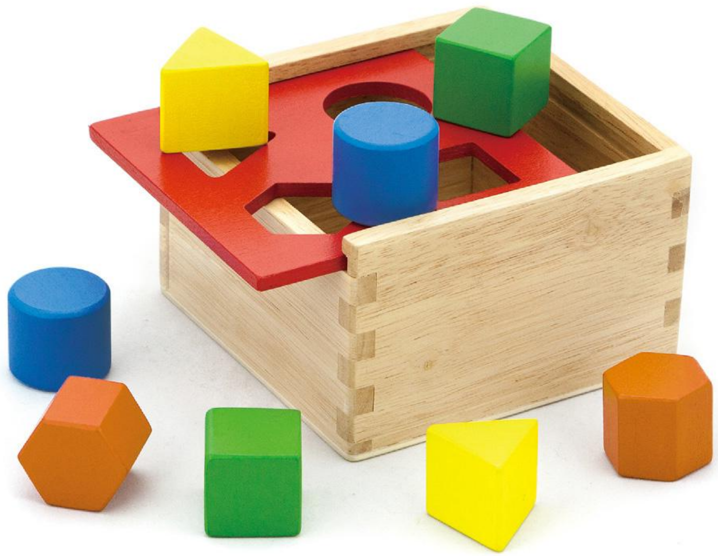
What Would it Take to Train an Agent to Play with a Shape-Sorter?



Feryal Behbahani

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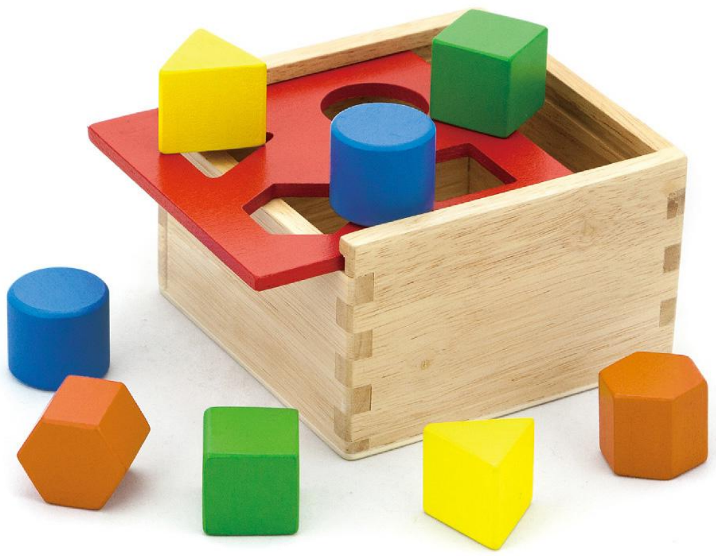
Shape sorter?

- Simple children toy: **put shapes in the correct holes**
- Trivial for adults
- Yet children cannot fully solve until 2 years old (!)

Requirements

- Recognize different shapes
- Grasp objects and manipulate them
- Understand the task and how to succeed
- Mentally / physically rotate shapes into position
- Move precisely to fit object into hole



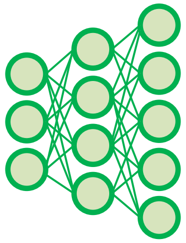
How to do it?

- Classical robotic control pipeline approach

Observations → State estimation → Modeling & prediction → Planning → Low-level control → controls

- Deep robotic end-to-end learning

End-to-end learning

Observations …………  ………… controls

Using simulations as a proxy

- How many samples do we need to train a good behaviour?
  - Real robot/car: stuck to real time speed
  - MuJoCo simulator: up to 10000x real time

Udacity car simulator

Real Jaco arm

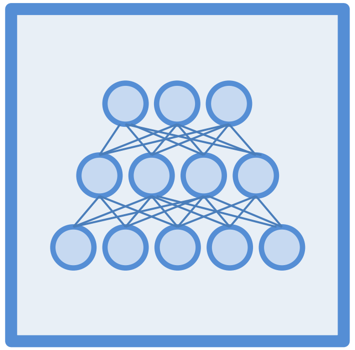
MuJoCo simulation

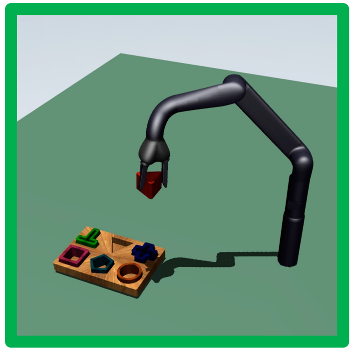
Finger tracking with CyberGlove synced with 3D reconstruction in MuJoCo

[Todorov et al., 2012 & Behbahani et al., 2016]

