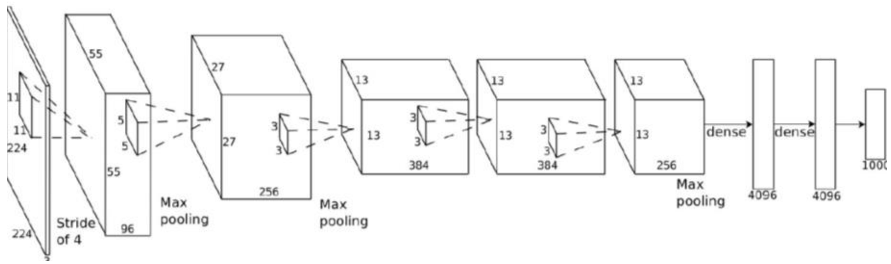
Deep Robotic Learning

Sergey Levine

University of Washington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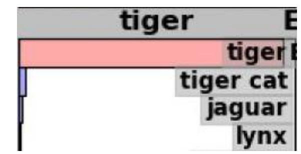
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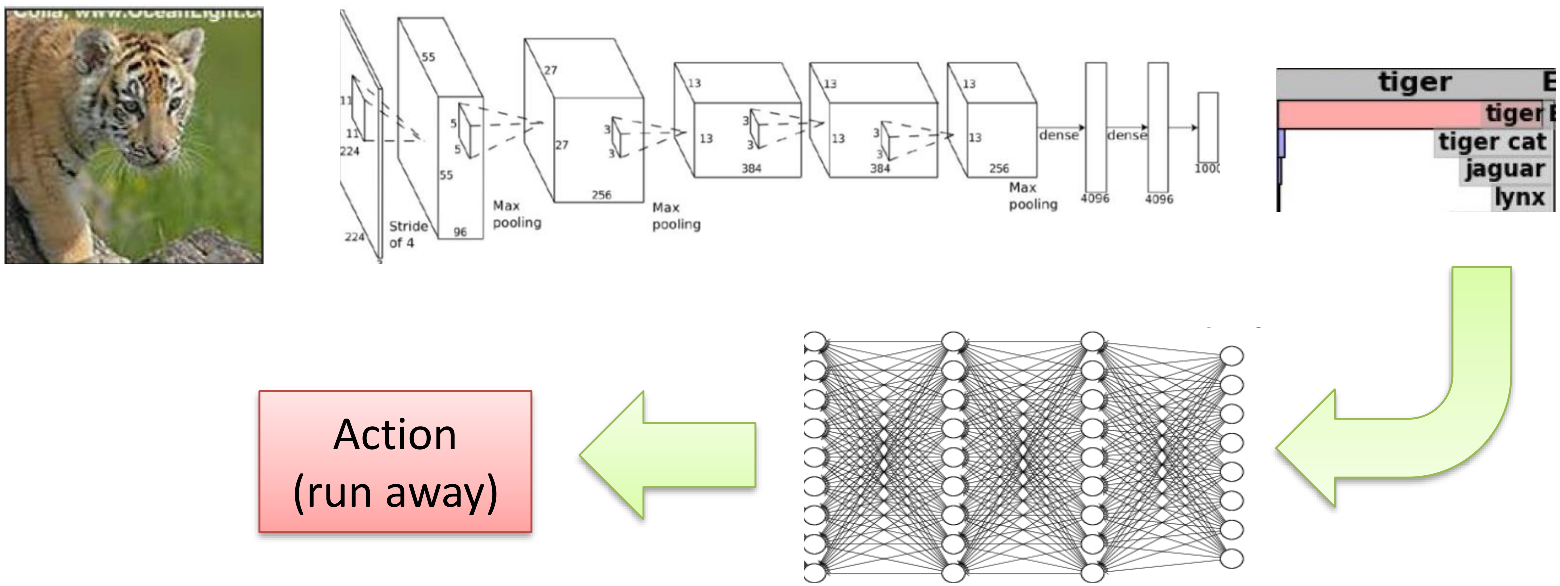
tiger cat
jaguar
lynx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tiger
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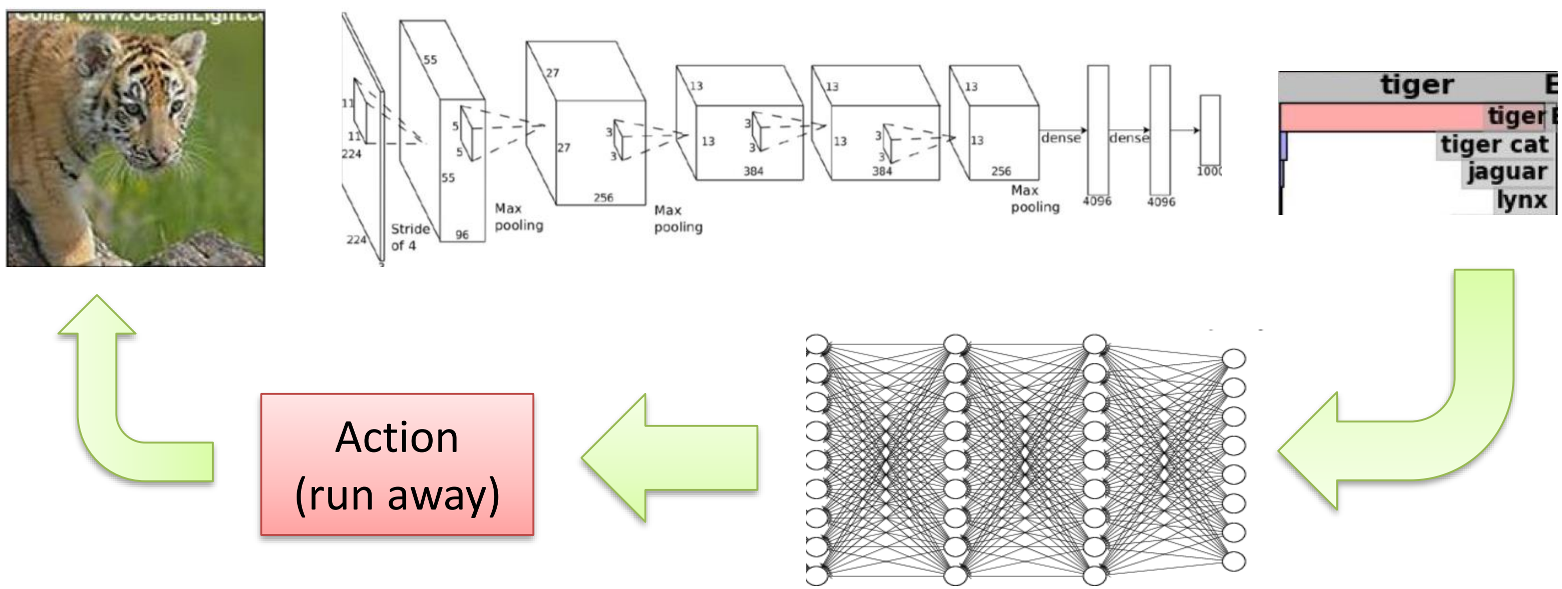
tiger cat
jaguar
lynx
Action
(run away)



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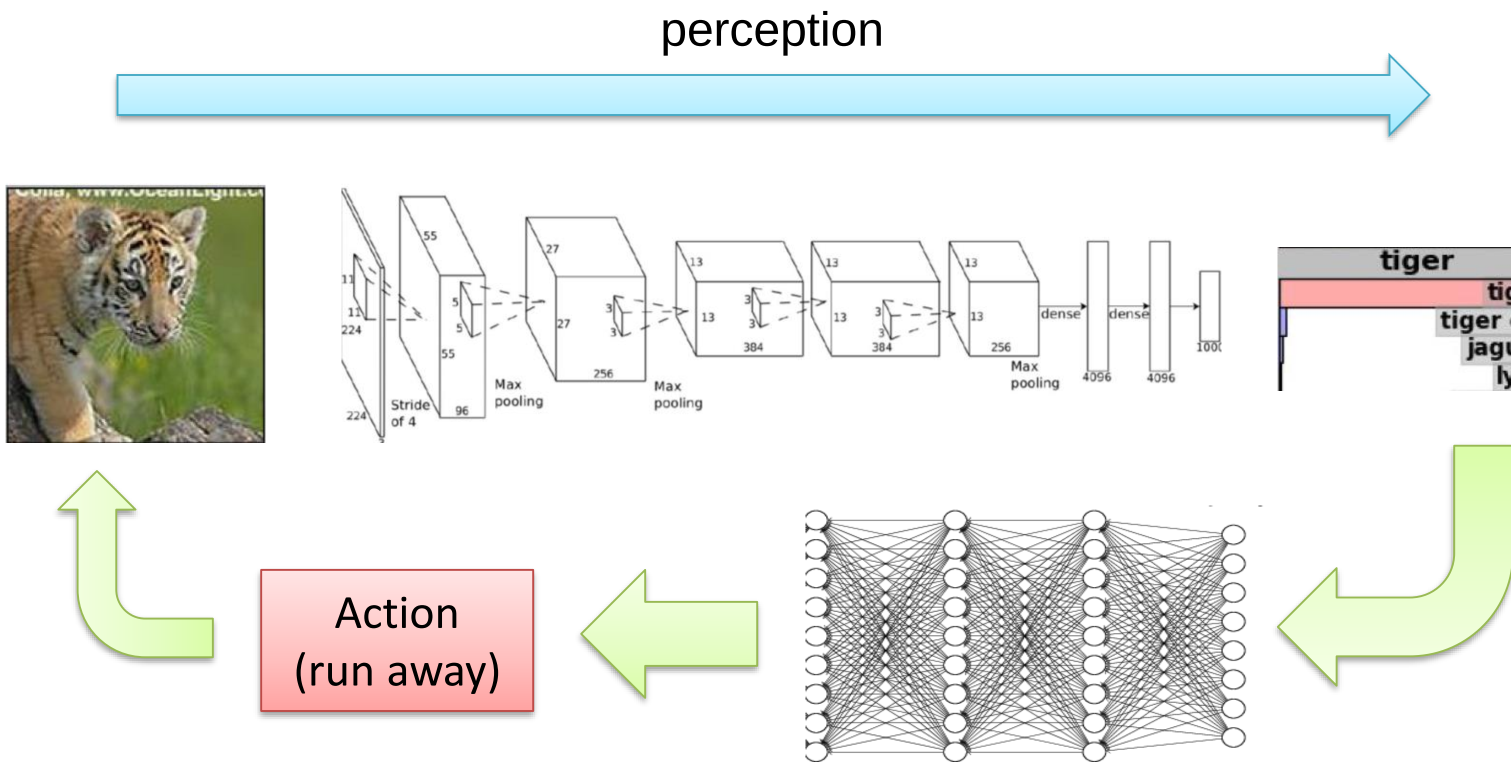
perception
Stride of 4
Max pooling
Max pooling
Max pooling
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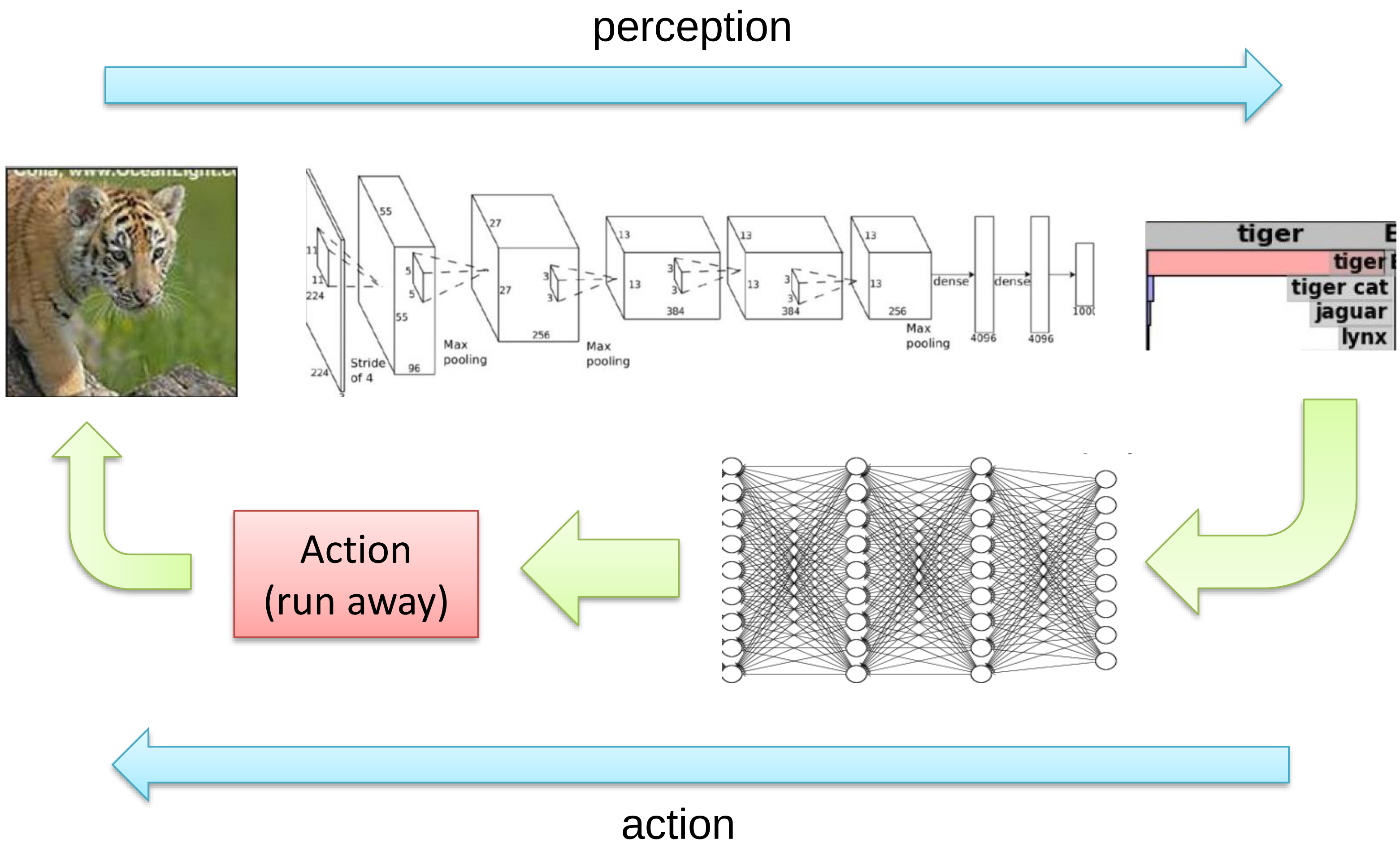
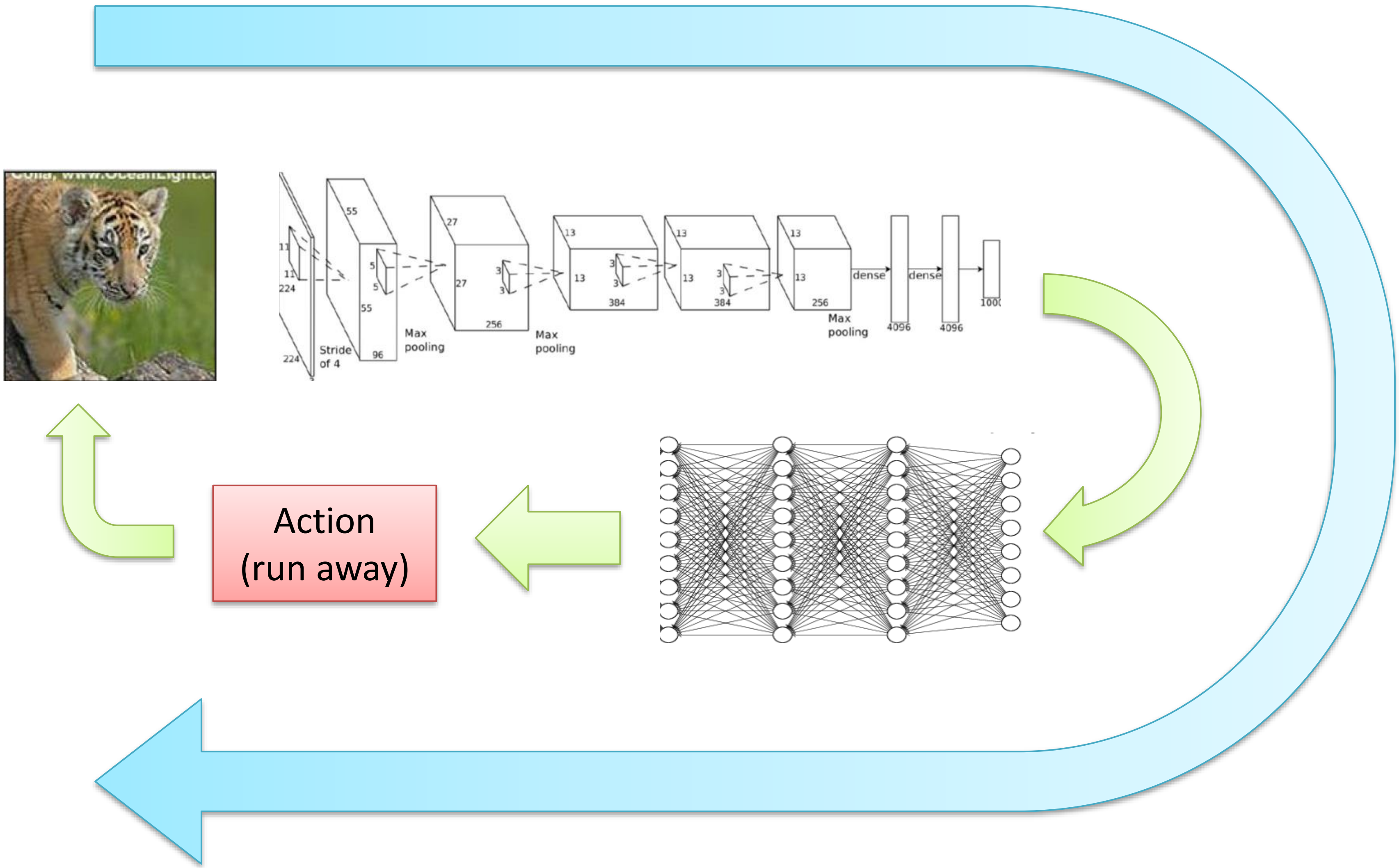
Action
(run away)



perception
Stride of 4
Max pooling
Max pooling
Max pooling
dense
dense
tiger
tiger
tiger cat
jaguar
lynx
Action
(run away)
action

sensorimotor loop



"When a man throws a ball high in the air and catches it again, he behaves as if he had solved a set of differential equations in predicting the trajectory of the ball … at some subconscious level, something functionally equivalent to the mathematical calculations is going on."

-- Richard Dawkins

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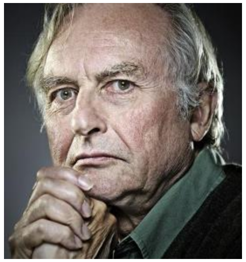
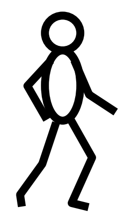


McLeod & Dienes. Do fielders know where to go to catch the ball or only how to get there? Journal of Experimental Psychology 1996, Vol. 22, No. 3, 531-543



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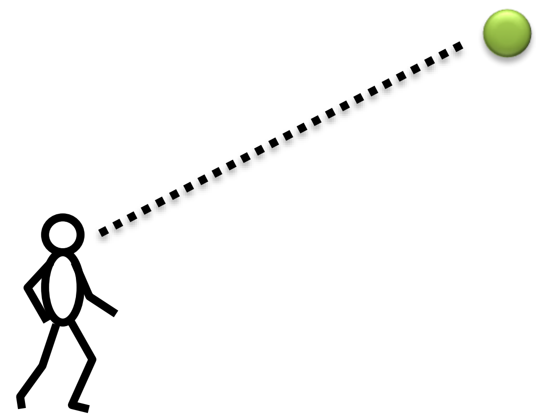

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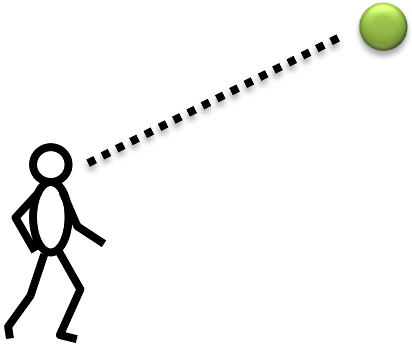

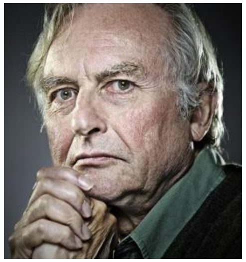

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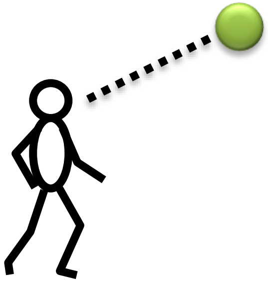

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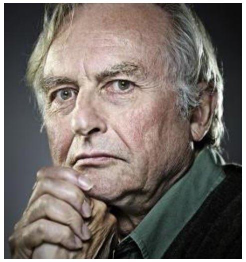

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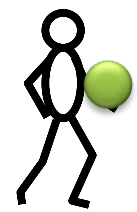

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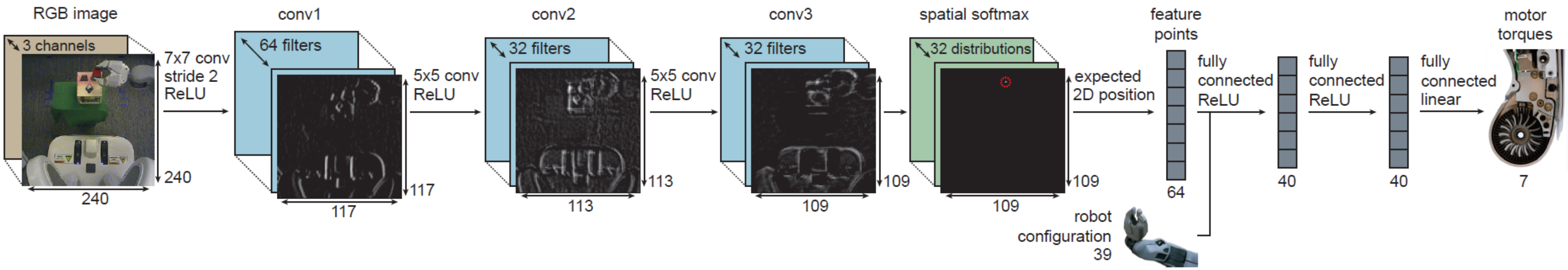
KAIST’s DRC-HUBO opening a door

DARPA Robotics Challenge 2015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spatial softmax
32 distributions
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2D position
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points
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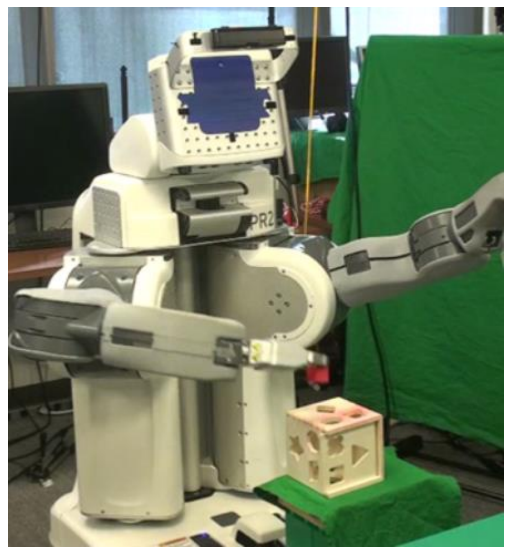

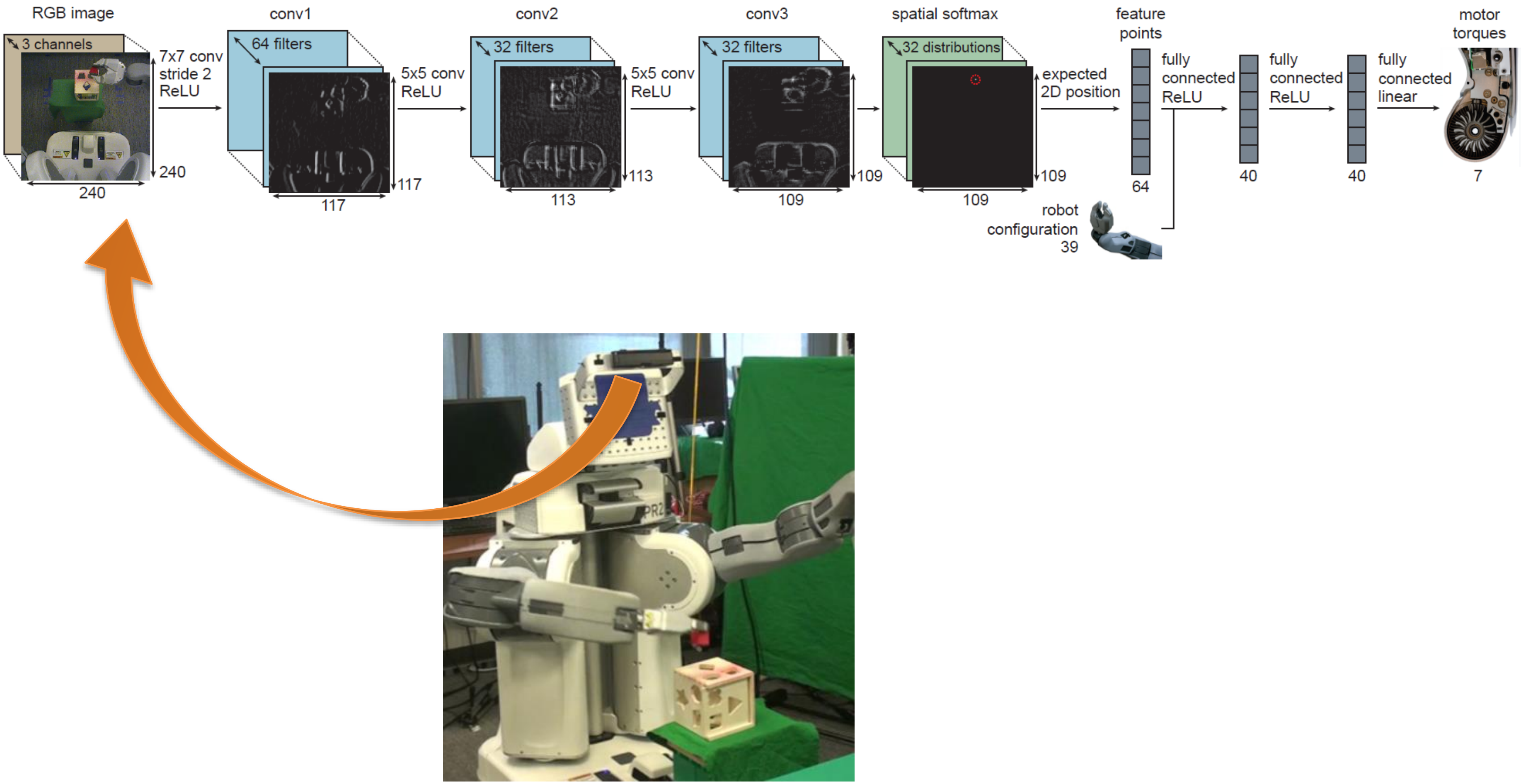
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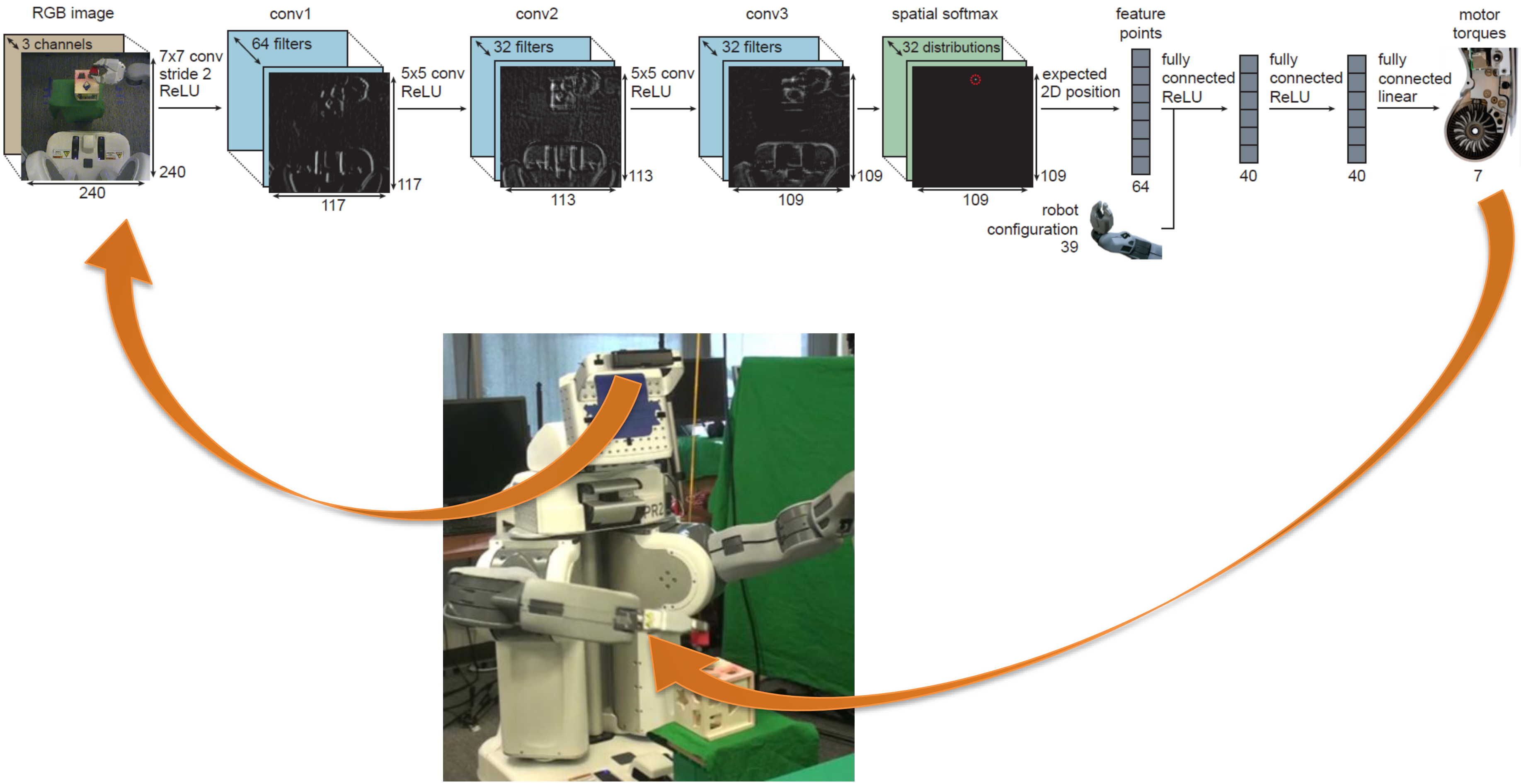

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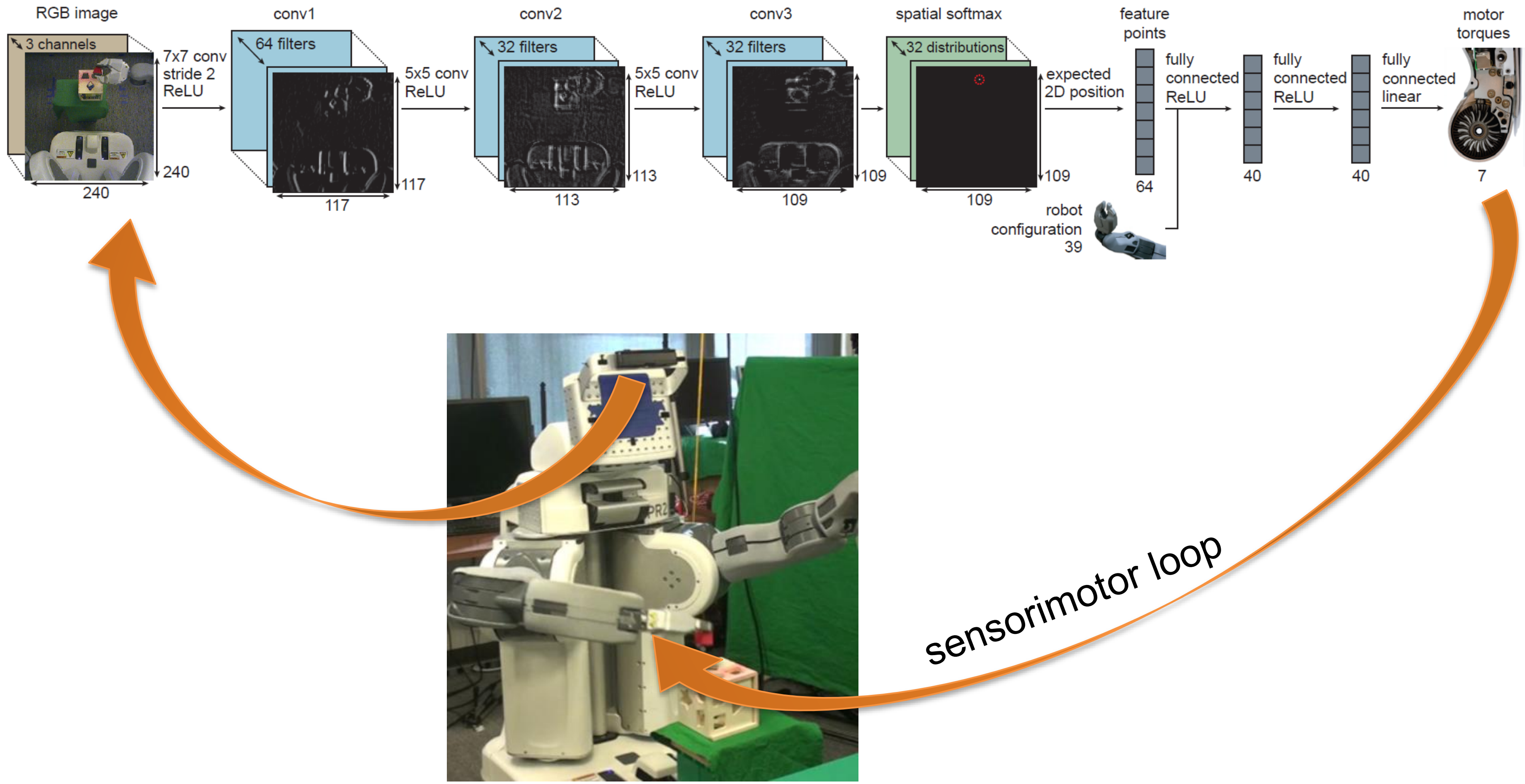
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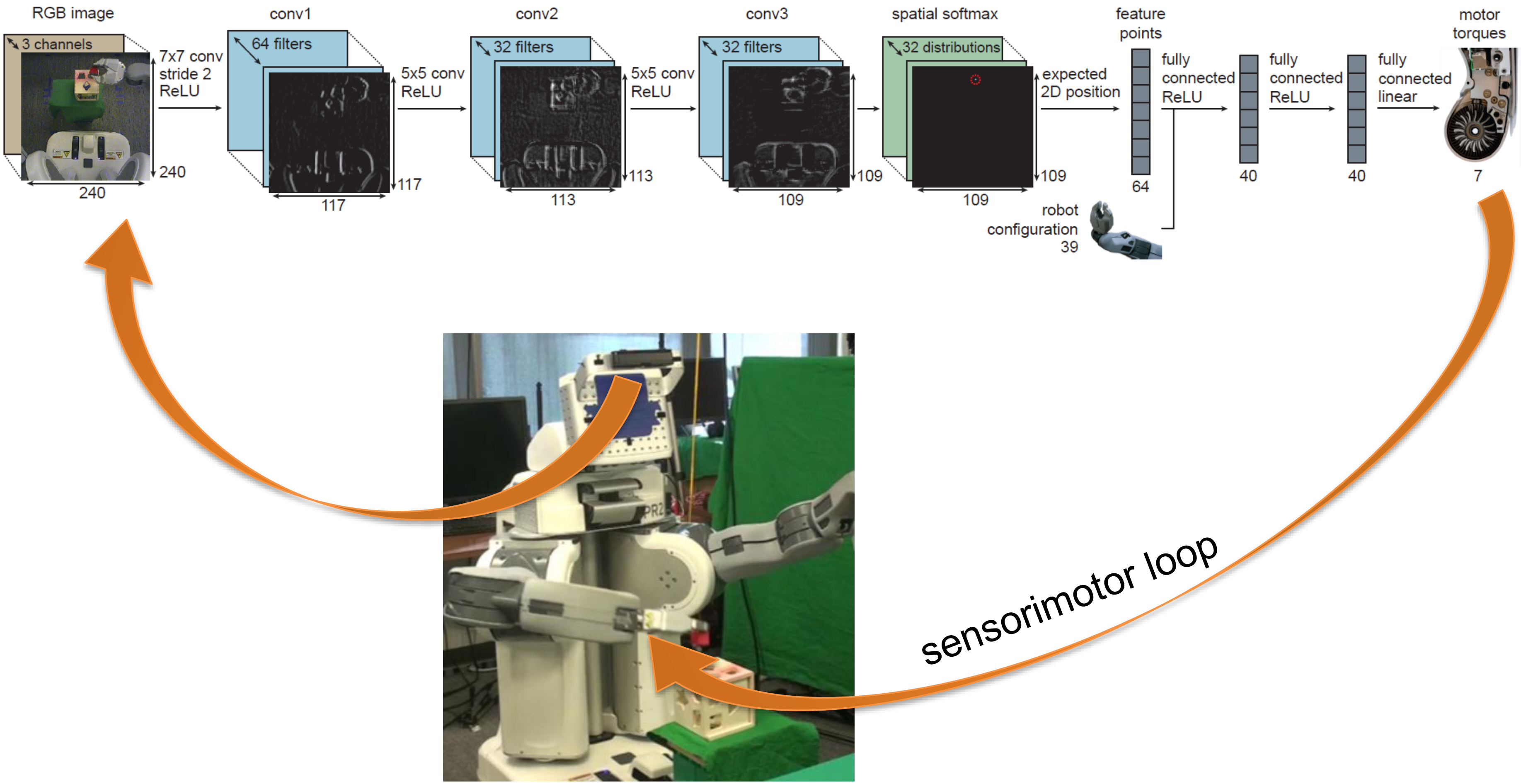
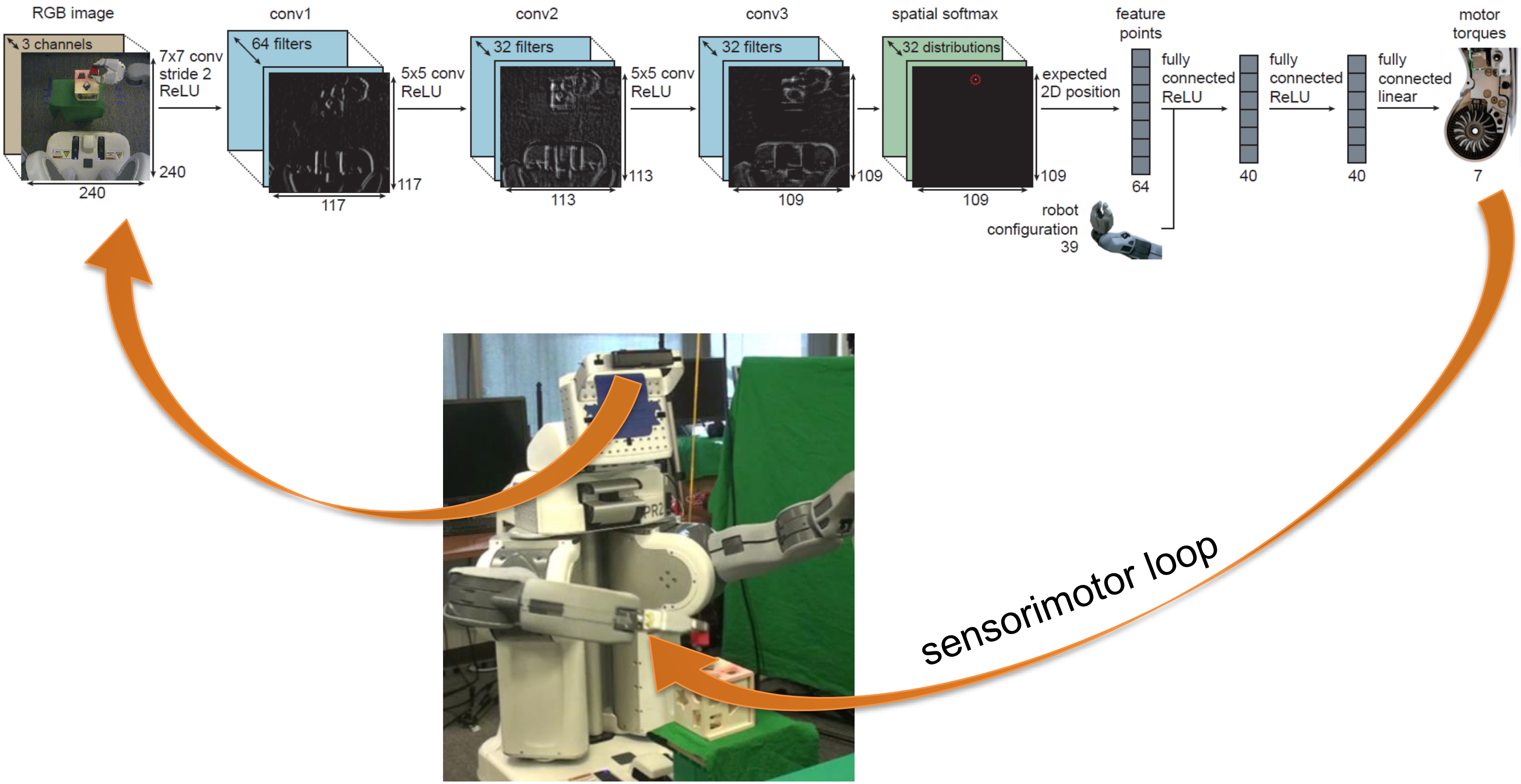


