



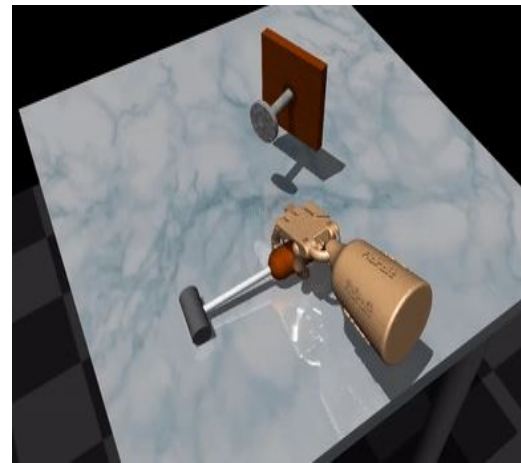
Reinforcement Learning in Robotics

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PhD student, Computer Science

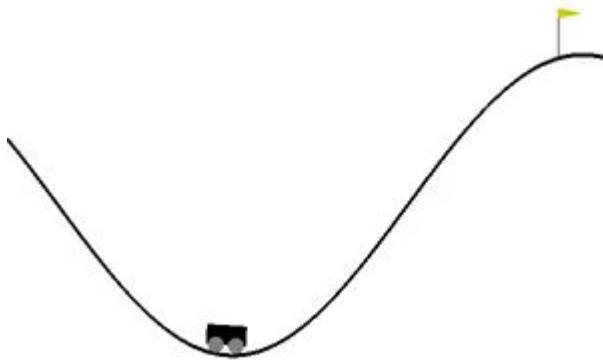
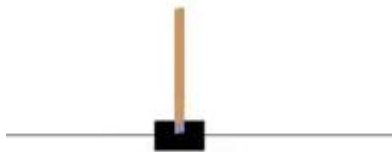
Creative Machines Lab

<http://www.cs.columbia.edu/~bchen/>



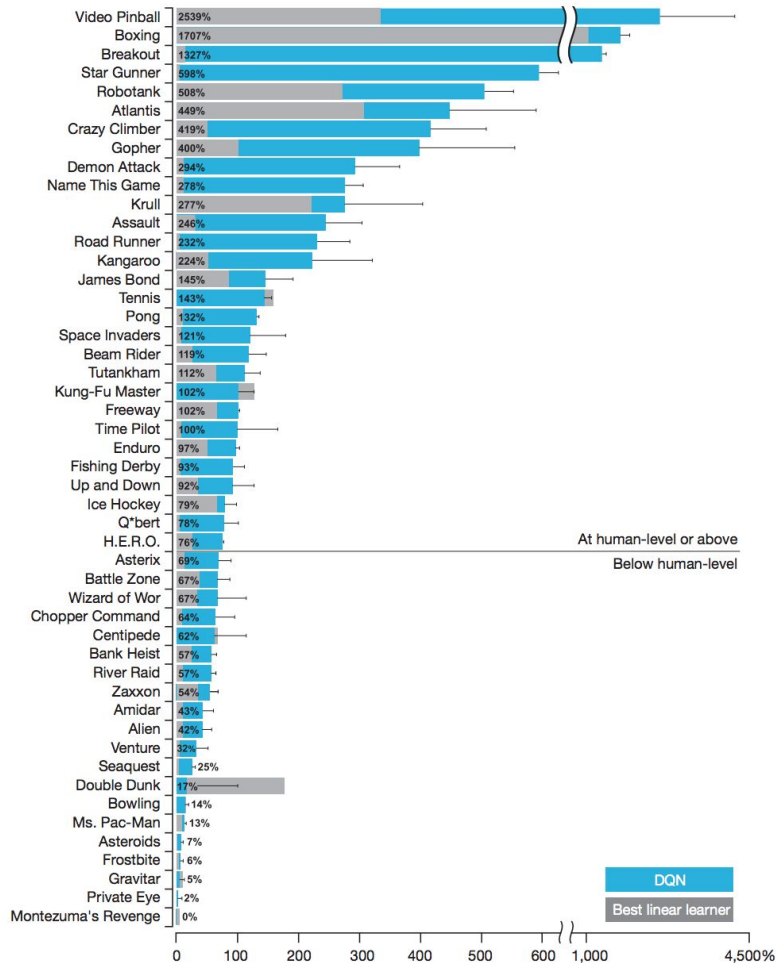
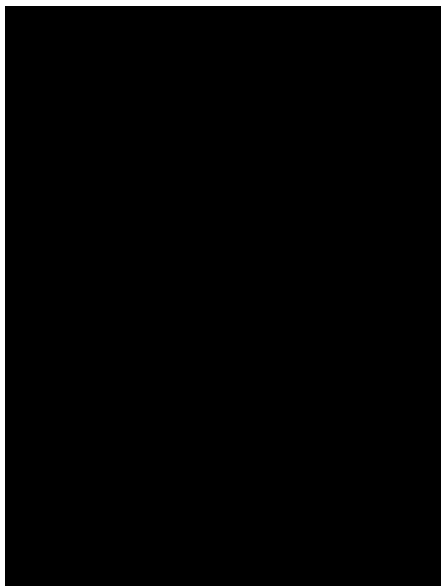
A great time for RL ...