Deep Reinforcement Learning for control

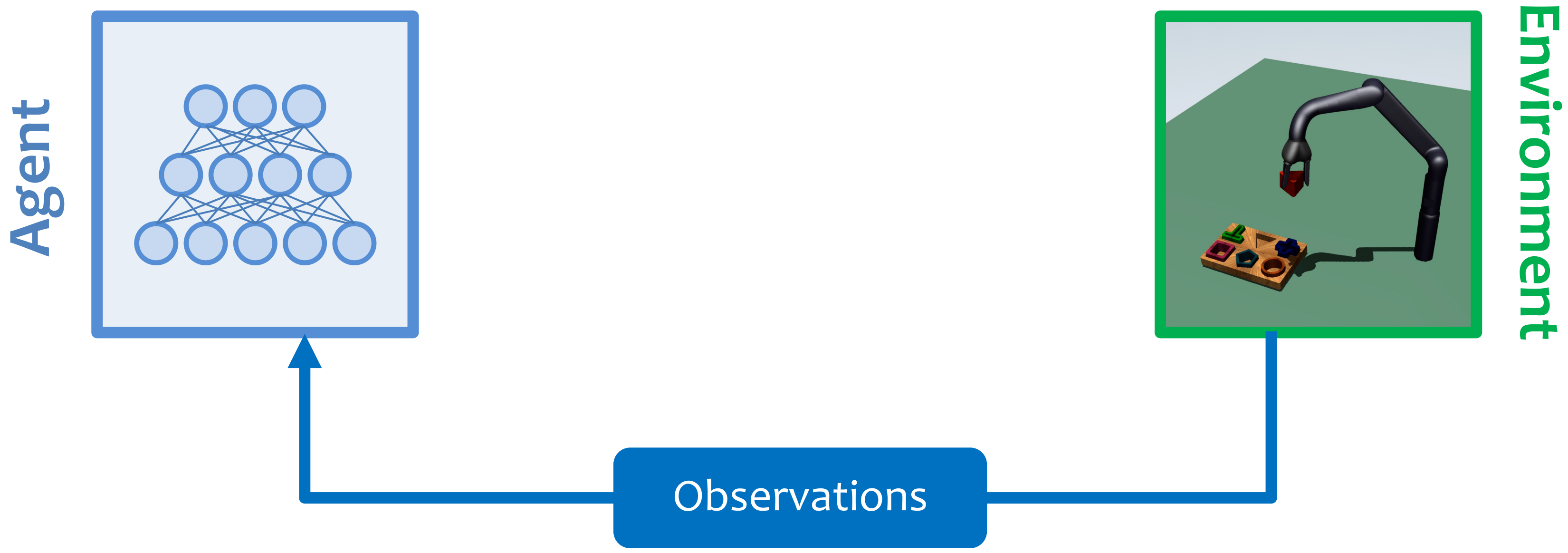
Agent



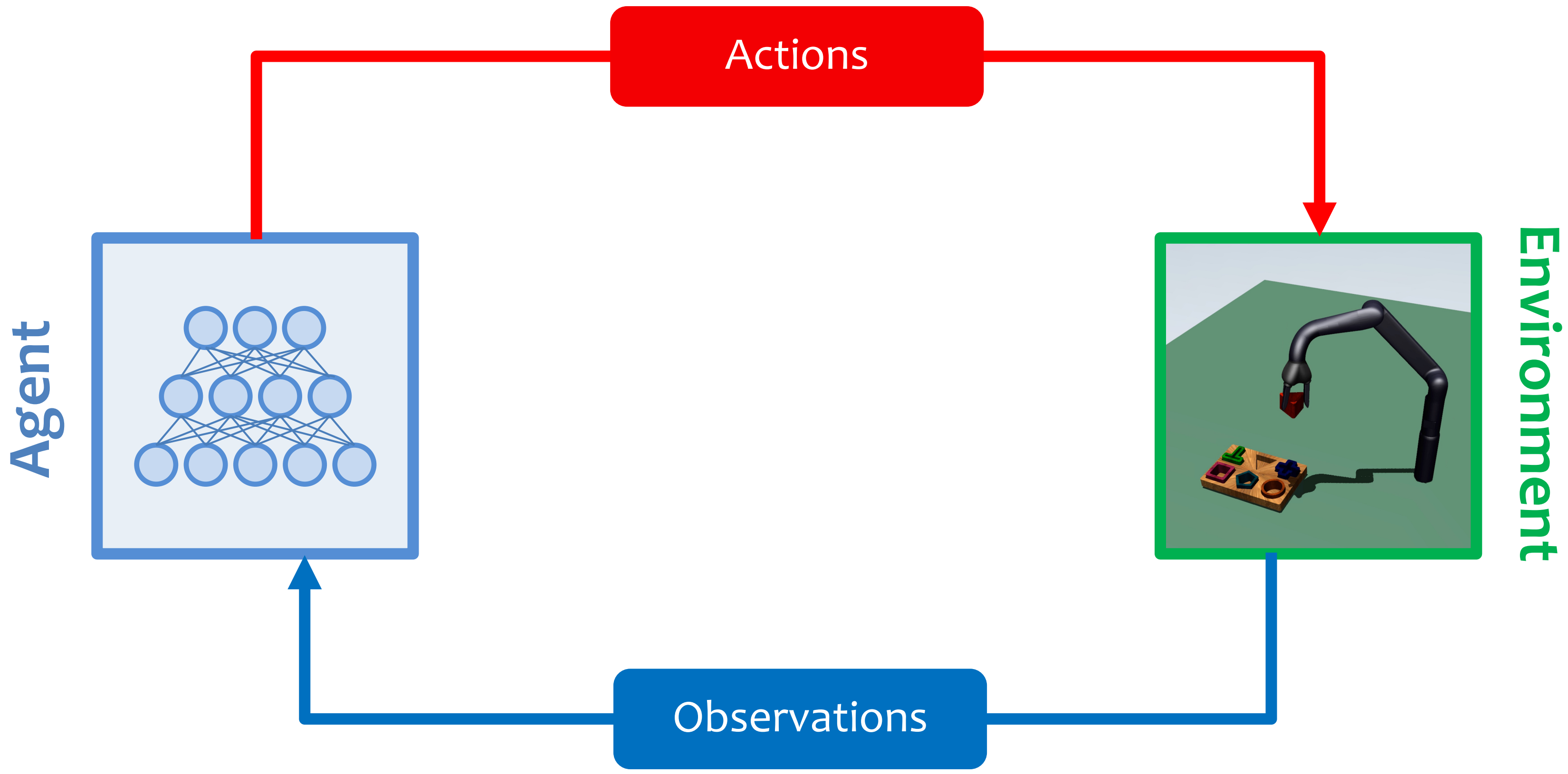


Environment

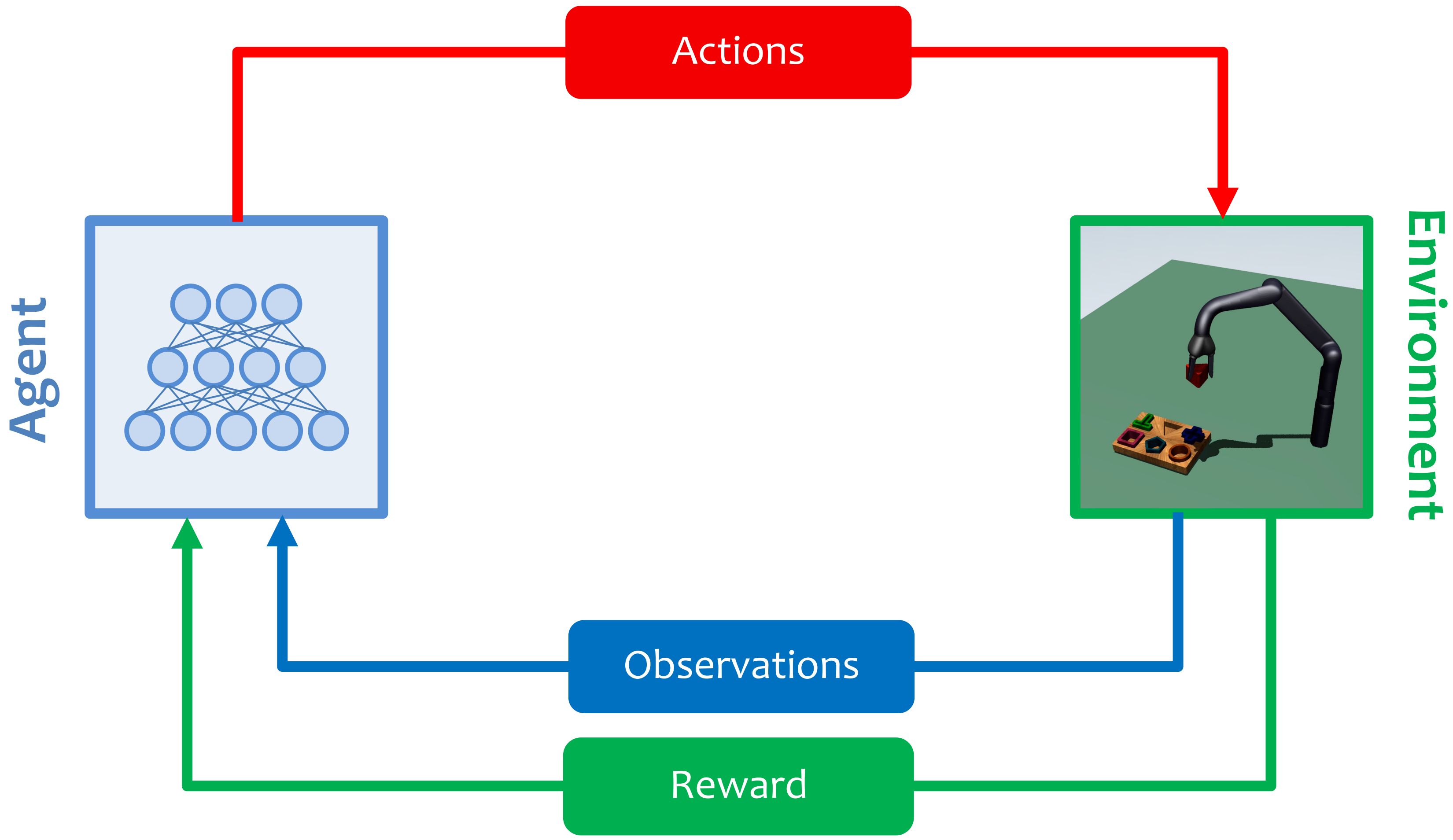
Deep Reinforcement Learning for control



Deep Reinforcement Learning for control