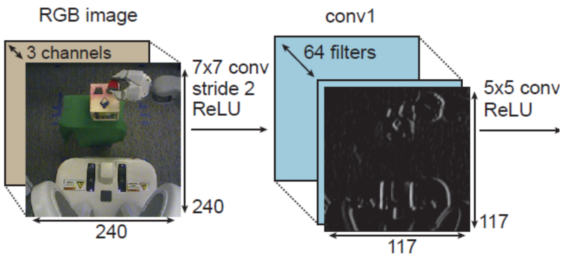
no direct supervision



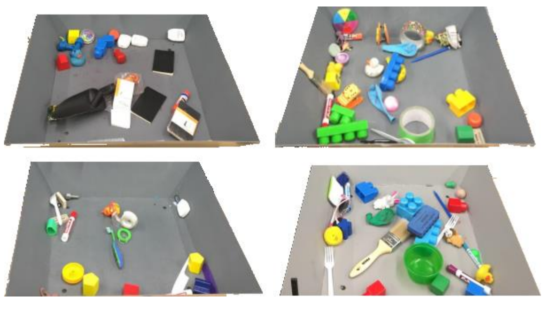
no direct supervision

actions have consequences

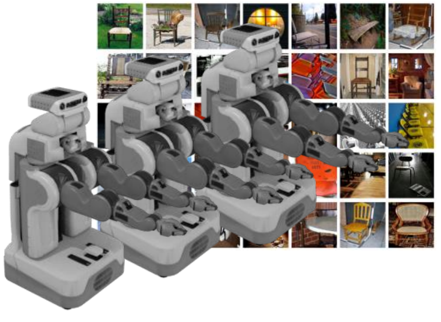
Overview



Training visuomotor policies

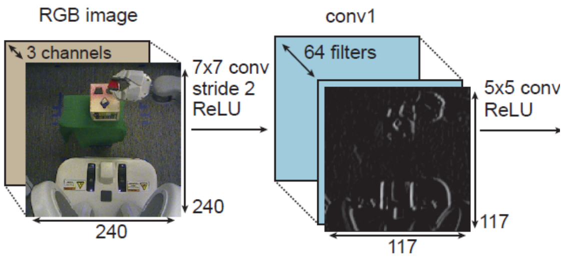


Deep robotic learning at scale



Future directions

Overview



Training visuomotor policies

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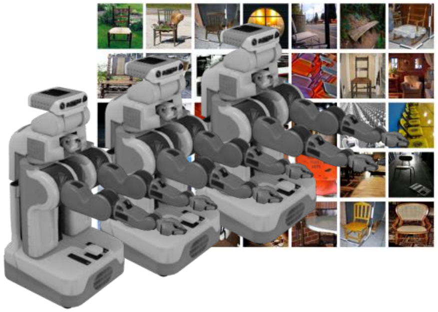

Future directions

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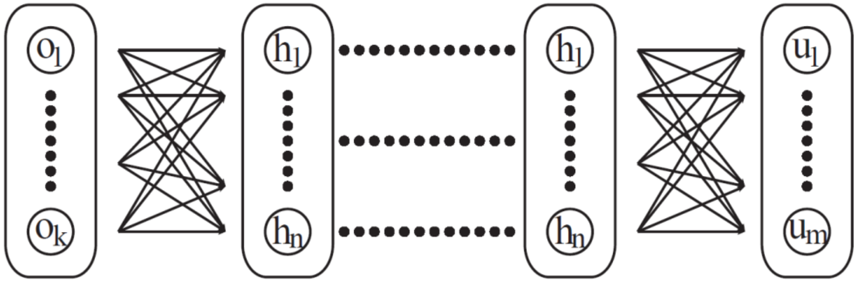
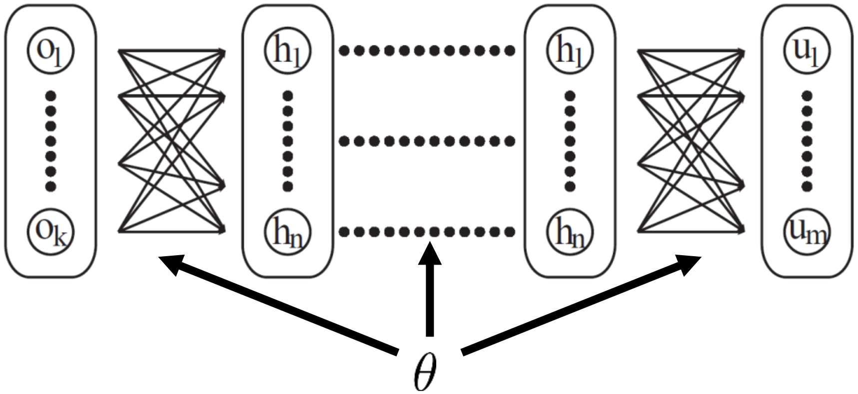


general-purpose neural network policy

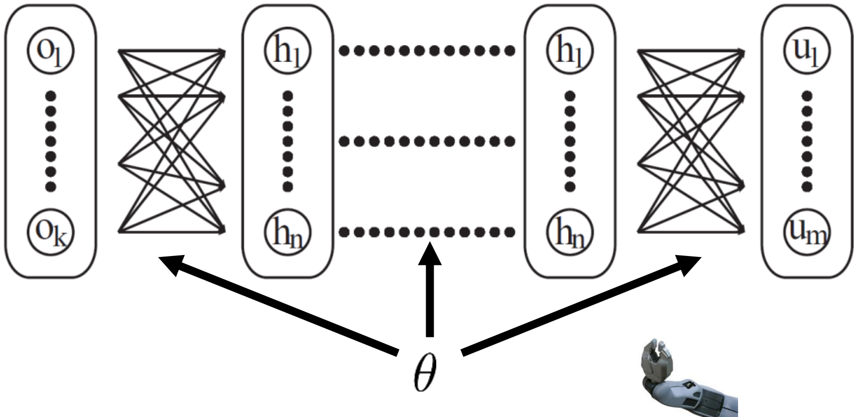


$$\theta = \arg\min_\theta E_{\pi_\theta}[\sum_{t=1}^T c(\mathbf{x}_t, \mathbf{u}_t)]$$

$$\pi_\theta(\mathbf{u}_t|\mathbf{o}_t) \text{ -- control policy}$$

$$\mathbf{o}_t \text{ -- observation (may or may not be equal to } \mathbf{x}_t\text{)}$$

general-purpose neural network policy



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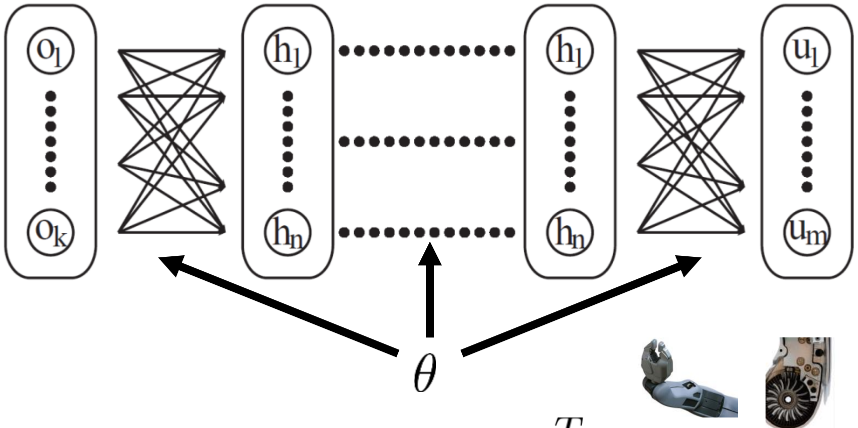

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$\pi_\theta(\mathbf{u}_t|\mathbf{o}_t)$ – control policy

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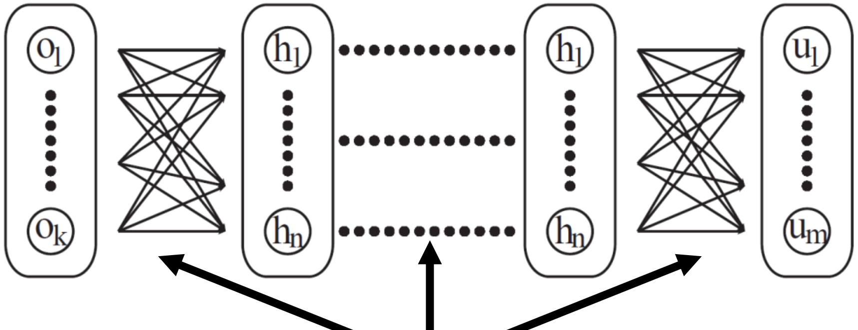

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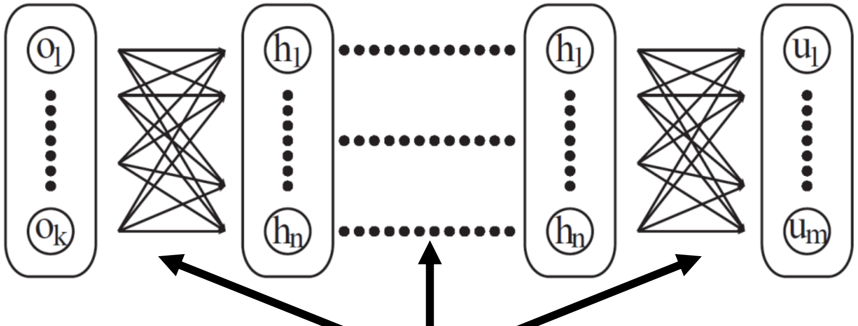

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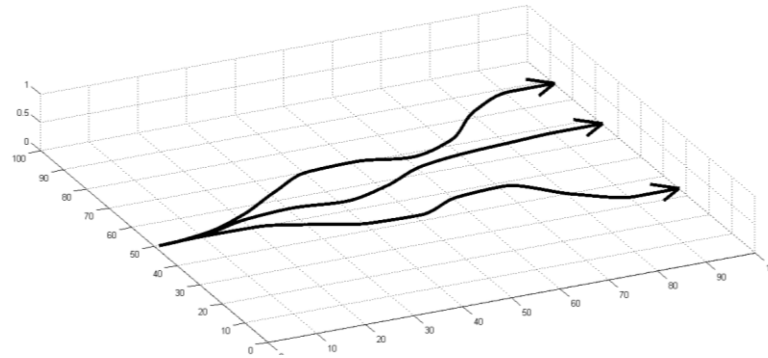

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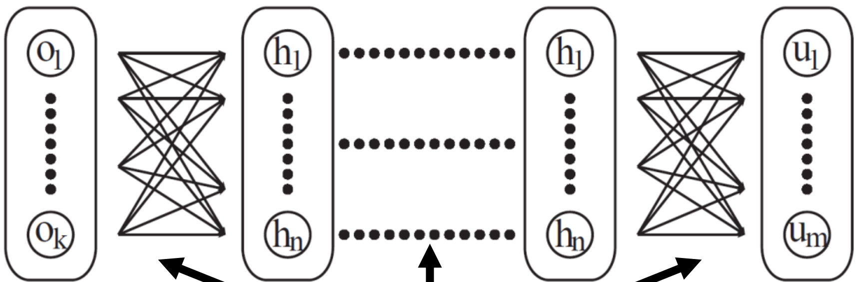

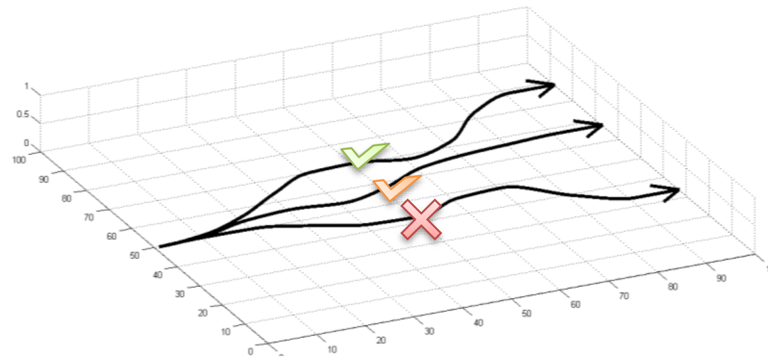

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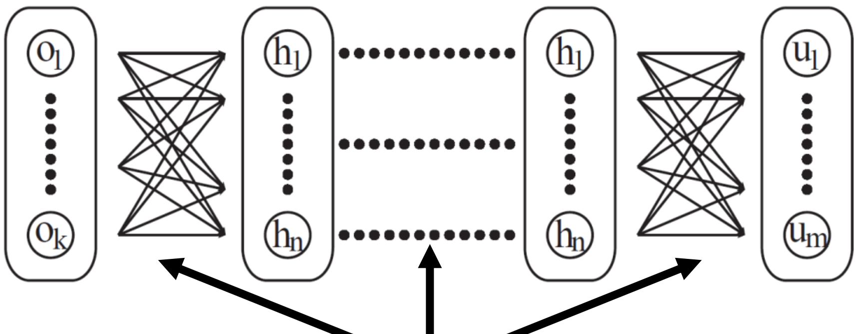

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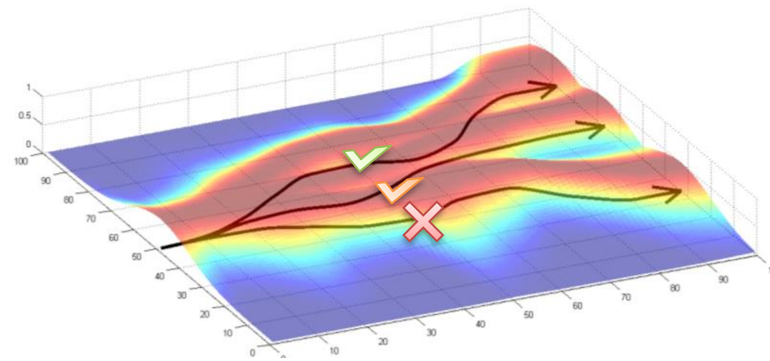

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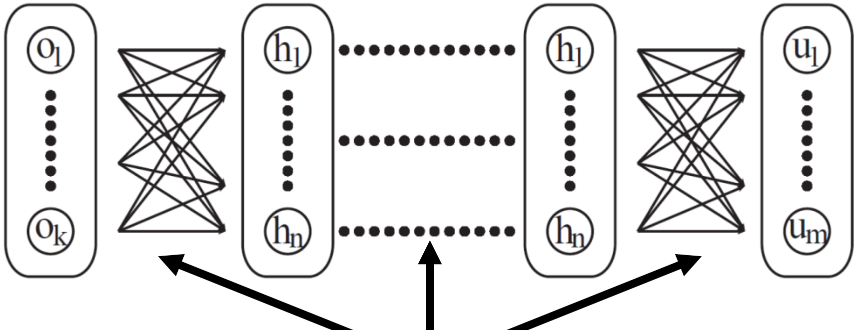

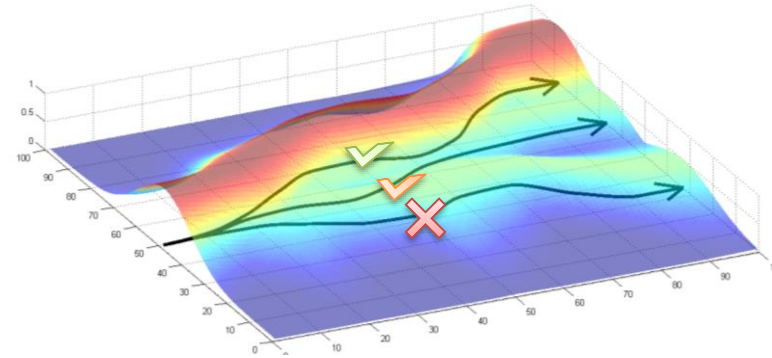

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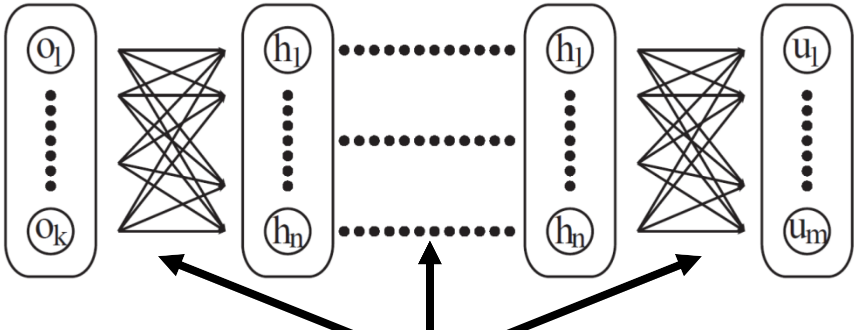

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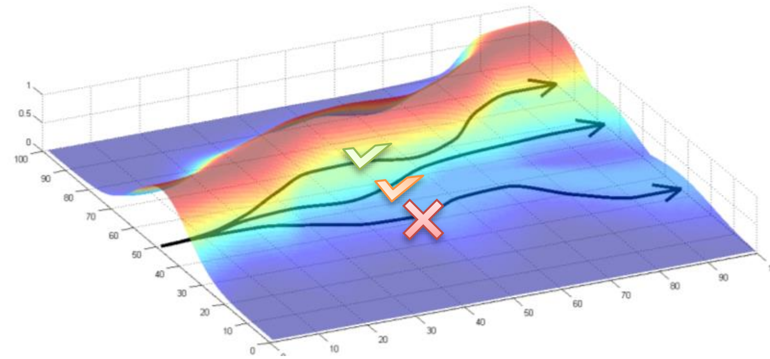

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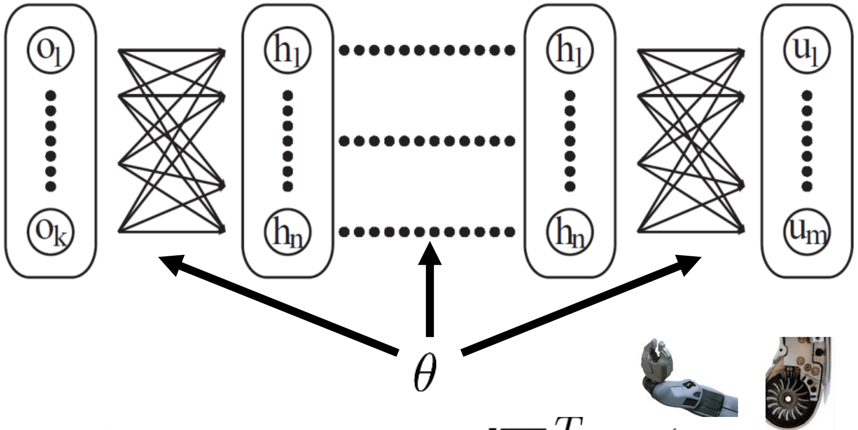

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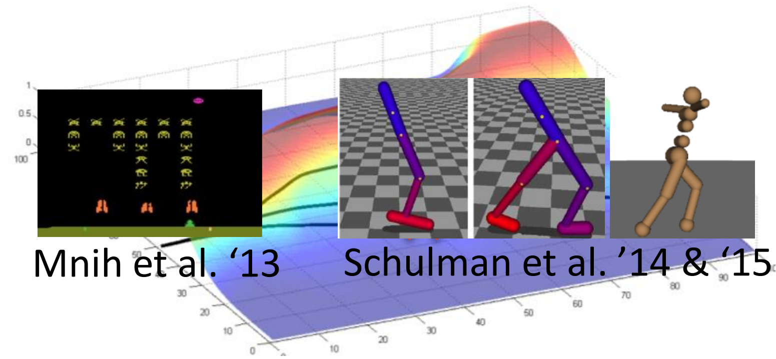
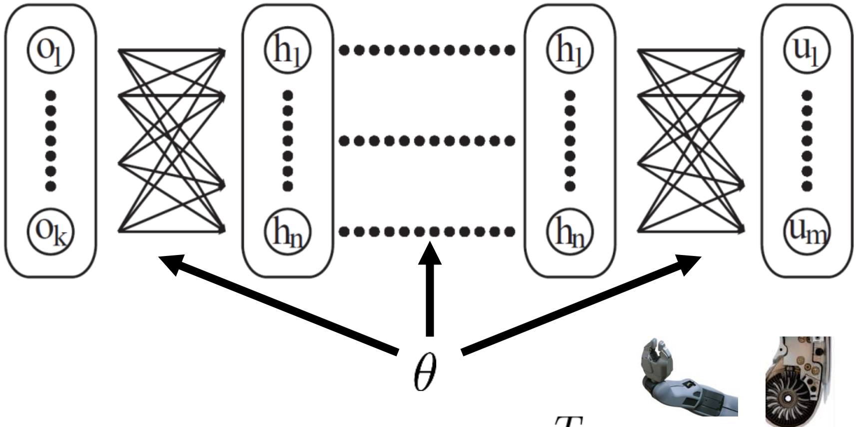


Mnih et al. '13 Schulman et al. '14 & '15

general-purpose neural network policy



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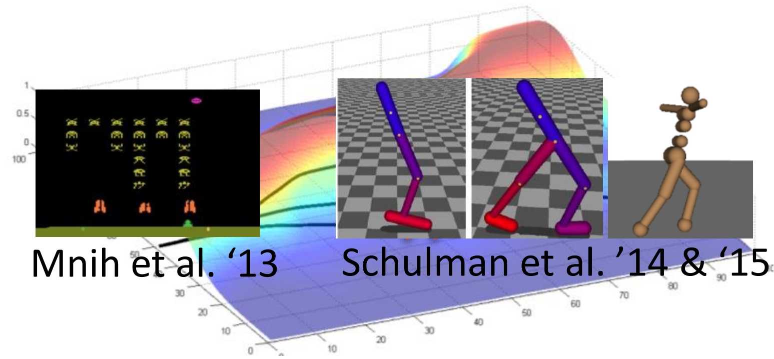
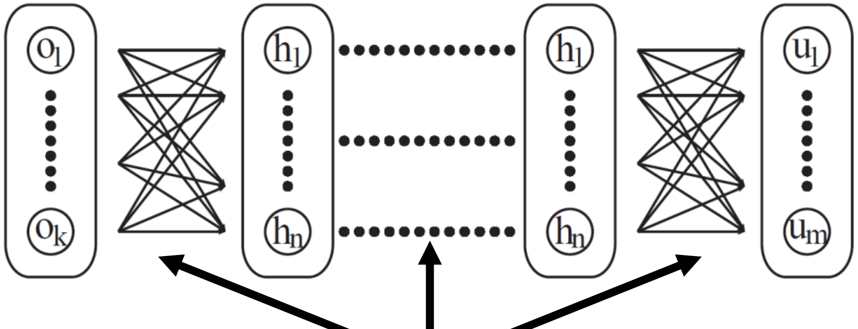


Mnih et al. '13 Schulman et al. '14 & '15

policy search (RL)

general-purpose neural network policy



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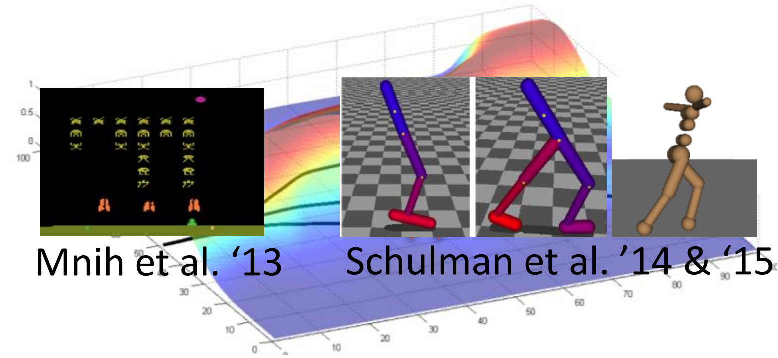
$$\mathbf{o}_t \text{ – observation (may or may not be equal to } \mathbf{x}_t\text{)}$$



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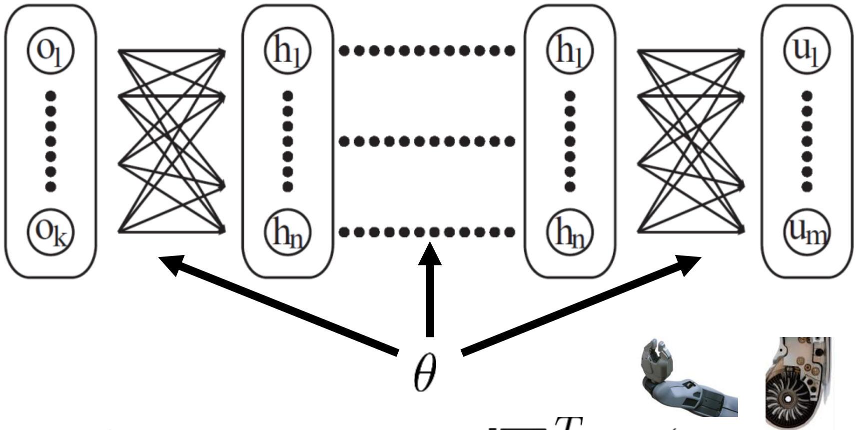
policy search (RL)

complex dynamics

general-purpose neural network policy



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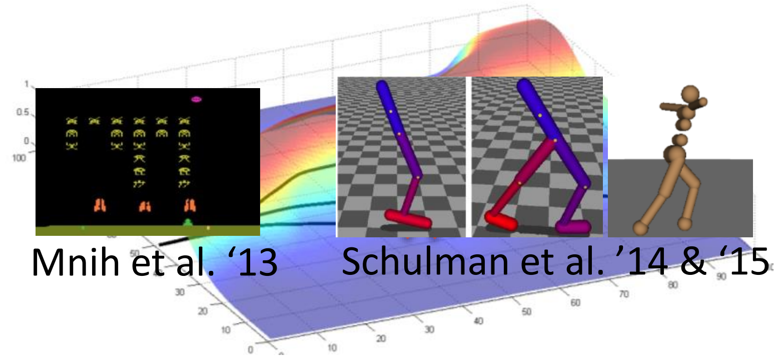

policy search (RL)

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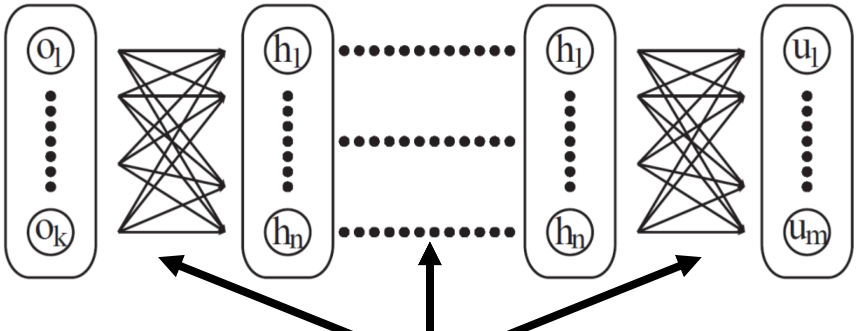

θ

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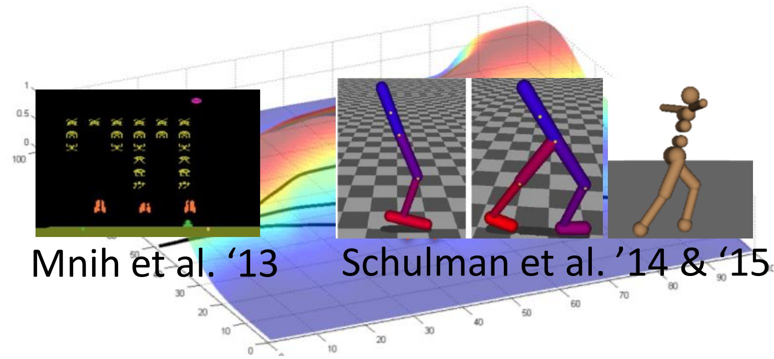
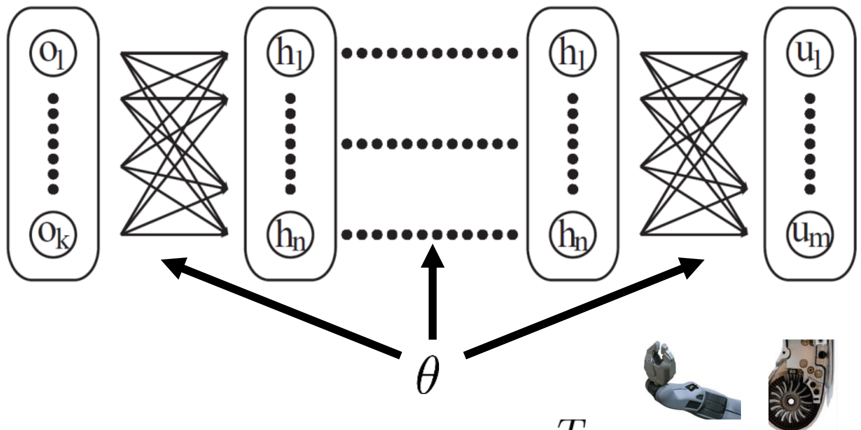


policy search (RL) complex dynamics complex policy HARD

general-purpose neural network policy



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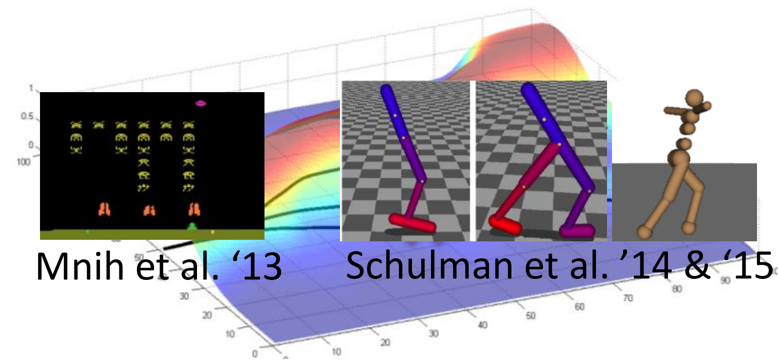
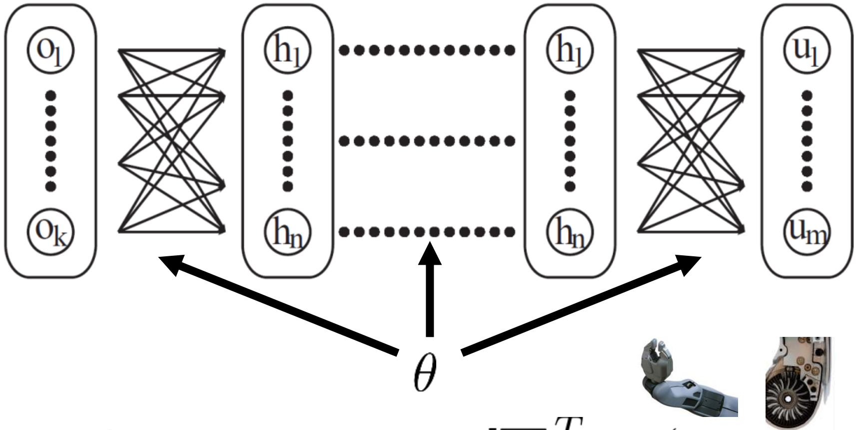


policy search (RL) complex dynamics complex policy HARD

supervised learning

general-purpose neural network policy



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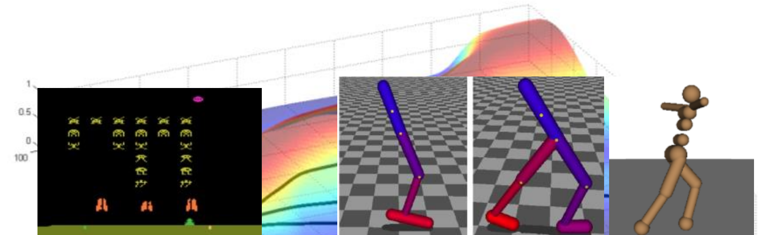

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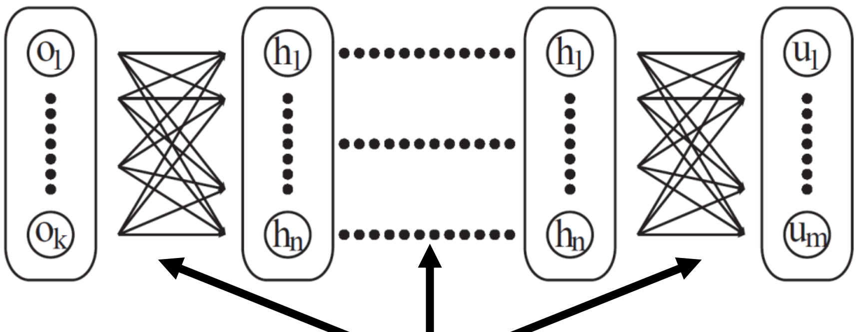
$$\mathbf{o}_t - \text{observation (may or may not be equal to } \mathbf{x}_t)$$

policy search (RL) complex dynamics complex policy HARD

supervised learning ~~complex dynamics~~

general-purpose neural network policy



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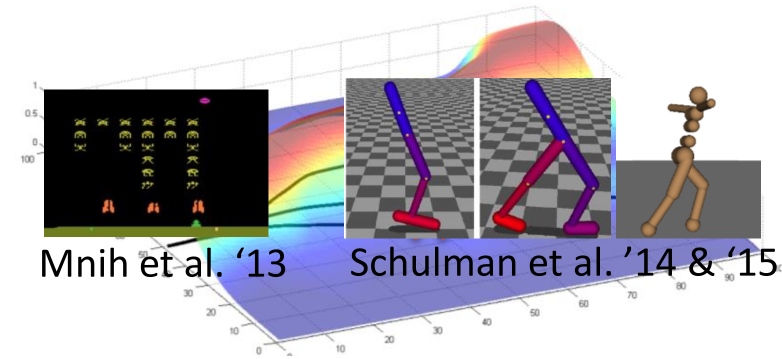

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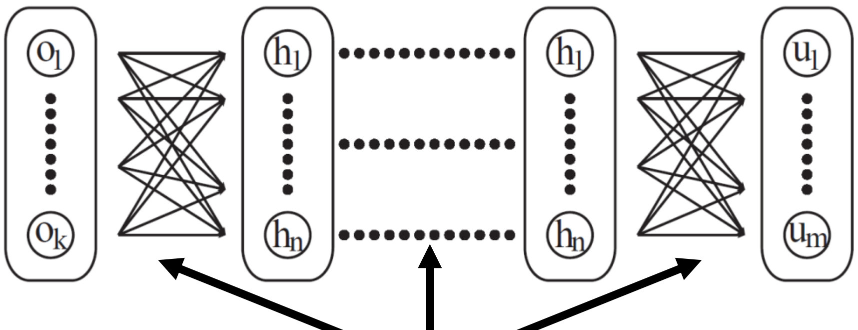
policy search (RL) complex dynamics complex policy HARD

supervised learning ~~complex dynamics~~ complex policy

general-purpose neural network policy



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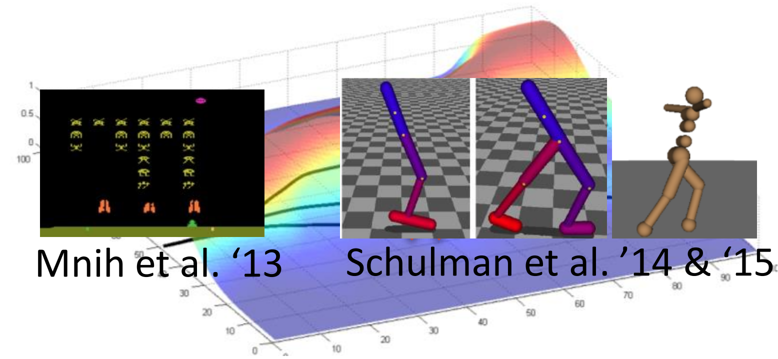
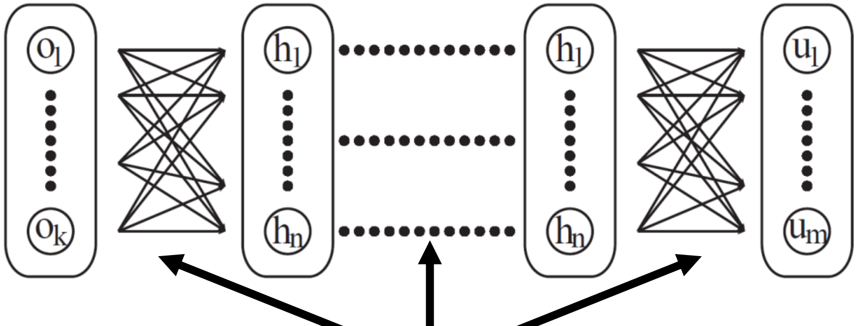


$$\mathbf{o}_t \text{ – observation (may or may not be equal to } \mathbf{x}_t)$$

policy search (RL)	complex dynamics	complex policy	HARD
supervised learning	~~complex dynamics~~	complex policy	EASY

general-purpose neural network policy



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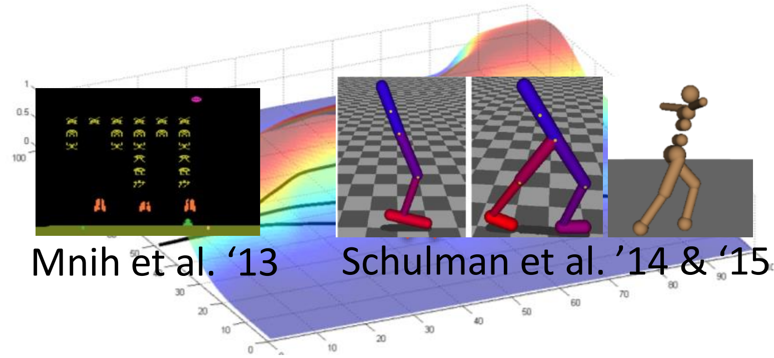

