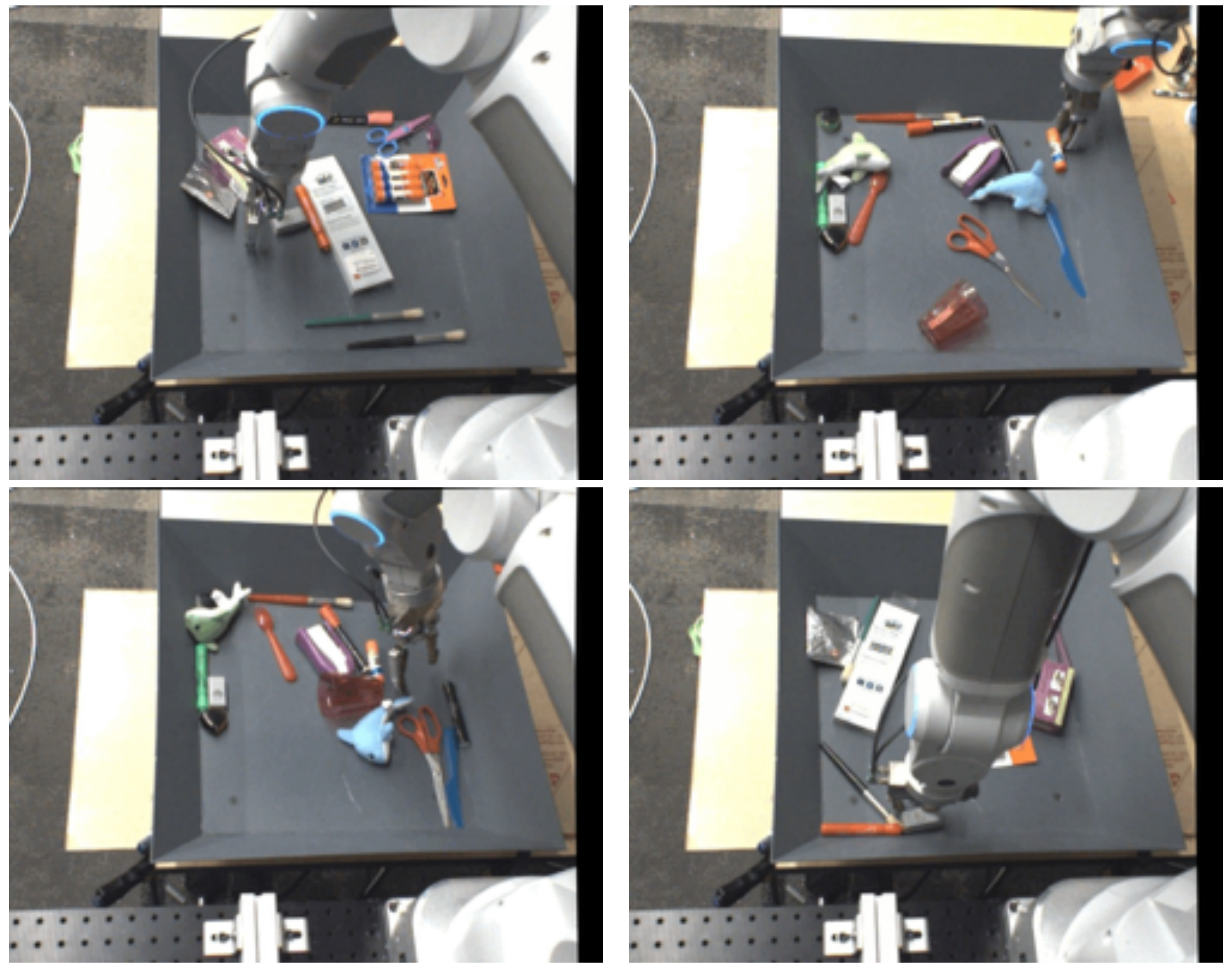
Deep Visual Foresight for Planning Robot Motion

Chelsea Finn[1,2] and Sergey Levine[1,2]

Data collection - 50k sequences (1M+ frames)



test set with
novel objects



data publicly available for download **sites.google.com/site/brainrobotdata**

Train 8-step predictive model

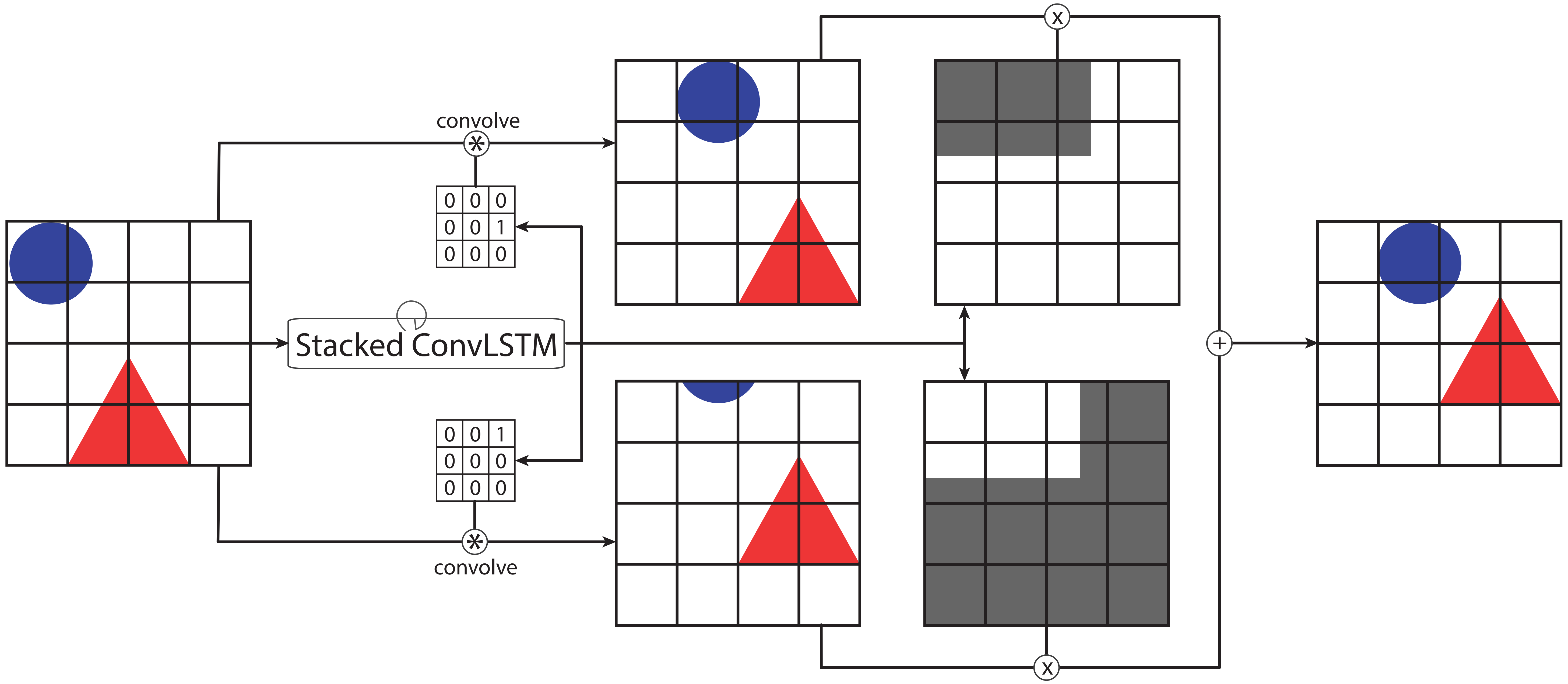
Atari recurrent model

evaluate on held-out objects

— > doesn't have capacity to represent real images.