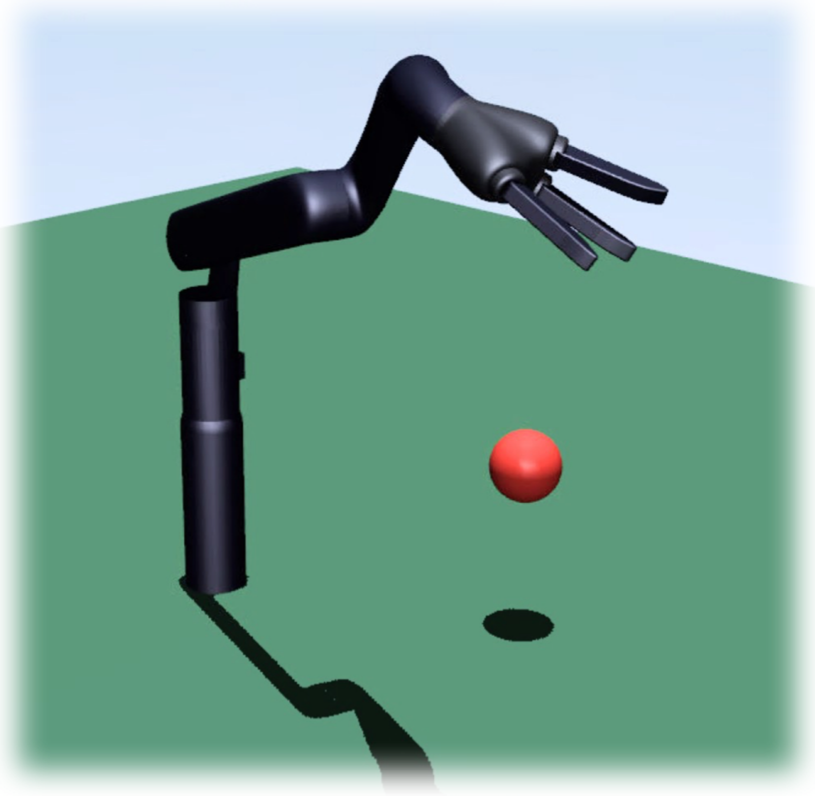


Deep Reinforcement Learning for control



Learning to reach

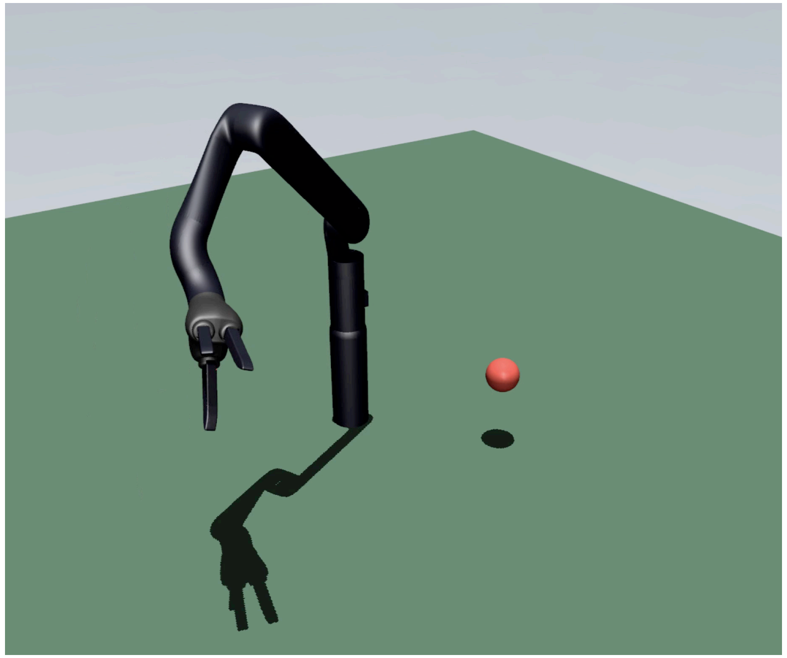
- Let's first try to reach to a target and grasp it.
- Should be able to do this regardless of object location

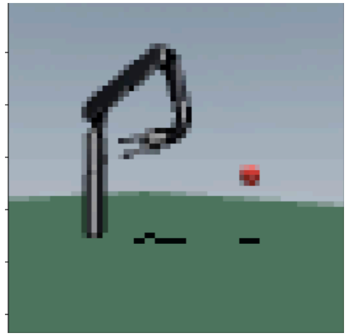


Task and setup

- **Reach red target**
  - Reward of 1 if target inside hand
  - Random position each episode
    40 x 40 x 40 cm
- **Observation space:**
  - Two camera views
- **Action space:**
  - Joint velocities
    9 actuators, 5 possible velocities