Classic Control:



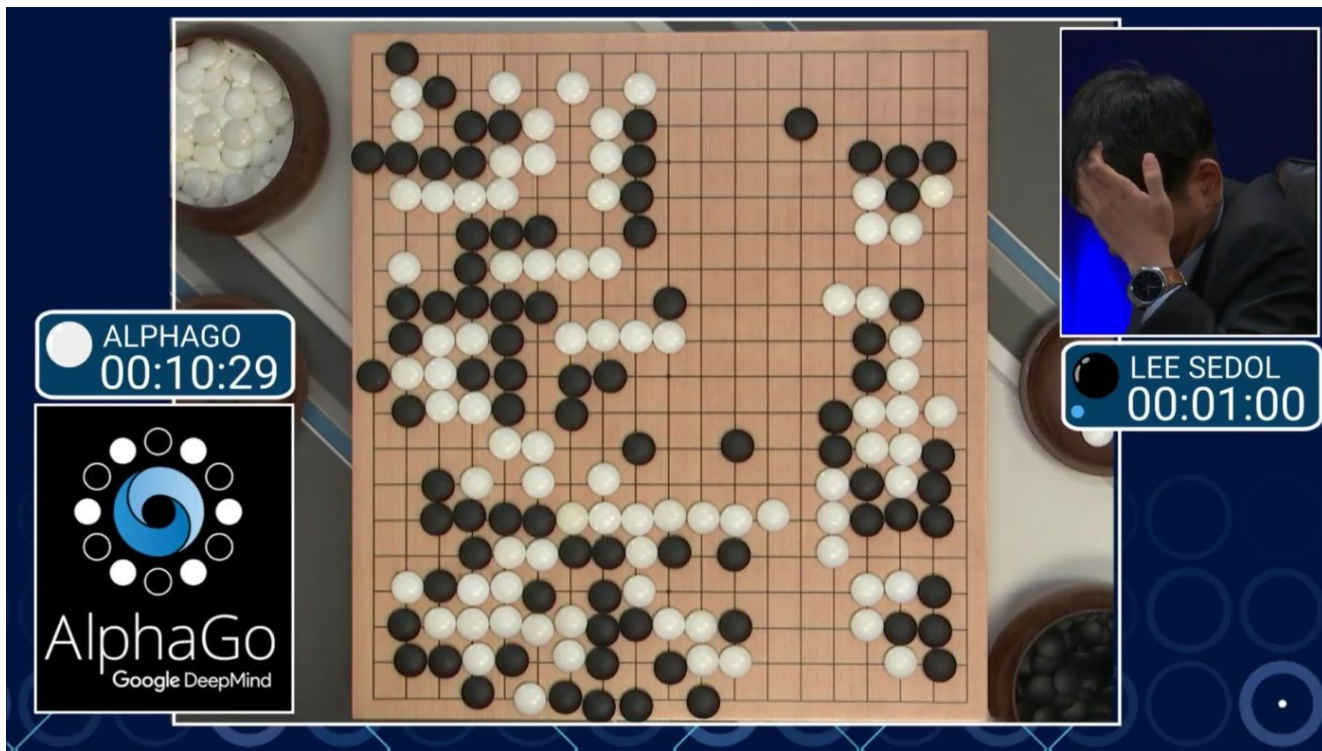
A great time for RL ...