Train predictive model

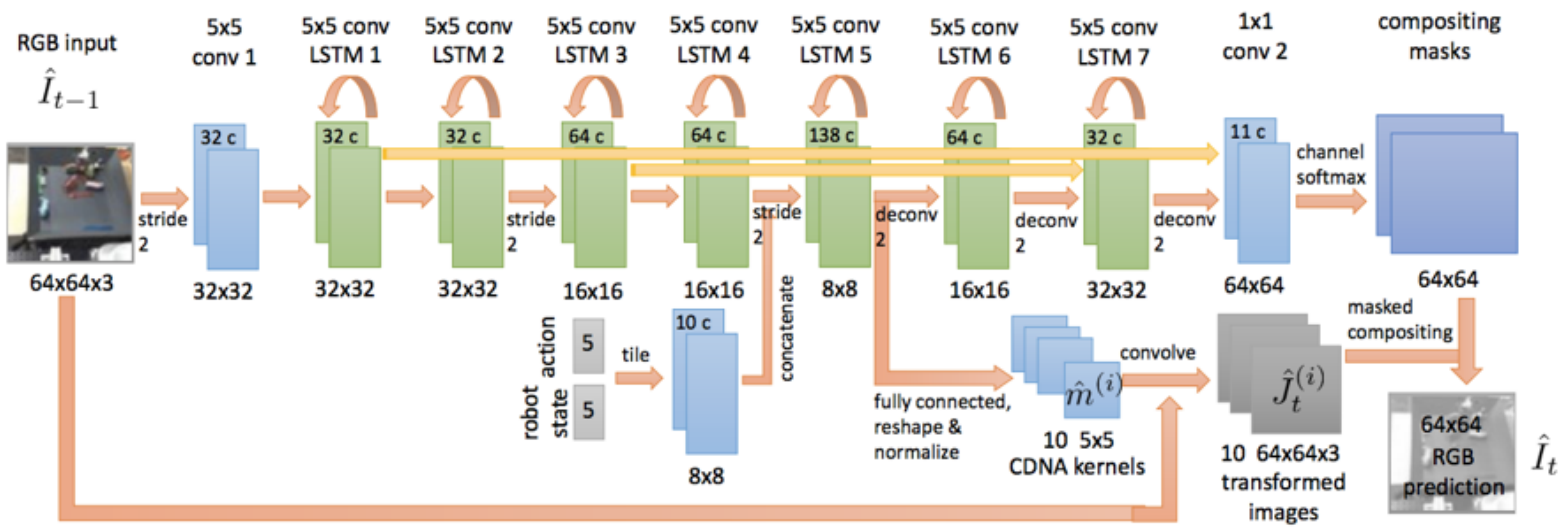
action-conditioned multi-frame video prediction
via **flow prediction**



- feed back model's predictions for multi-frame prediction
- trained with l_2 loss

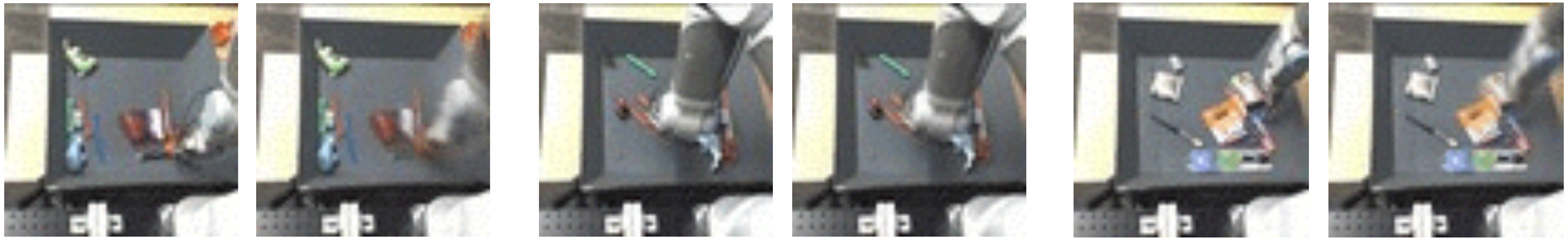
Train predictive model

convolutional LSTMs



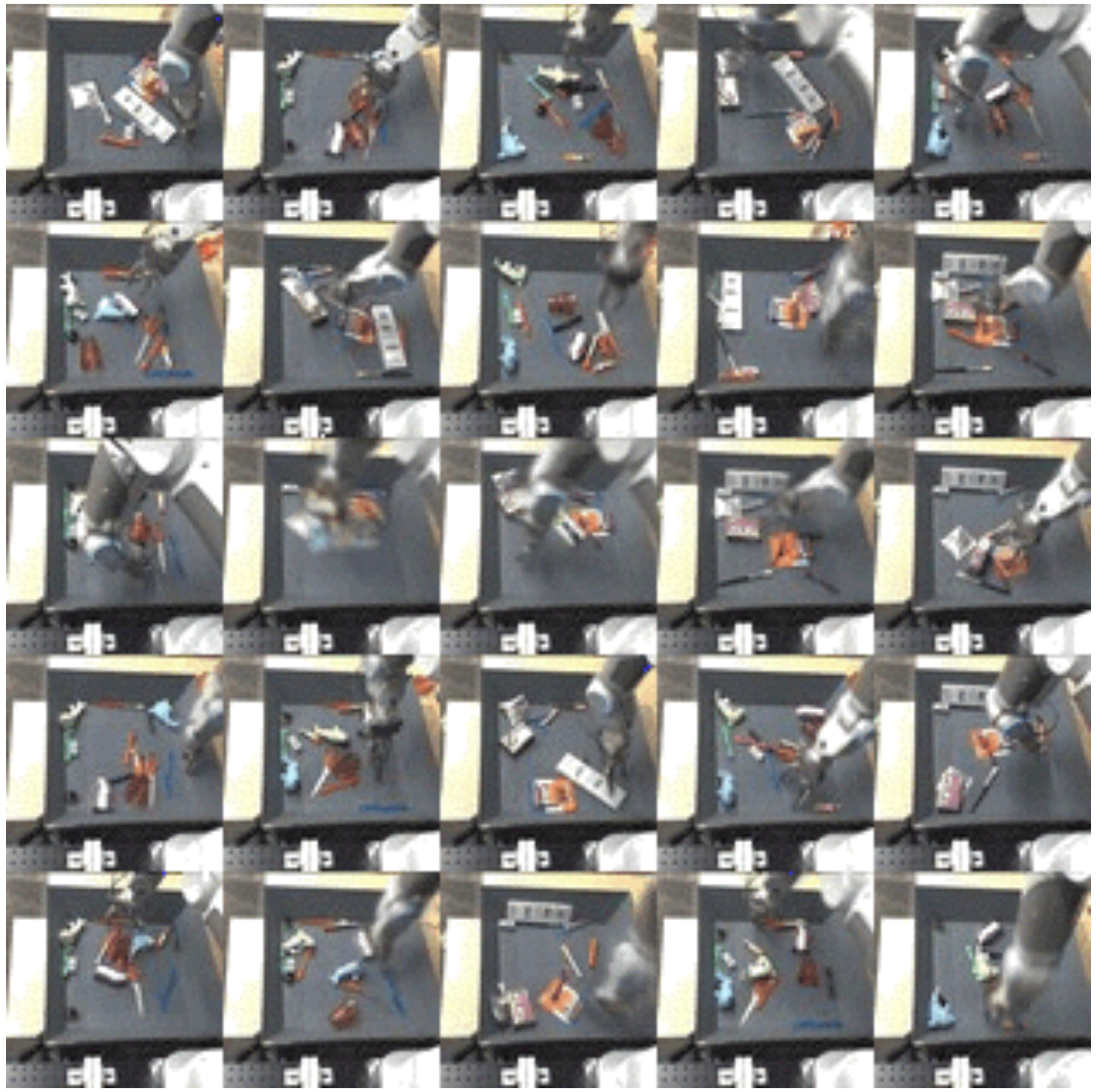
action-conditioned **stochastic flow prediction**