Random agent

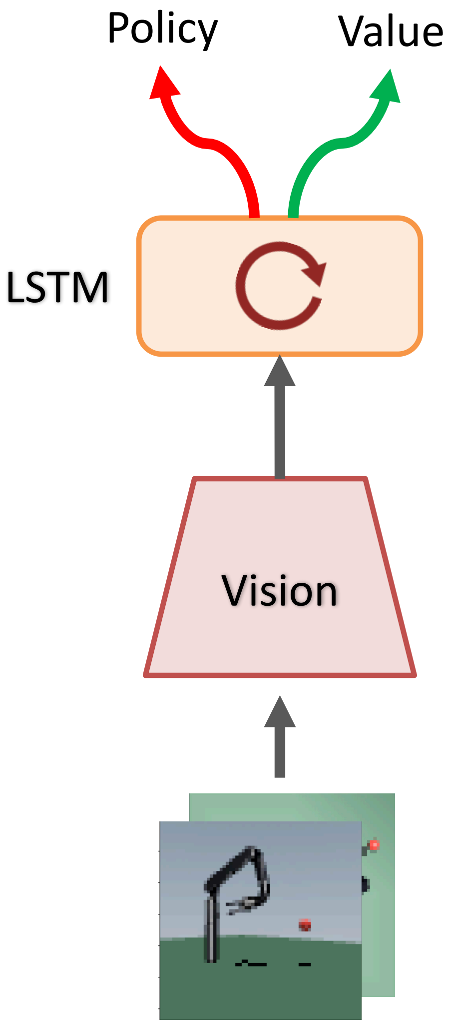




View 1

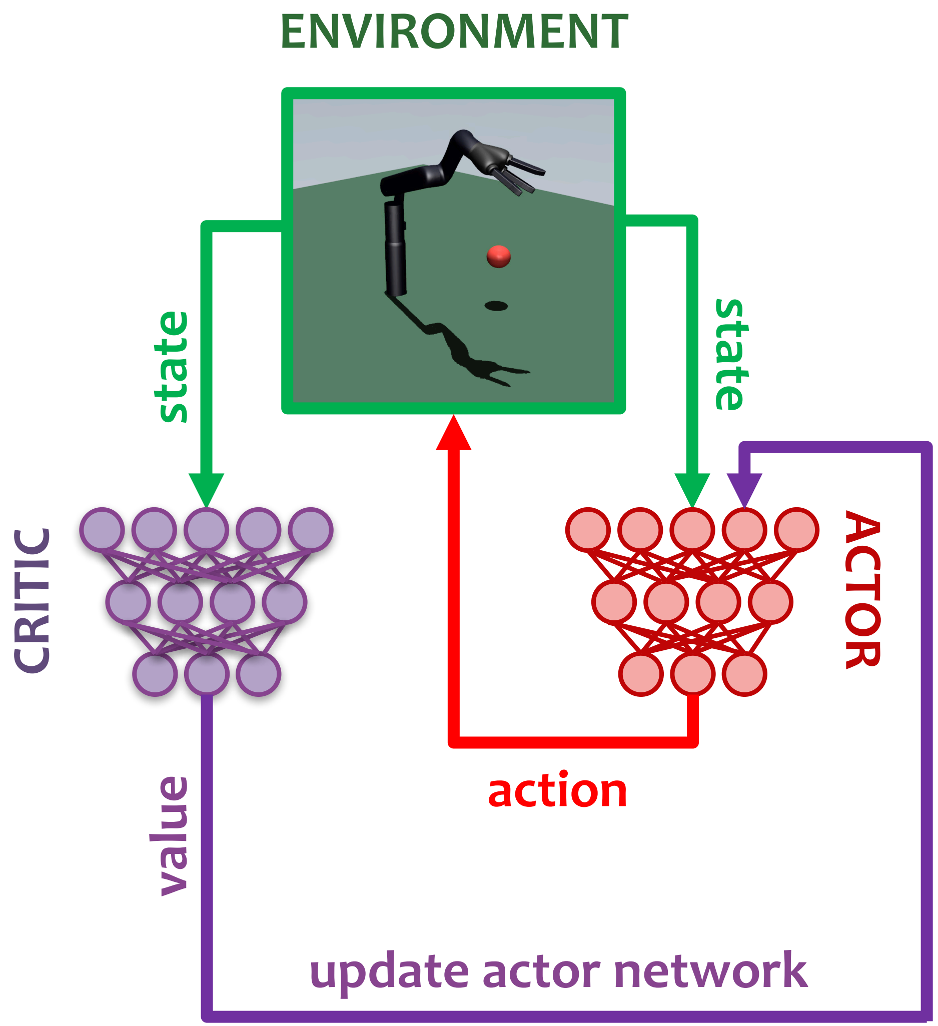
View 2

Agent architecture



- **Inputs:**
  - 64 x 64 x 6 channels
- **Vision**
  - ConvNet 2 layers
  - ReLU activations
- **LSTM** (recurrent core)
  - 128 units
- **Policy**
  - Softmax per actuator (5 values)
- **Value**
  - Linear layer to scalar

Asynchronous Advantage Actor-Critic (A3C)



Agent acts for T timesteps (e.g., T=100)

For each timestep t, compute

$$\hat{R}_t = r_t + \gamma r_{t+1} + \ldots + \gamma^{T-t+1} r_{T-1} + \gamma^{T-t}\hat{V}(s_T)$$

$$\hat{A}_t = \hat{R}_t - \hat{V}(s_t)$$

Compute loss gradient:

$$g = \nabla_\theta \sum_{t=1}^{T} -\log \pi(a_t|s_t)\hat{A}_t + \left(\hat{V}(s_t) - \hat{R}_t\right)^2$$

Plug g into a stochastic gradient descent optimiser (e.g. RMSprop)

Multiple workers interact with their own environments and send gradient updates asynchronously

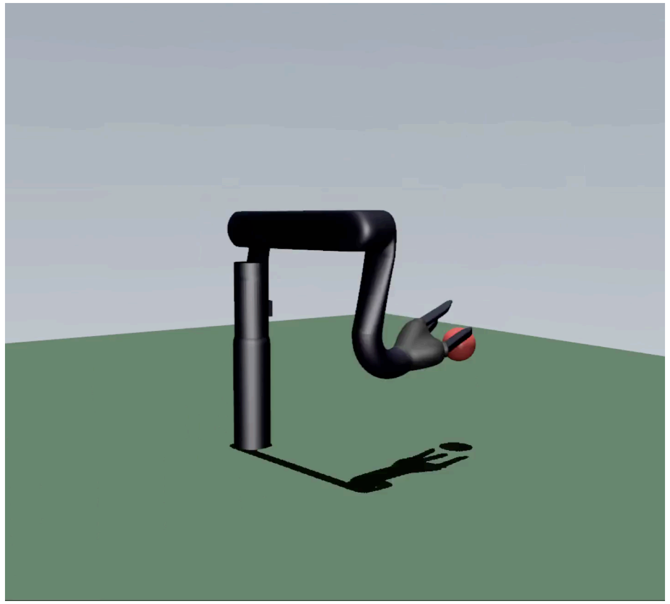
This helps with robustness and experience diversity

[Mnih et al, 2016, Rusu et al., 2016]

Results

- Successfully learns to reach to all target locations with sparse rewards
  ~6 million training steps