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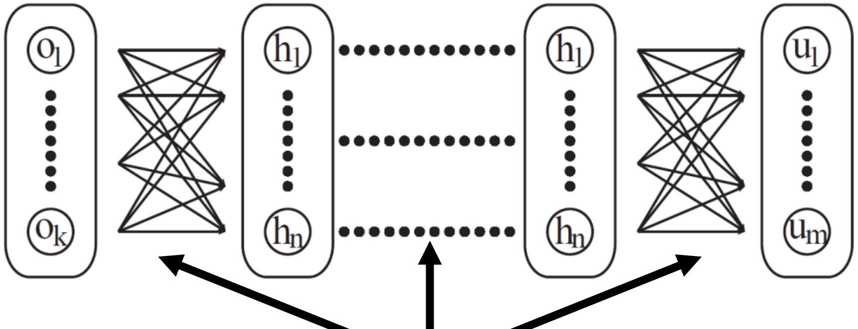
$$\mathbf{o}_t \text{ -- observation (may or may not be equal to } \mathbf{x}_t)$$

policy search (RL)	complex dynamics	complex policy	HARD
supervised learning	~~complex dynamics~~	complex policy	EASY
optimal control			

general-purpose neural network policy



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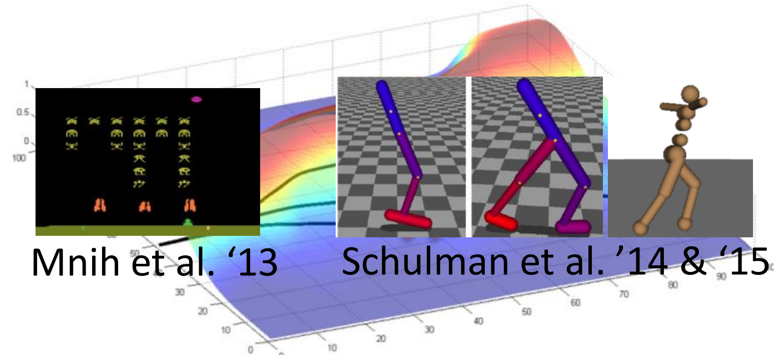

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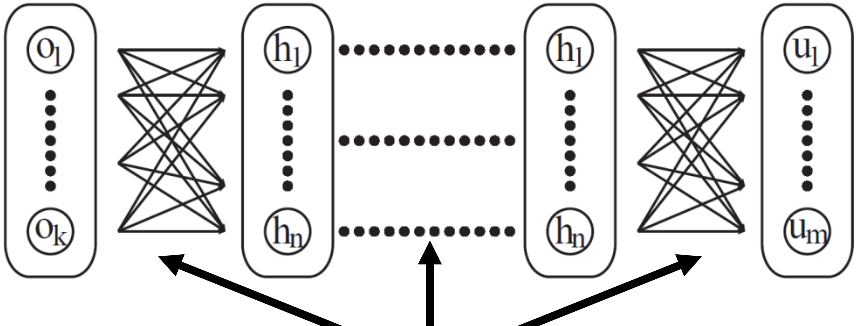
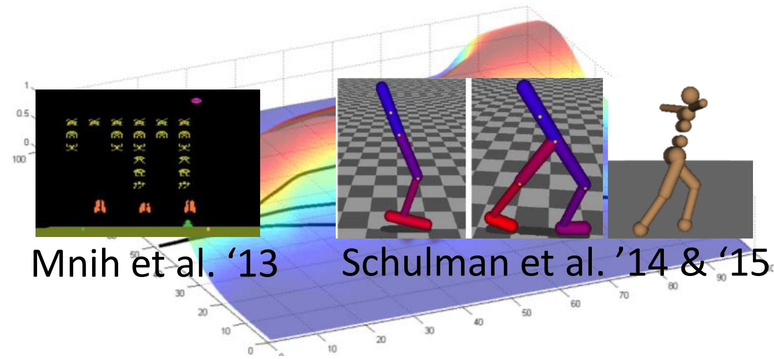
policy search (RL)	complex dynamics	complex policy	HARD
supervised learning	~~complex dynamics~~	complex policy	EASY
optimal control	complex dynamics		

general-purpose neural network policy





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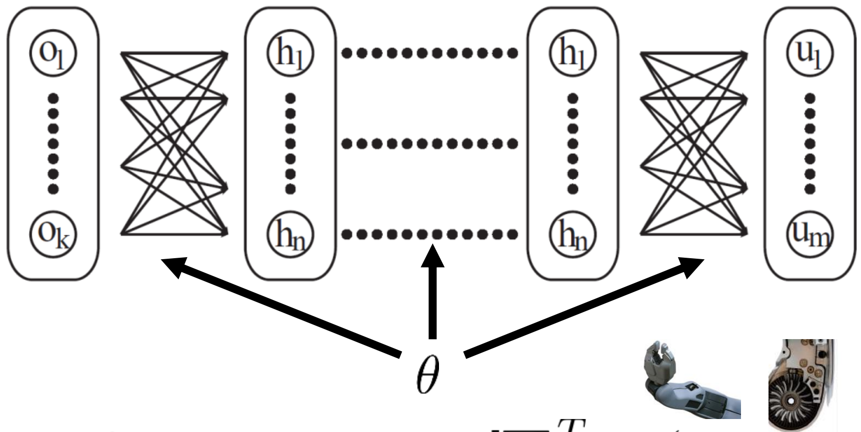
policy search (RL)	complex dynamics	complex policy	HARD
supervised learning	~~complex dynamics~~	complex policy	EASY
optimal control	complex dynamics	~~complex policy~~	

general-purpose neural network policy



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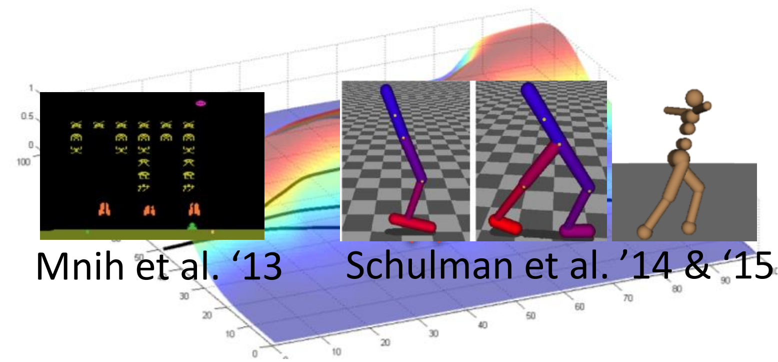

$\mathbf{o}_t$ – observation (may or may not be equal to $\mathbf{x}_t$)

policy search (RL)	complex dynamics	complex policy	HARD
supervised learning	~~complex dynamics~~	complex policy	EASY
optimal control	complex dynamics	~~complex policy~~	EASY

1. break up the task:
   separately solve N
   different task instances

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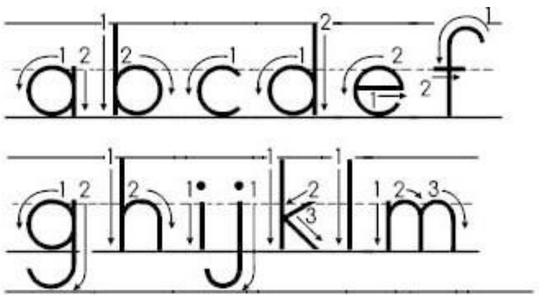

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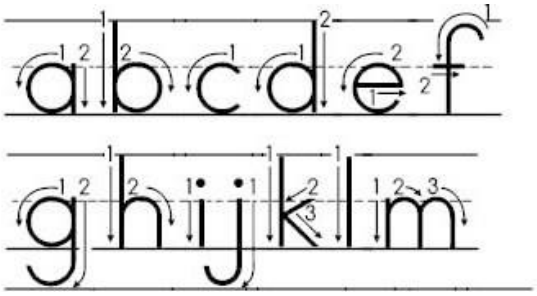

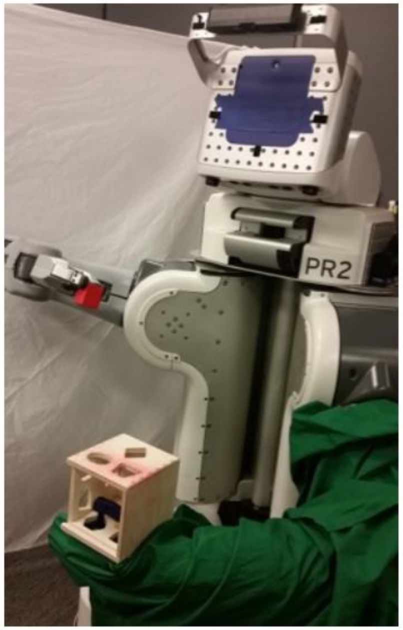

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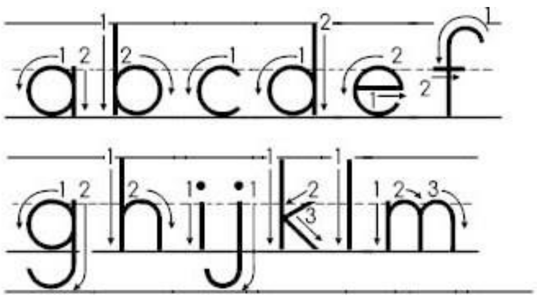

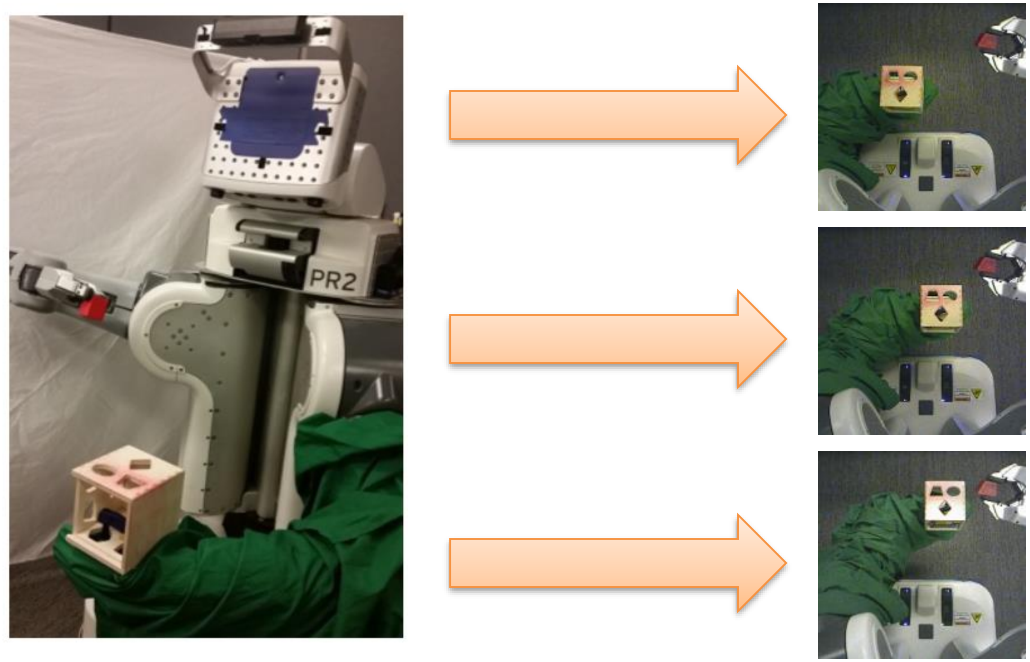

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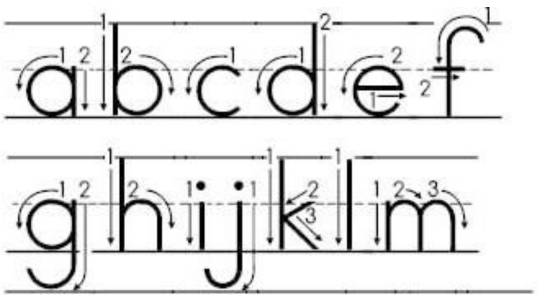

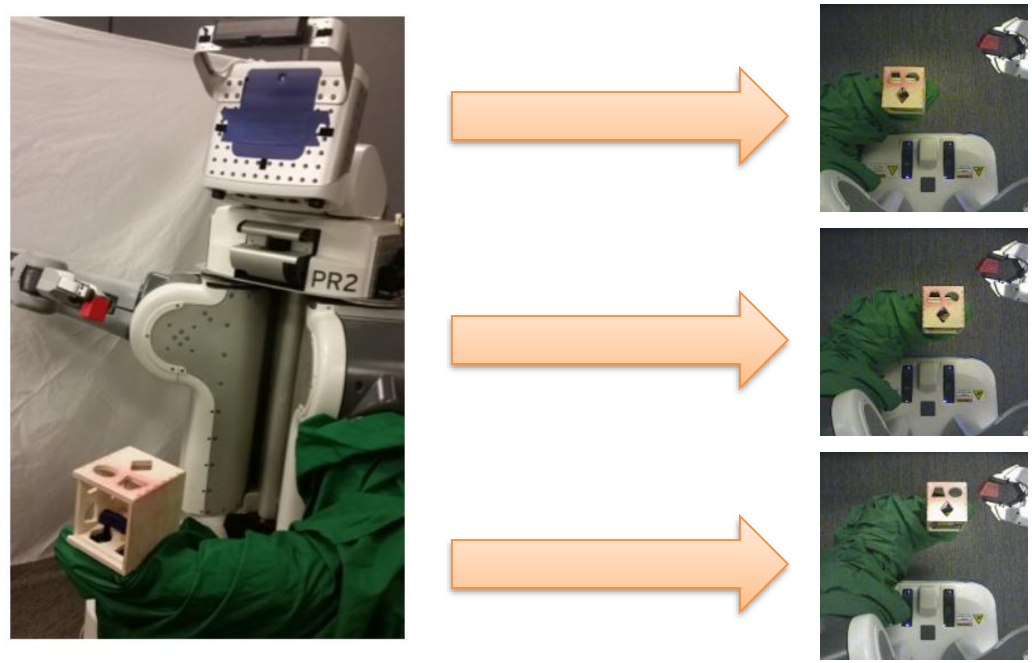

2. use supervised learning

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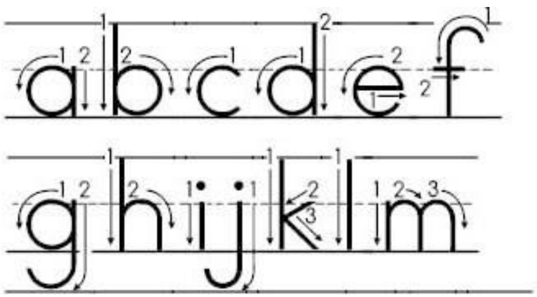
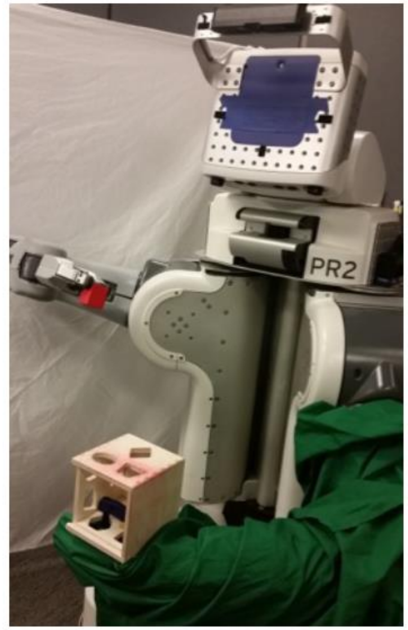
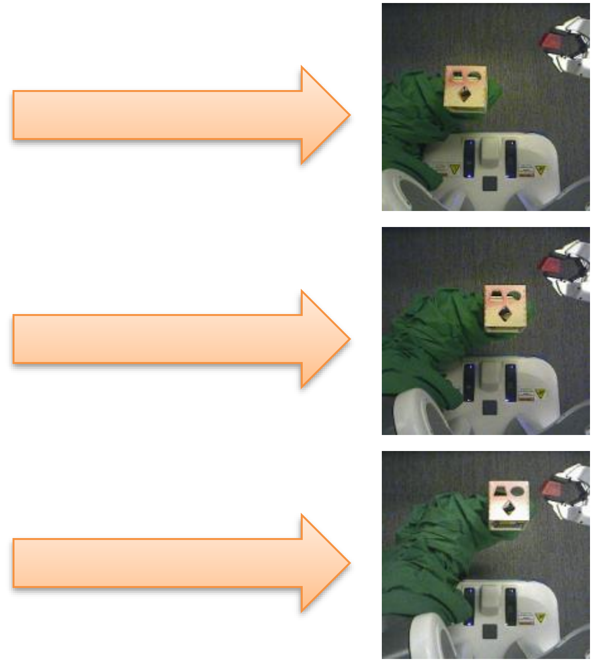
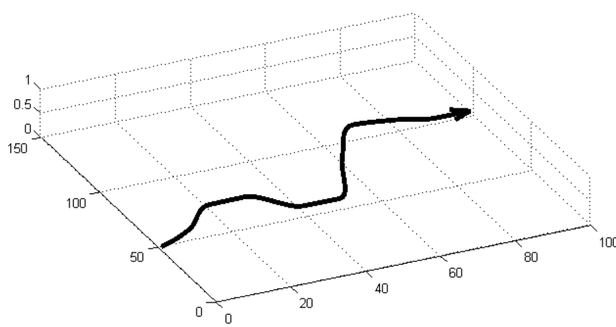






2. use supervised learning

trajectory-centric RL
(fully observed)



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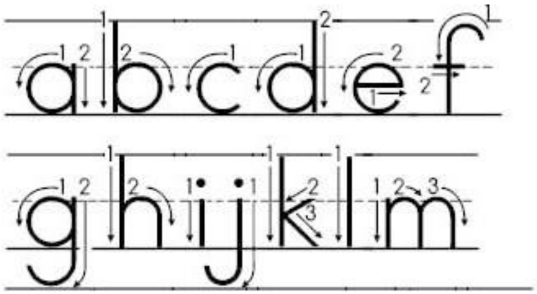

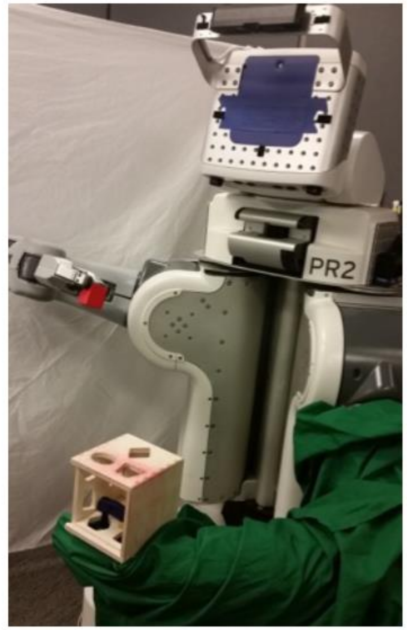

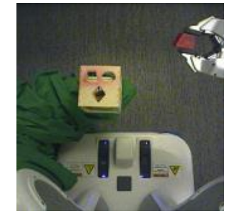

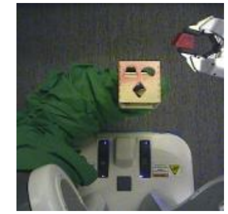

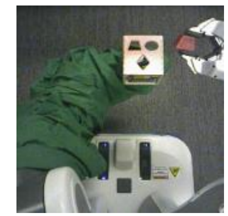

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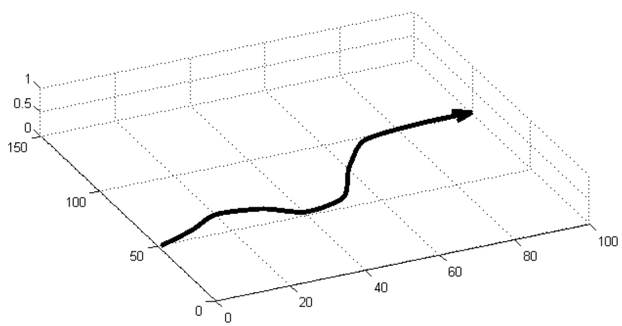

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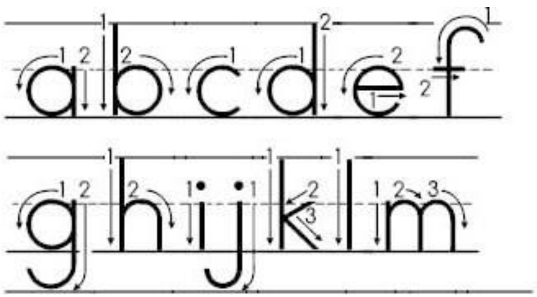

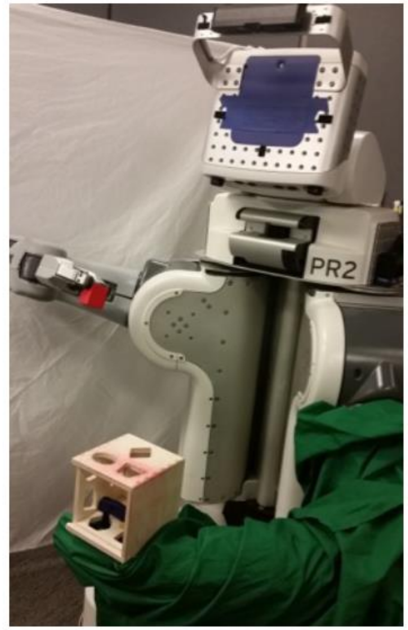

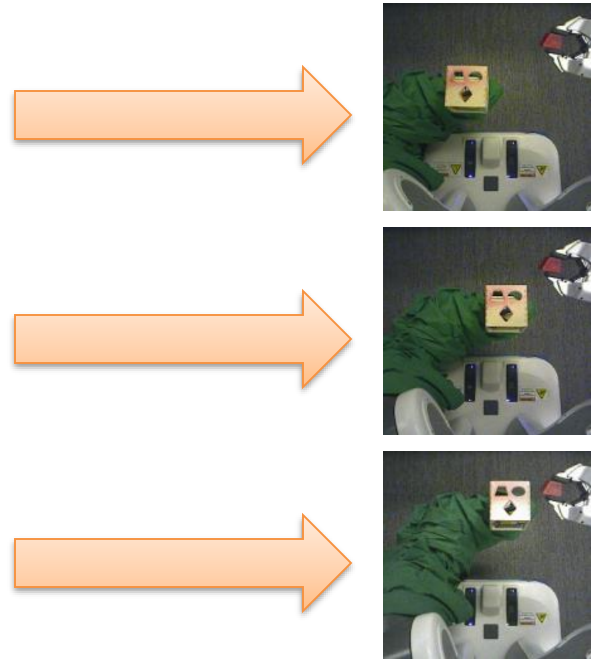

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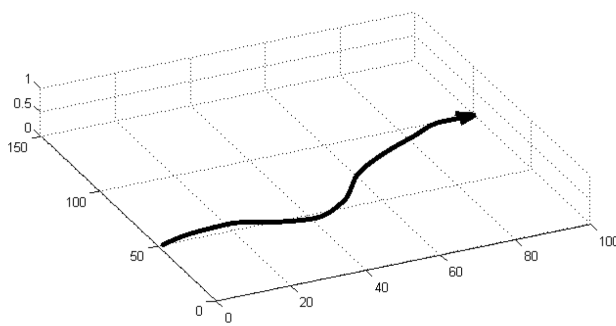

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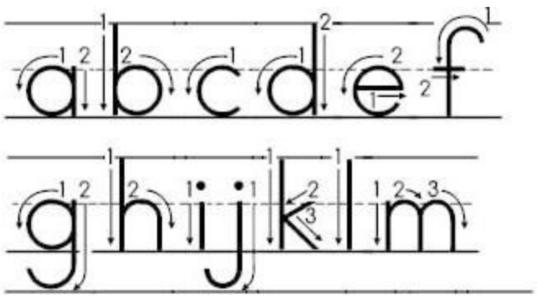

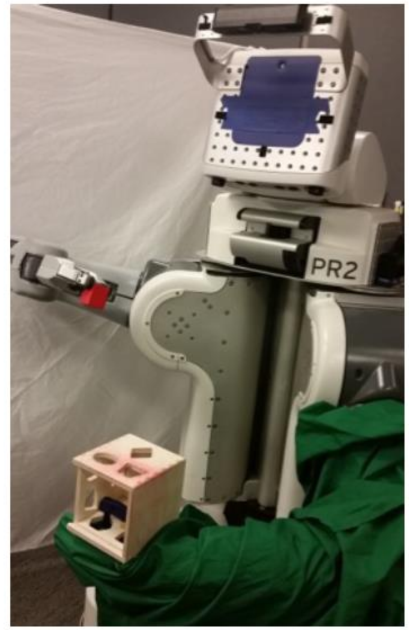

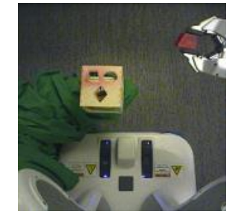

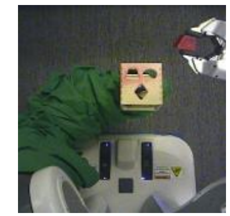

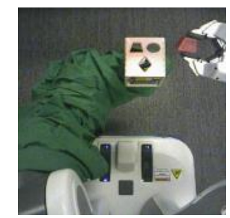

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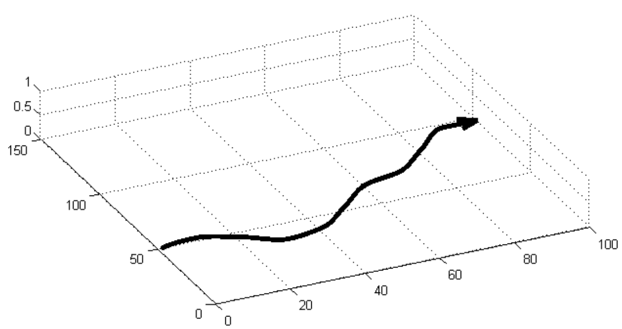

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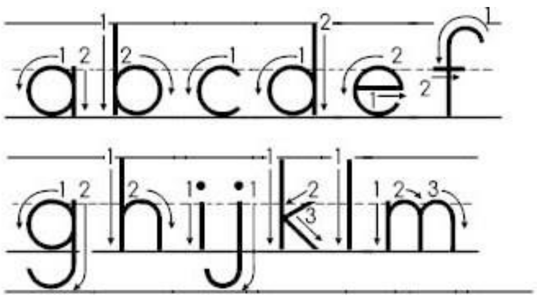

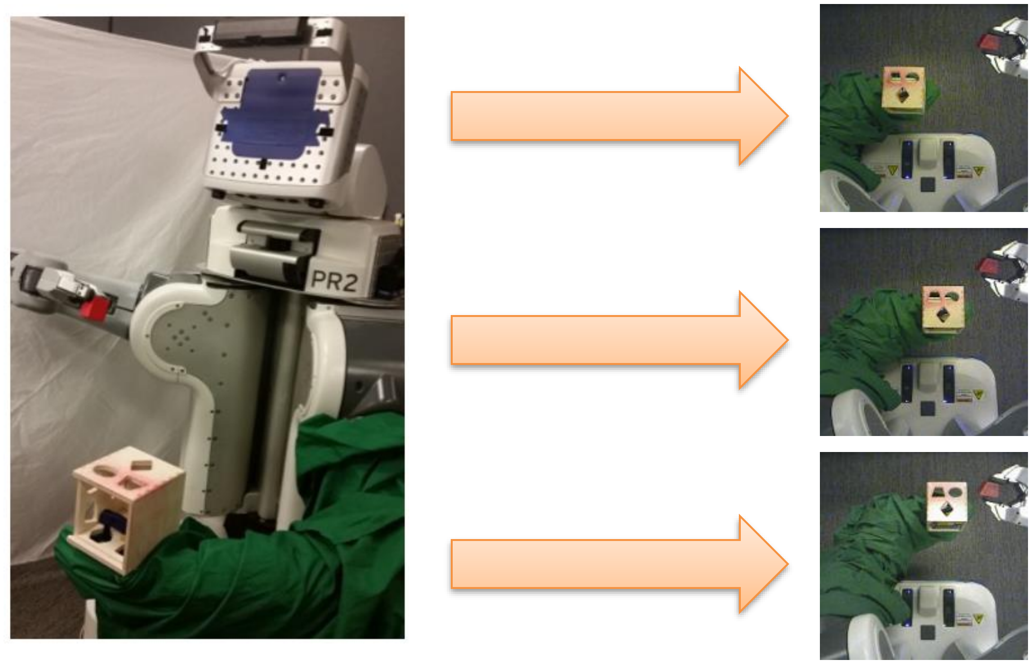

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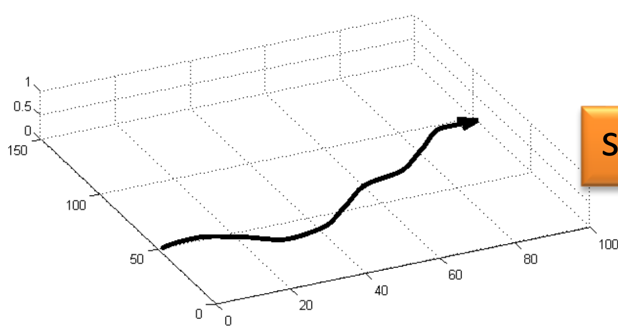

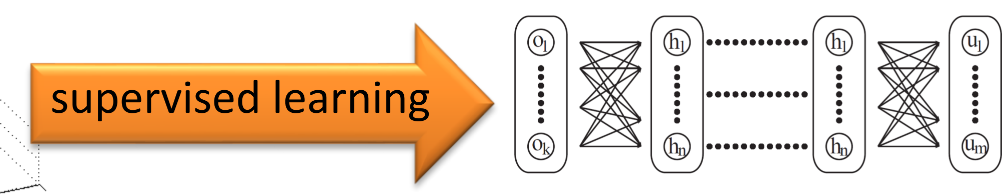

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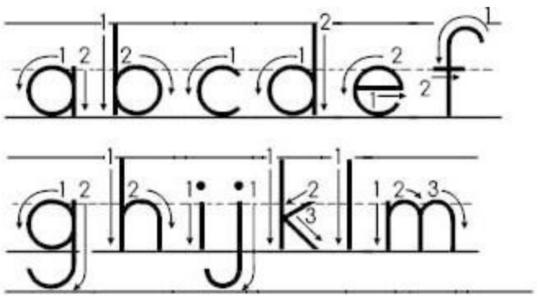

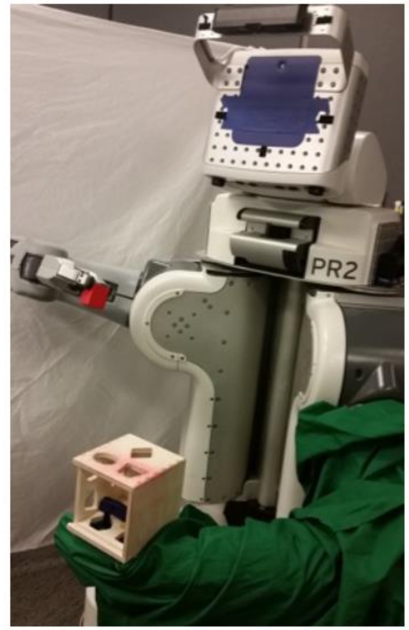

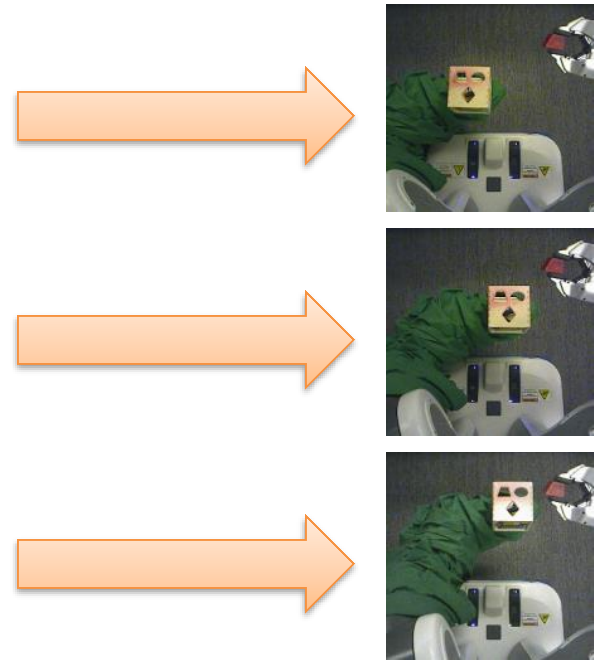

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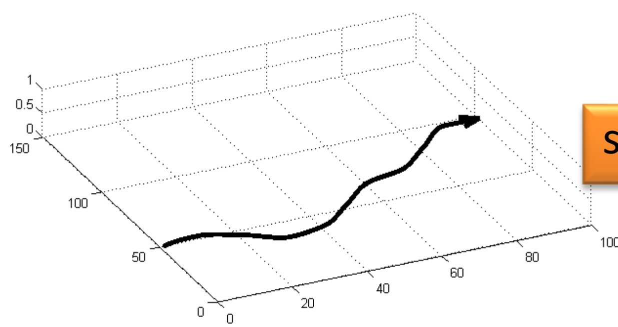
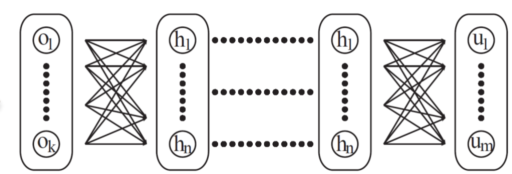