evaluate on held-out objects

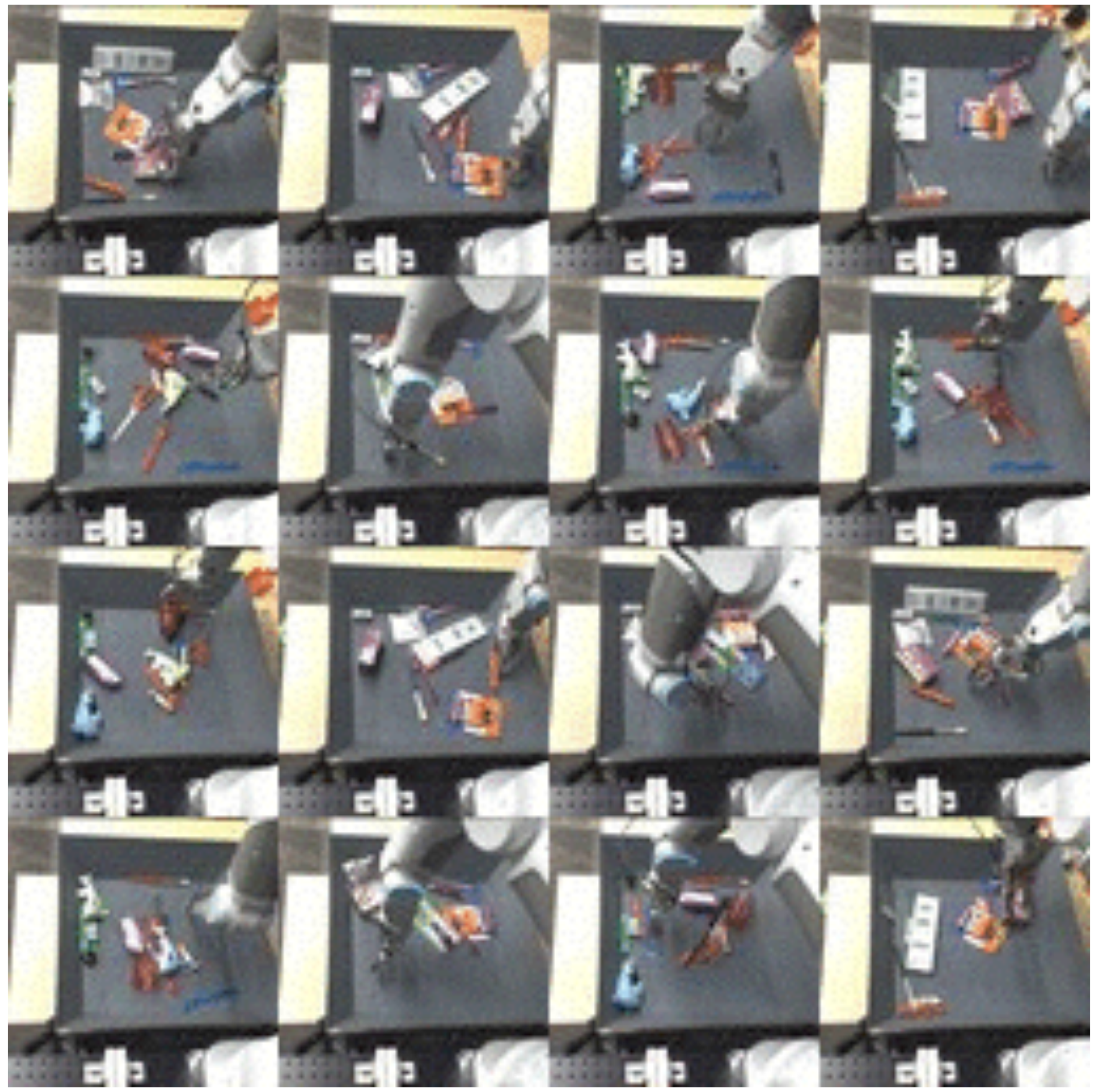


Train predictive model

Finn et al., '16



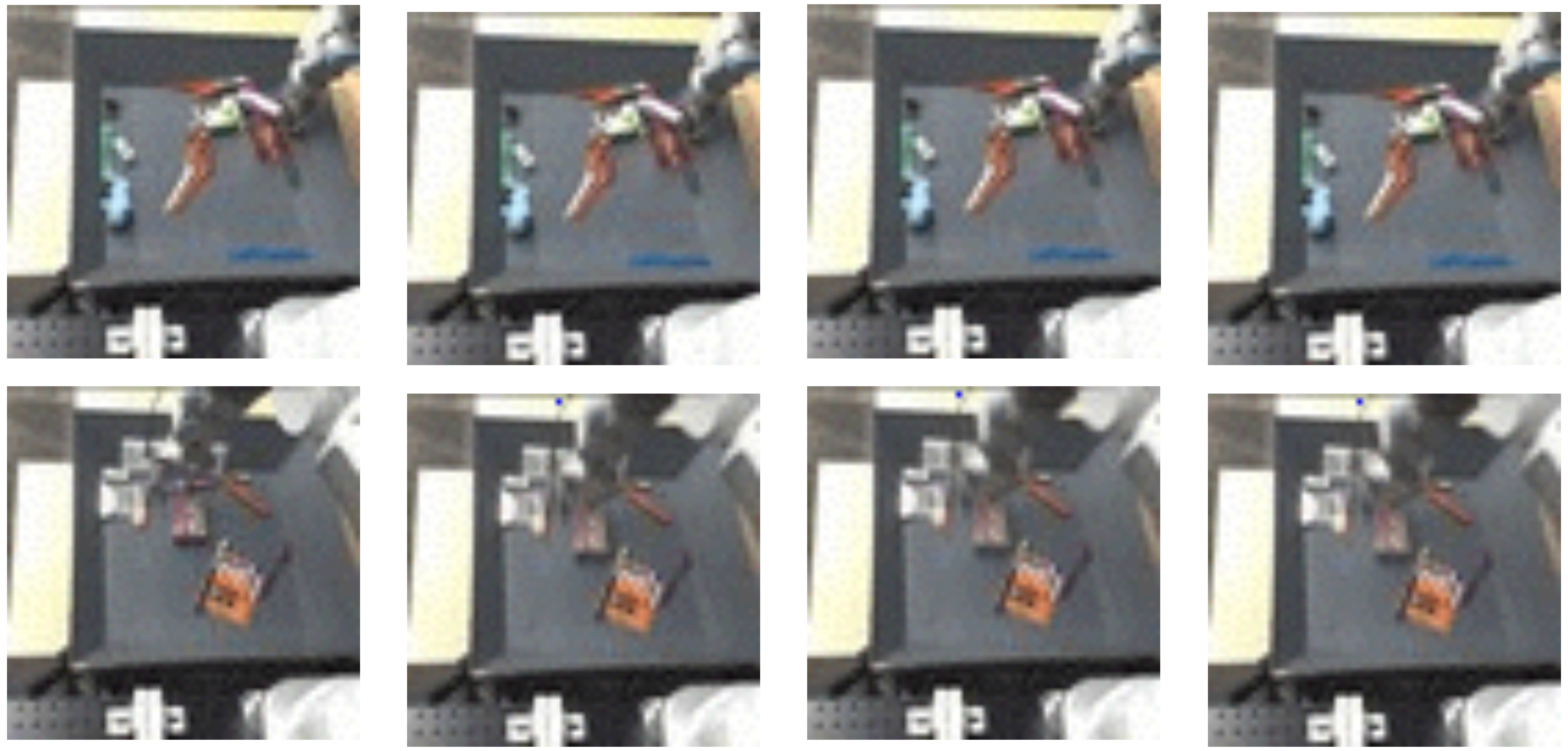
Kalchbrenner et al., '16



Are these predictions good? accurate? useful?