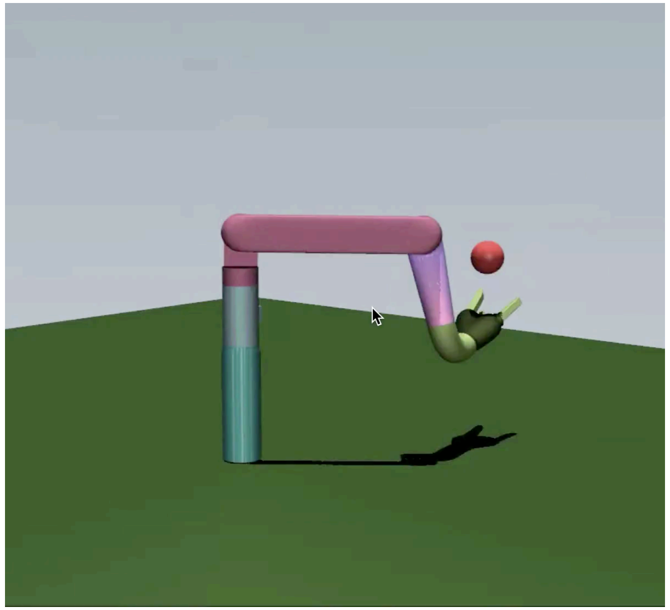
Camera side views



After ~6 million training step

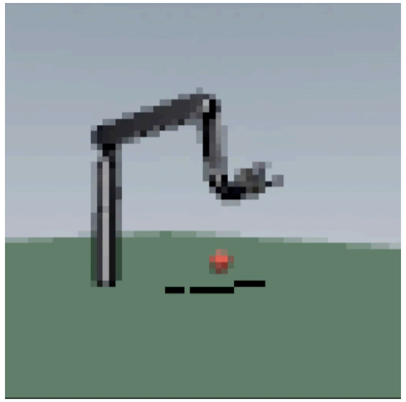
Each episode can last up to 100 steps

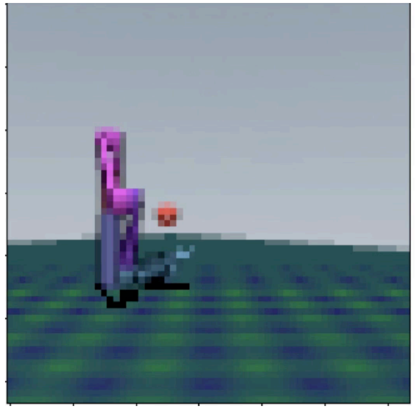
When learned ~7 steps



Domain randomisation

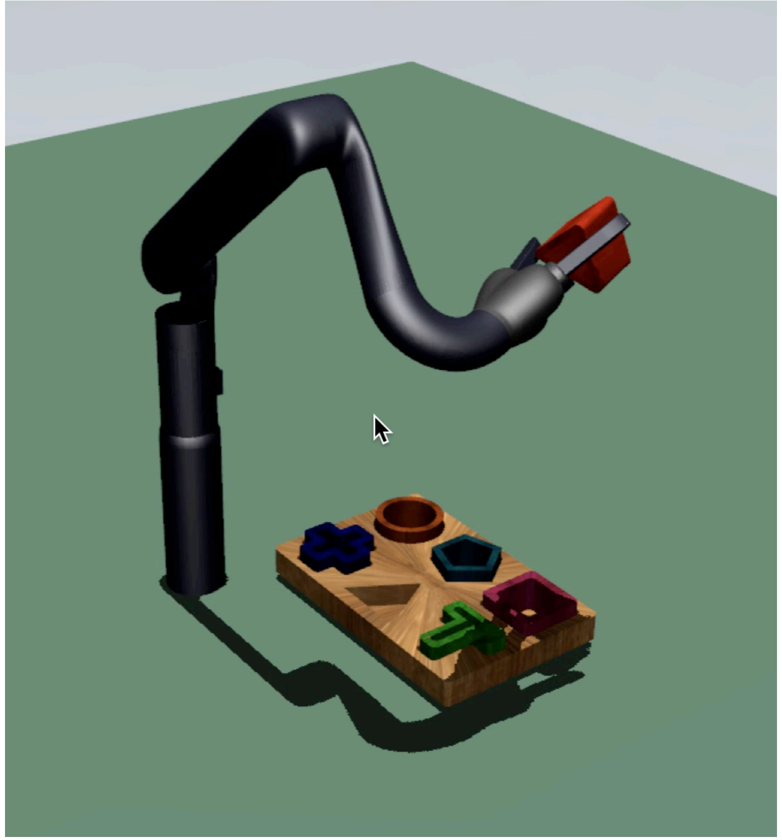
for robustness in transfer to real world

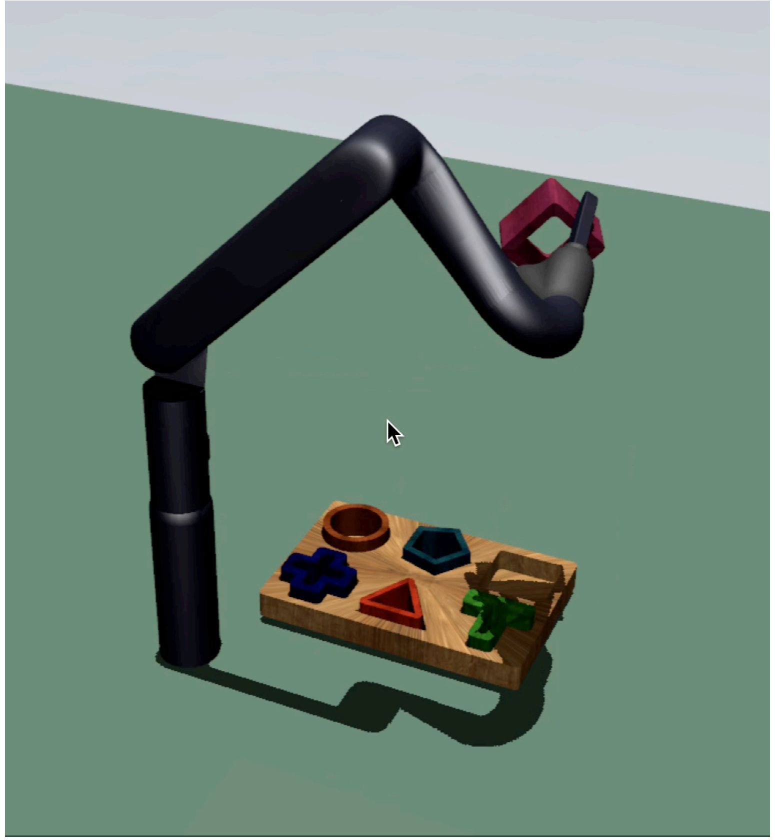




Place shape into its correct position

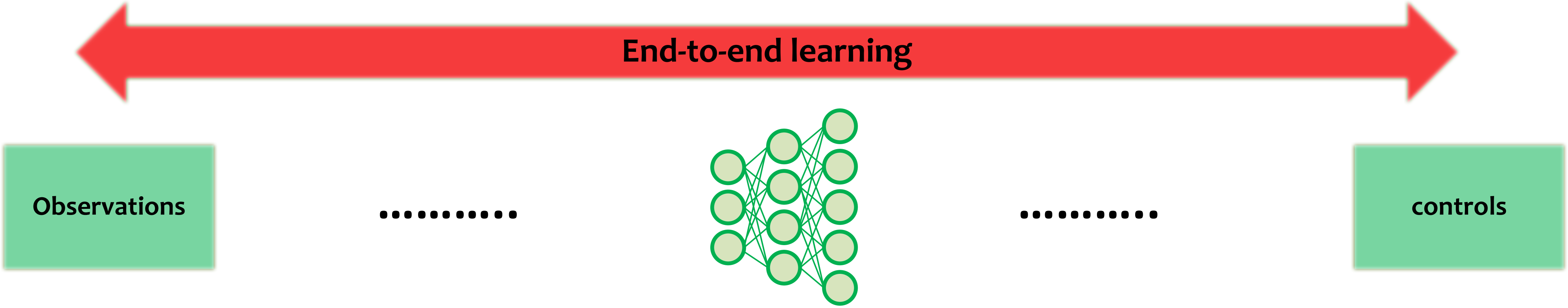
- Tries to place object in correct place but struggles to fit in





Deep RL end-to-end limitations

- Reward function definition is more of an art than science!
- Very sample inefficient
- Learning vision from scratch every time
- Policy does not transfer effectively to slightly different situations (e.g. move target by a few centimeters)