Atari Games:



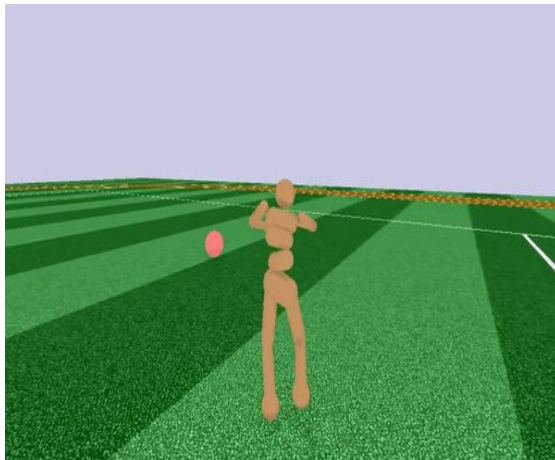
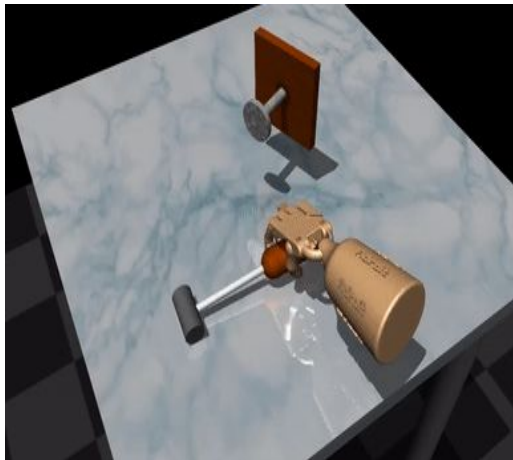
A great time for RL ...

Go:

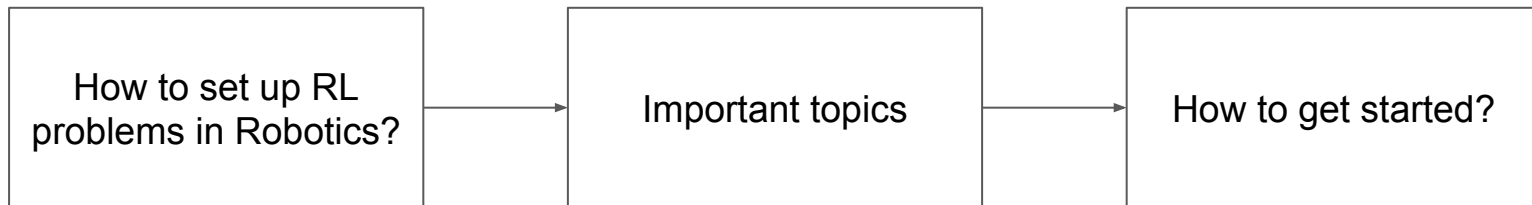


A great time for RL ...