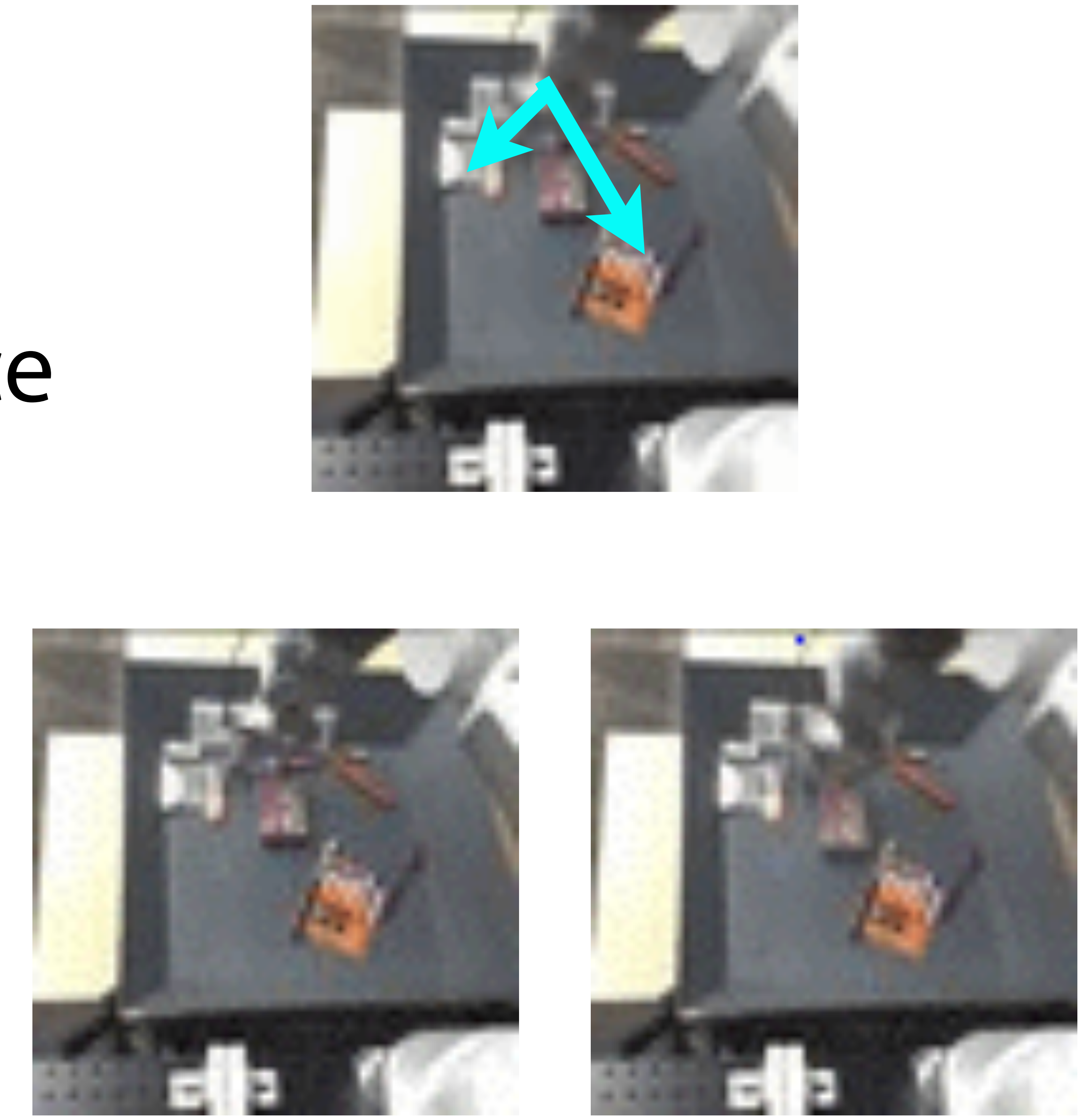
What is prediction good for?

action magnitude: 0x 0.5x 1x 1.5x



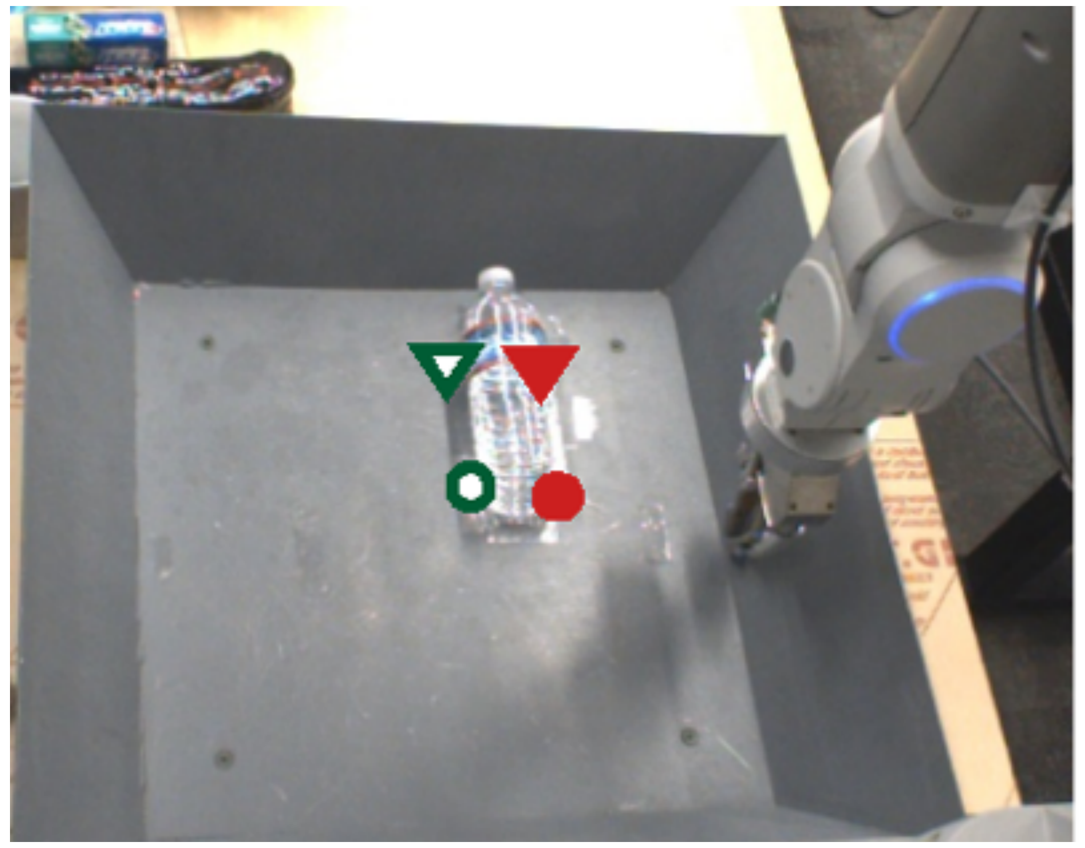
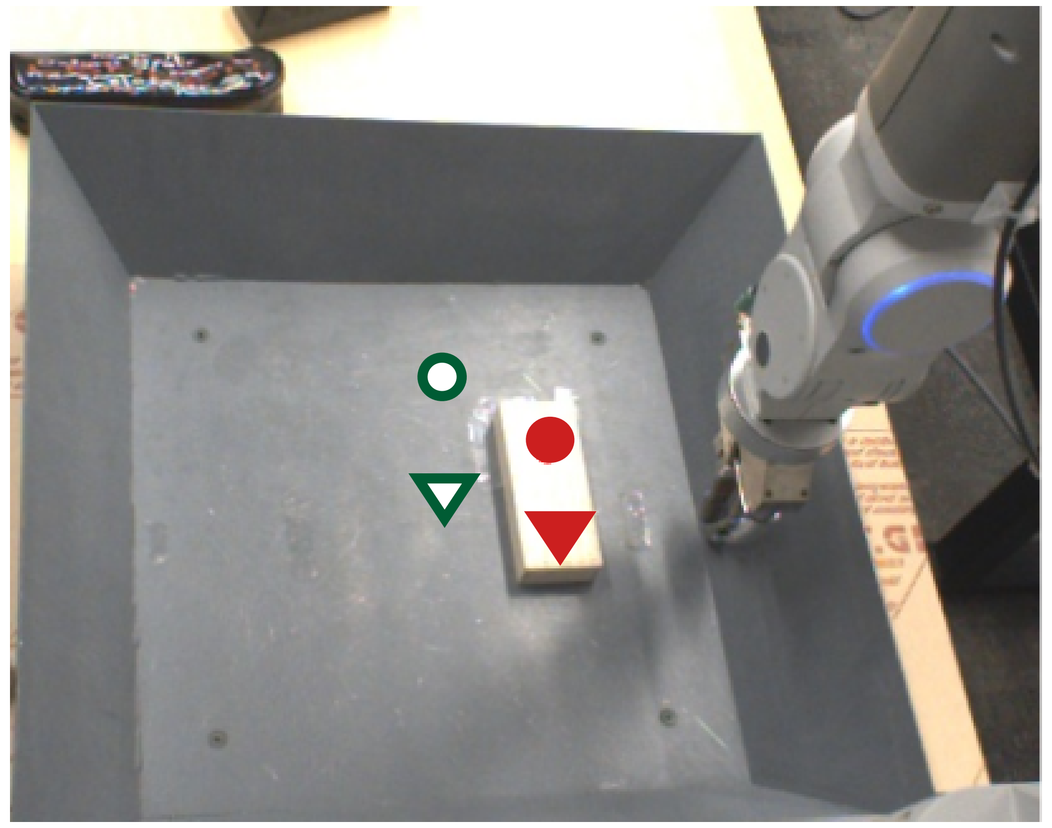
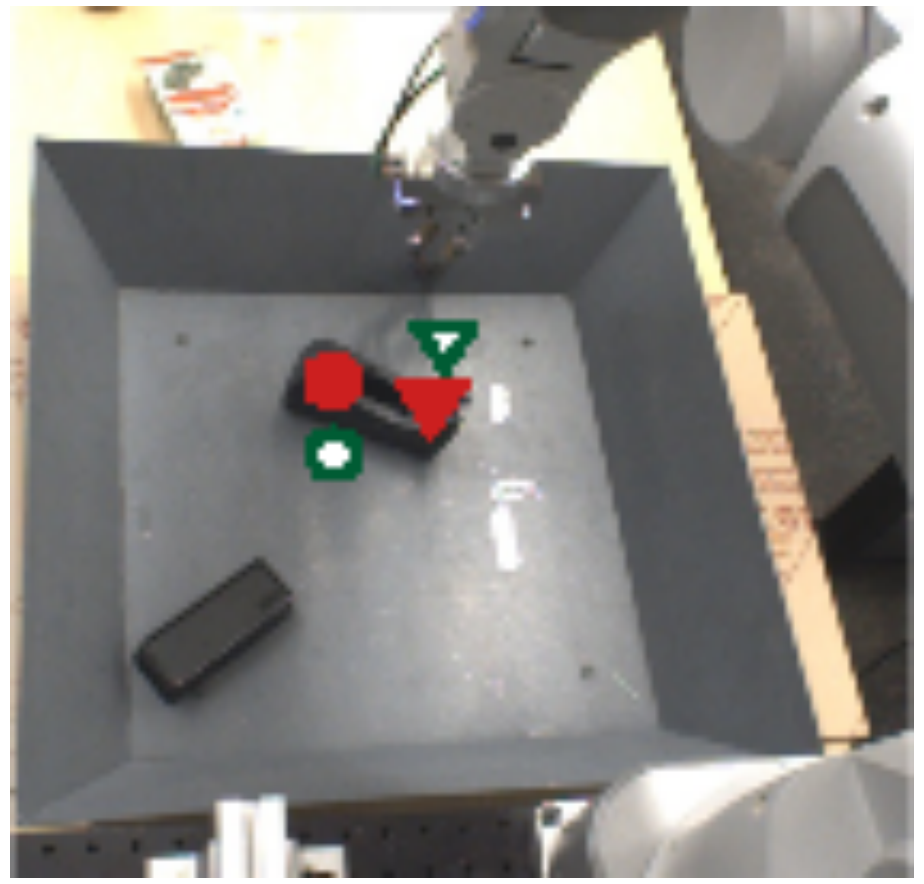
Planning with Visual Foresight (MPC)