A great recent overview of DRL methods →

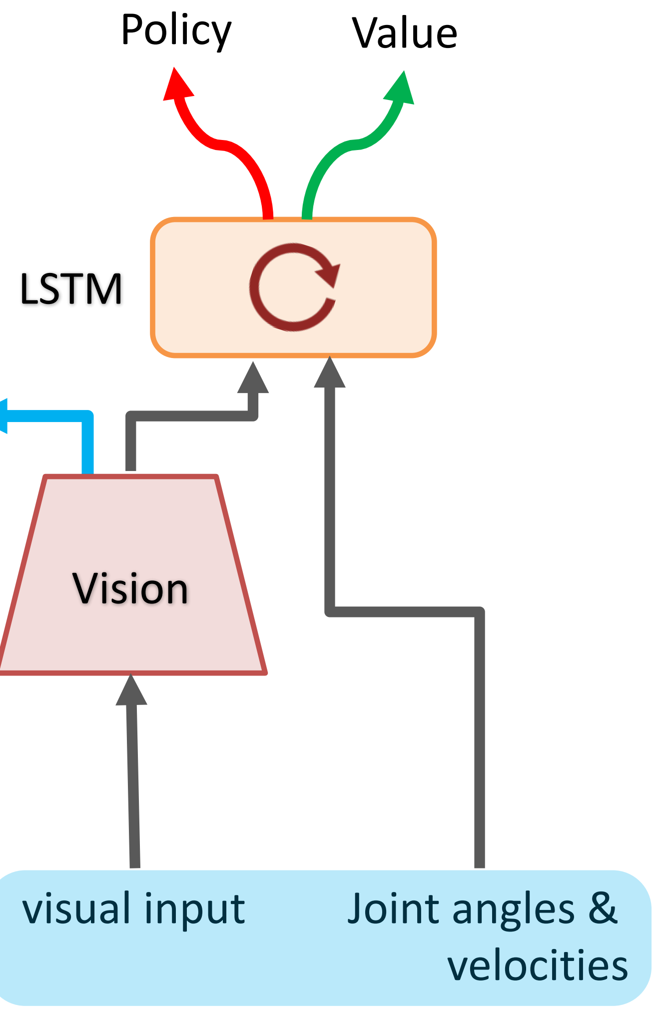
A Brief Survey of Deep Reinforcement Learning

Kai Arulkumaran, Marc Peter Deisenroth, Miles Brundage, Anil Anthony Bharath

Possible solutions

- **Learning with auxiliary information**

  Leverage extra information in simulation, forcing the agent to make sense of the geometry of what it sees. This accelerate and stabilises reinforcement learning



Auxiliary task:
Predict auxiliary Information: e.g. depth

Auxiliary input
Leverage information available only within simulation and learn to cope without them

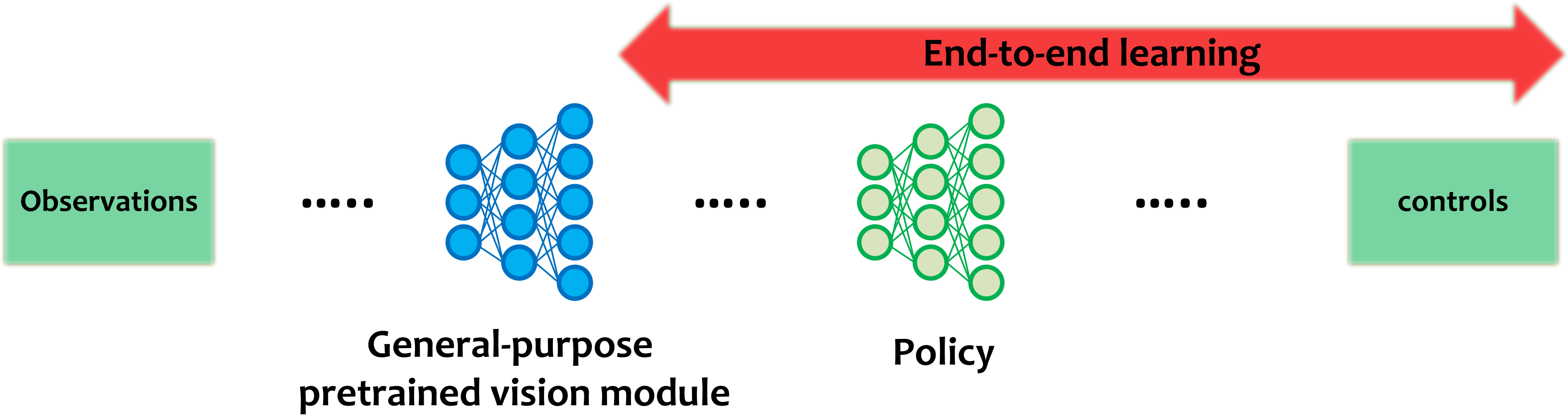
[e.g. Levine et al, 2016 & Mirowski et al., 2016]

Possible solutions

Separating learning vision from the control problem

Avoid learning vision every time, focus on the task at hand

Requires a “general” vision module, useful on many possible tasks.