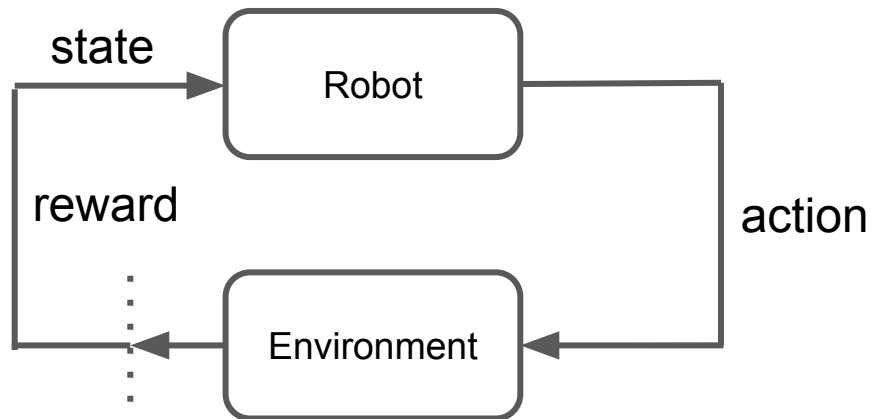
Robotics



Outline



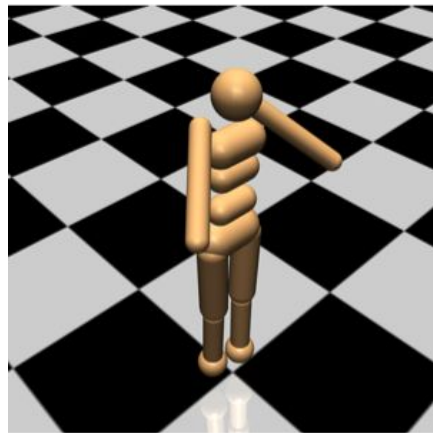
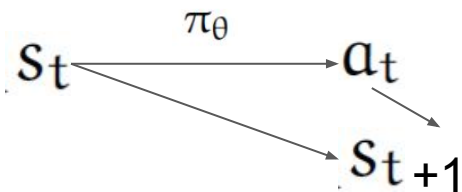
RL in Robotics



- No labelled data;
- No access to real model;
- No fixed rule
- Continuous space
- Complex transition dynamics

Problem Setting

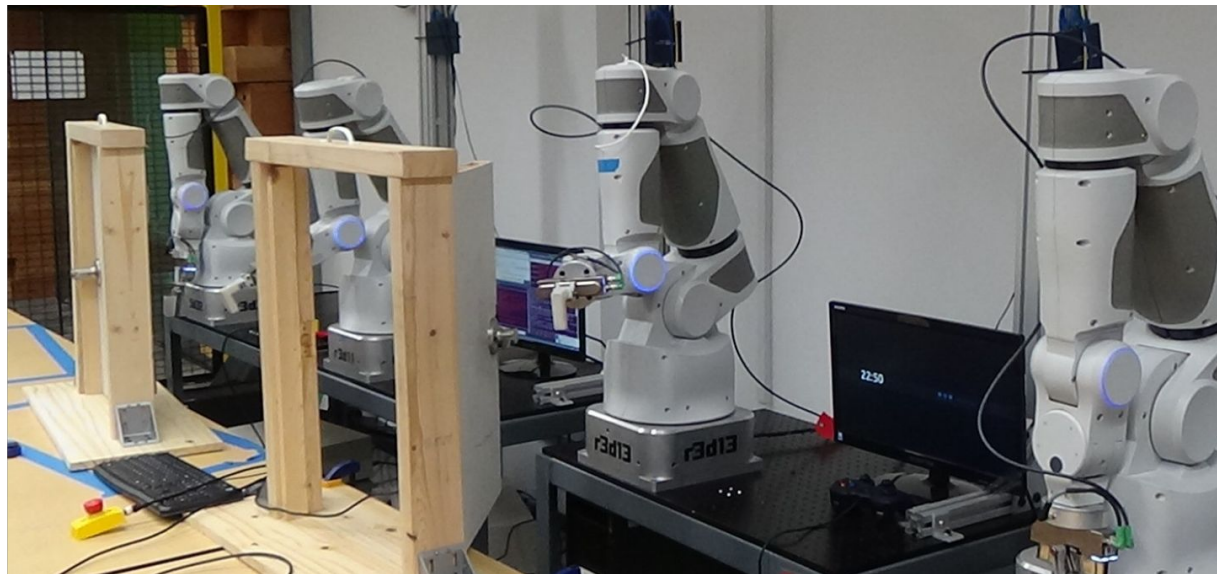
- MDP process defined by: $\mathcal{S}, \mathcal{A}, P, r, \rho_0, \gamma, T$
- Policy: $\pi_\theta : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}_{\geq 0}$
- Expected Reward: $\mathbb{E}_\tau \left[\sum_{t=0}^T \gamma^t r(s_t, a_t) \right]$
- Trajectories: $\tau = (s_0, a_0, \dots)$



Real robot?