1. Sample N potential action sequences
2. Predict the future for each action sequence
3. Pick best future & execute corresponding action
4. Repeat 1-3 to replan in real time



Which future is the best one?

Specify goal by selecting where pixels should move.

Select future with maximal probability of pixels reaching their respective goals.

How it works

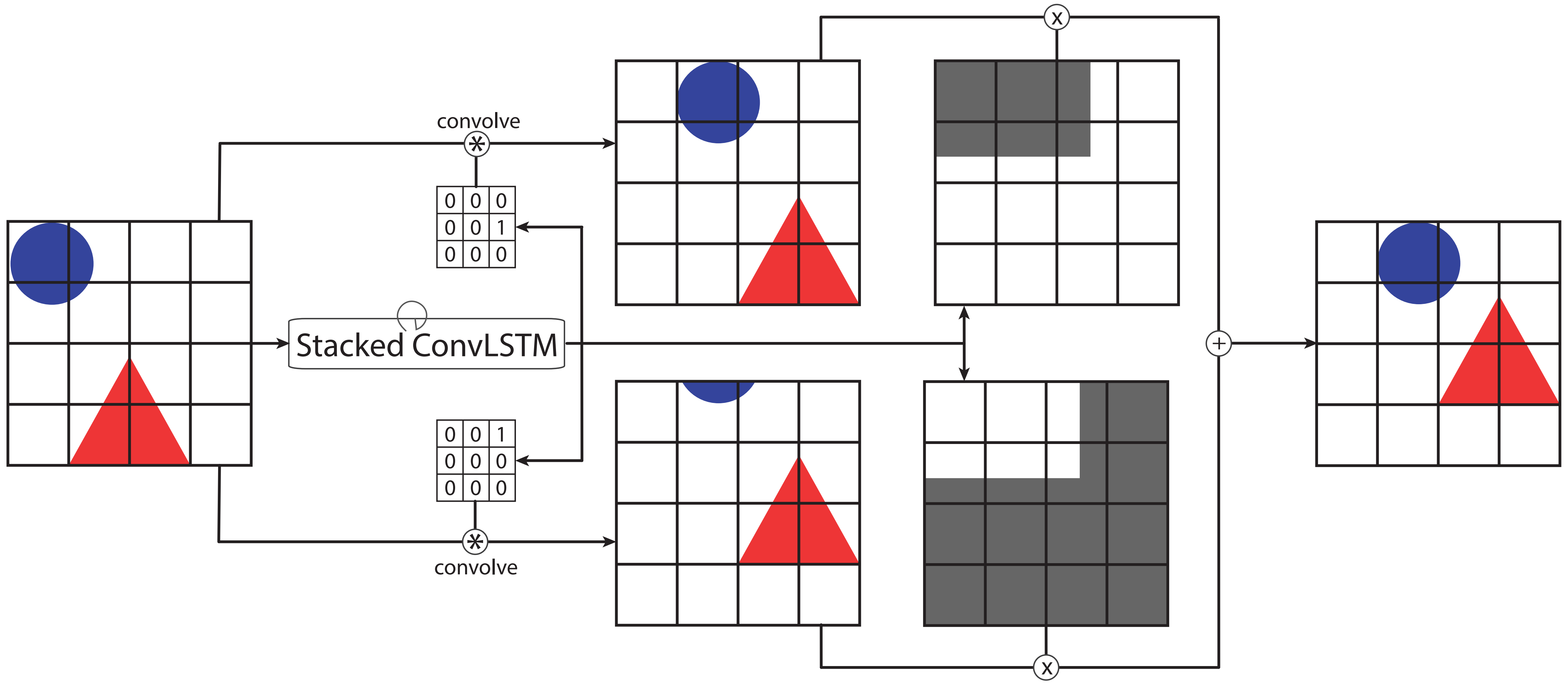
Does it work?