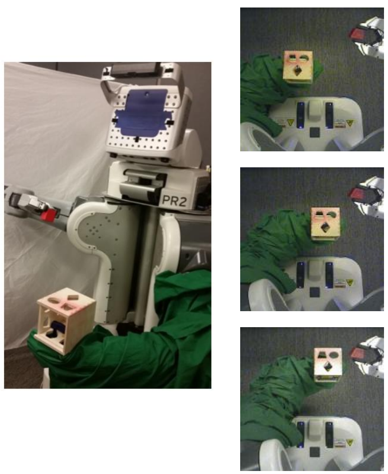
state to **action**

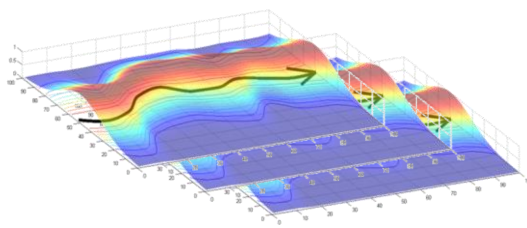


observation to **action**

Guided Policy Search

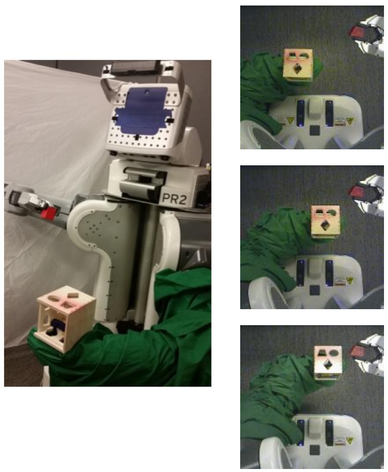
Guided Policy Search

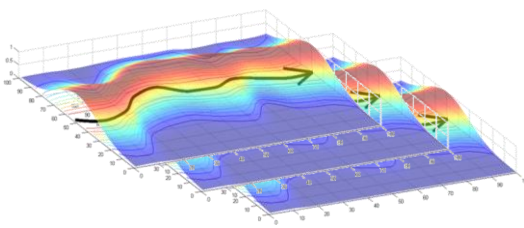




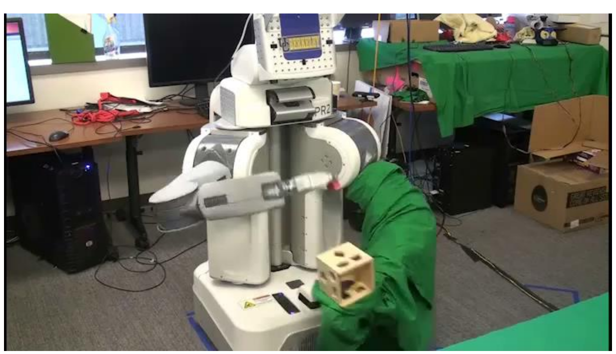
trajectory-centric RL

Guided Policy Search

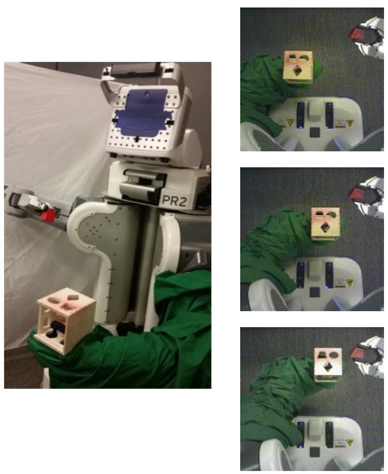


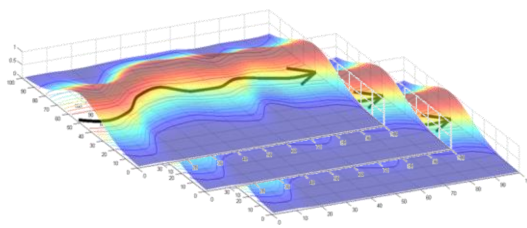


trajectory-centric RL

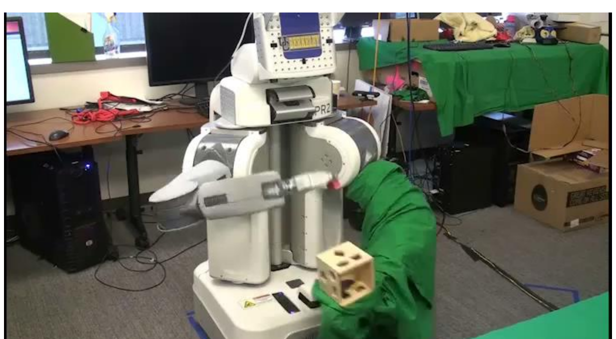


Guided Policy Search

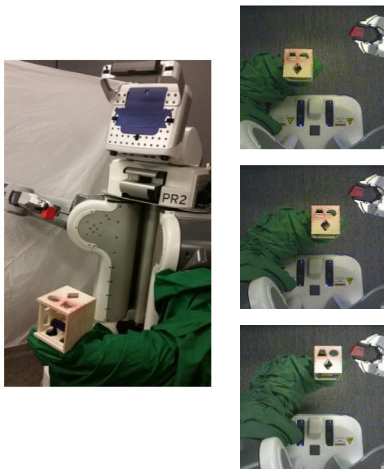


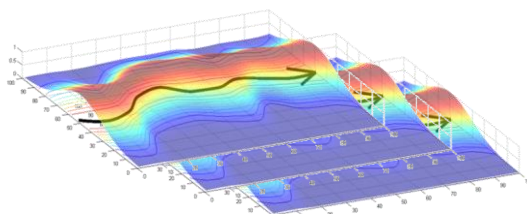


trajectory-centric RL

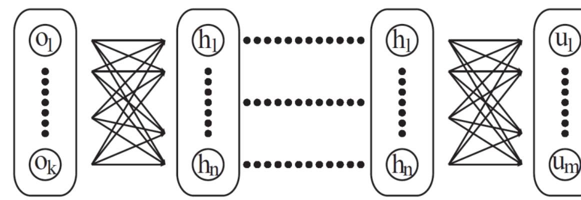


Guided Policy Search

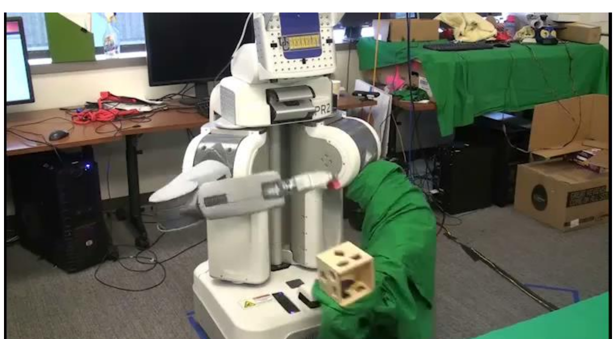




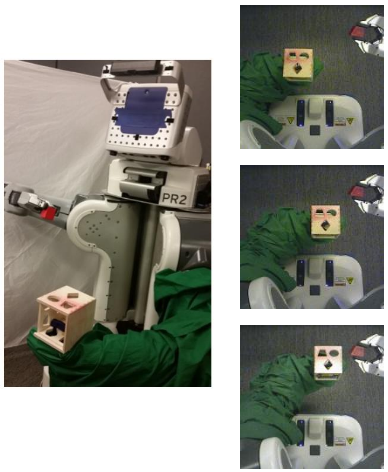
trajectory-centric RL

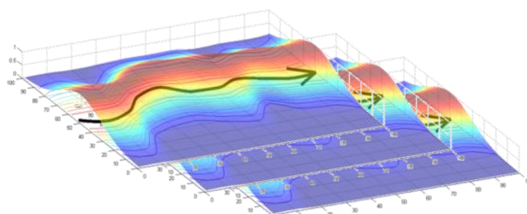


supervised learning

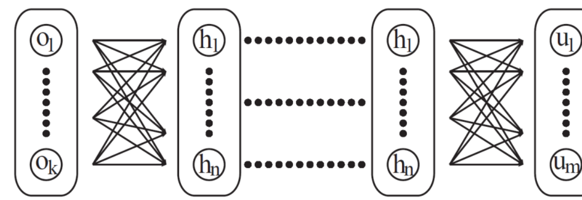


Guided Policy Search

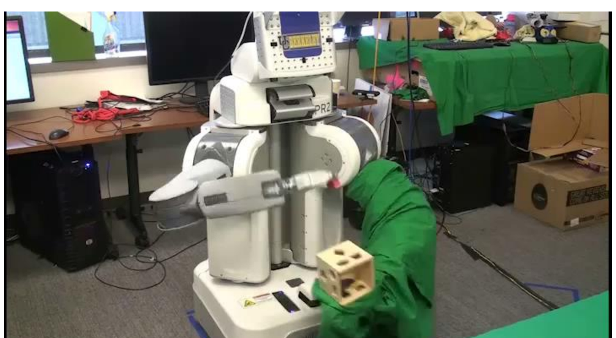




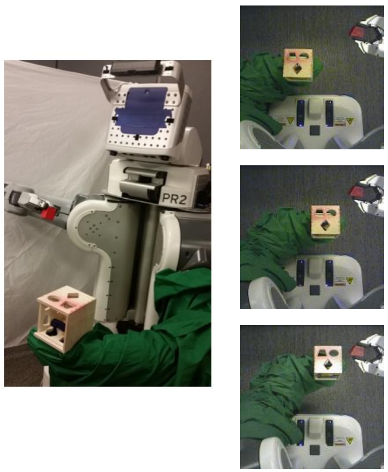
trajectory-centric RL

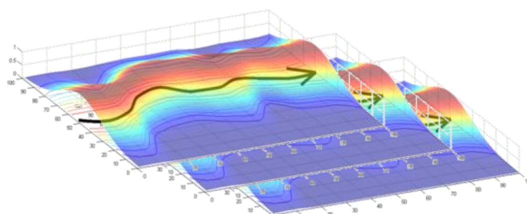


supervised learning



Guided Policy Search





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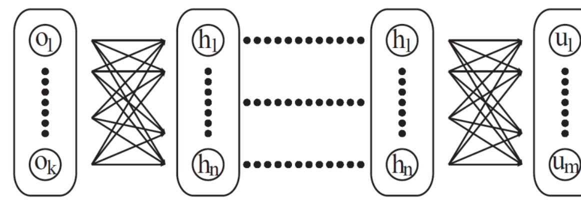
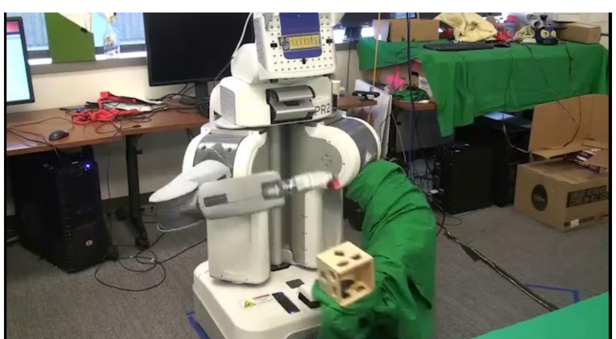


supervised learning



$$\min_{\theta} E_{\pi_\theta}[c(\tau)]$$

$$\min_{\theta} \overbrace{E_{\pi_\theta}}^{\text{expectation under current policy}}[c(\tau)]$$

$$\min_{\theta} \overbrace{E_{\pi_\theta}}^{\text{expectation under current policy}}[c(\tau)]$$

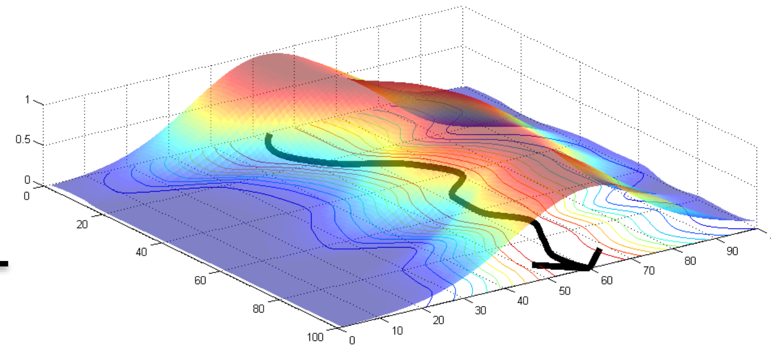
$$\min_{\theta, p(\tau)} \; E_p[c(\tau)]$$

$$s.t. \;\; \pi_\theta(\mathbf{u}_t|\mathbf{o}(\mathbf{x}_t)) = p(\mathbf{u}_t|\mathbf{x}_t) \;\; \forall t, \mathbf{x}_t, \mathbf{u}_t$$

$$\min_{\theta} \overbrace{E_{\pi_\theta}}^{\text{expectation under current policy}}[c(\tau)]$$

$$\min_{\theta, p(\tau)} \; E_p[c(\tau)]$$

trajectory distribution(s)



$$s.t. \;\; \pi_\theta(\mathbf{u}_t|\mathbf{o}(\mathbf{x}_t)) = p(\mathbf{u}_t|\mathbf{x}_t) \;\; \forall t, \mathbf{x}_t, \mathbf{u}_t$$

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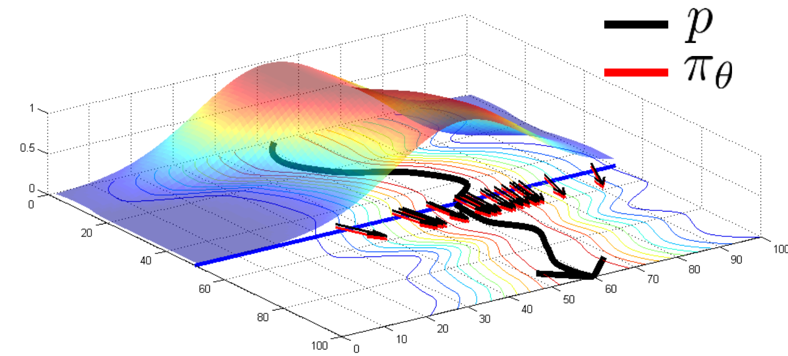
$$\min_{\theta, p(\tau)} \; E_p[c(\tau)]$$

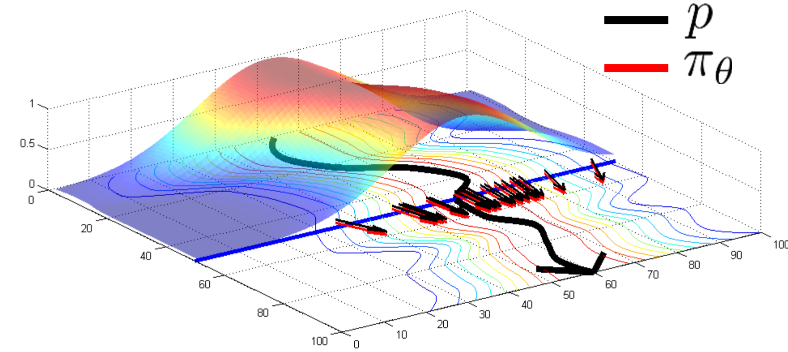
$$s.t. \;\; \pi_\theta(\mathbf{u}_t | \mathbf{o}(\mathbf{x}_t)) = p(\mathbf{u}_t | \mathbf{x}_t) \;\; \forall t, \mathbf{x}_t, \mathbf{u}_t$$



$$\min_\theta \overbrace{E_{\pi_\theta}}^{\text{expectation under current policy}}[c(\tau)]$$

$$\min_{\theta, p(\tau)} \ E_p[c(\tau)]$$

$$s.t. \ \ \pi_\theta(\mathbf{u}_t|\mathbf{o}(\mathbf{x}_t)) = p(\mathbf{u}_t|\mathbf{x}_t) \ \ \forall t, \mathbf{x}_t, \mathbf{u}_t$$

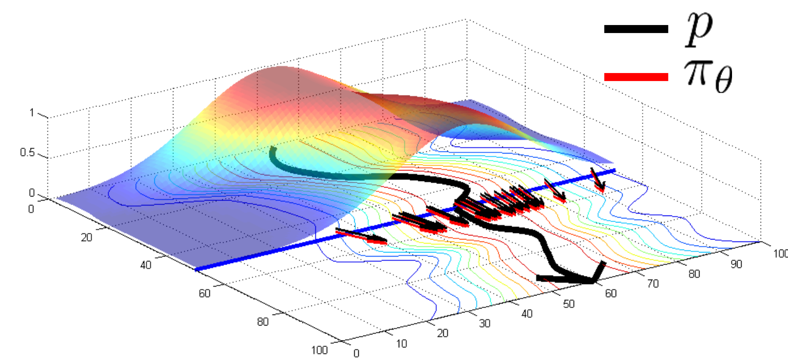


solve using Bregman ADMM (BADMM), a type of dual decomposition method

$$\min_{\theta} \overbrace{E_{\pi_\theta}}^{\text{expectation under current policy}}[c(\tau)]$$

$$\min_{\theta, p(\tau)} \; E_p[c(\tau)]$$

$$s.t. \;\; \pi_\theta(\mathbf{u}_t|\mathbf{o}(\mathbf{x}_t)) = p(\mathbf{u}_t|\mathbf{x}_t) \;\; \forall t, \mathbf{x}_t, \mathbf{u}_t$$



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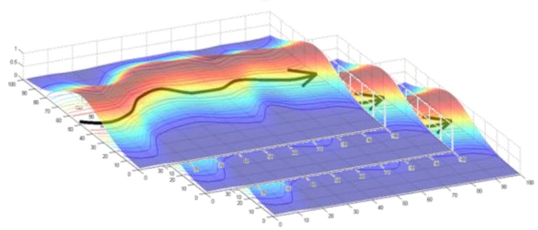
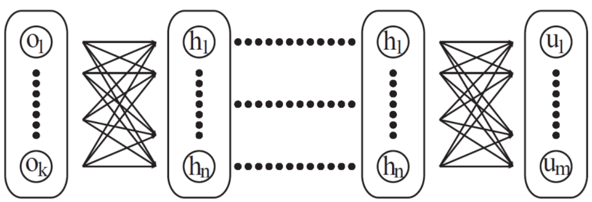


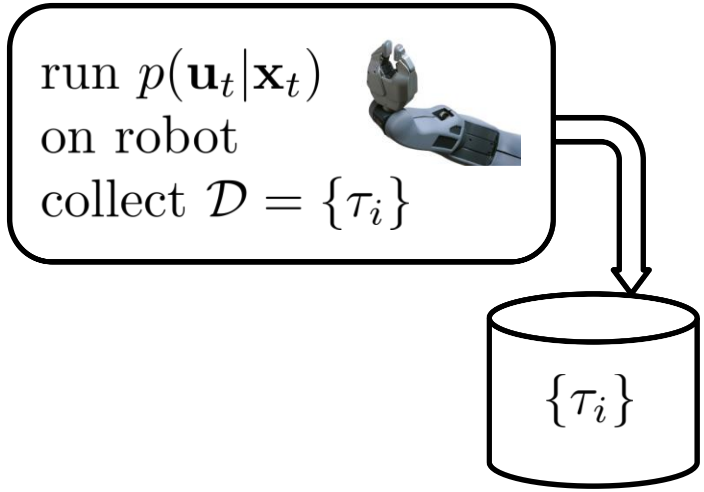
trajectory-centric RL



supervised learning

run $p(\mathbf{u}_t|\mathbf{x}_t)$
on robot
collect $\mathcal{D} = \{\tau_i\}$

[see L. et al. NIPS ‘14 for details]

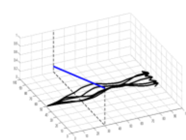


[see L. et al. NIPS ‘14 for details]

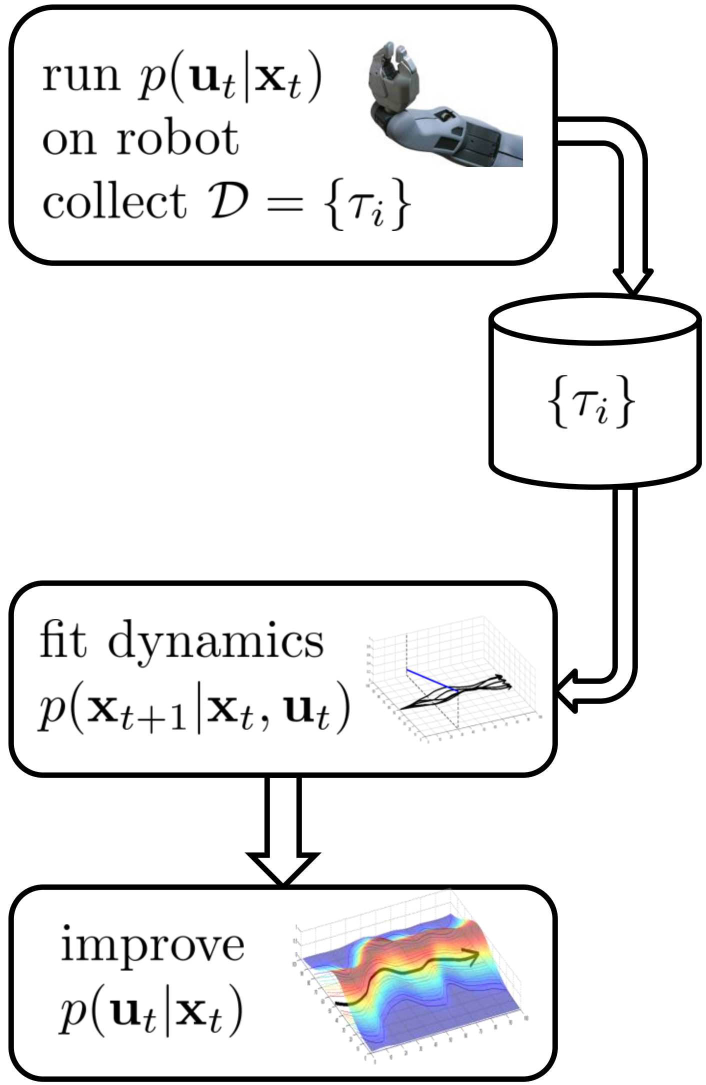
run $p(\mathbf{u}_t|\mathbf{x}_t)$
on robot
collect $\mathcal{D} = \{\tau_i\}$

$\{\tau_i\}$

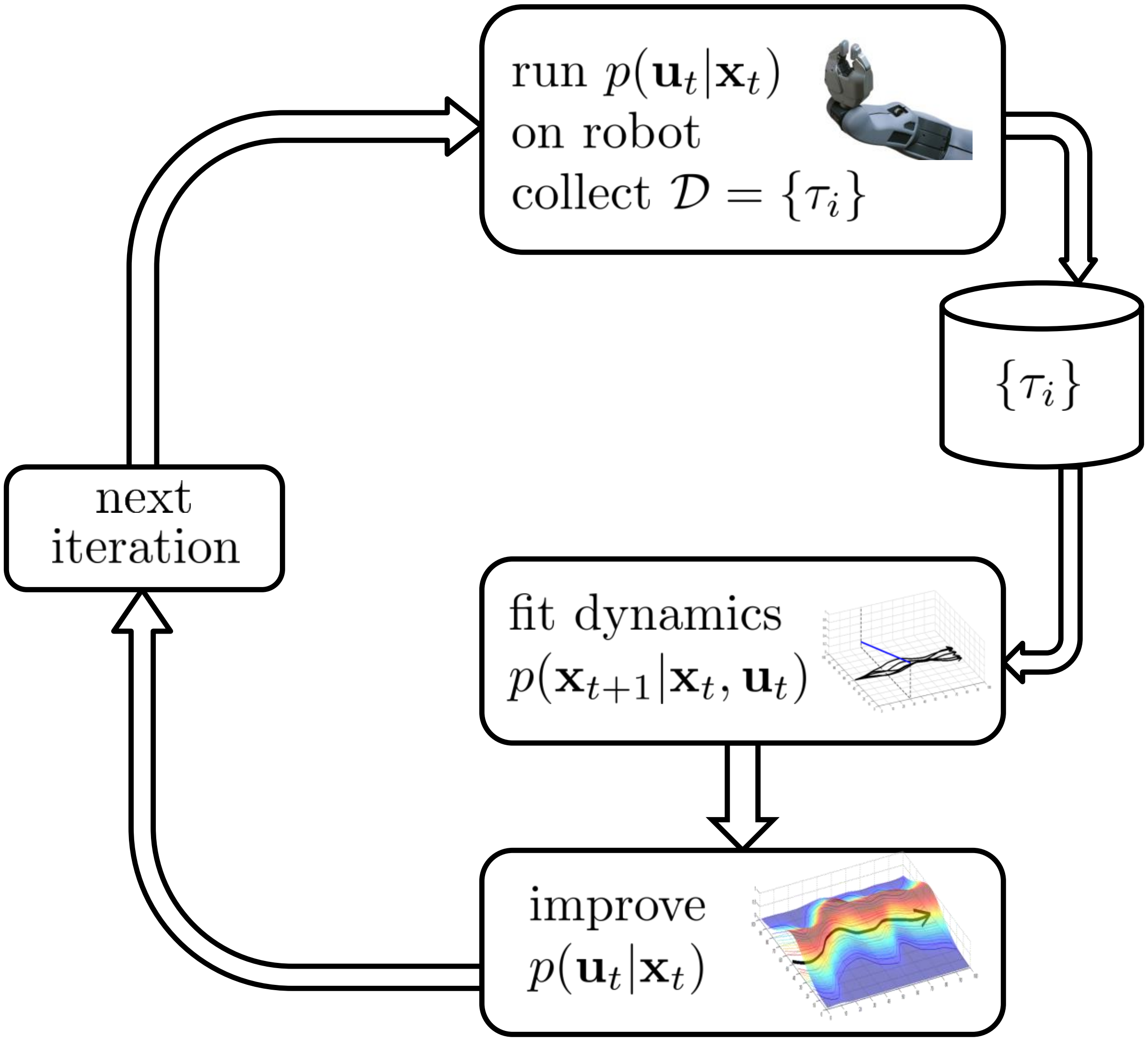
fit dynamics
$p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t)$



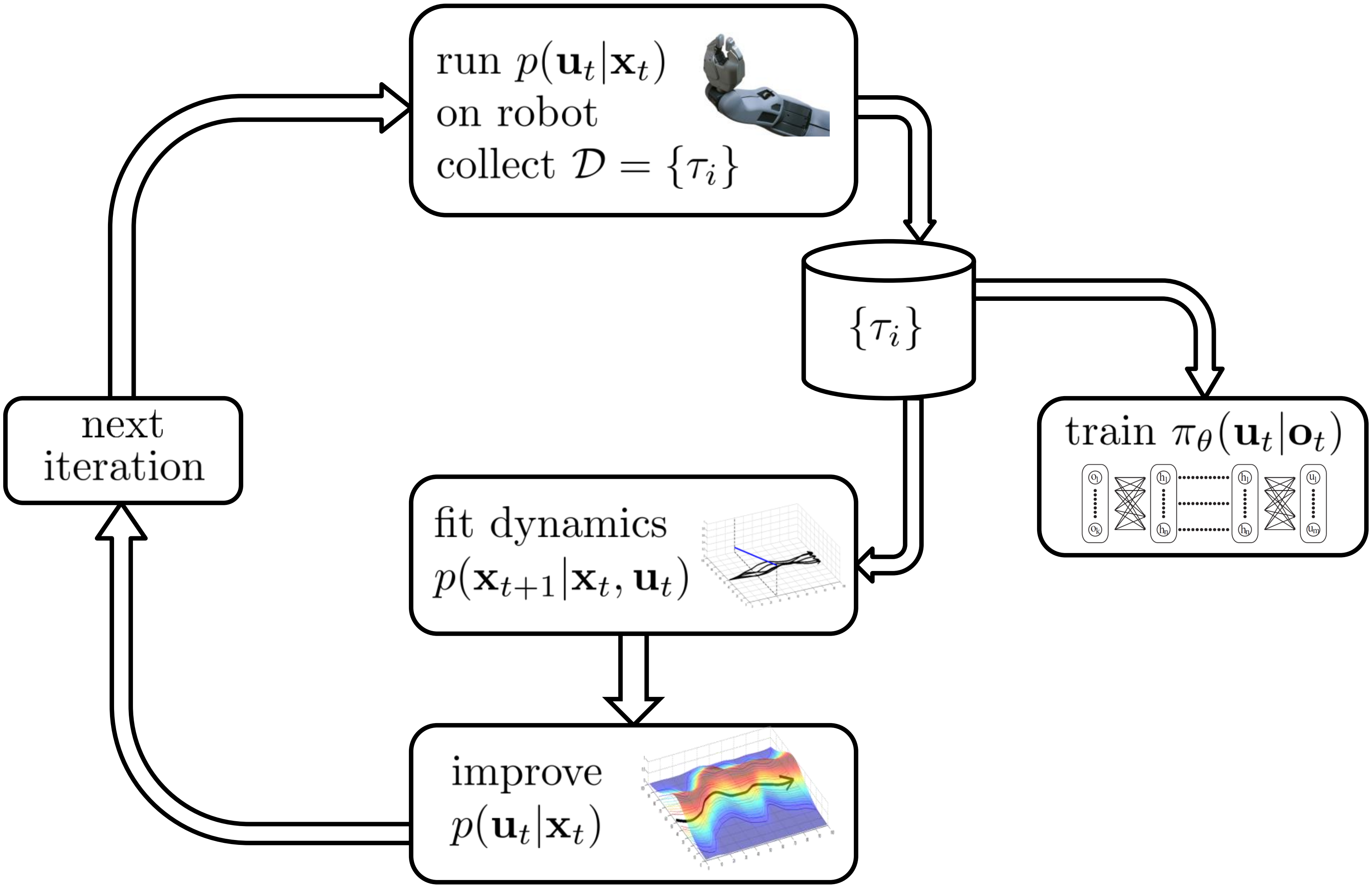
[see L. et al. NIPS '14 for details]



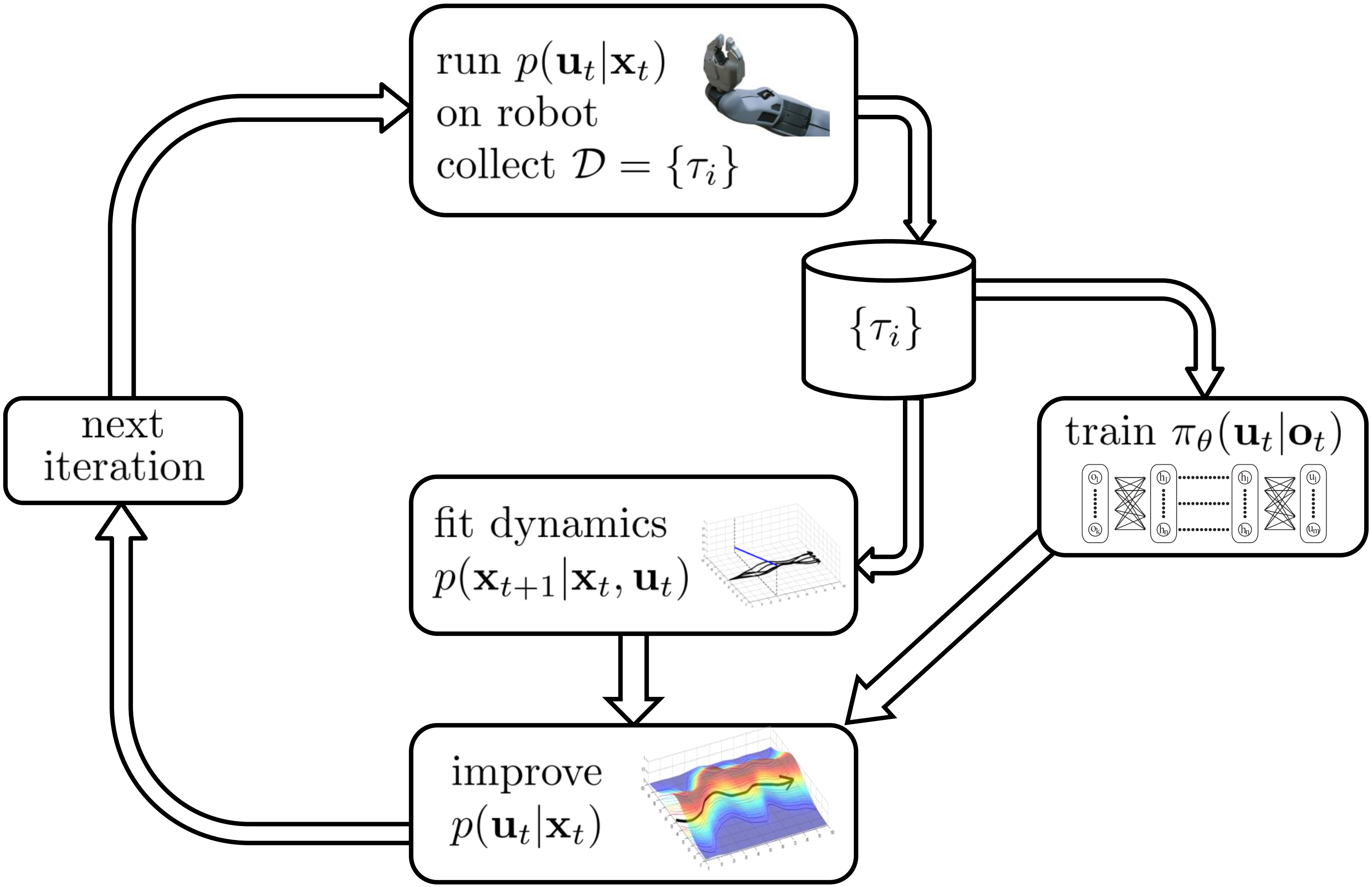
[see L. et al. NIPS '14 for details]



[see L. et al. NIPS '14 for details]



[see L. et al. NIPS ‘14 for details]

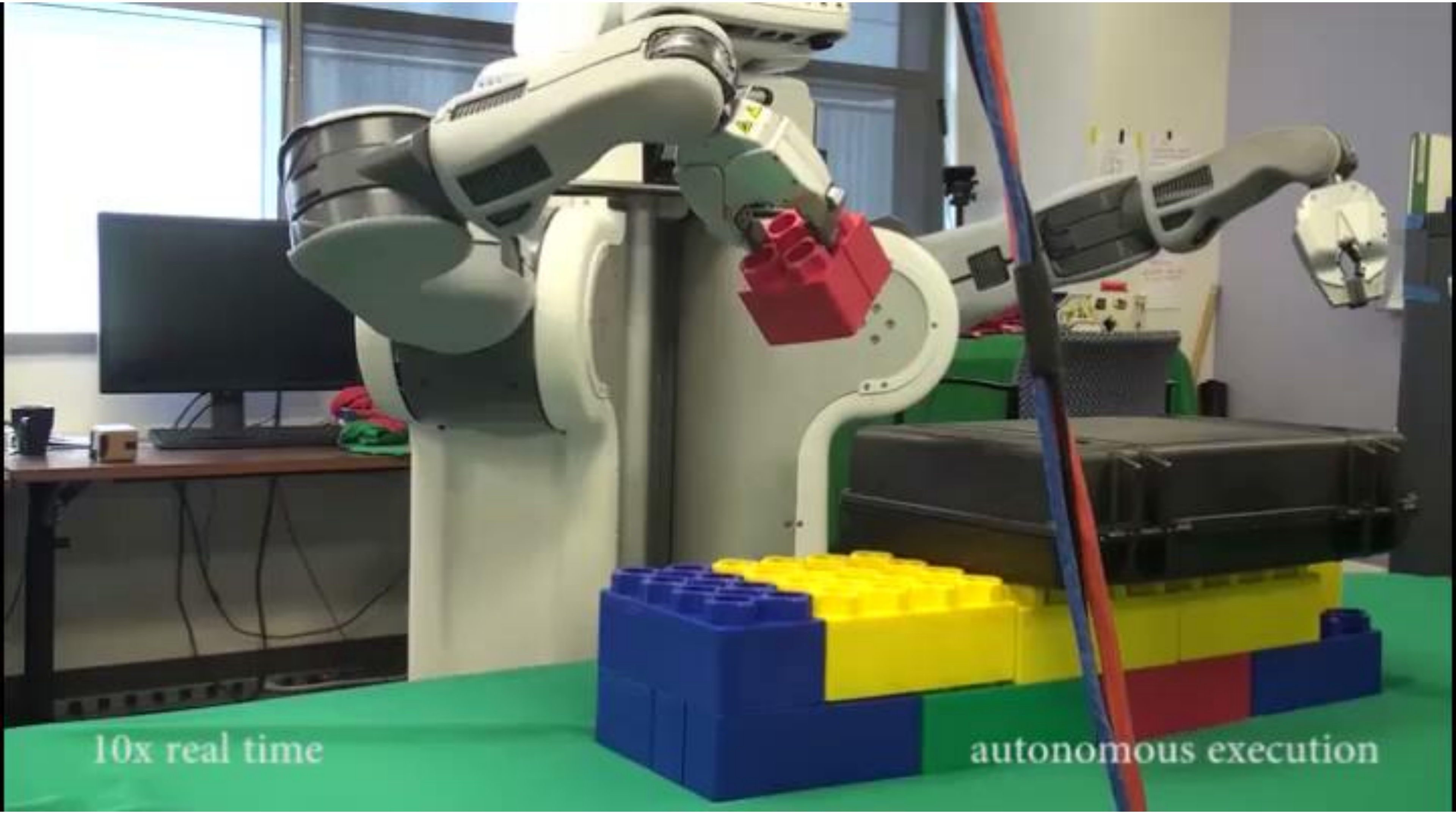


[see L. et al. NIPS '14 for details]

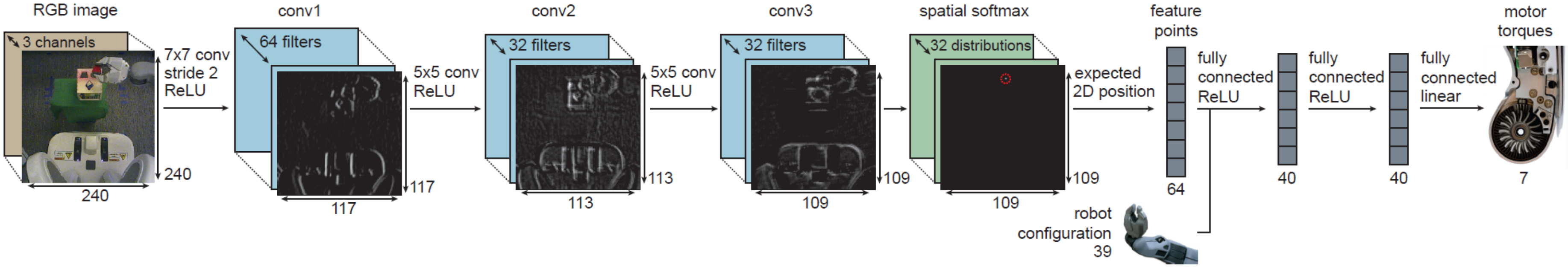
Learning on PR2

[L. et al. ICRA '15]

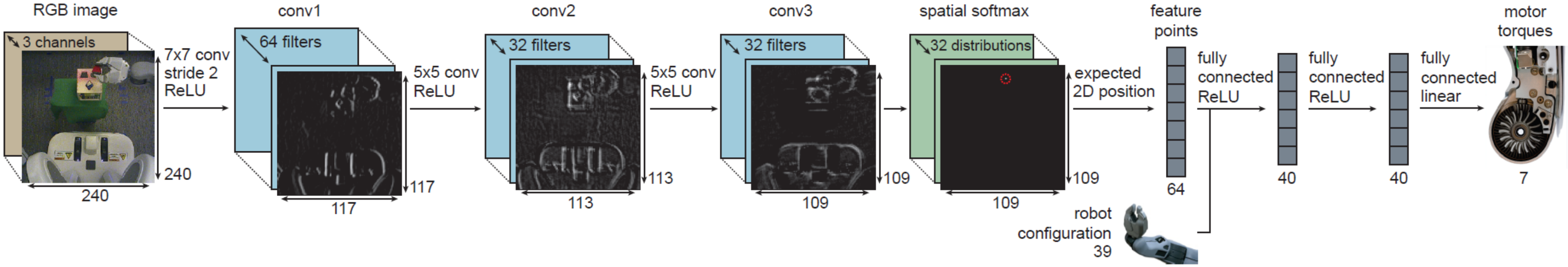
Learning on PR2



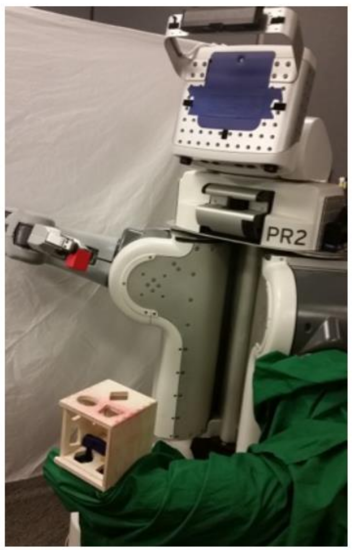
[L. et al. ICRA '15]