Learn robust and transferable vision module

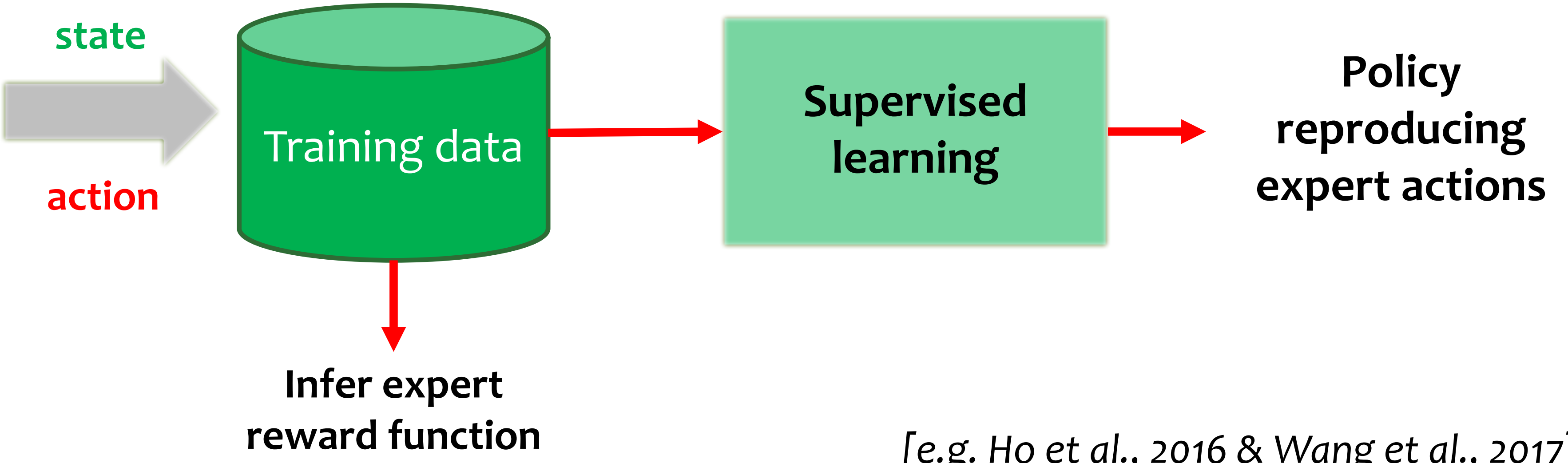
e.g. *[Higgins et al. 2017 & Finn et al. 2017]*

Possible solutions

- **Learning from Demonstrations**

  Imitation Learning: Directly copy the expert (e.g. supervised learning)

  Inverse RL: First infer what the expert is trying to do (learn its reward function **r**), then learn your own optimal policy to achieve it using RL.



[e.g. Ho et al., 2016 & Wang et al., 2017]

Possible solutions

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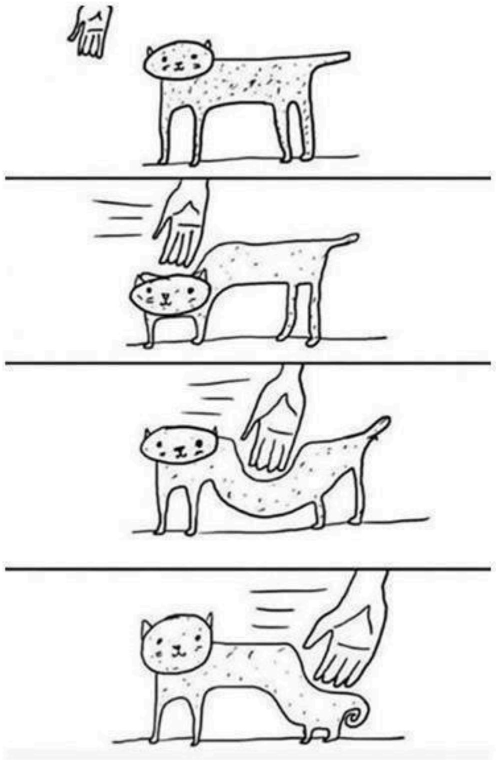
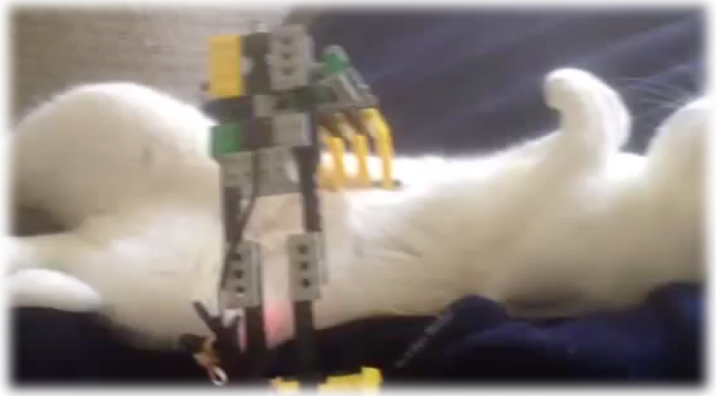


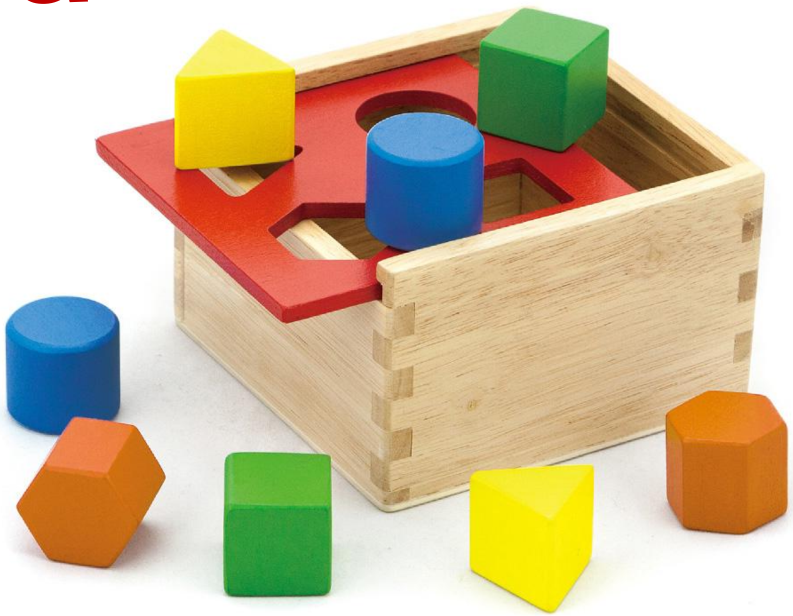


YouTube **World's first cat-petting robotic arm!**

Modelling for deformable objects is challenging!

Current simulators fail to capture full variability of deformable objects and even small differences can break the robot!

Thank you



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