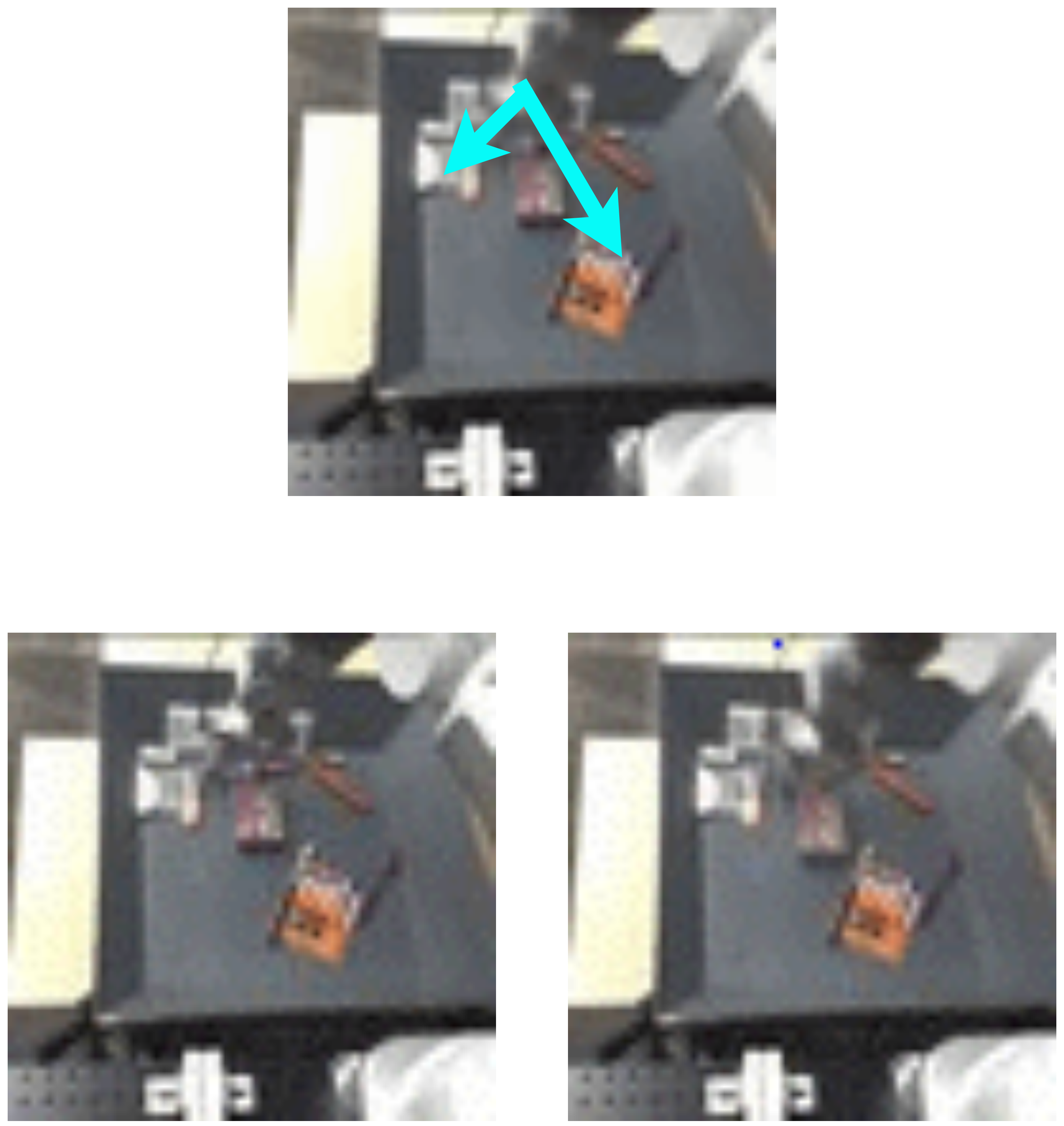
- evaluation on short pushes of **novel objects**

- translation & rotation

Only human involvement during training is:
programming initial motions and providing objects to play with.

action-conditioned multi-frame video prediction via **flow prediction**





Pros:

+ Real images
+ Very limited human involvement (self-supervised)
+ Approach should improve as video prediction methods improve

Cons:

- Despite real images, limited background variability
- Somewhat simple skills
- Compute intensive at test-time

Outline

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Inverse Models

Thought exercise revisited:
Why reconstruct the image?

Learn embedding via inverse model $f(\mathbf{o}_t, \mathbf{o}_{t+1}) = \mathbf{u}_t$

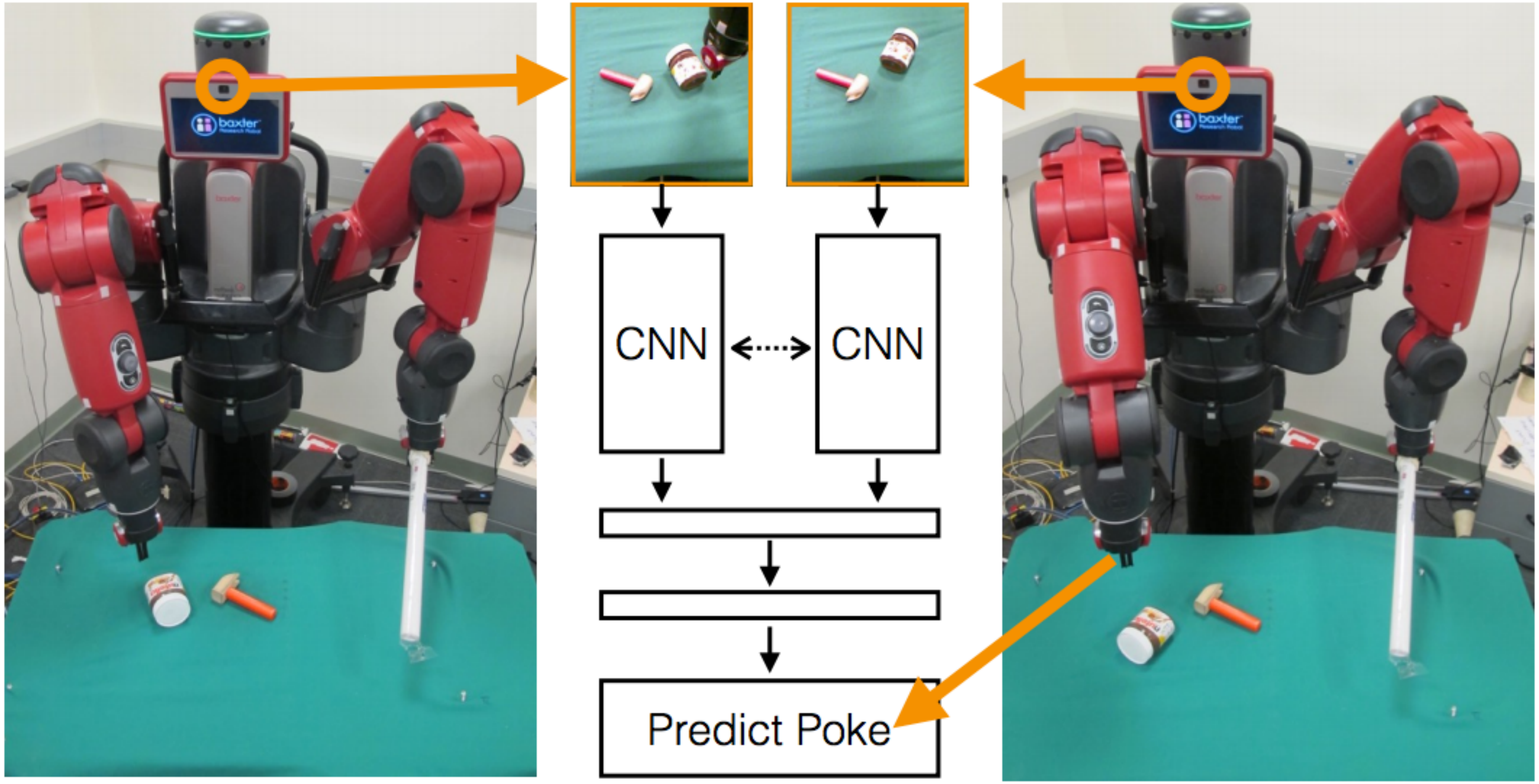
Inverse Models

Learn embedding via inverse model $f(\mathbf{o}_t, \mathbf{o}_{t+1}) = \mathbf{u}_t$

Learning to Poke by Poking: Experiential Learning of Intuitive Physics

Pulkit Agrawal* **Ashvin Nair*** **Pieter Abbeel** **Jitendra Malik** **Sergey Levine**
Berkeley Artificial Intelligence Research Laboratory (BAIR)
University of California Berkeley