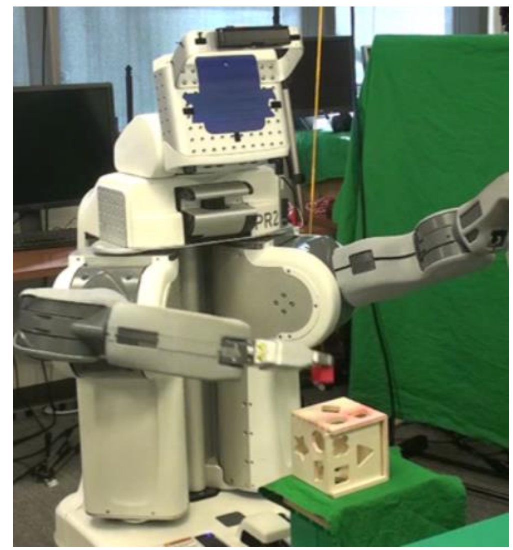
L.*, Finn*, Darrell, Abbeel '15



training time



test time



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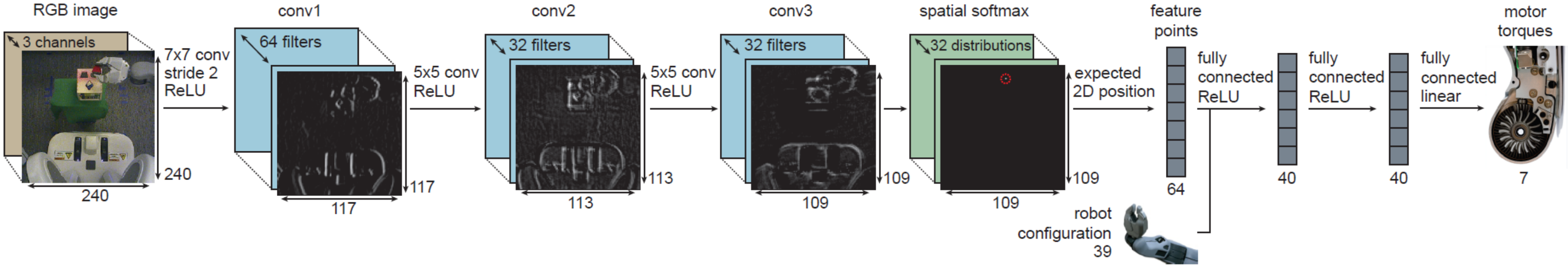
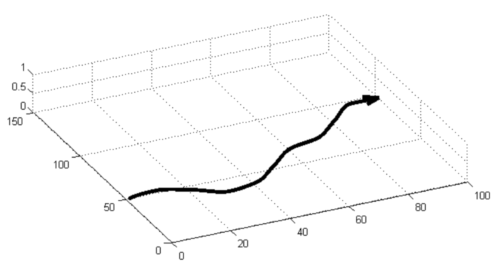
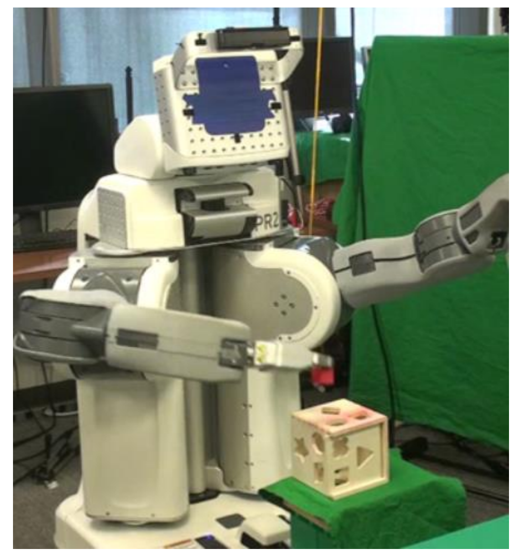


training time

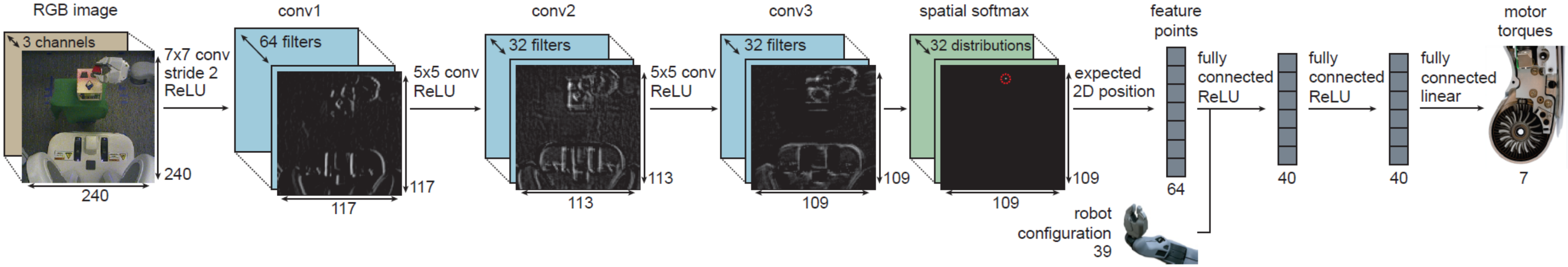
$$\mathbf{x}_t \rightarrow \mathbf{u}_t$$



test time

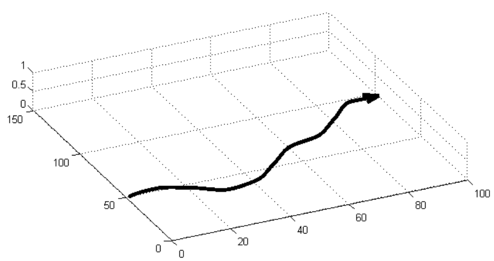


L.*, Finn*, Darrell, Abbeel '15

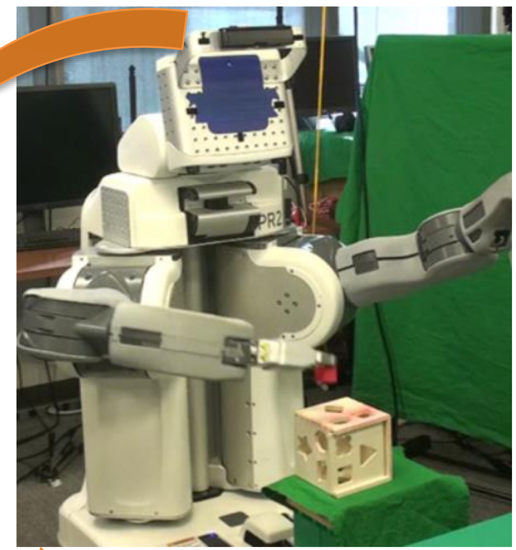


training time

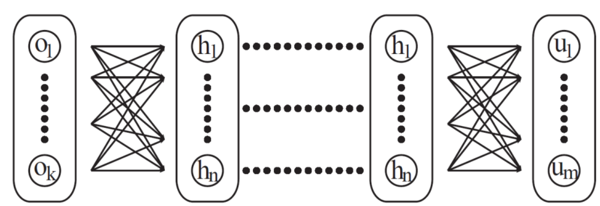
$$\mathbf{x}_t \rightarrow \mathbf{u}_t$$



test time



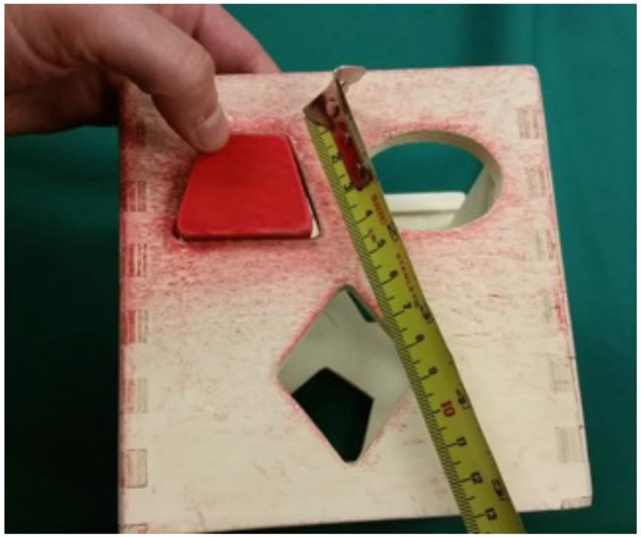
$$\mathbf{o}_t \rightarrow \mathbf{u}_t$$



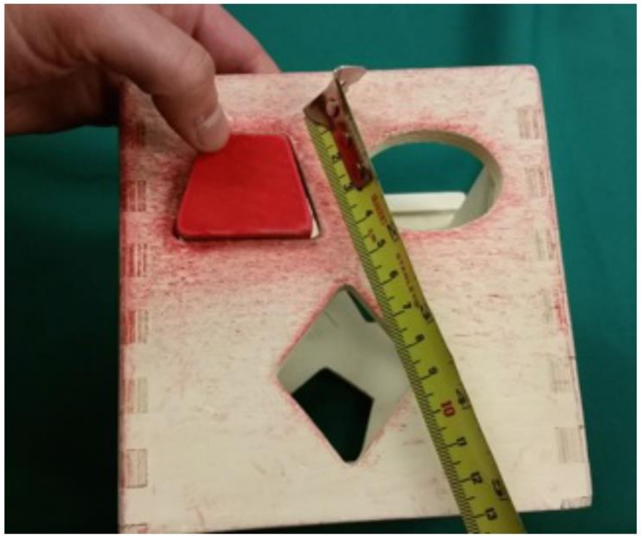
L.*, Finn*, Darrell, Abbeel '15

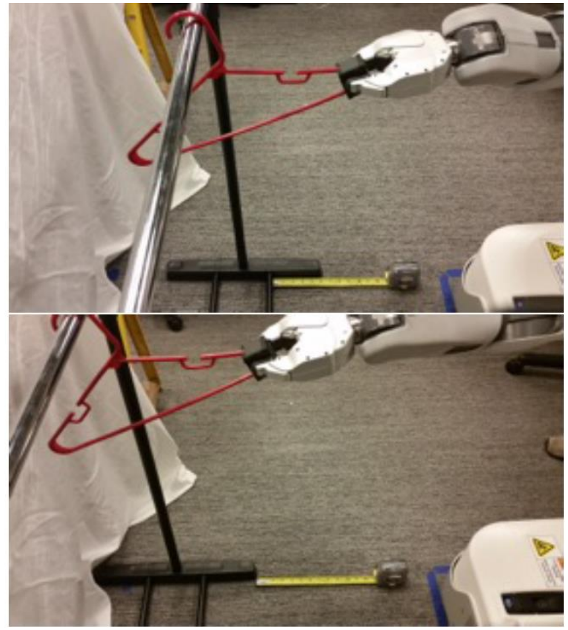
Experimental Tasks

Experimental Tasks



Experimental Tasks





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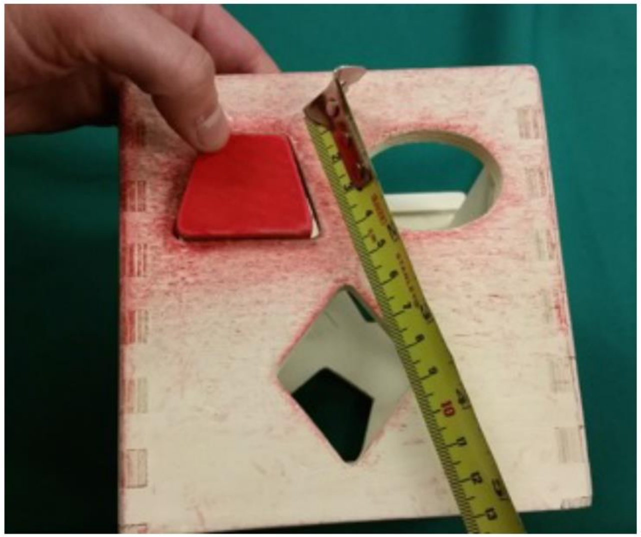

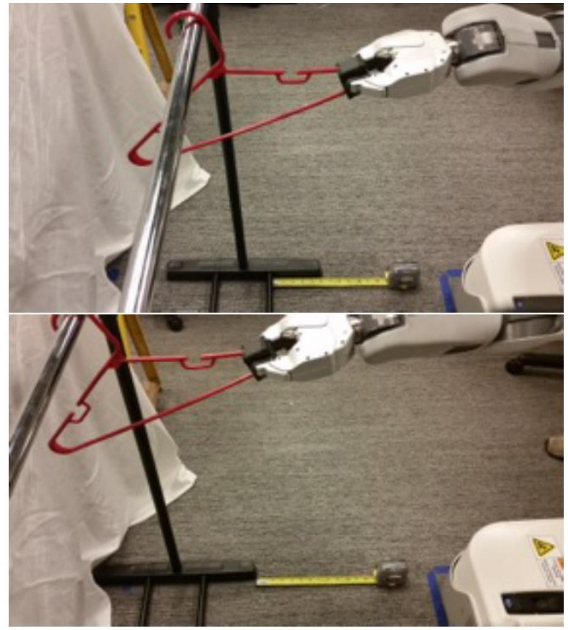

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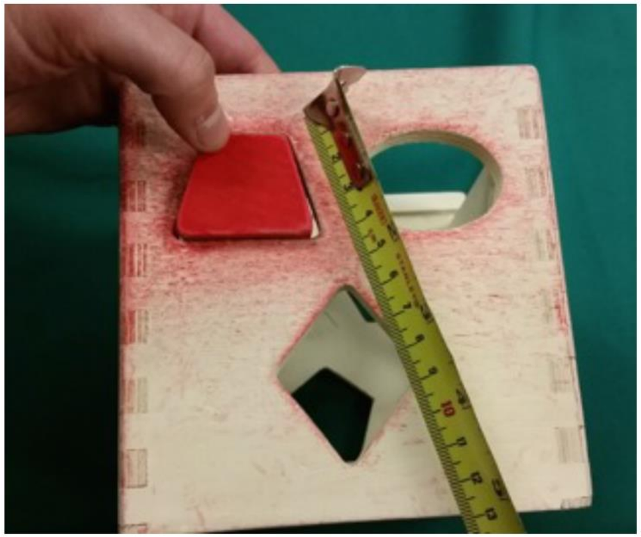
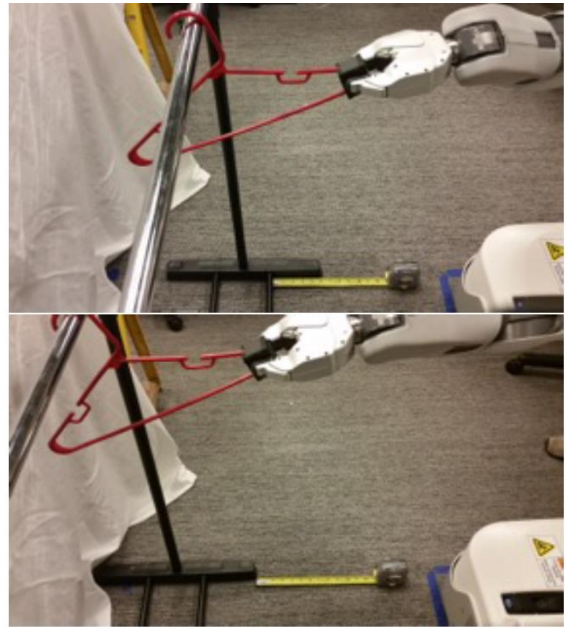
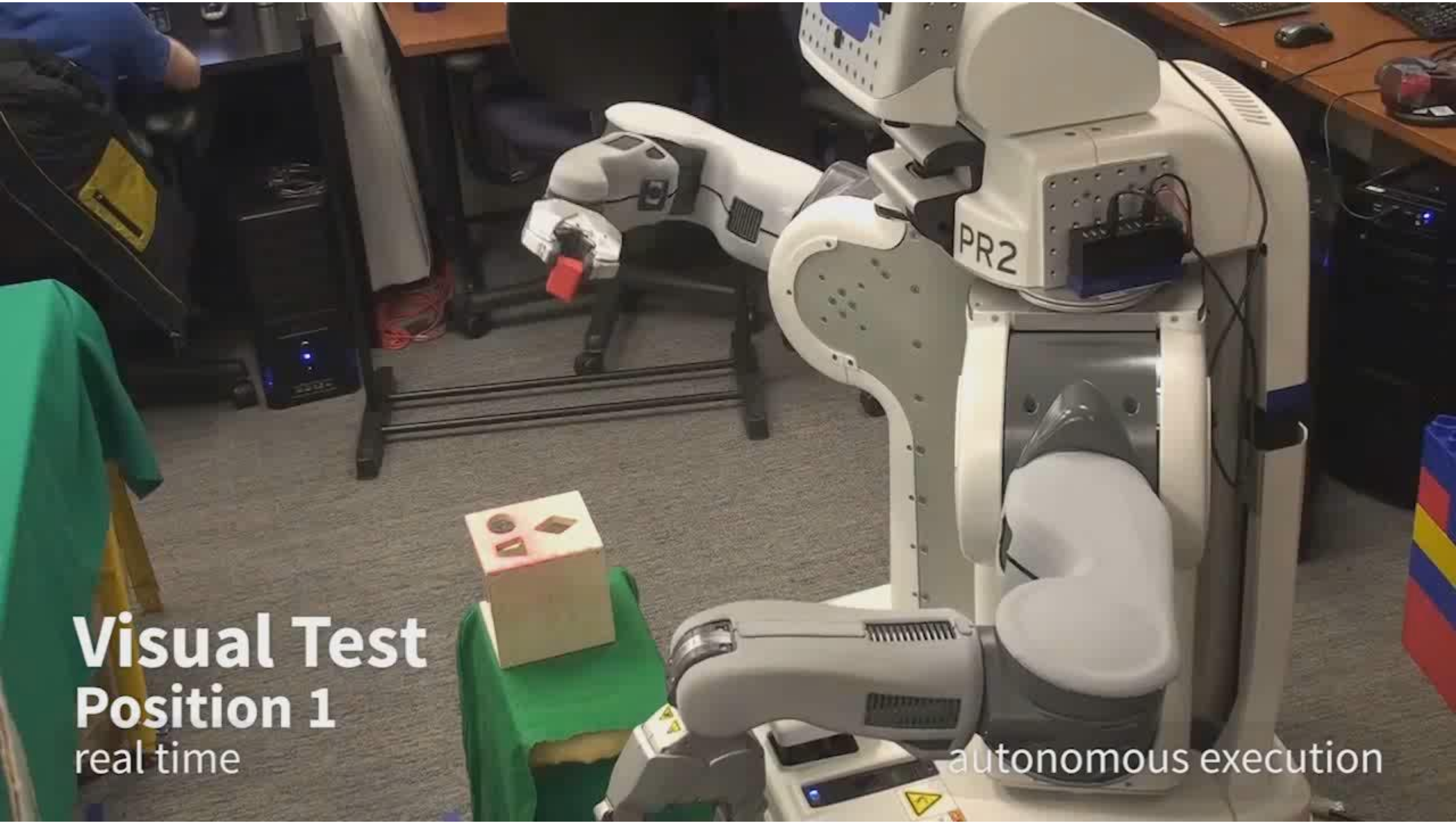


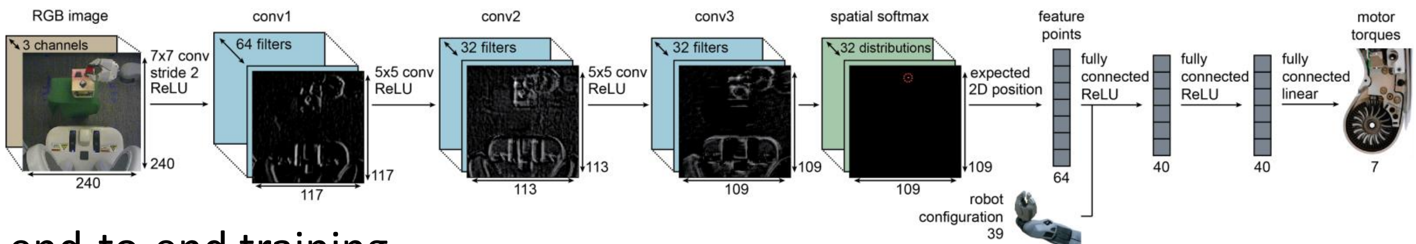


Experimental Tasks

Generalization Experiments

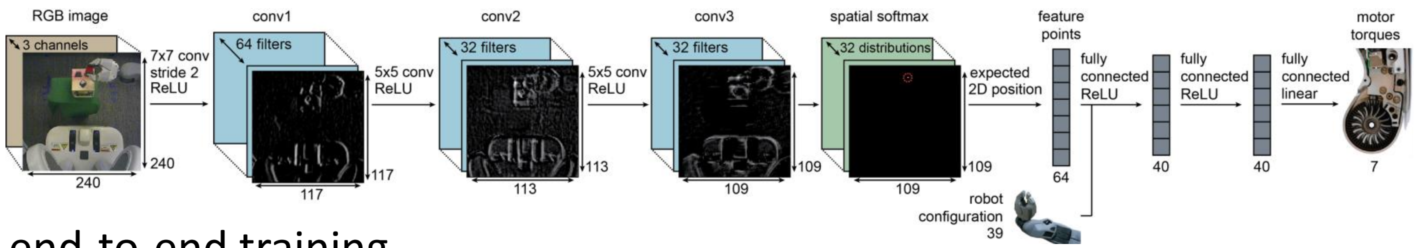


Comparisons

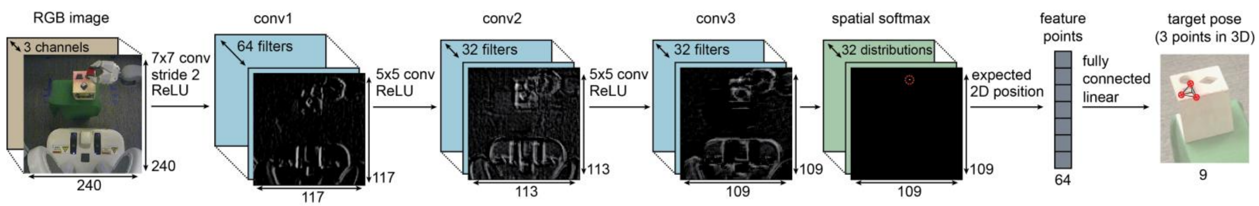


end-to-end training

Comparisons

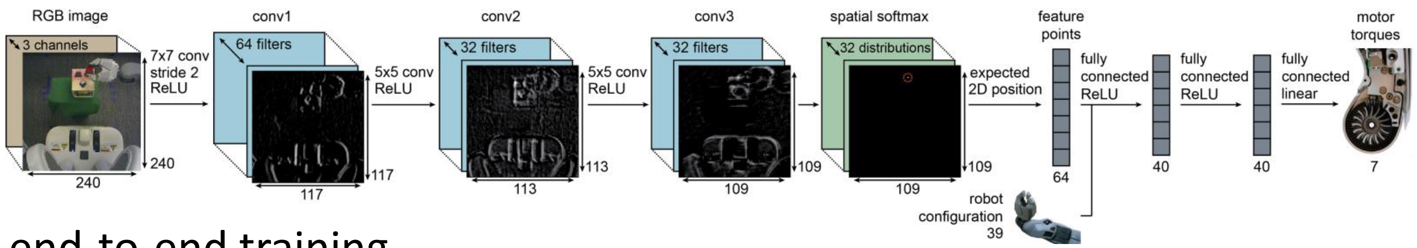


end-to-end training



pose prediction

Comparisons



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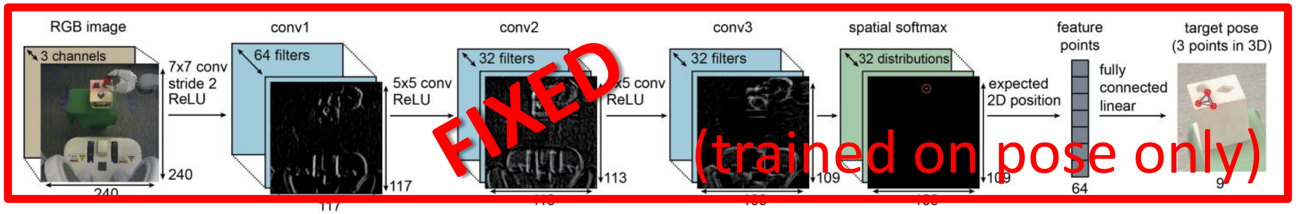

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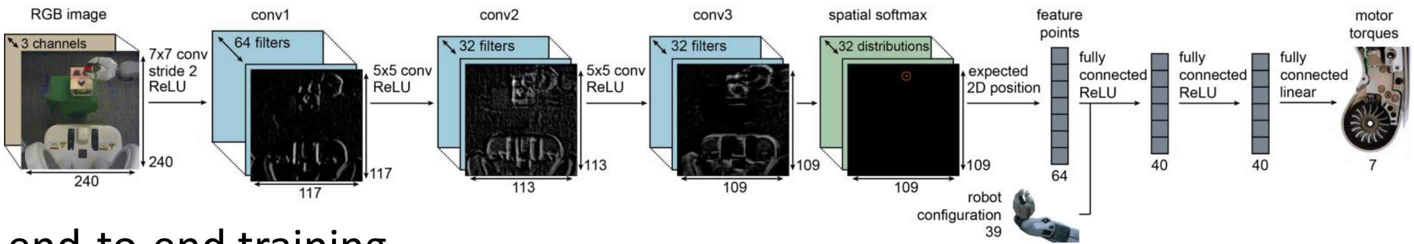

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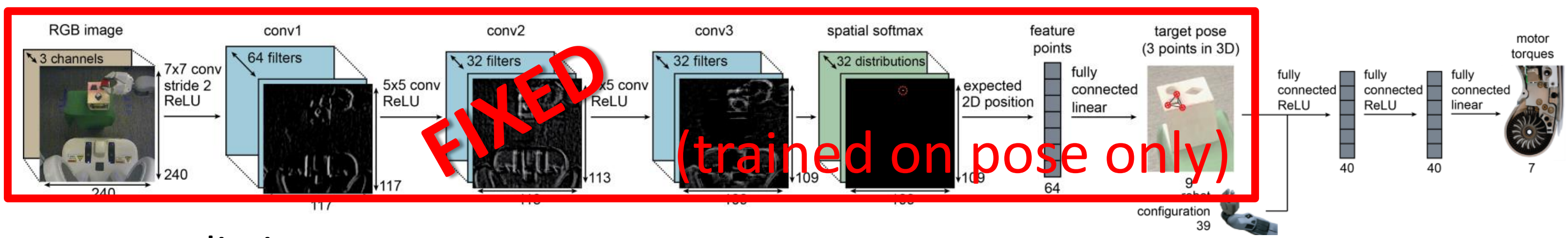

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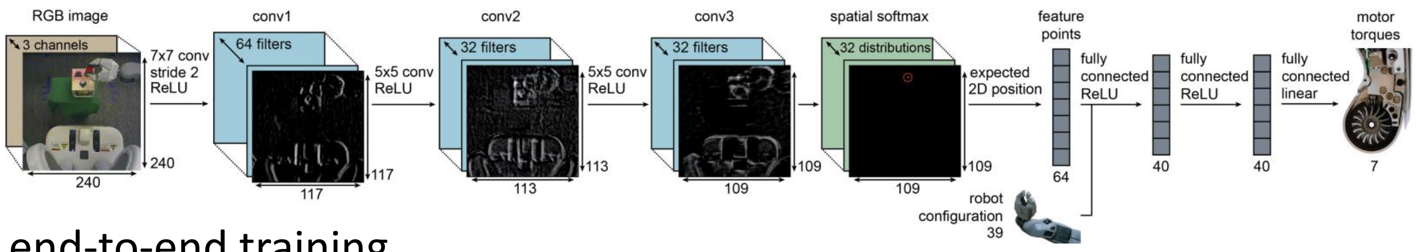
Comparisons



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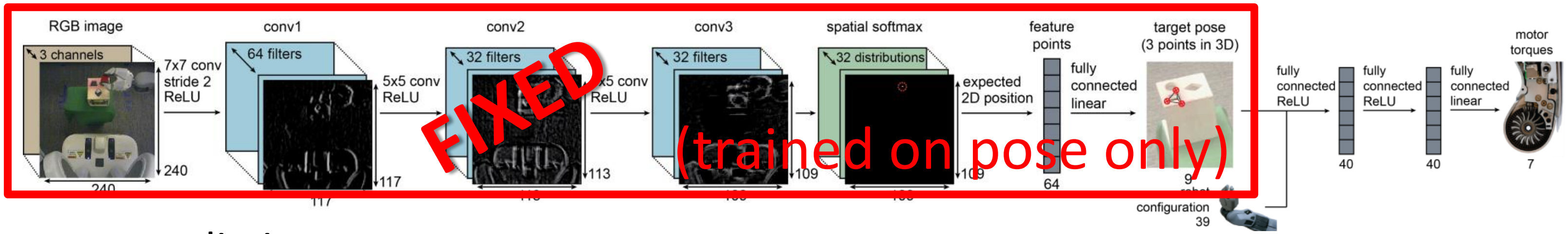
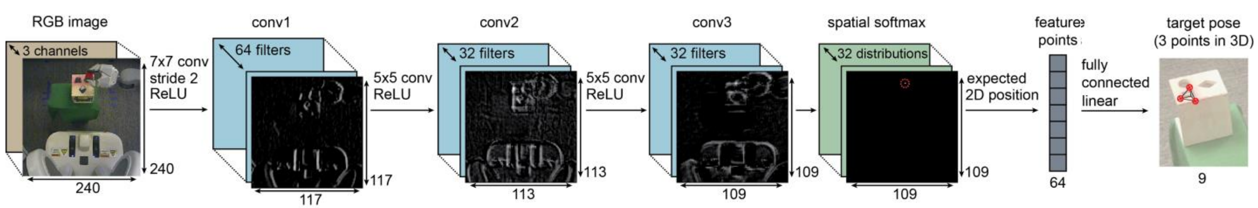
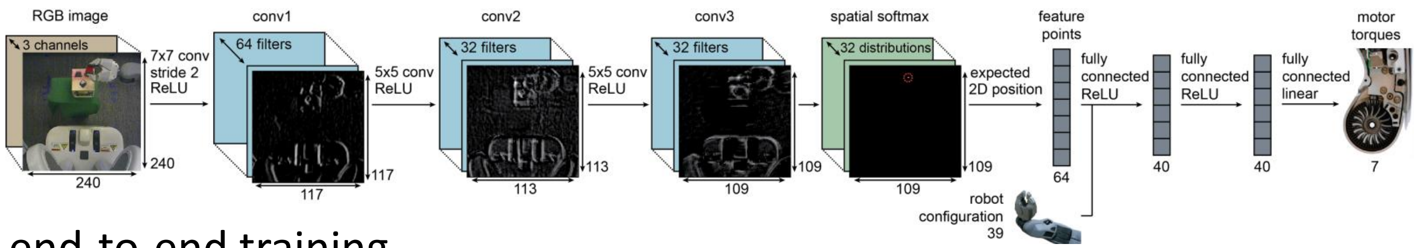


pose prediction

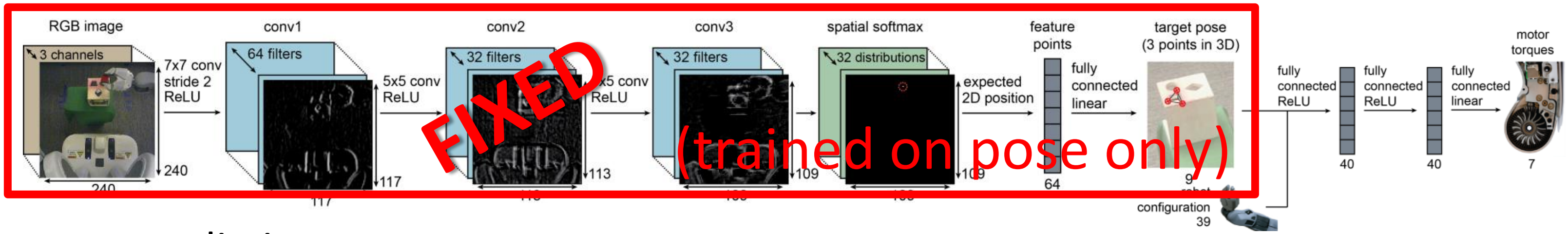


pose features

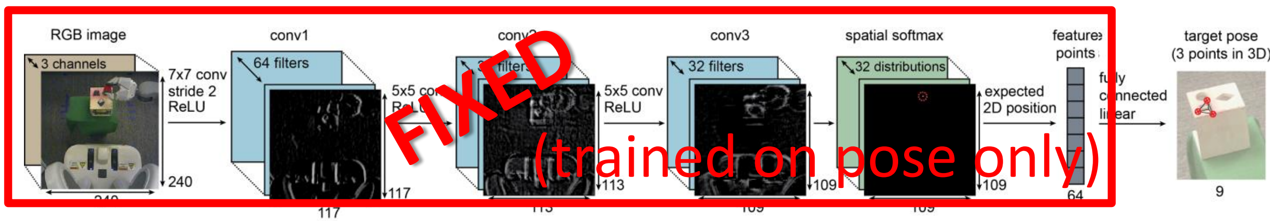
Comparisons



end-to-end training

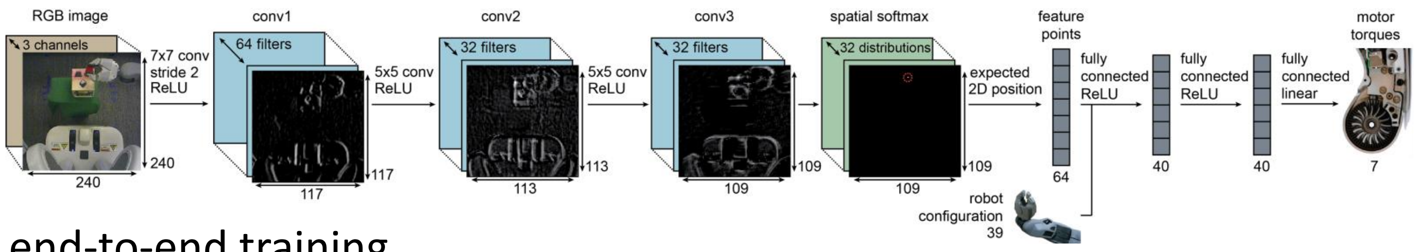


pose prediction



pose features

Comparisons



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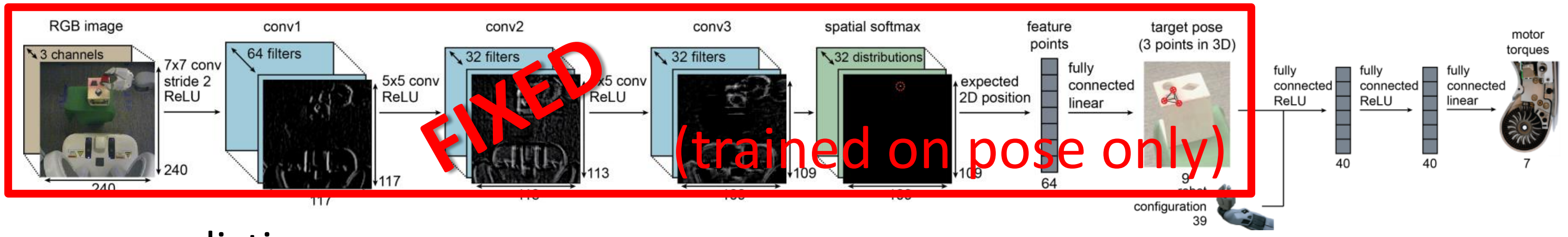

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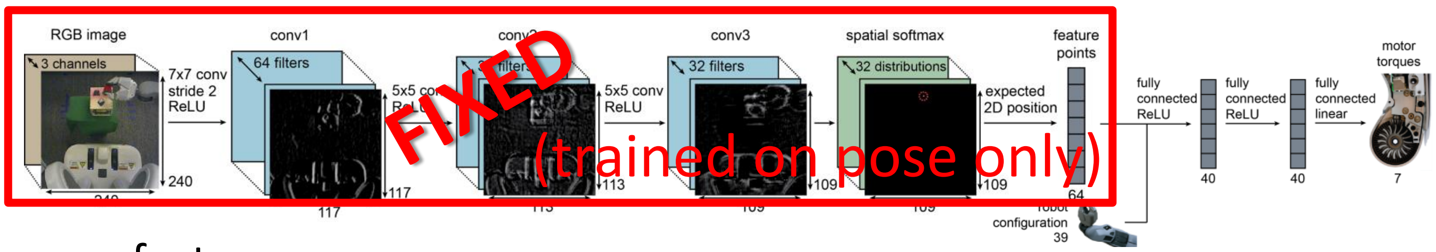

pose features

Comparisons

Comparisons

coat hanger	success rate
pose prediction	55.6%

shape sorting cube	success rate
pose prediction	0%

toy claw hammer	success rate
pose prediction	8.9%

bottle cap	success rate
pose prediction	n/a

Comparisons

coat hanger	success rate
pose prediction	55.6%
pose features	88.9%

shape sorting cube	success rate
pose prediction	0%
pose features	70.4%

toy claw hammer	success rate
pose prediction	8.9%
pose features	62.2%

bottle cap	success rate
pose prediction	n/a
pose features	55.6%

Comparisons

coat hanger	success rate
pose prediction	55.6%
pose features	88.9%
end-to-end training	**100%**

shape sorting cube	success rate
pose prediction	0%
pose features	70.4%
end-to-end training	**96.3%**

toy claw hammer	success rate
pose prediction	8.9%
pose features	62.2%
end-to-end training	**91.1%**

bottle cap	success rate
pose prediction	n/a
pose features	55.6%
end-to-end training	**88.9%**

Comparisons

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end-to-end training	**100%**

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end-to-end training	**88.9%**

network architecture	test error (cm)
softmax + feature points (**ours**)	$\mathbf{1.30 \pm 0.73}$
softmax + fully connected layer	2.59 ± 1.19
fully connected layer	4.75 ± 2.29
max-pooling + fully connected	3.71 ± 1.73

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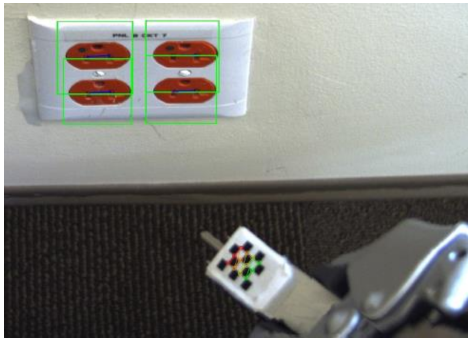

Meeussen et al. (Willow Garage)

Comparisons

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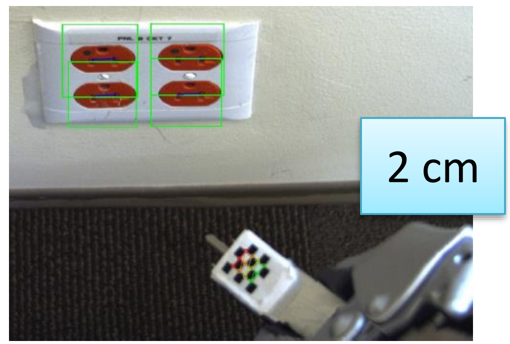

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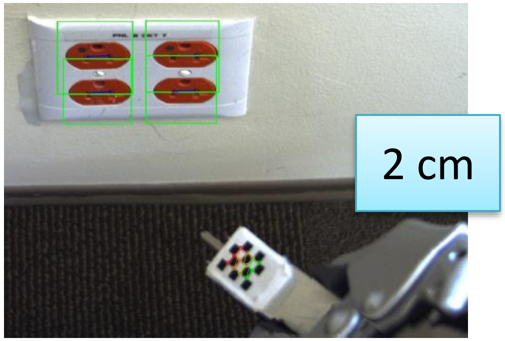

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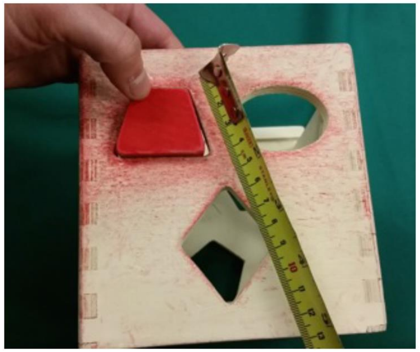

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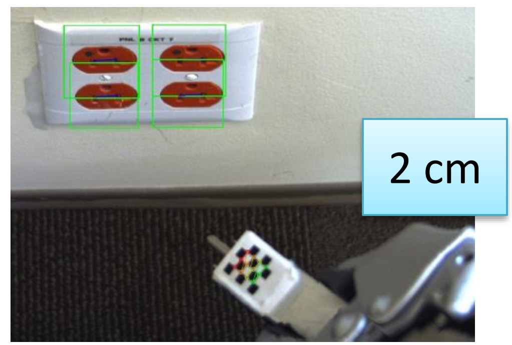