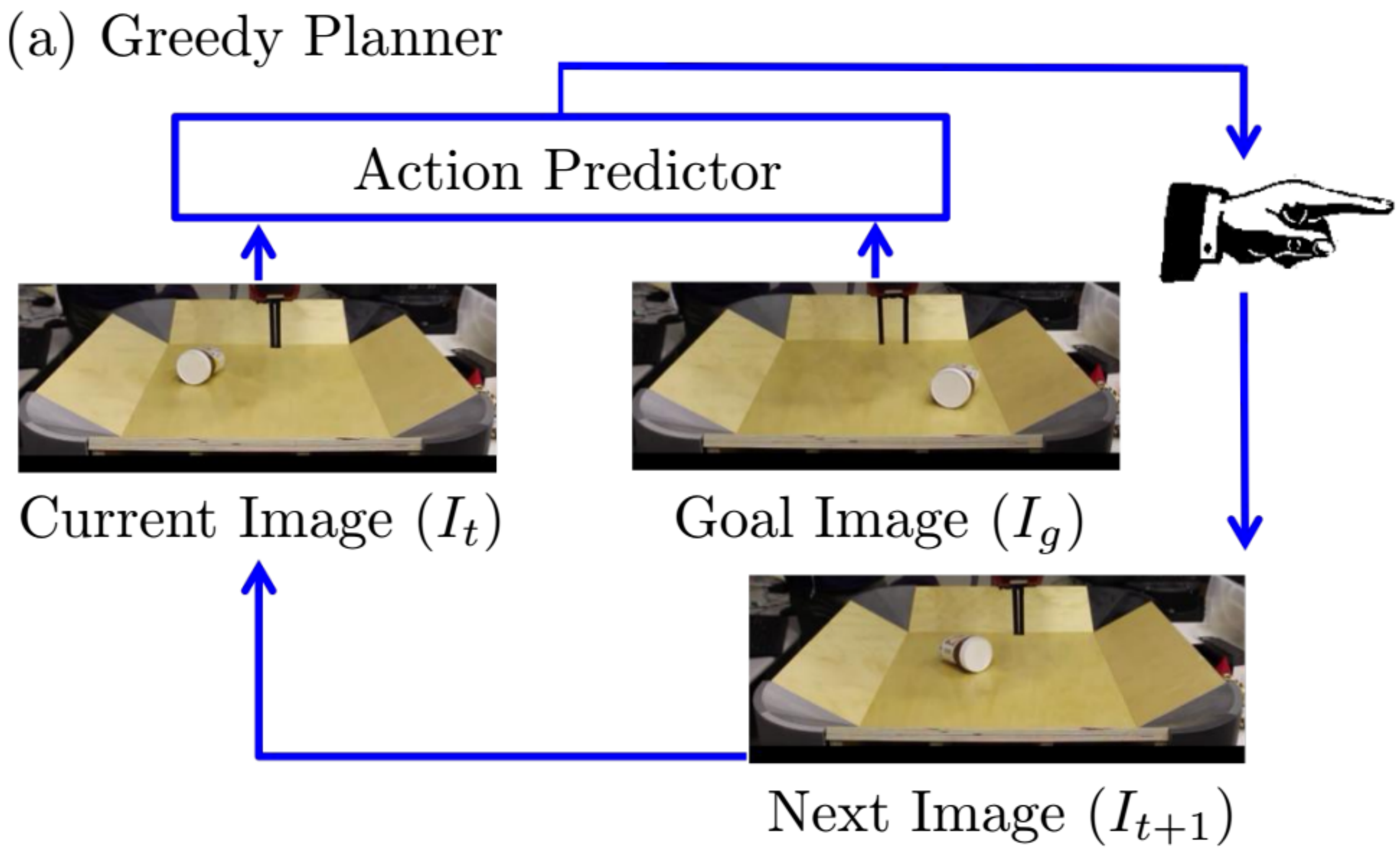
Learn embedding via inverse model $f(\mathbf{o}_t, \mathbf{o}_{t+1}) = \mathbf{u}_t$

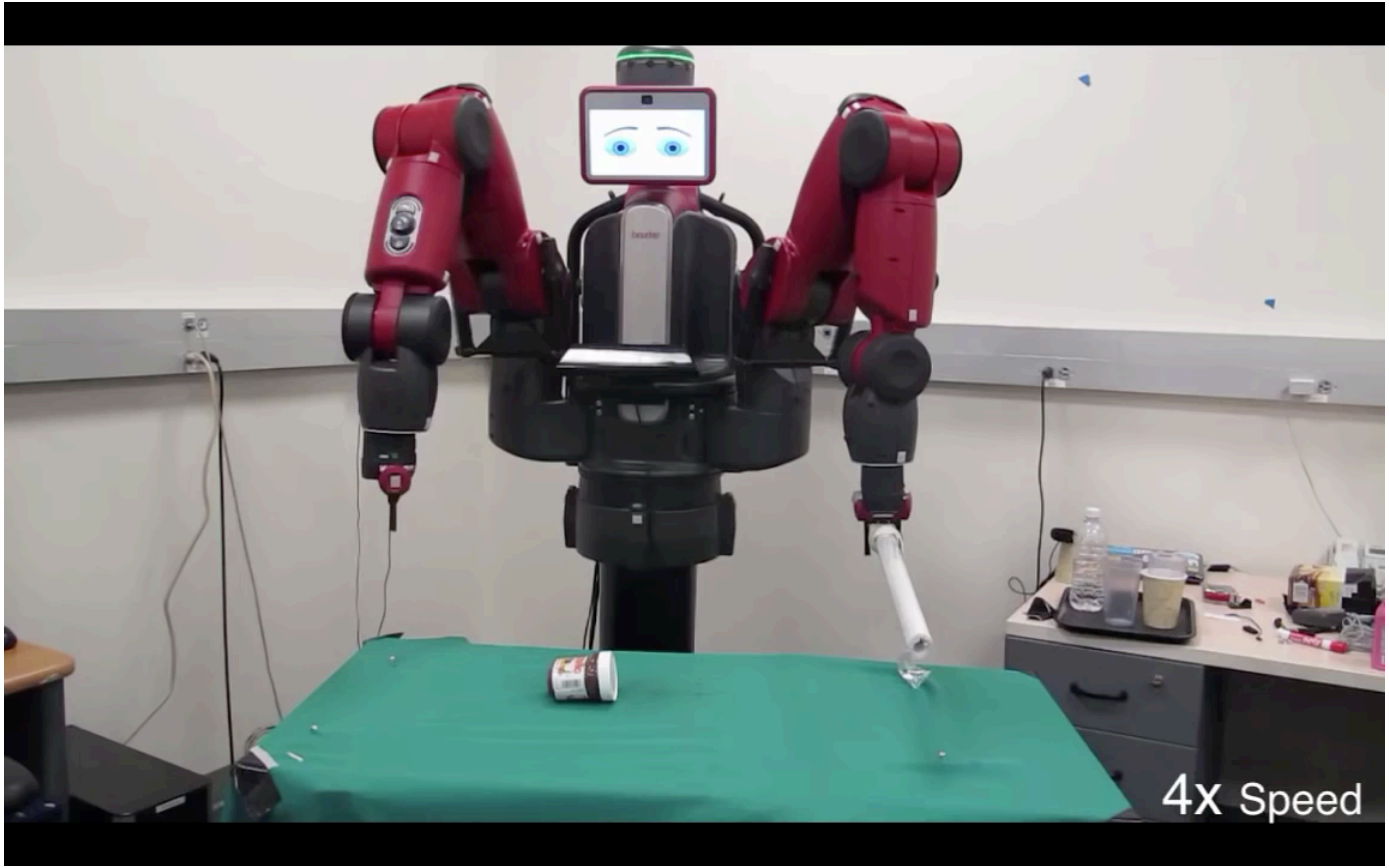


regularize embedding with forward model

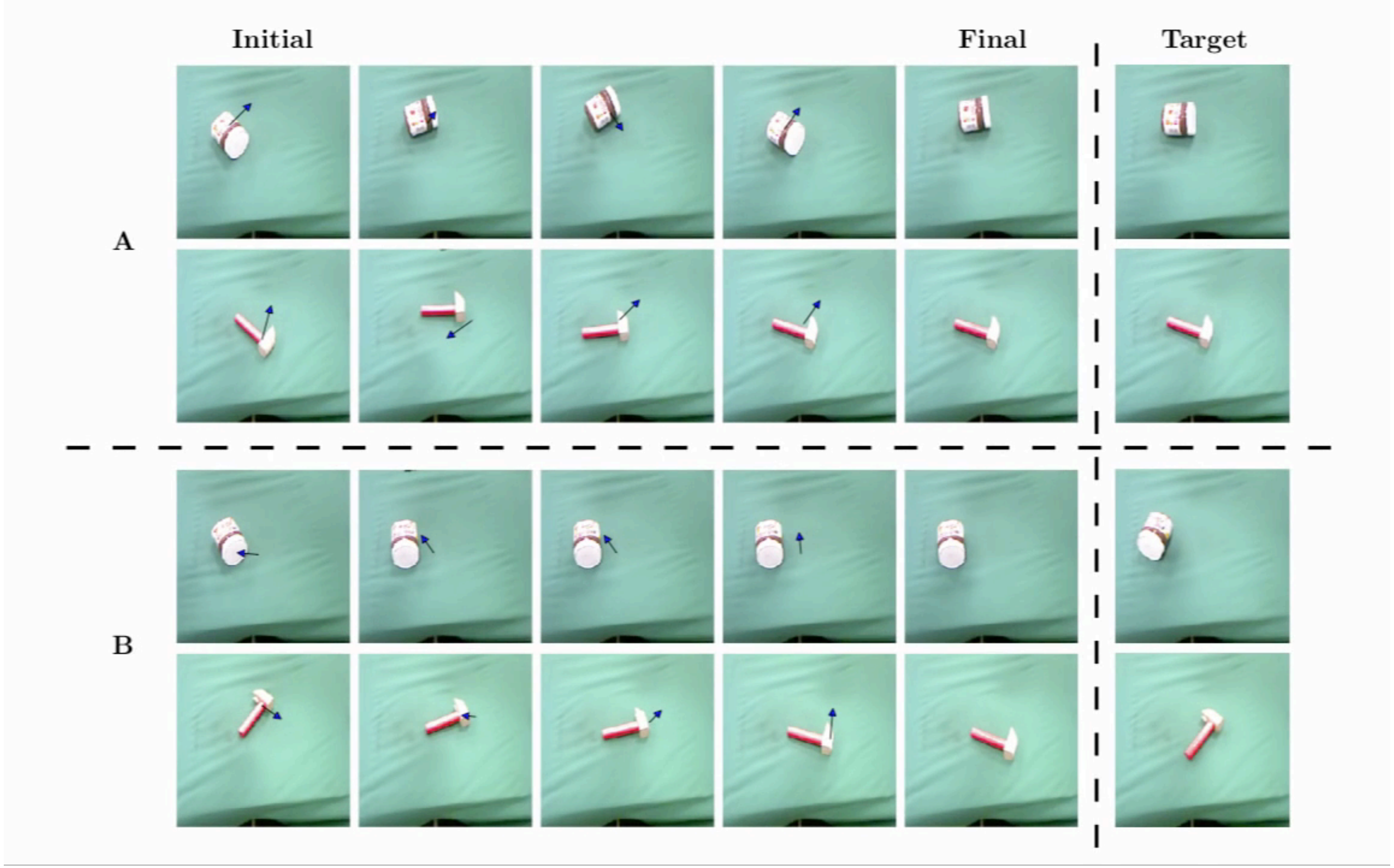
Learn embedding via inverse model $f(\mathbf{o}_t, \mathbf{o}_{t+1}) = \mathbf{u}_t$

Greedily plan with inverse model and image of goal

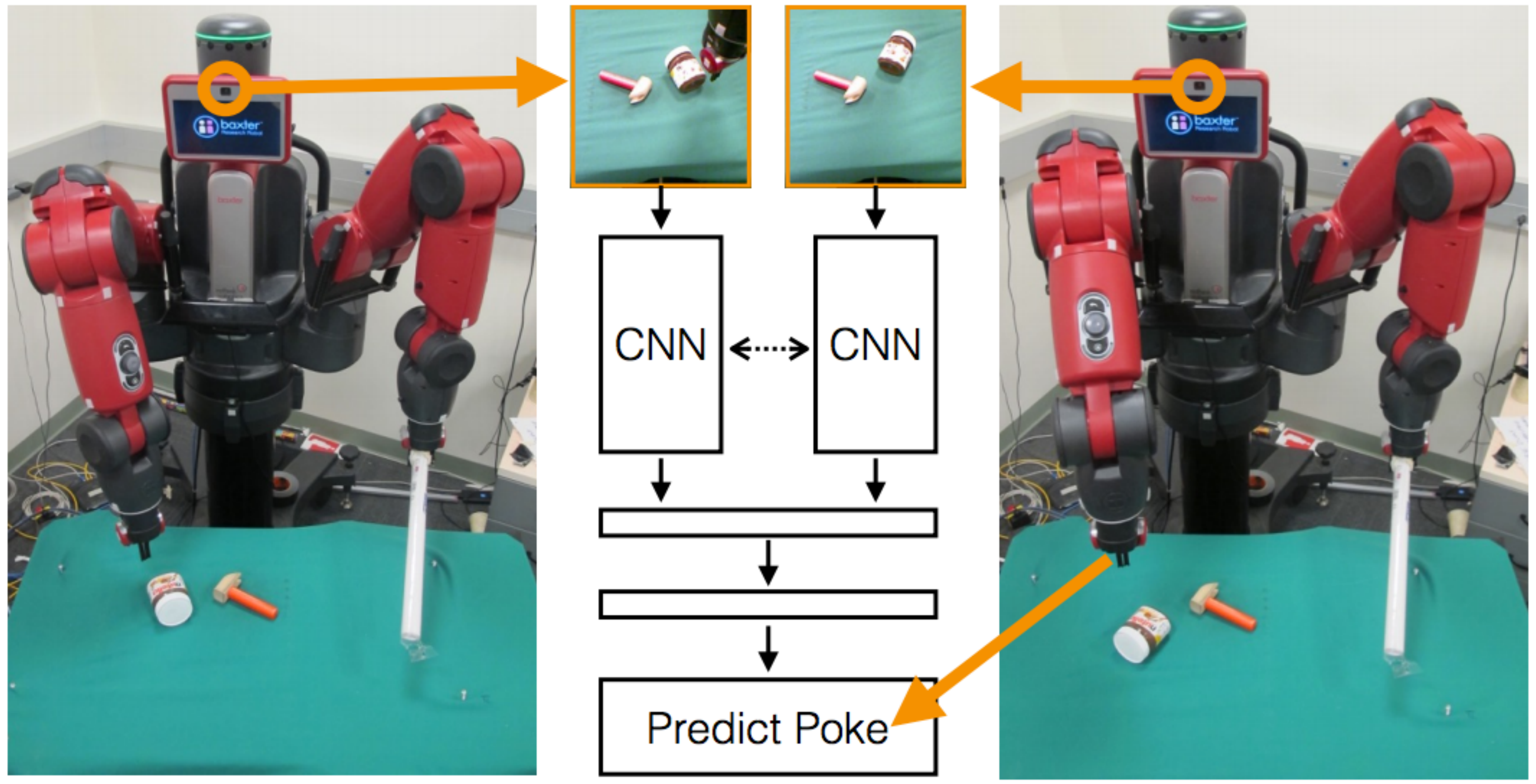



4x Speed

Qualitative Results



Learn embedding via inverse model $f(\mathbf{o}_t, \mathbf{o}_{t+1}) = \mathbf{u}_t$



Pros:

\+ Very limited human involvement (self-supervised)

\+ Don't have to reconstruct image

Cons:

\- Can't plan with inverse model

\- Inverse model objective just cares about action

Model-Based vs. Model-Free Learning

Models:

+ Easy to collect data in a scalable way (self-supervised)
+ Possibility to transfer across tasks
+ Typically require a smaller quantity of supervised data
- Models don't optimize for task performance
- Sometimes harder to learn than a policy
- Often need assumptions to learn complex skills (continuity, resets)

Model-Free:

+ Makes little assumptions beyond a reward function
+ Effective for learning complex policies
- Require a lot of experience (slower)
- Not transferable across tasks

Advanced Model Learning Takeaways

- Learning the **right** features is important

- Need to think about reward/objective when using models of observations

Next time: advanced imitation learning