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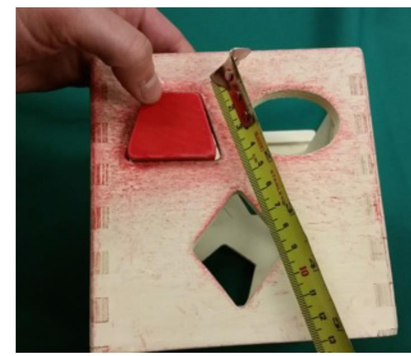


Guided Policy Search Applications

Guided Policy Search Applications

manipulation

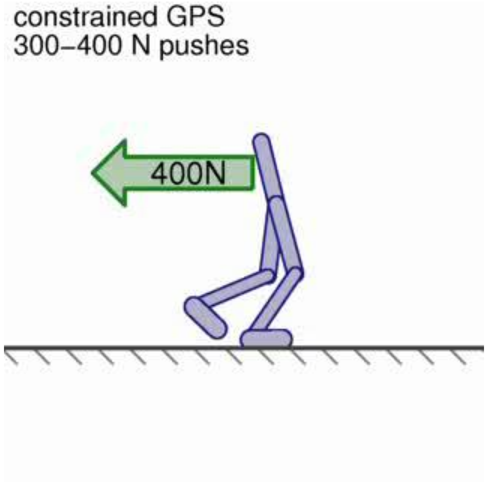
with N. Wagener and P. Abbeel

Guided Policy Search Applications

manipulation

with N. Wagener and P. Abbeel

locomotion



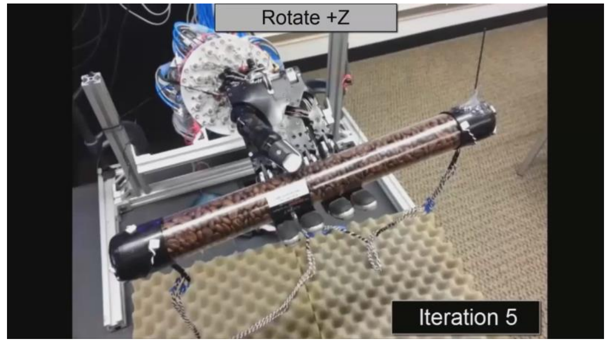
with V. Koltun

Guided Policy Search Applications

manipulation

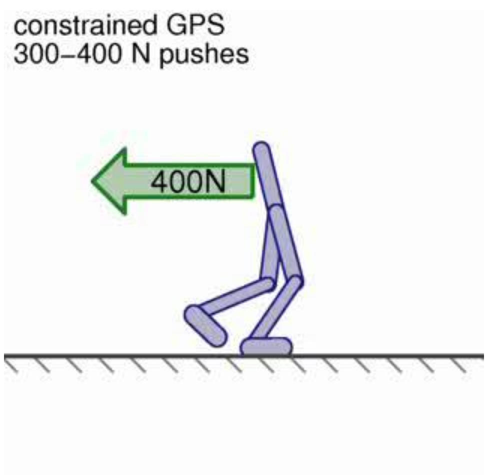
with N. Wagener and P. Abbeel

dexterous hands



with V. Kumar and E. Todorov

locomotion



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Guided Policy Search Applications

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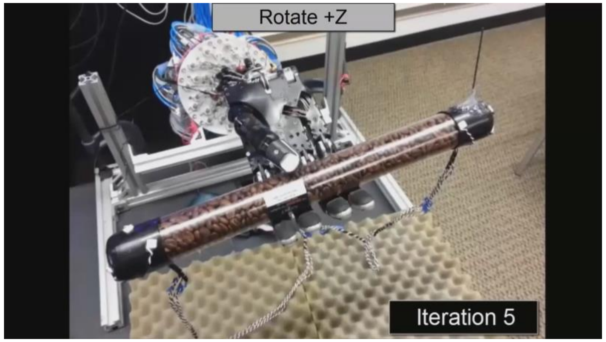
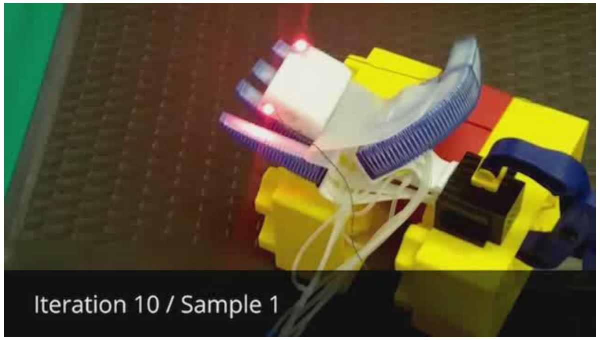


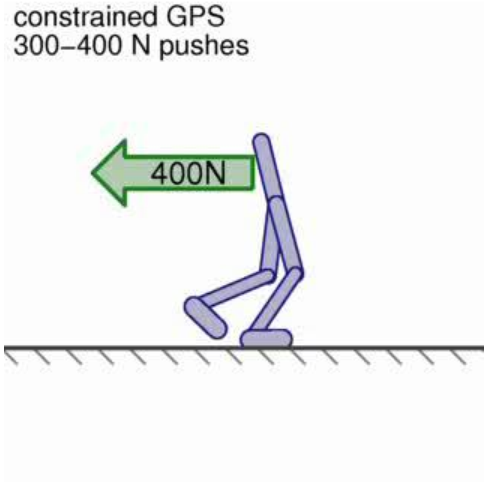
with V. Kumar and E. Todorov

soft hands



with A. Gupta, C. Eppner, P. Abbeel

locomotion



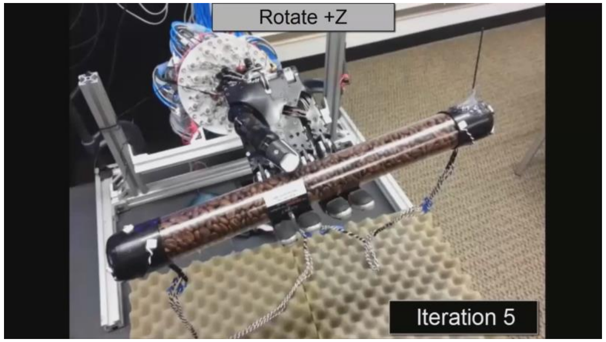
with V. Koltun

Guided Policy Search Applications

manipulation

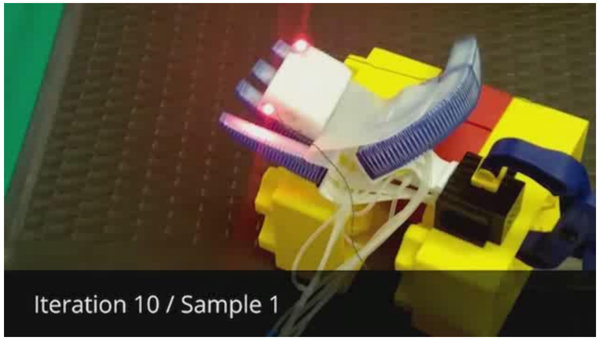
with N. Wagener and P. Abbeel

dexterous hands



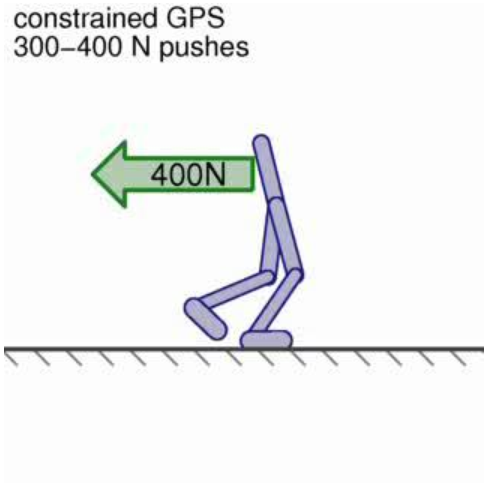
with V. Kumar and E. Todorov

soft hands



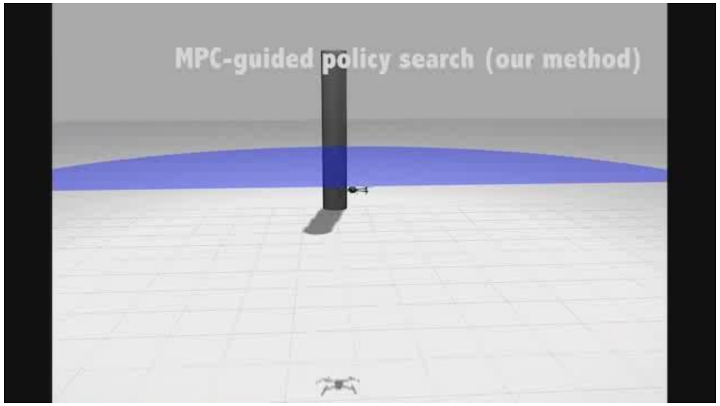
with A. Gupta, C. Eppner, P. Abbeel

locomotion



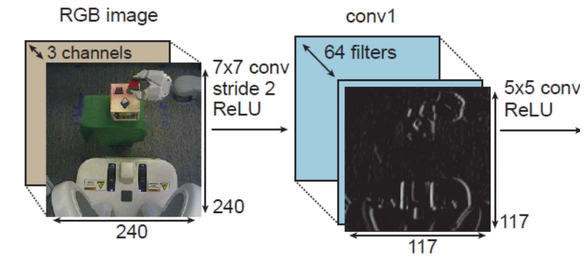
with V. Koltun

aerial vehicles



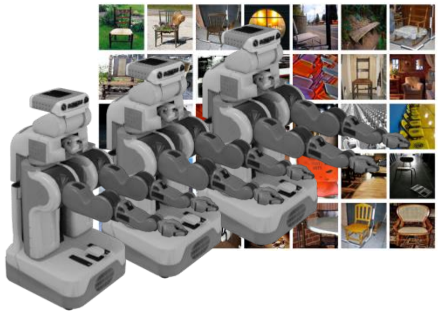
with G. Kahn, T. Zhang, P. Abbeel

Overview



Training visuomotor policies

Deep robotic learning at scale



Future directions

ingredients for success in learning:

supervised learning:

ingredients for success in learning:

supervised learning:

- ✓ computation

ingredients for success in learning:

supervised learning:

- ✓ computation
- ✓ algorithms

ingredients for success in learning:

supervised learning:

- ✓ computation
- ✓ algorithms
- ✓ data

ingredients for success in learning:

supervised learning:

- ✓ computation
- ✓ algorithms
- ✓ data

learning sensorimotor skills:

ingredients for success in learning:

supervised learning:

- ✓ computation
- ✓ algorithms
- ✓ data

learning sensorimotor skills:

- ✓ computation

ingredients for success in learning:

supervised learning:

- ✓ computation
- ✓ algorithms
- ✓ data

learning sensorimotor skills:

- ✓ computation
- ~ algorithms

ingredients for success in learning:

supervised learning:	learning sensorimotor skills:
✓ computation	✓ computation
✓ algorithms	~ algorithms
✓ data	? data

ingredients for success in learning:

supervised learning:

- ✓ computation
- ✓ algorithms
- ✓ data

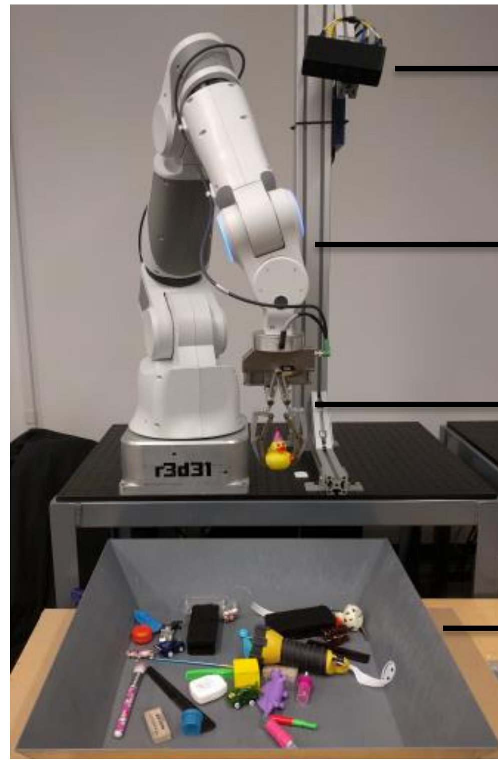
learning sensorimotor skills:

- ✓ computation
- ~ algorithms
- ? data

L., Pastor, Krizhevsky, Quillen ‘16

Grasping with Learned Hand-Eye Coordination

- 800,000 grasp attempts for training (3,000 robot-hours)
- monocular camera (no depth)
- 2-5 Hz update
- no prior knowledge



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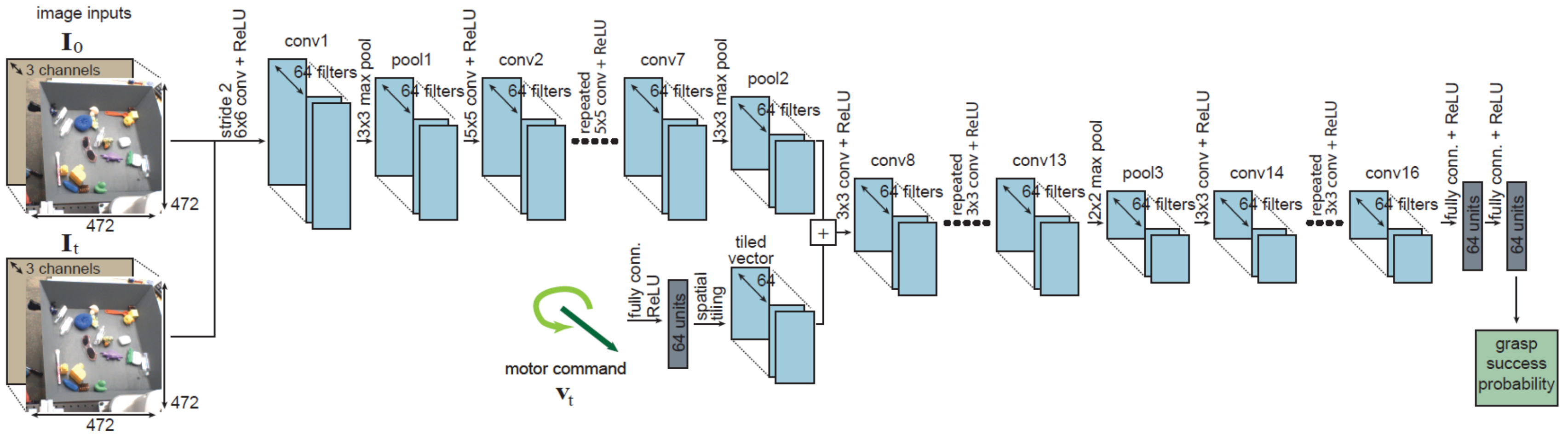
Using Grasp Success Prediction



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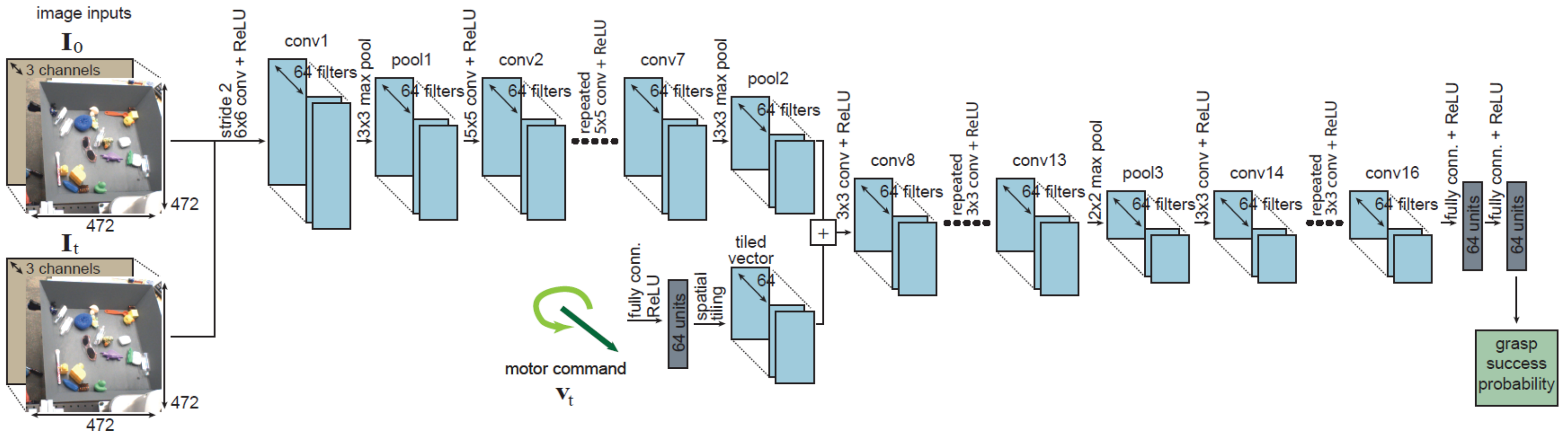
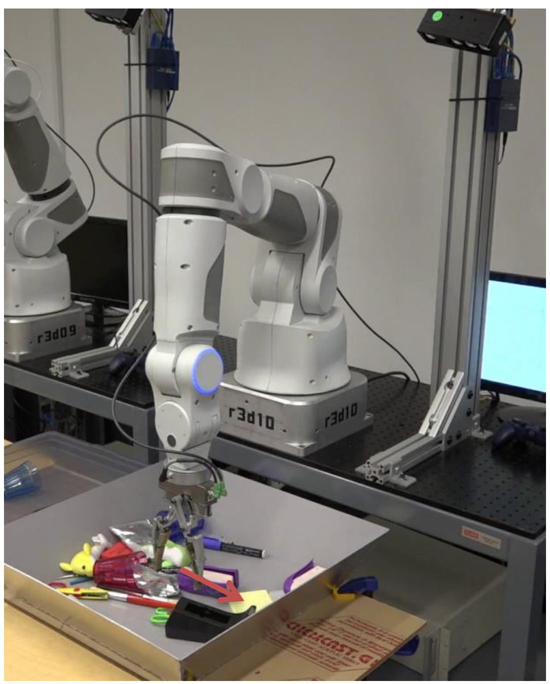
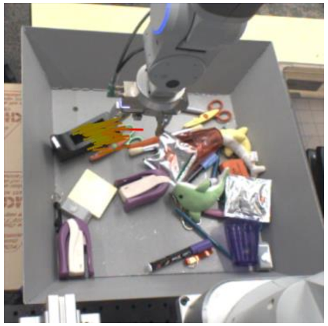
Using Grasp Success Prediction





training



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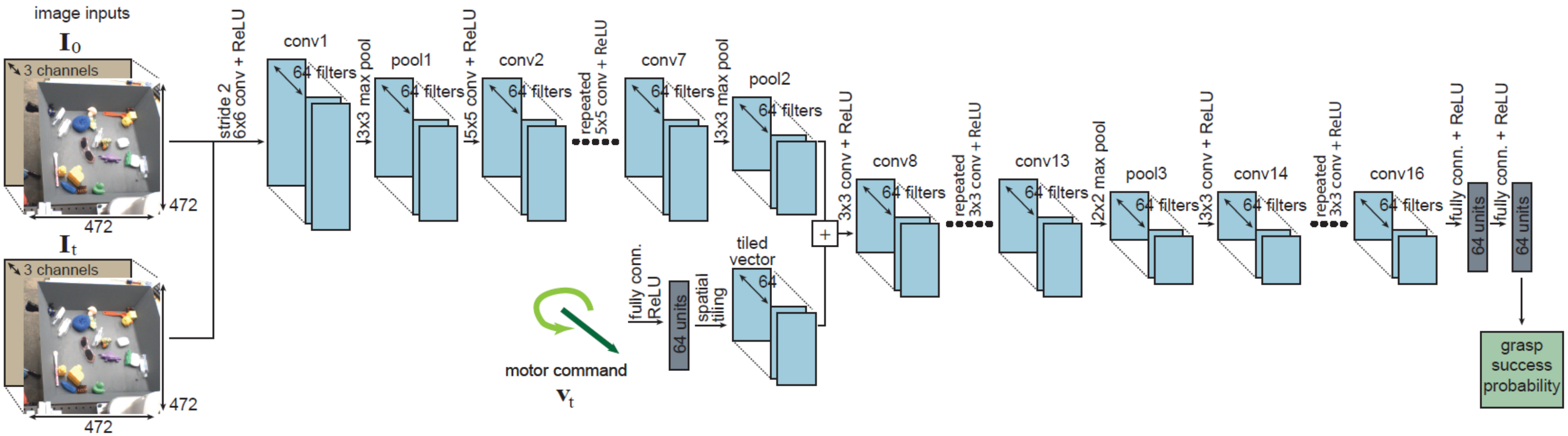
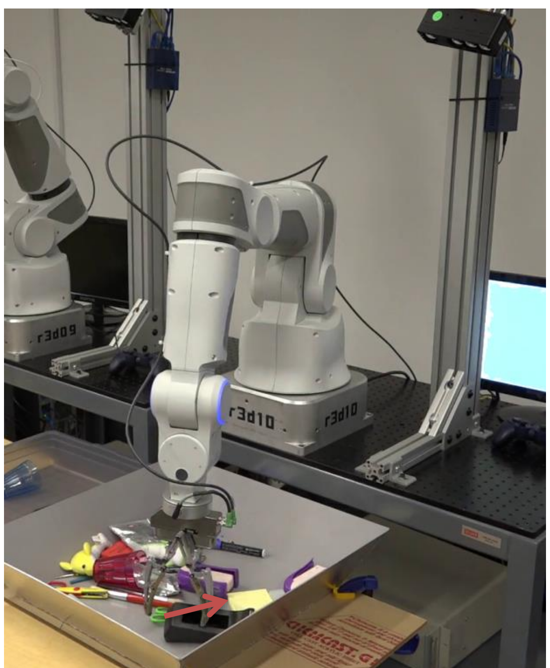
Using Grasp Success Prediction





training

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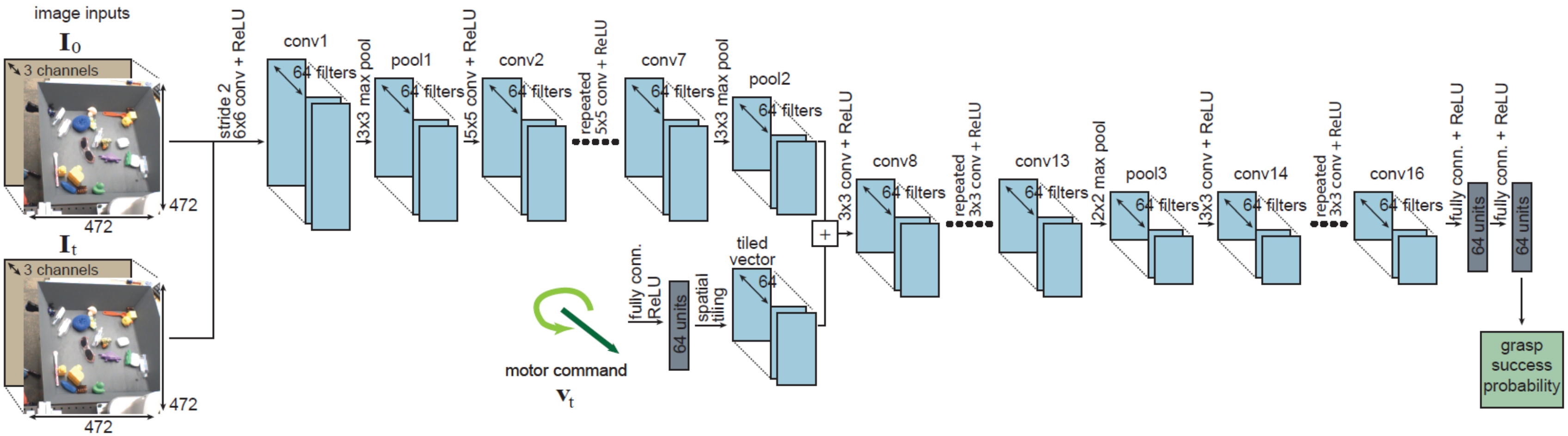

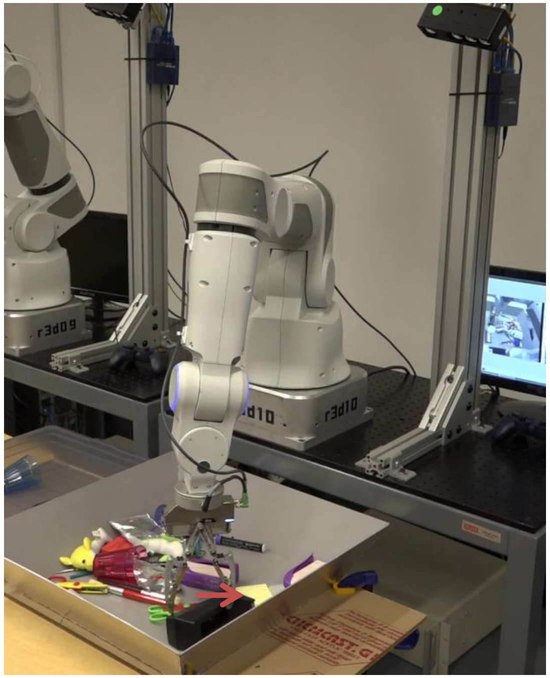

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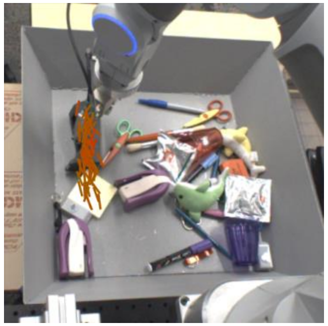

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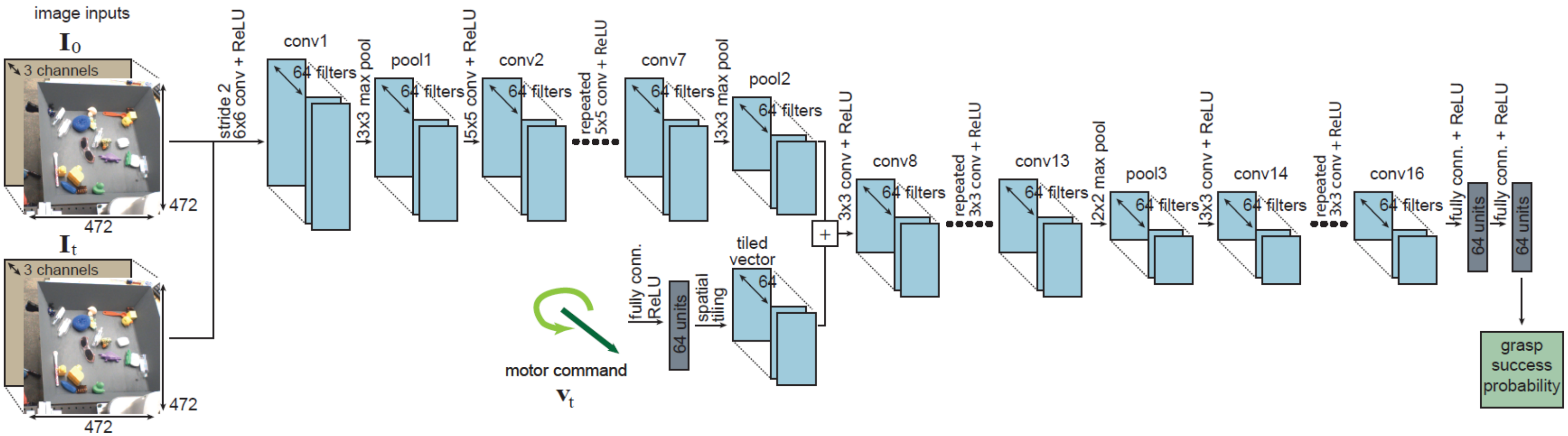
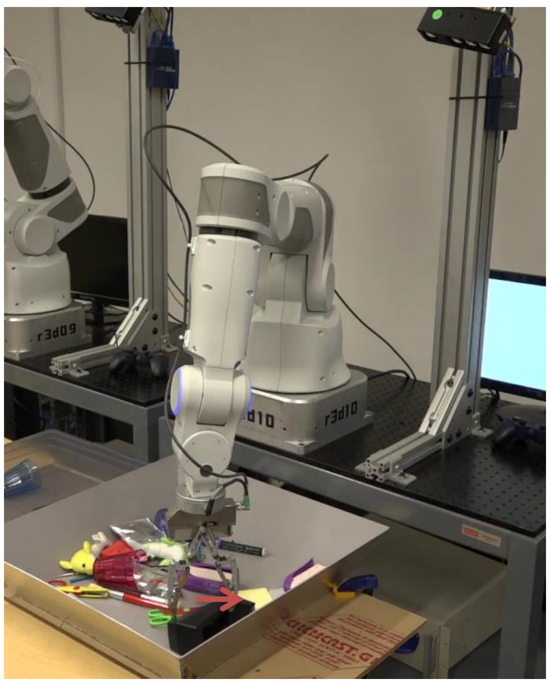
Using Grasp Success Prediction





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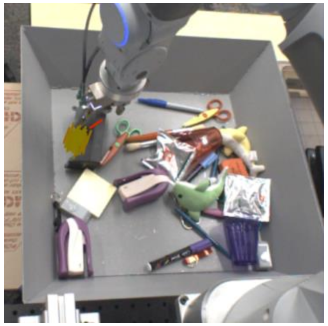

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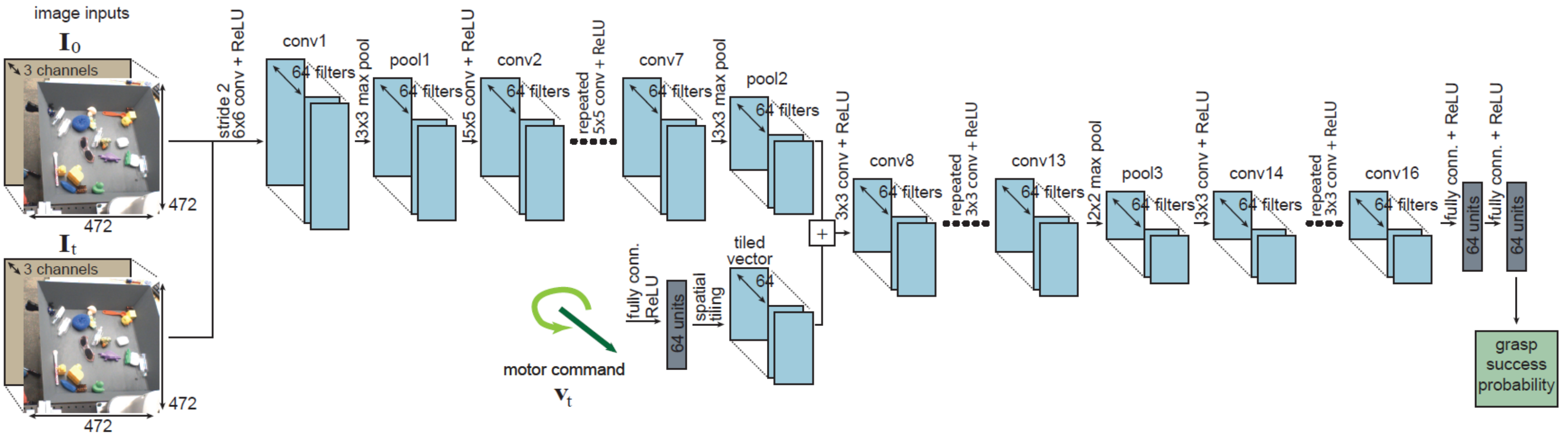

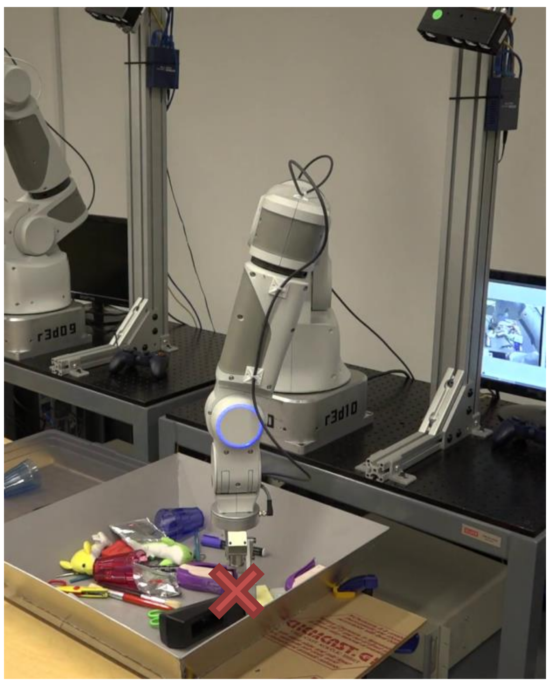

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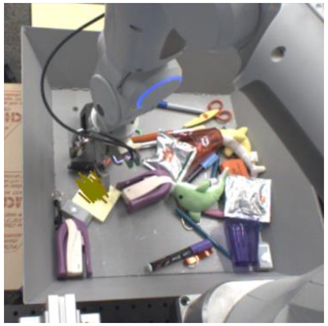

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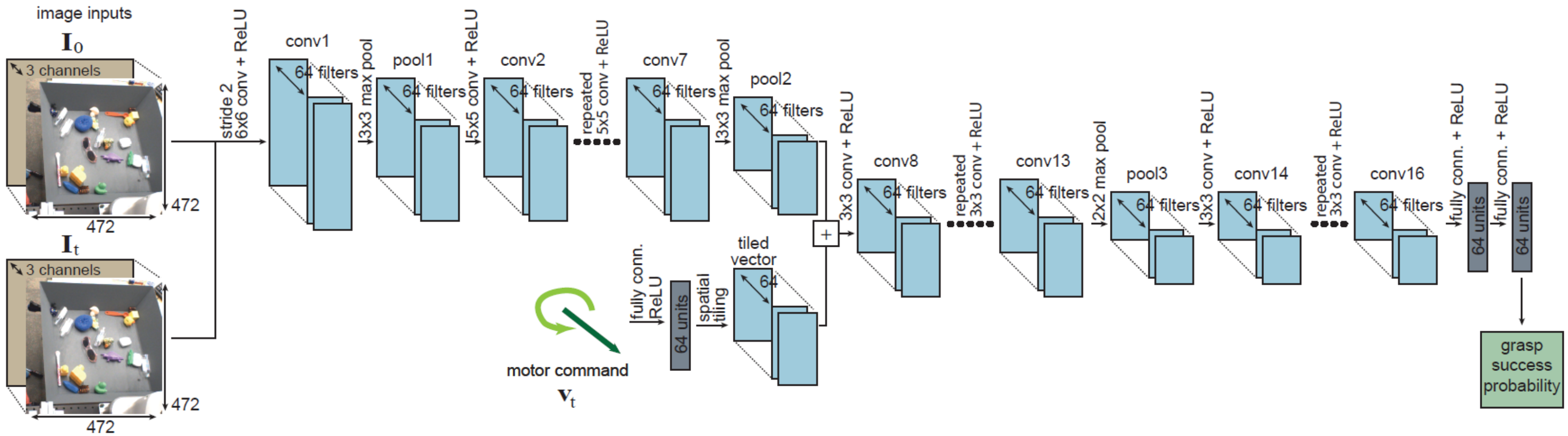

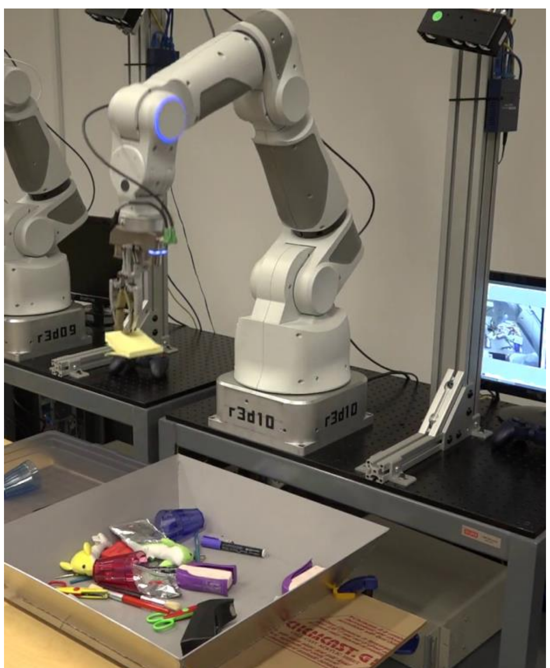

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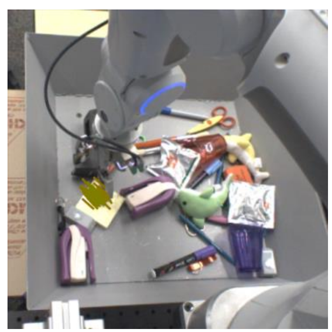

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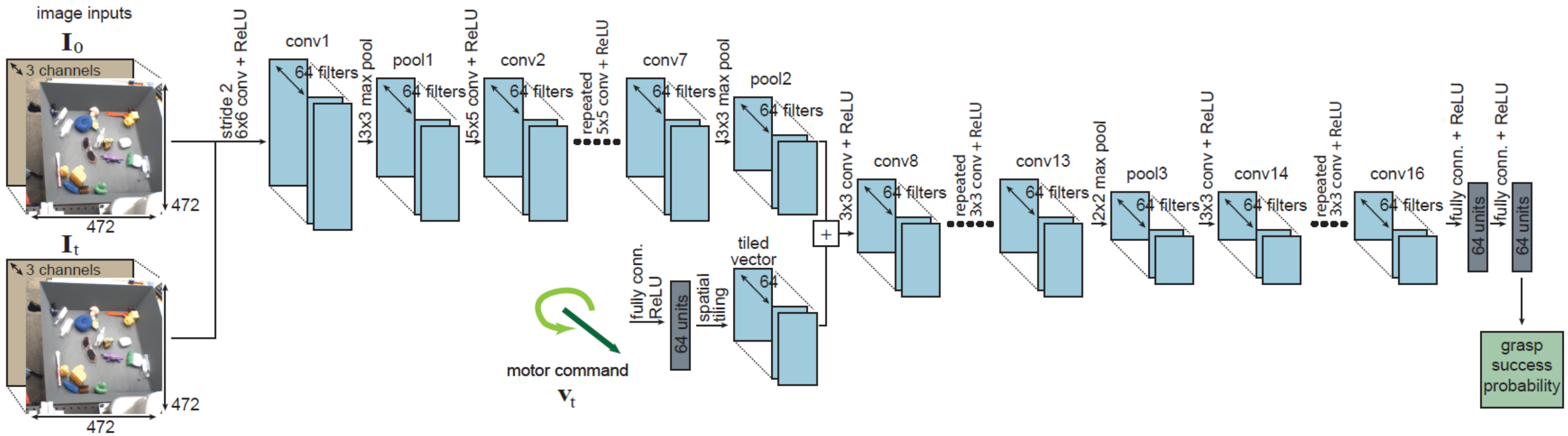
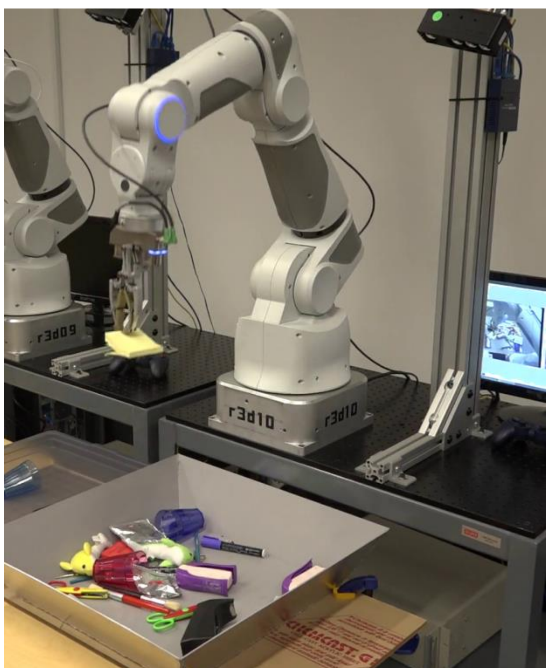
Using Grasp Success Prediction





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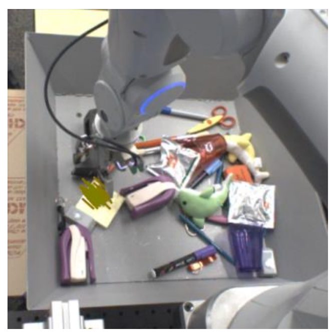

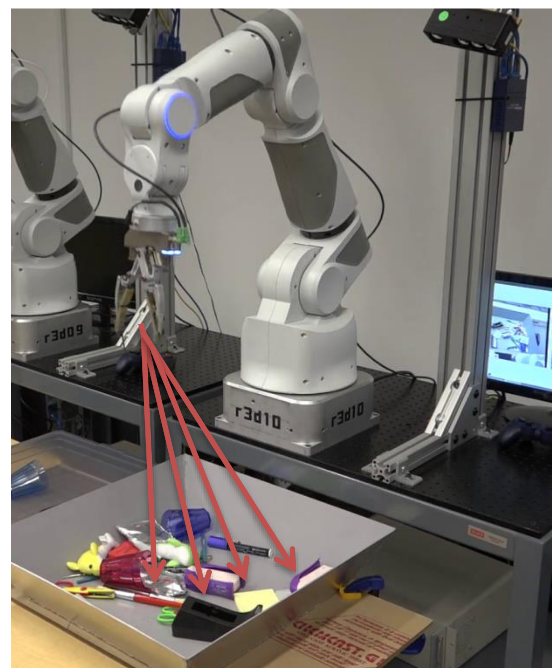

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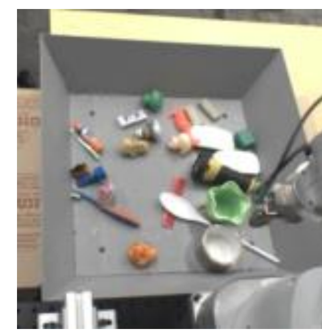
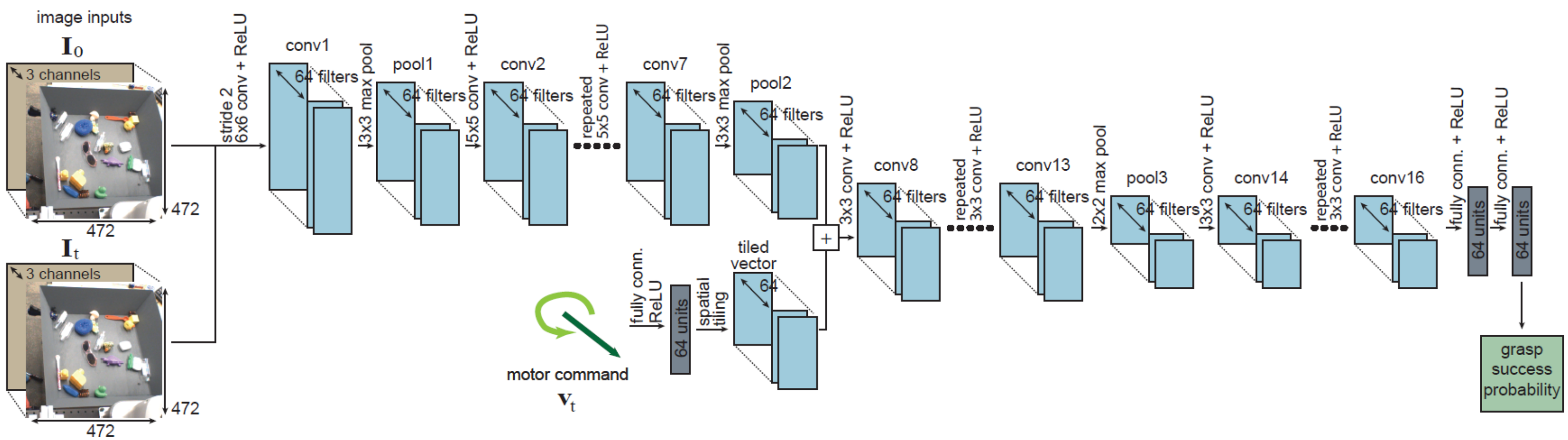
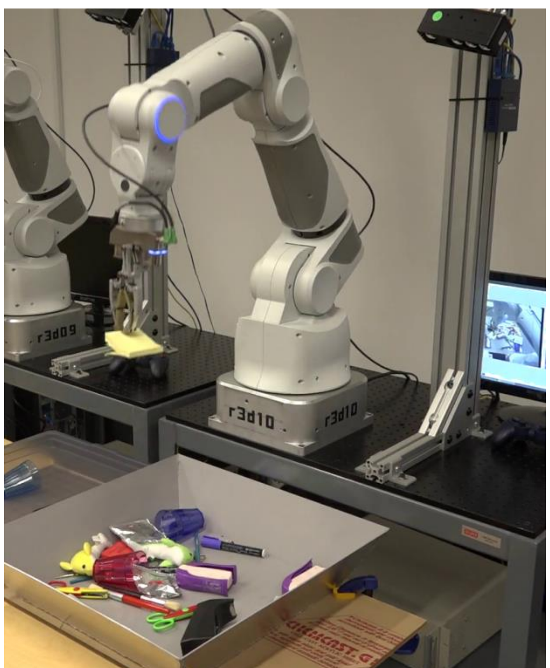


L., Pastor, Krizhevsky, Quillen '16

Using Grasp Success Prediction





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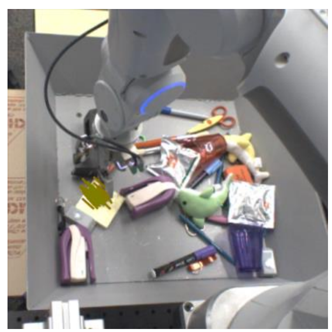

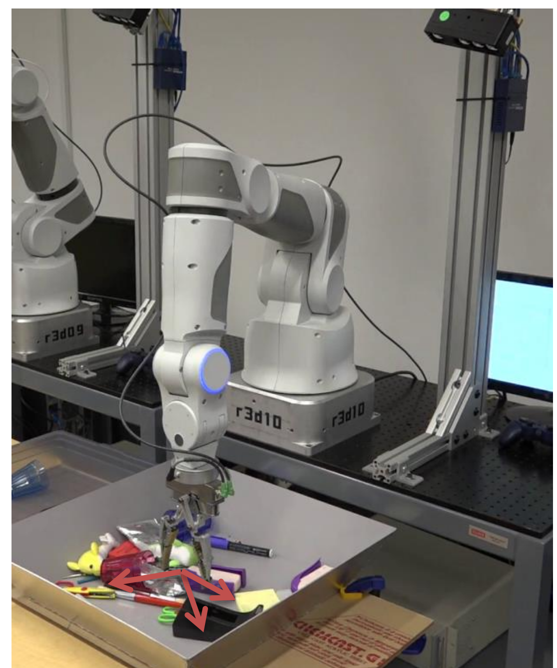

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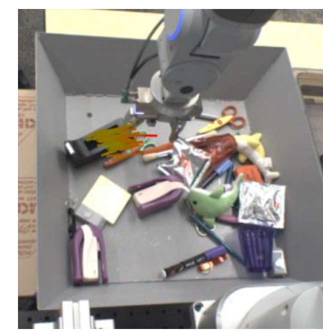

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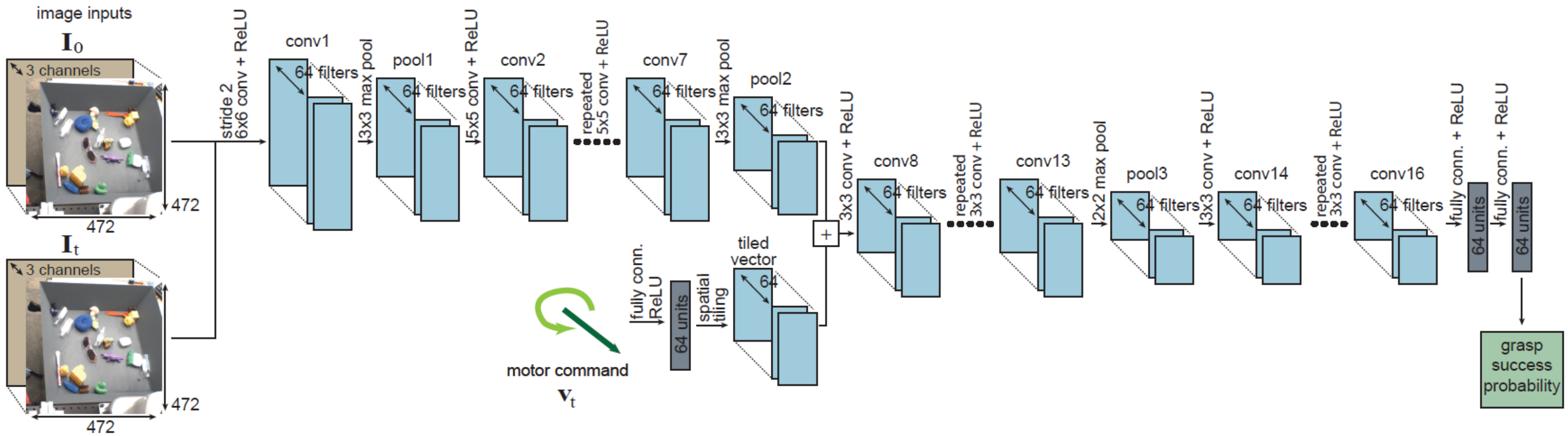
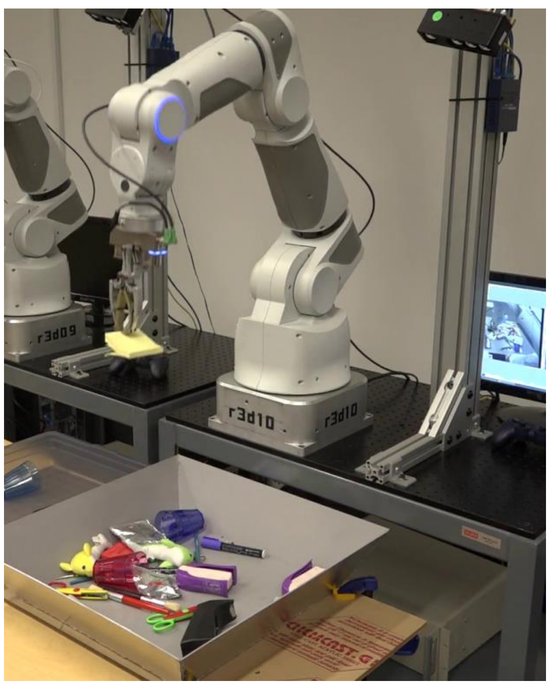
Using Grasp Success Prediction





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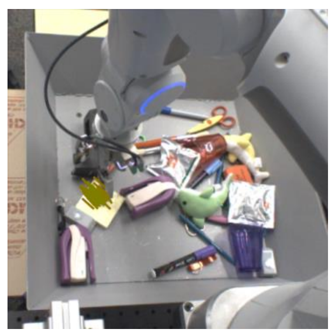

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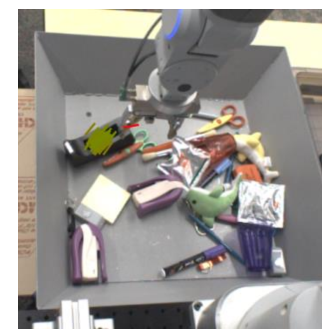

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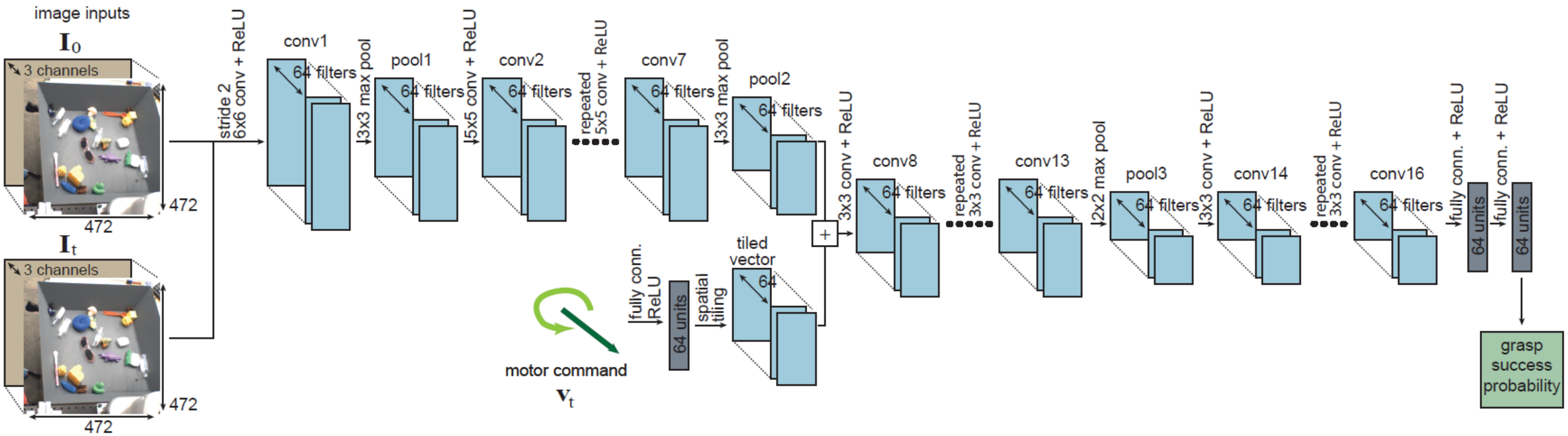
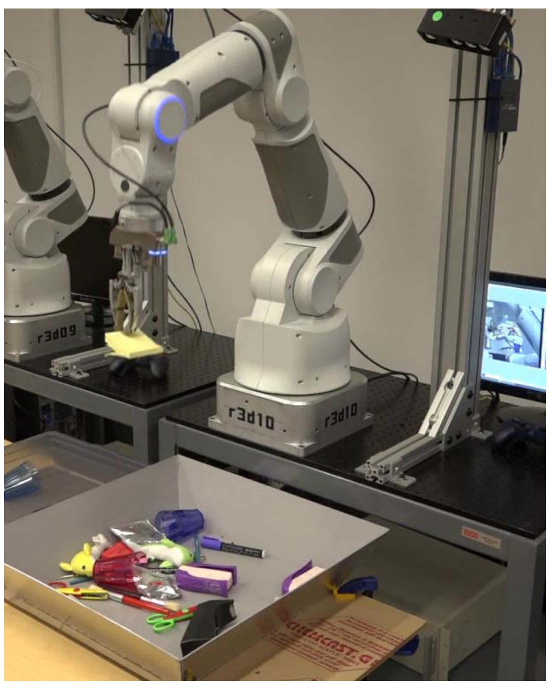
Using Grasp Success Prediction





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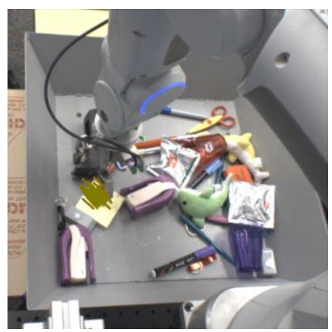

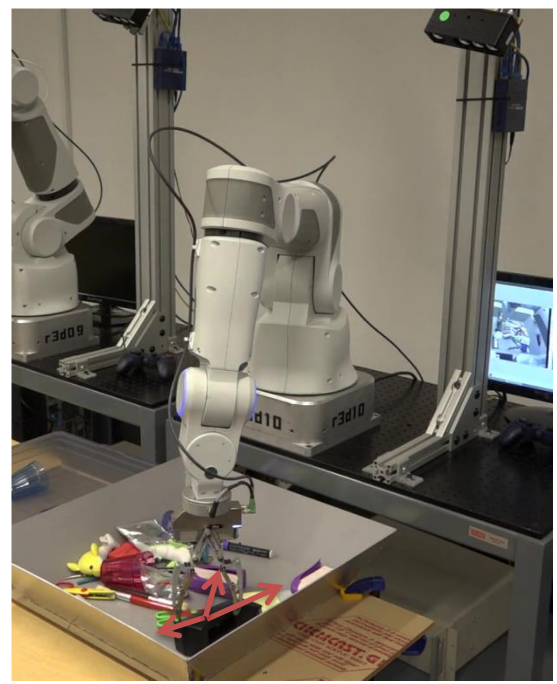

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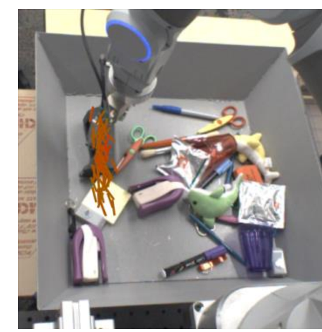

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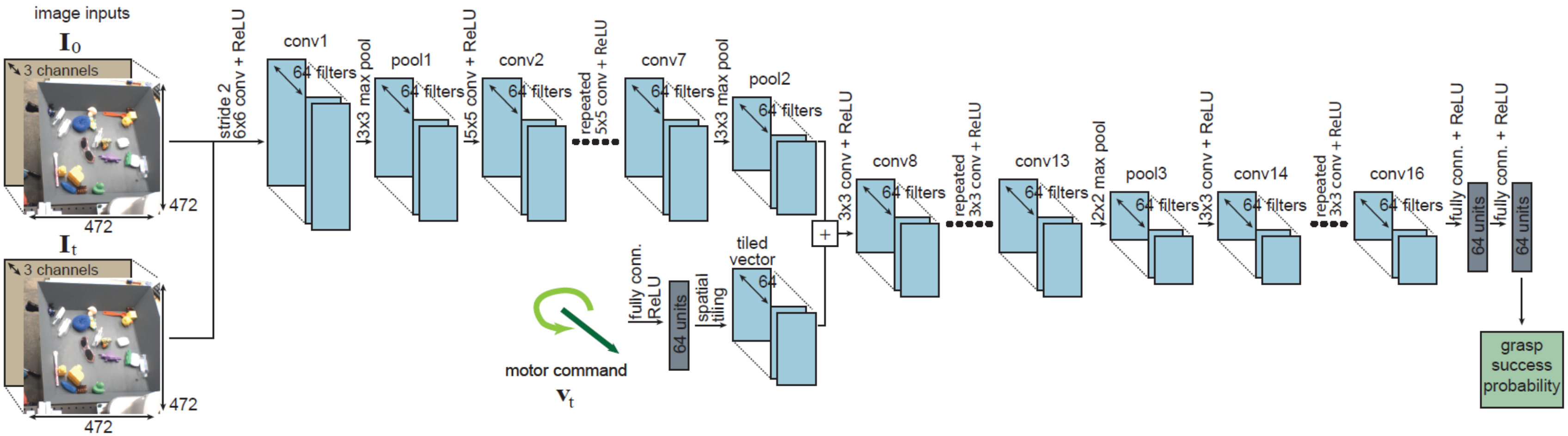

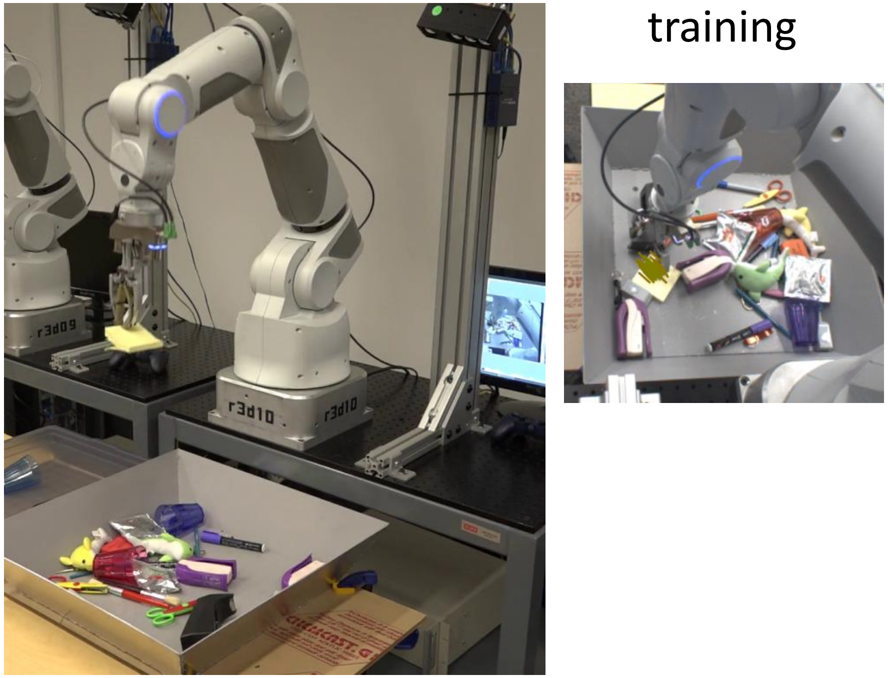

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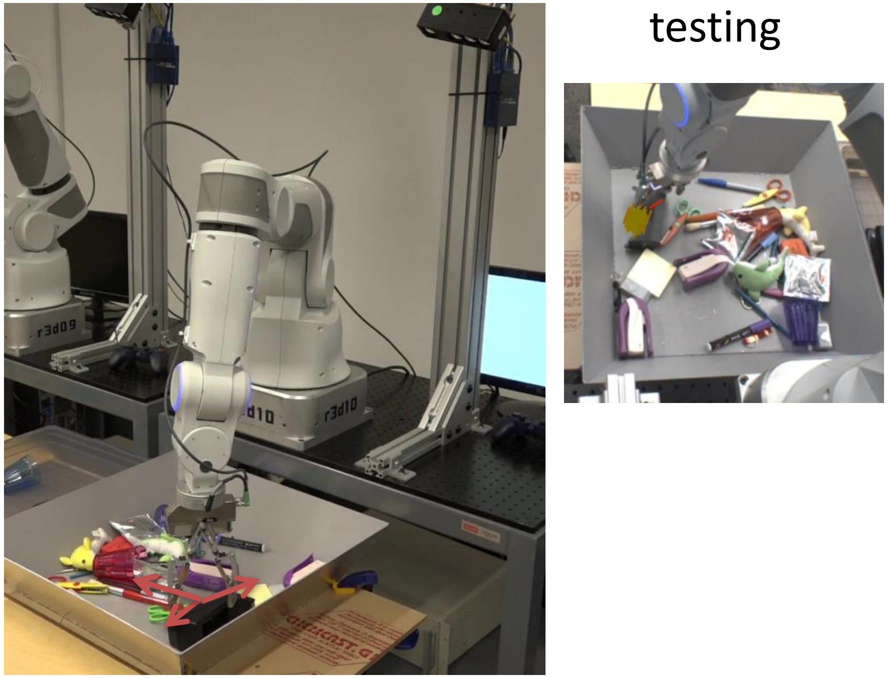

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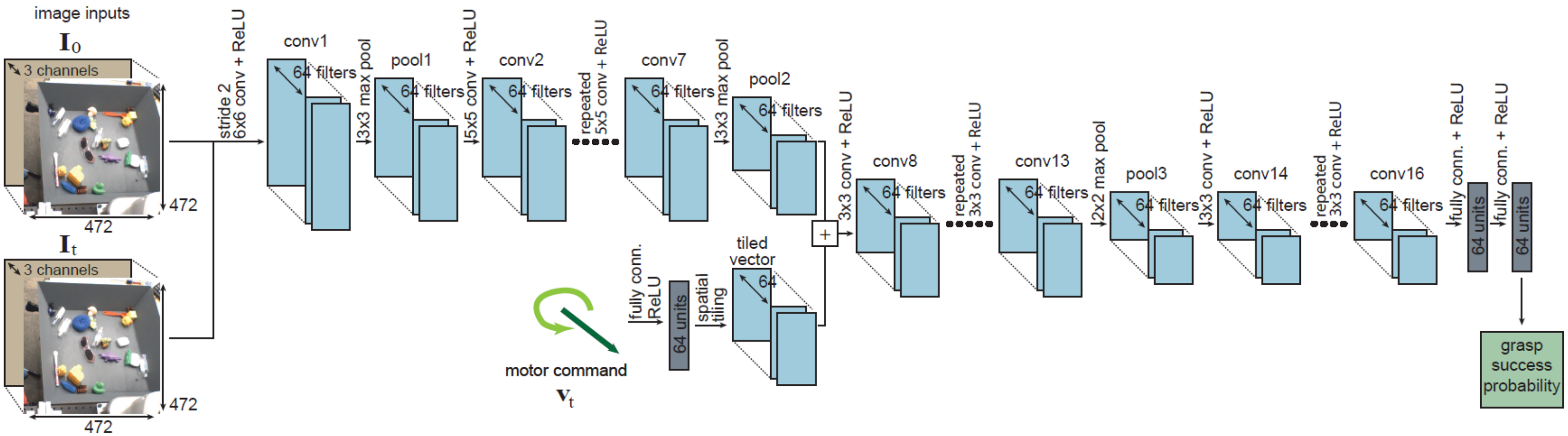

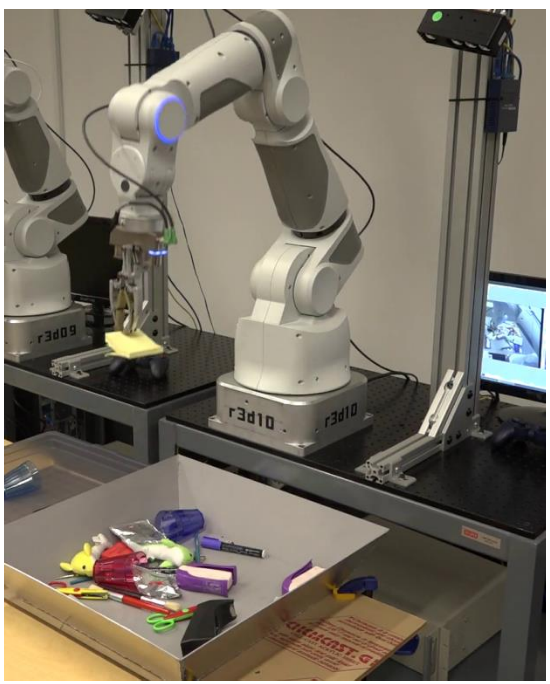

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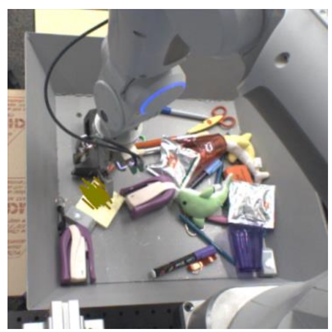

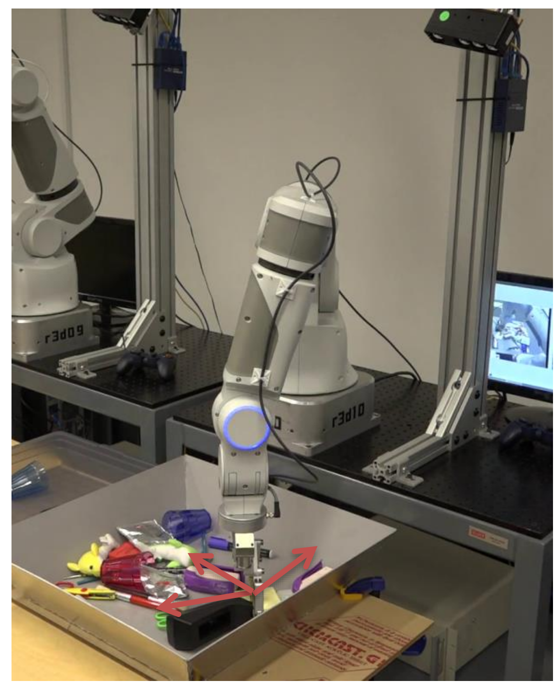

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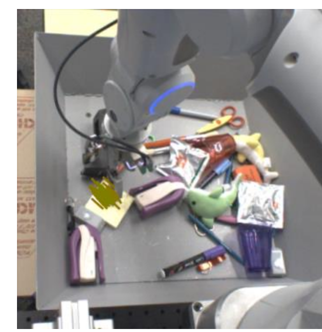

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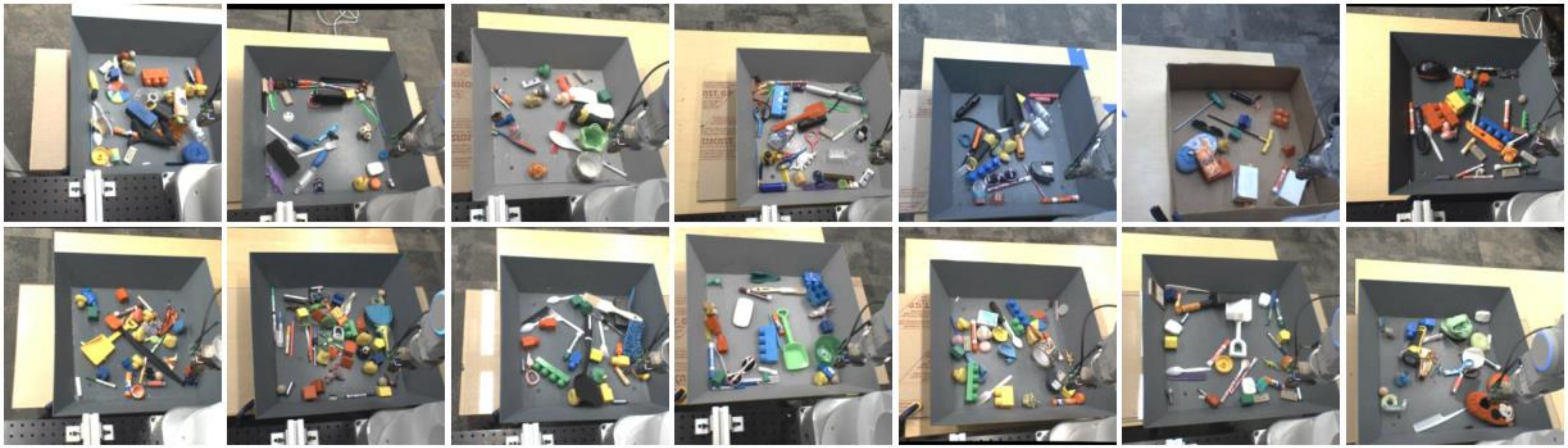
Using Grasp Success Prediction



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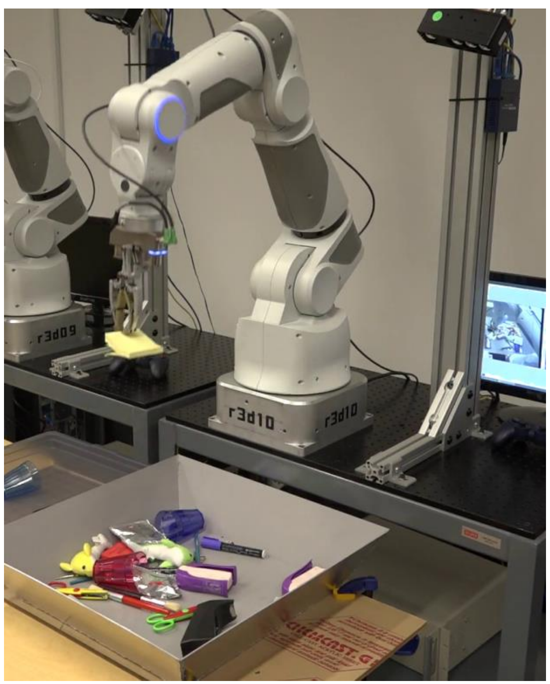

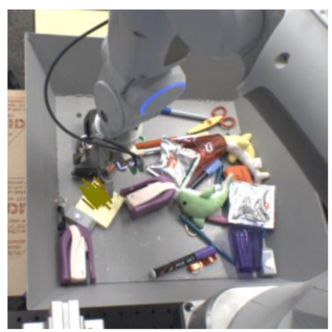

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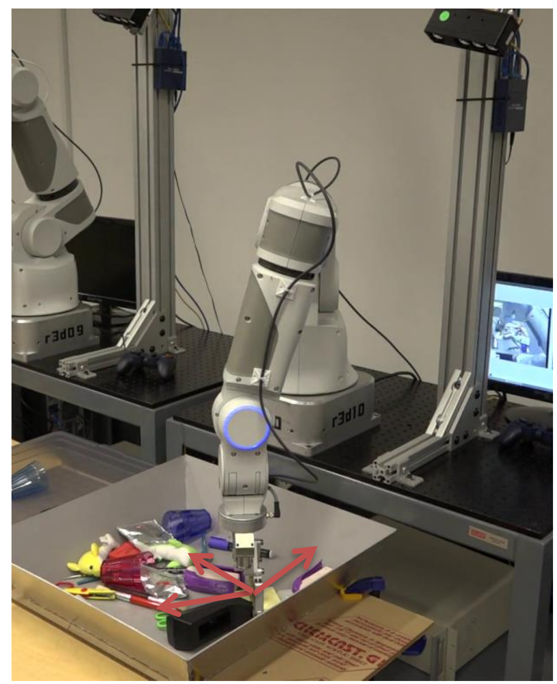

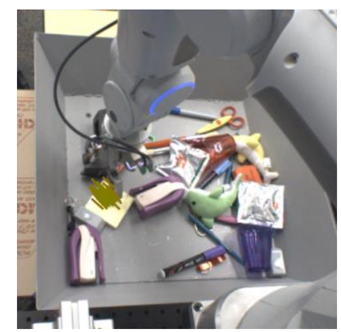

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Open-Loop vs. Closed-Loop Grasping

open-loop grasping

closed-loop grasping

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Open-Loop vs. Closed-Loop Grasping

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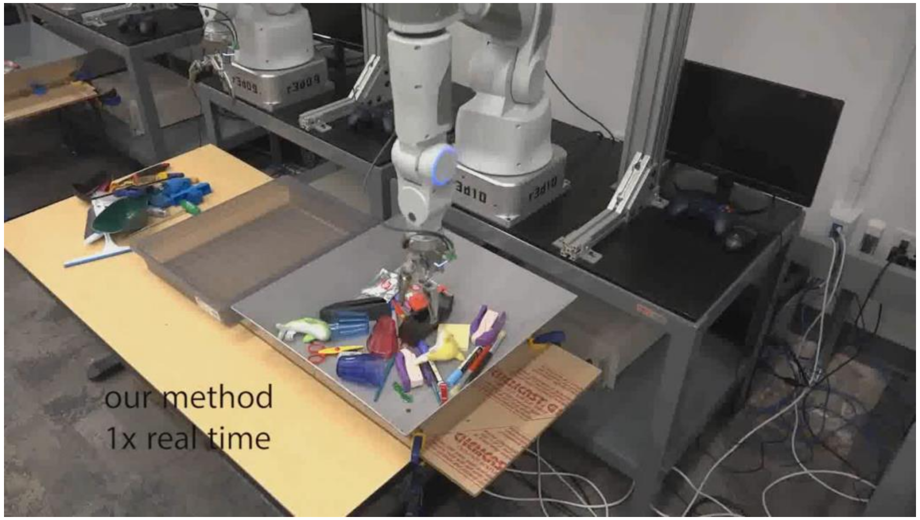
closed-loop grasping



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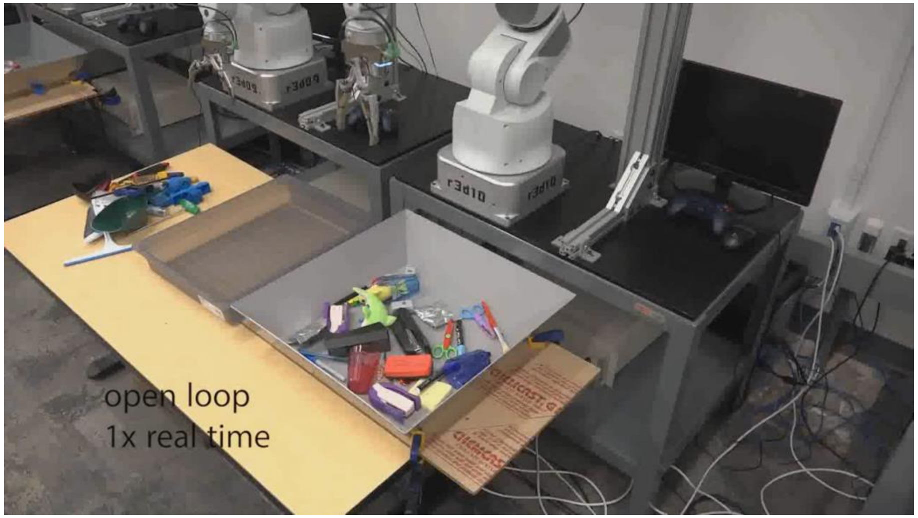
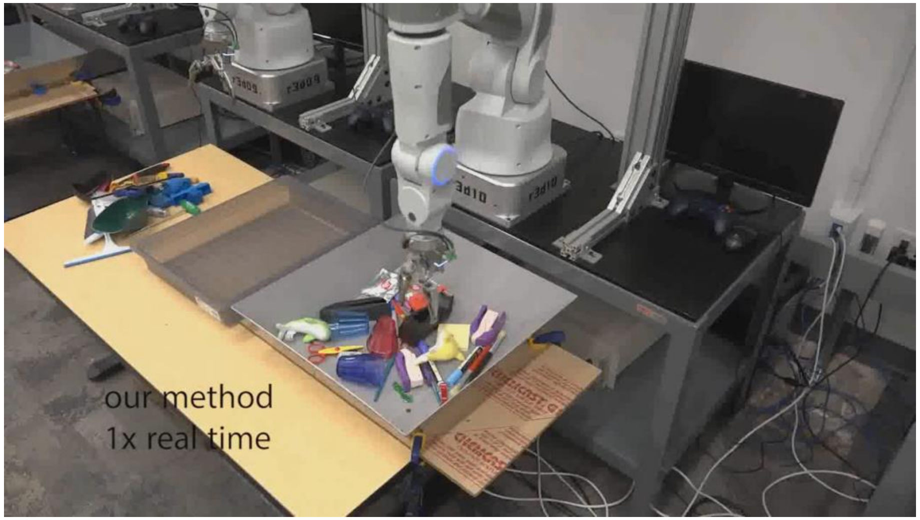


closed-loop grasping



Pinto & Gupta, 2015

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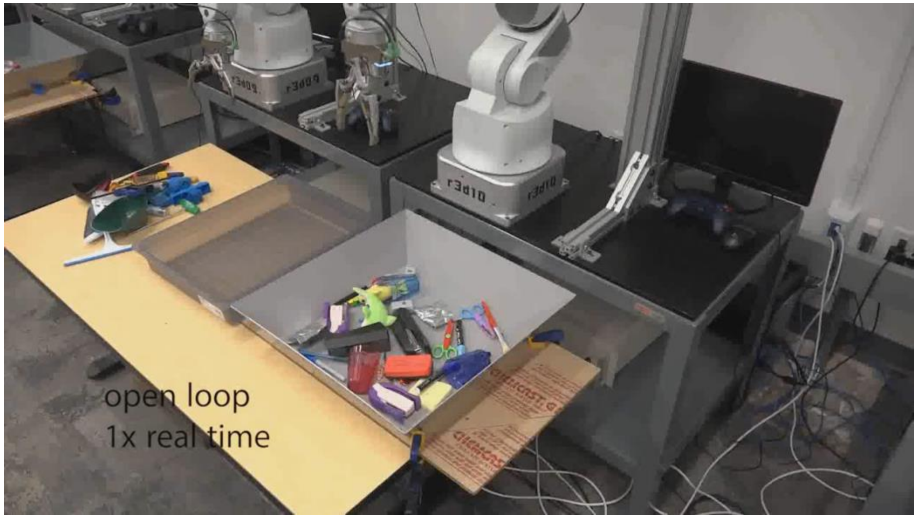

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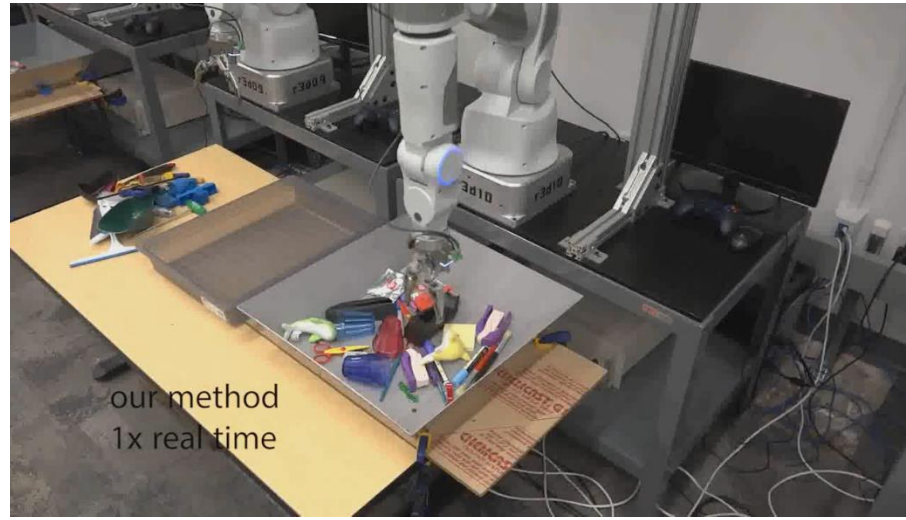

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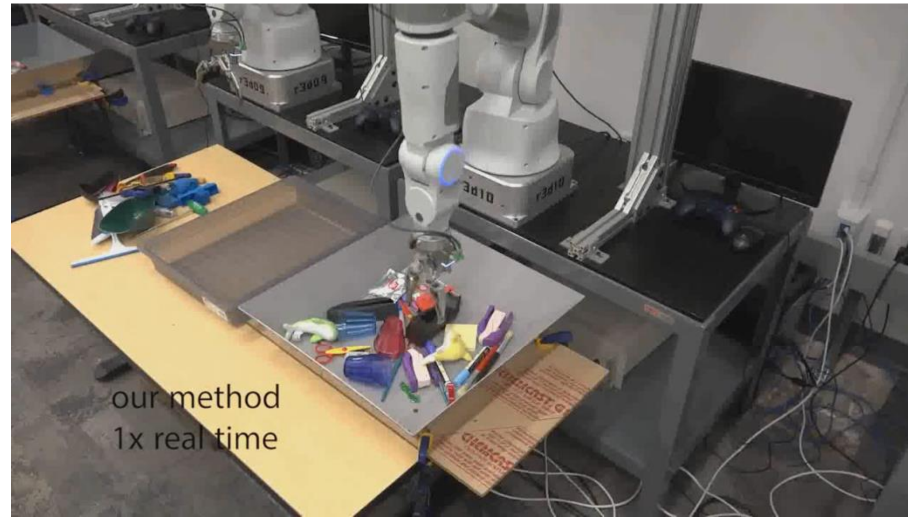

failure rate: 33.7%

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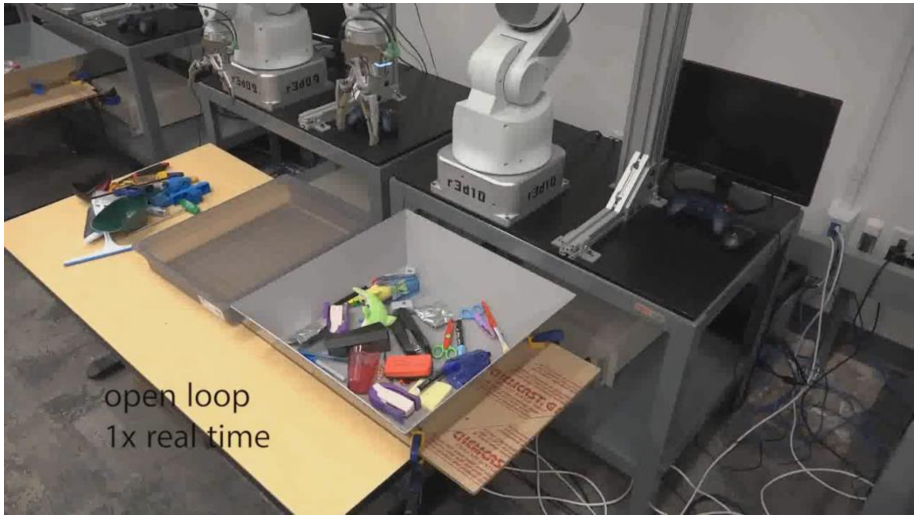

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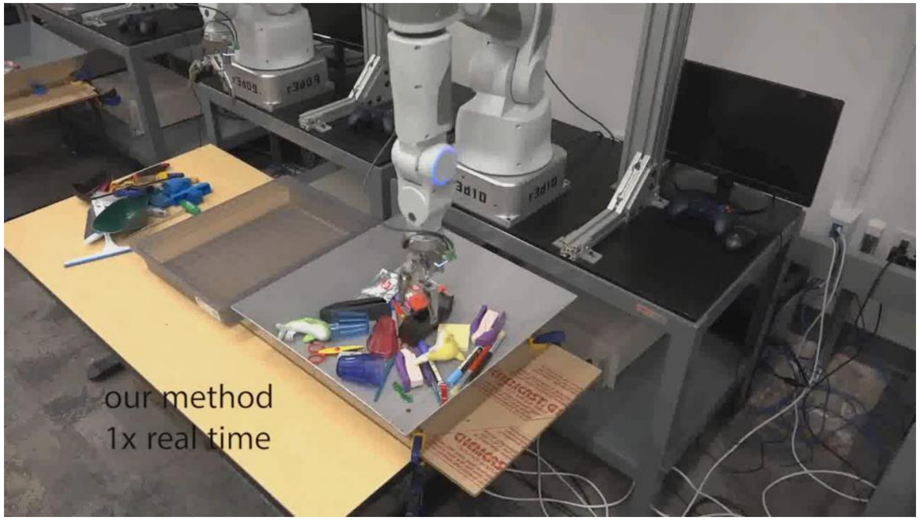

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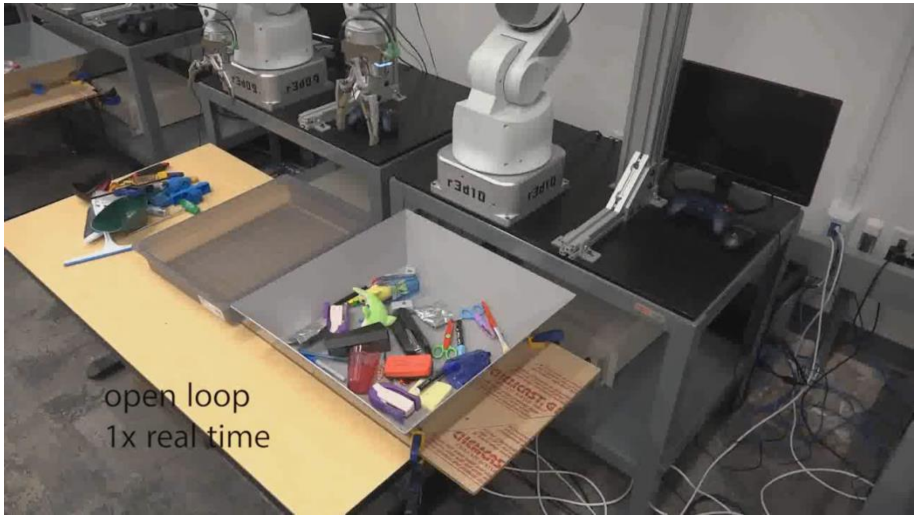

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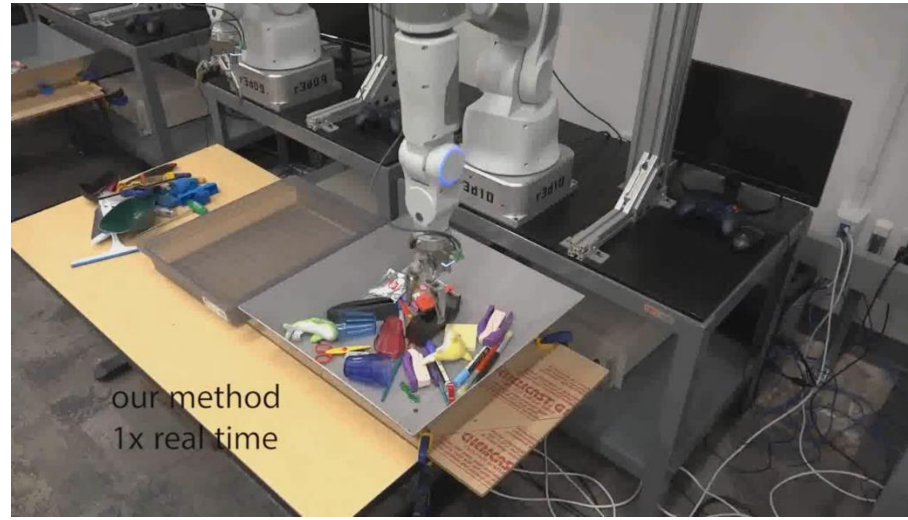
closed-loop grasping



failure rate: 17.5%

depth + segmentation
failure rate: 35%

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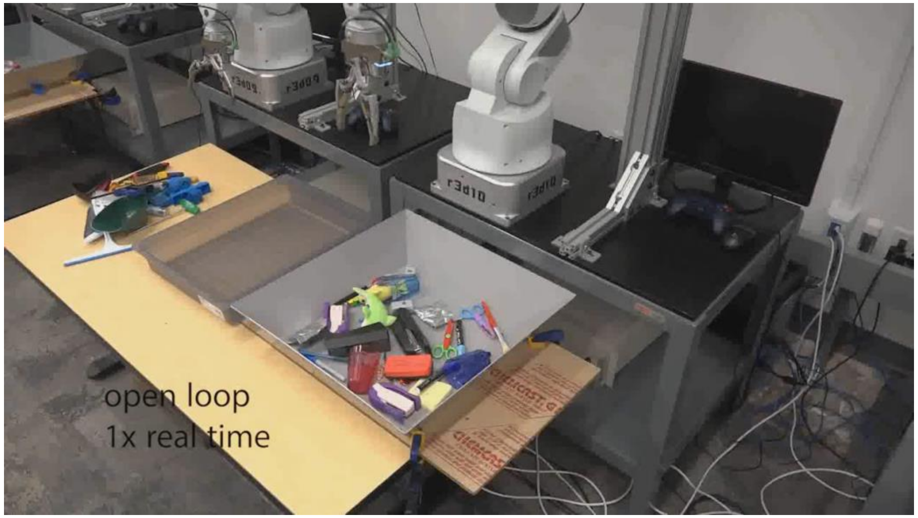
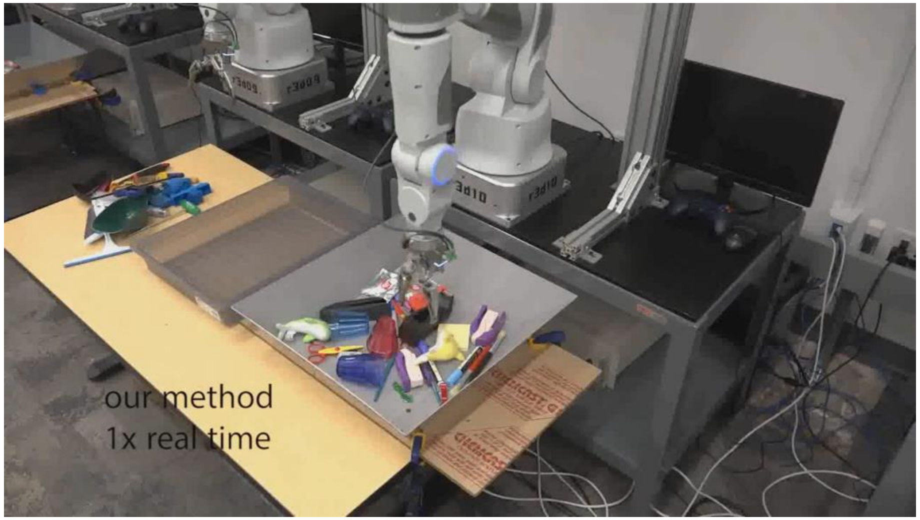
Open-Loop vs. Closed-Loop Grasping

open-loop grasping



closed-loop grasping



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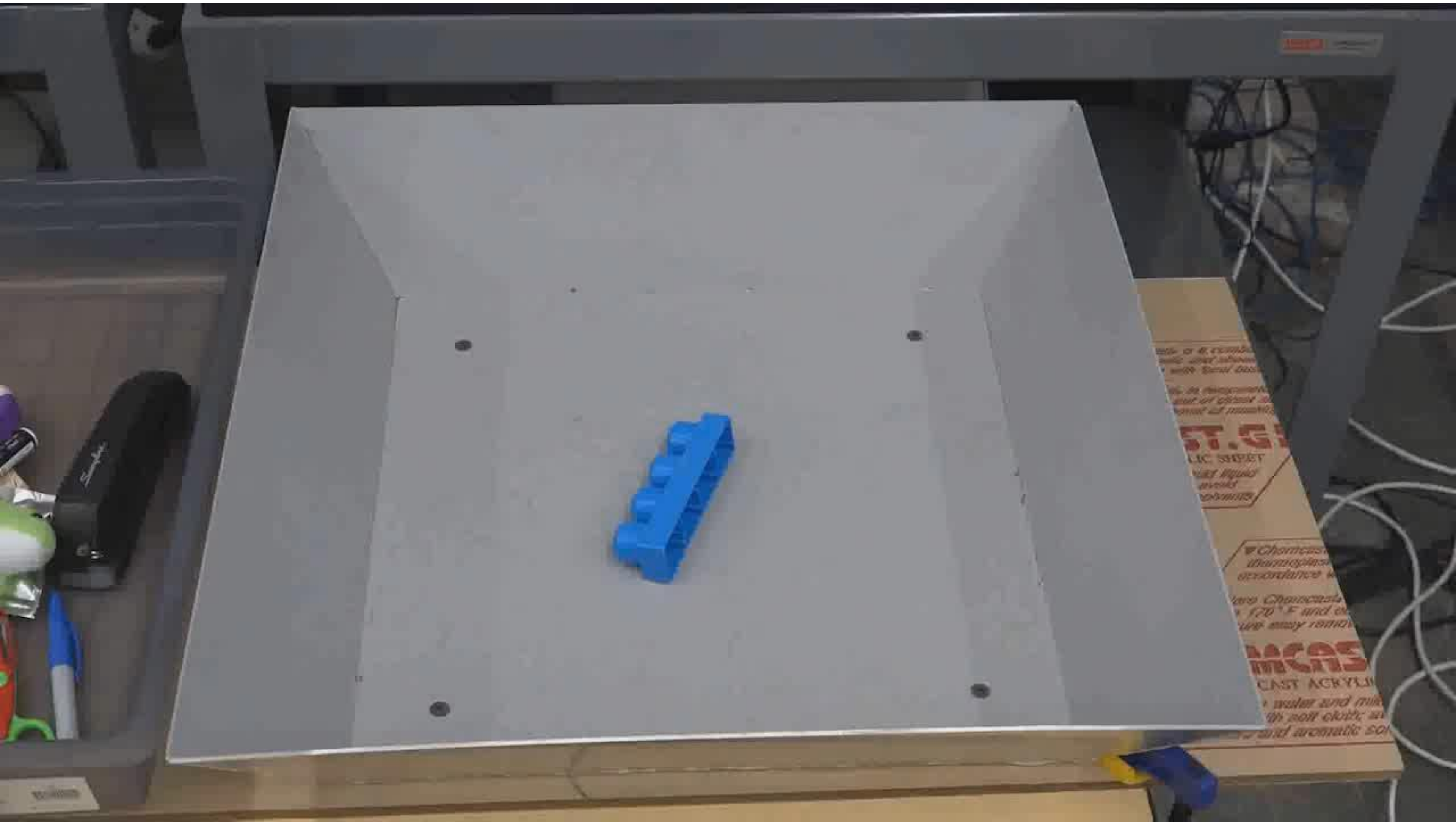
Grasping Experiments



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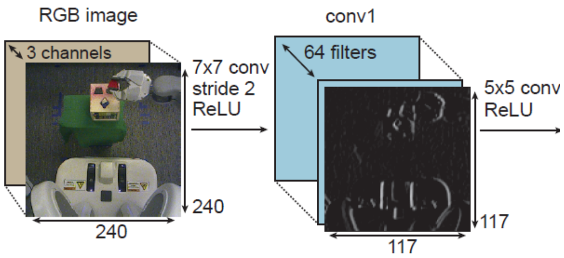
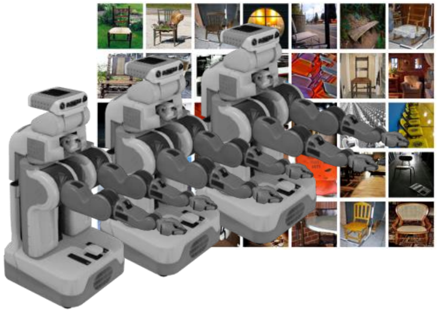
Overview



Training visuomotor policies

Deep robotic learning at scale



Future directions

ingredients for success in learning:

supervised learning:	learning sensorimotor skills:
✓ computation	✓ computation
✓ algorithms	~ algorithms
✓ data	? data

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supervised learning:

- ✓ computation
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learning sensorimotor skills:

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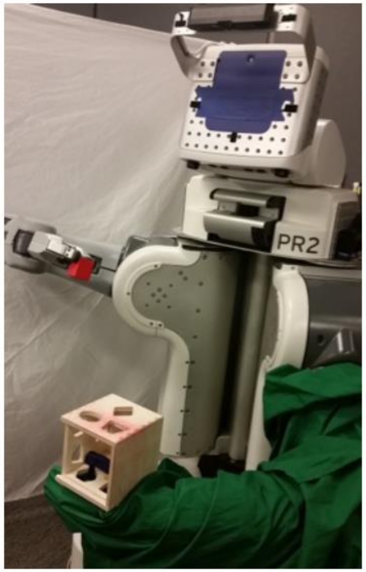
Learning what Success Means



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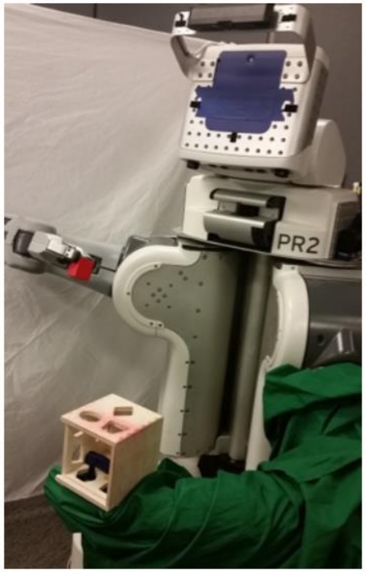
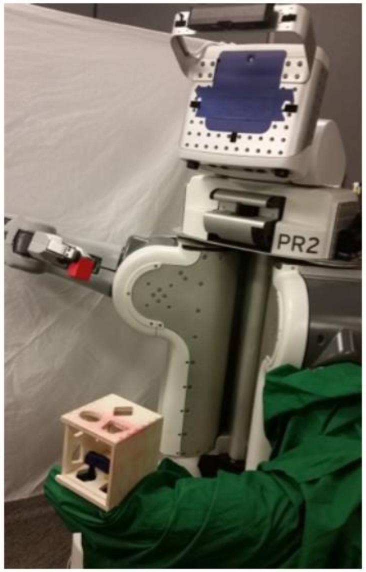
Learning what Success Means

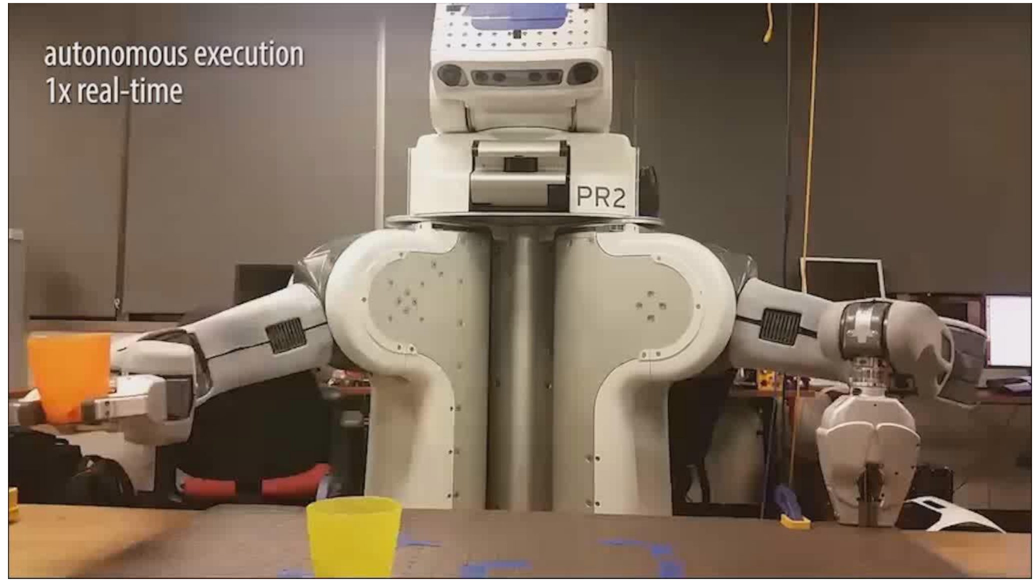


$$c(\mathbf{x}, \mathbf{u}) =$$
$$w_1 f_{\text{target}}(\mathbf{x}) +$$
$$w_2 f_{\text{torque}}(\mathbf{u})$$

Finn, L., Abbeel '16

Learning what Success Means





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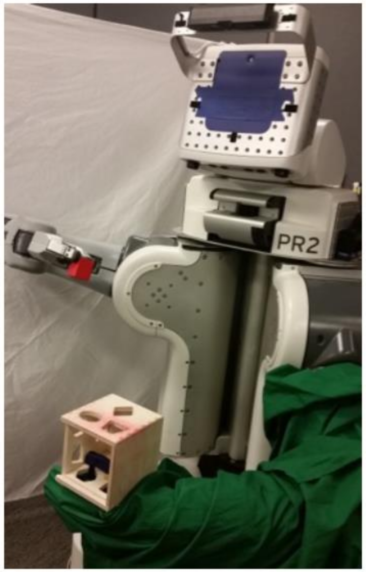

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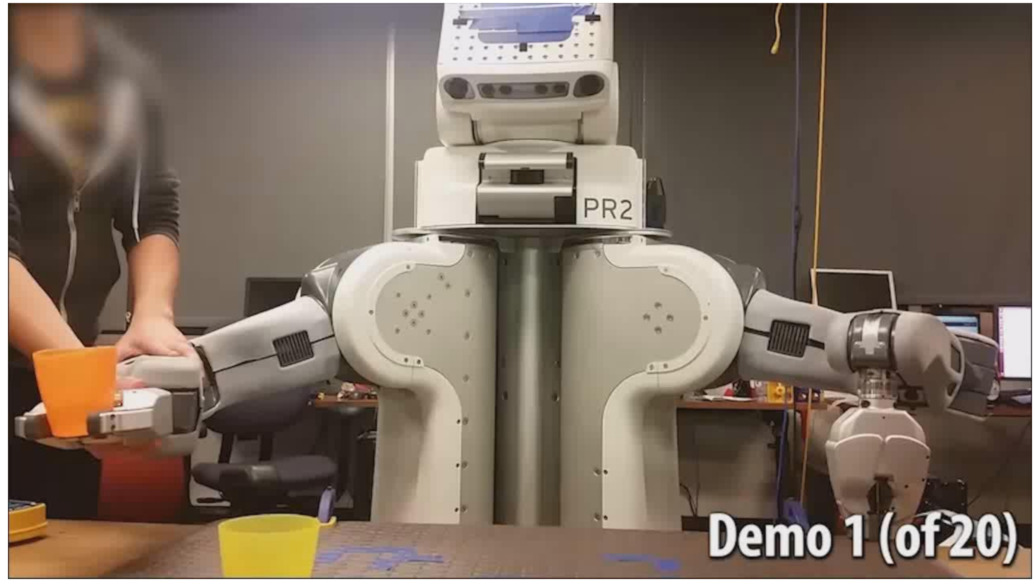

can we *learn* the cost with visual features?

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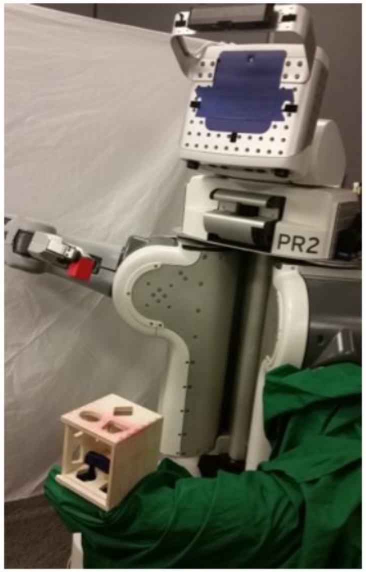
Learning what Success Means



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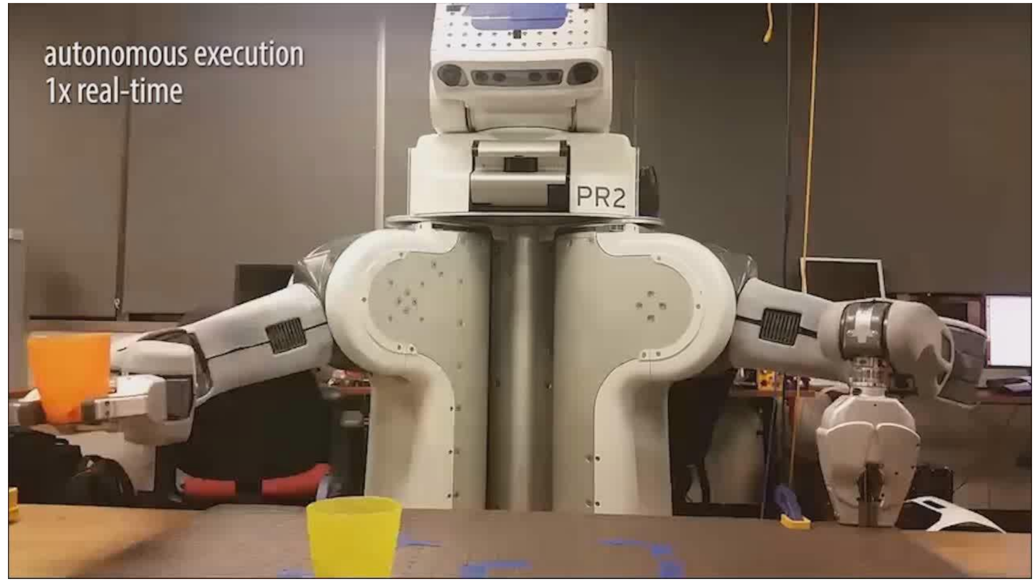

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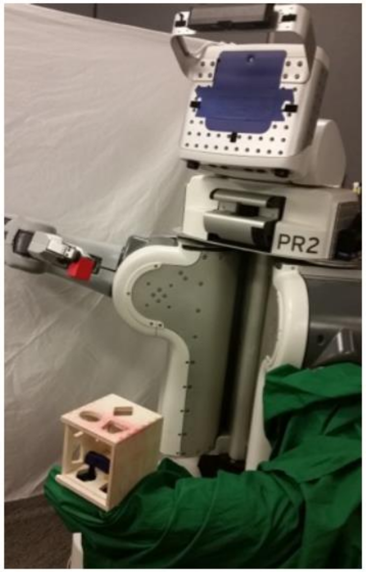

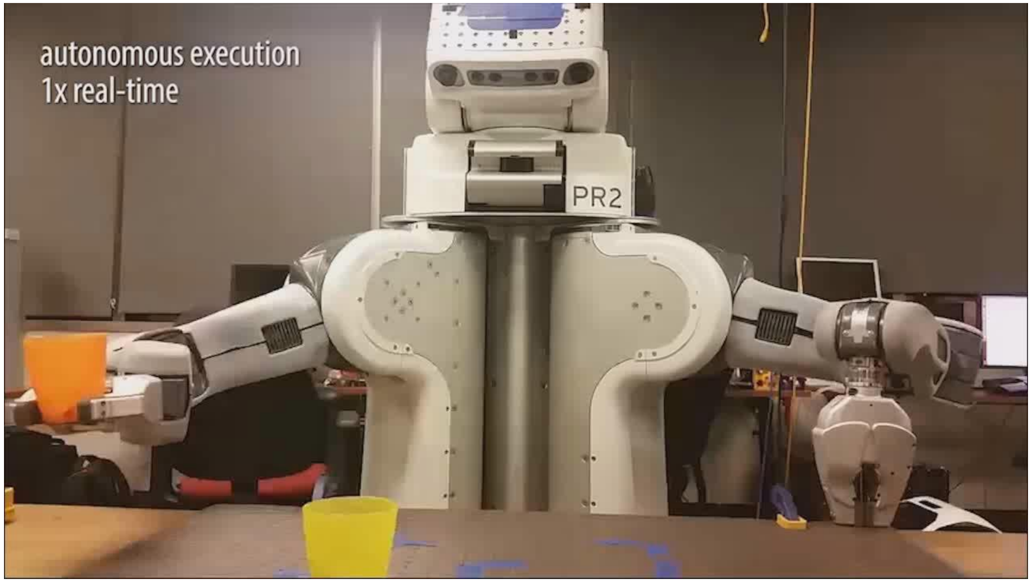

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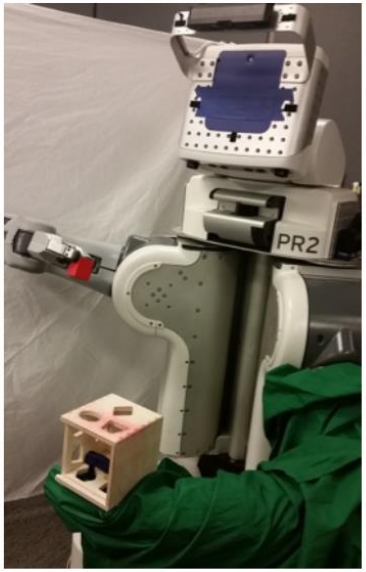
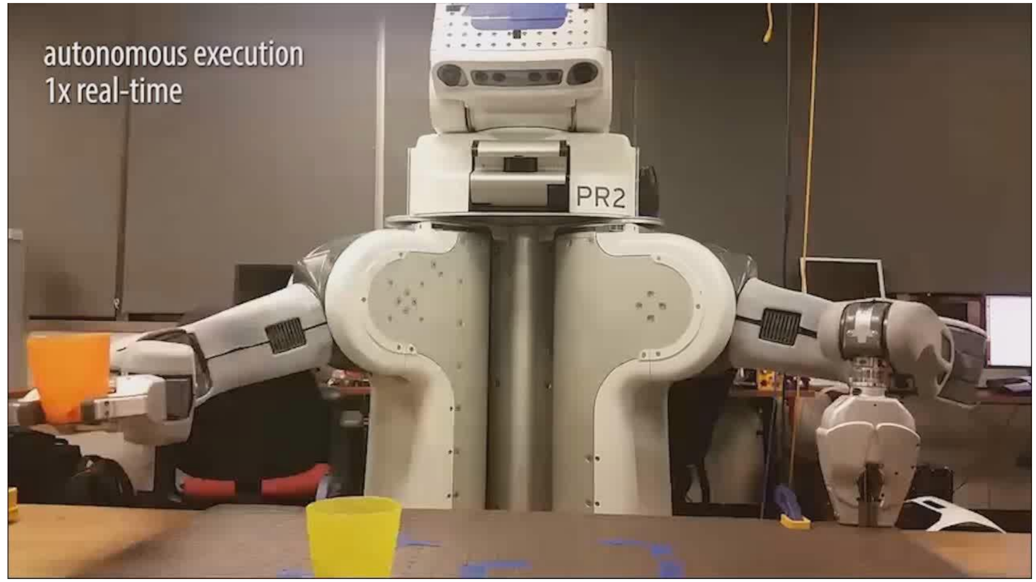
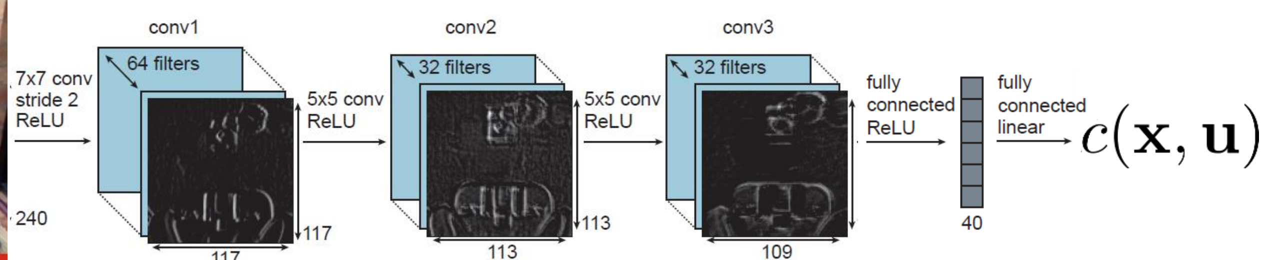




$$c(\mathbf{x}, \mathbf{u}) = w_1 f_{\text{target}}(\mathbf{x}) + w_2 f_{\text{torque}}(\mathbf{u})$$

can we *learn* the cost with visual features?



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Broader implications: end-to-end learning for decision making in the real world

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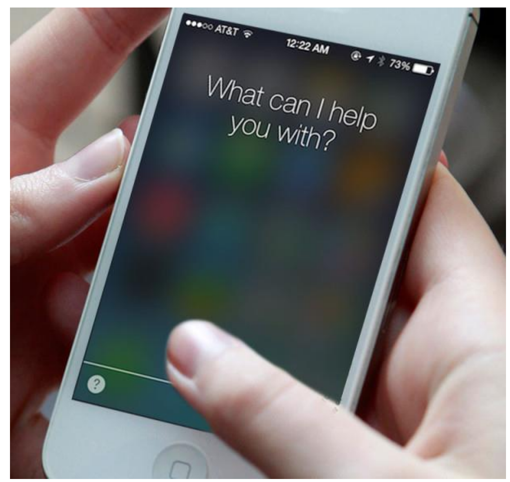
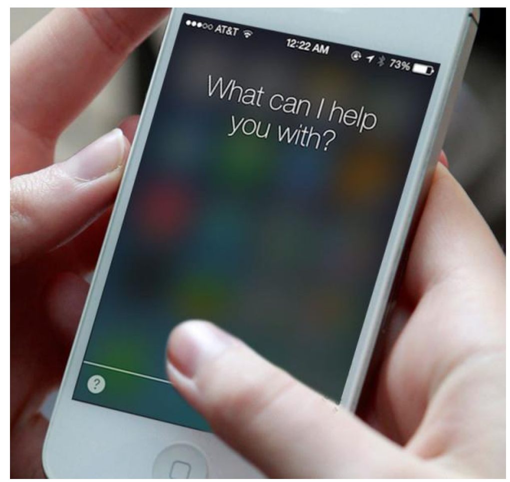
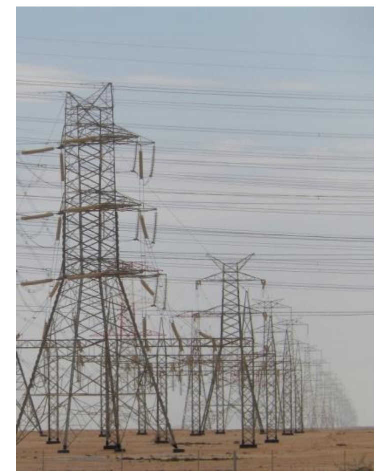


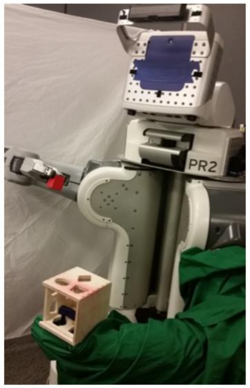
Broader implications: end-to-end learning for decision making in the real world





Acknowledgements

BRETT

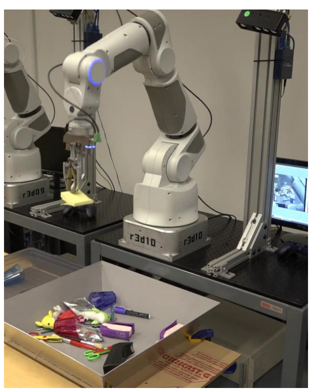


Chelsea Finn

Trevor Darrell

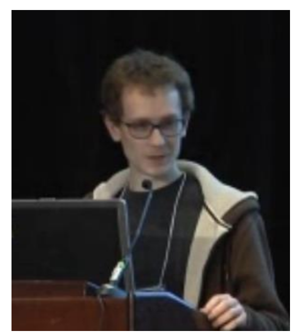
Pieter Abbeel

r3d10



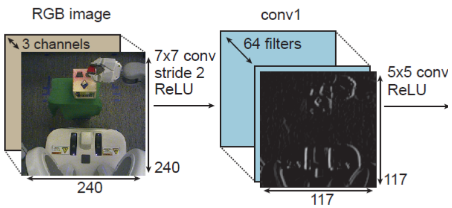
Peter Pastor

Alex Krizhevsky



Deirdre Quillen

Questions?



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