Topics: Manipulation

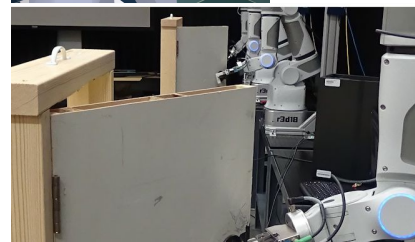
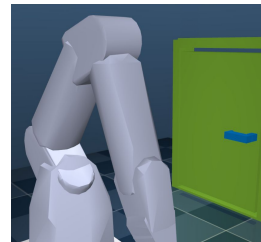
Deep Reinforcement Learning for Robotics Manipulation with Asynchronous Off-Policy Updates: Gu et al, 2016.



Topics: Manipulation

Contribution:

- DeepRL
 - Real complex robot system
 - Complex task
 - Asynchronous data collection
- Safety Exploration



Topics: Manipulation

Off-policy Deep Q-function based algorithms:

$$Q^{\pi_n}(\mathbf{x}_t, \mathbf{u}_t) = \mathbb{E}_{r_{i \geq t}, \mathbf{x}_{i > t} \sim E, \mathbf{u}_{i > t} \sim \pi_n} [R_t | \mathbf{x}_t, \mathbf{u}_t]$$

$$\boldsymbol{\mu}_{n+1}(\mathbf{x}_t) = \arg \max_{\mathbf{u}} Q^{\pi_n}(\mathbf{x}_t, \mathbf{u}_t)$$

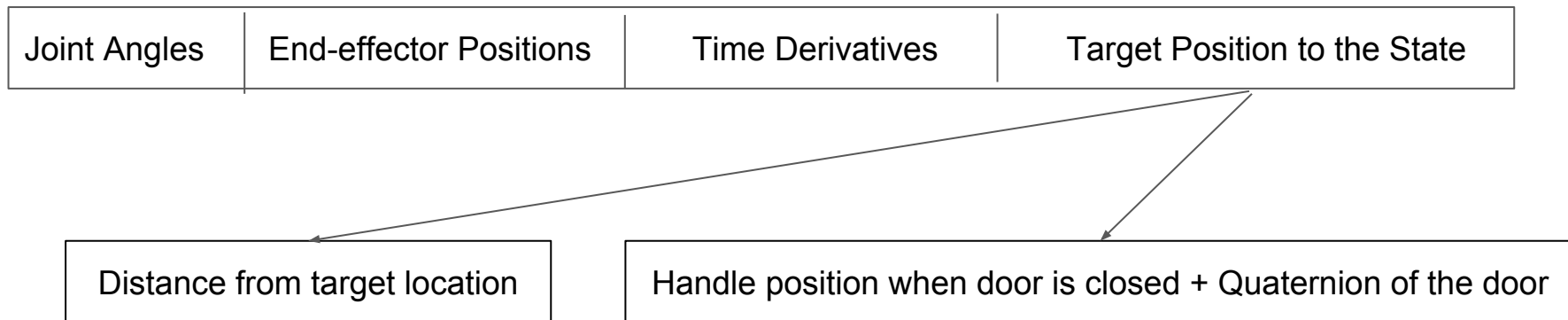
- DDPG (Deep Deterministic Policy Gradient) Actor-Critic
- NAF (Normalized Advantage Function)

$$Q(\mathbf{x}, \mathbf{u} | \theta^Q) = A(\mathbf{x}, \mathbf{u} | \theta^A) + V(\mathbf{x} | \theta^V)$$

$$A(\mathbf{x}, \mathbf{u} | \theta^A) = -\frac{1}{2}(\mathbf{u} - \boldsymbol{\mu}(\mathbf{x} | \theta^\mu))^T \mathbf{P}(\mathbf{x} | \theta^P)(\mathbf{u} - \boldsymbol{\mu}(\mathbf{x} | \theta^\mu))$$

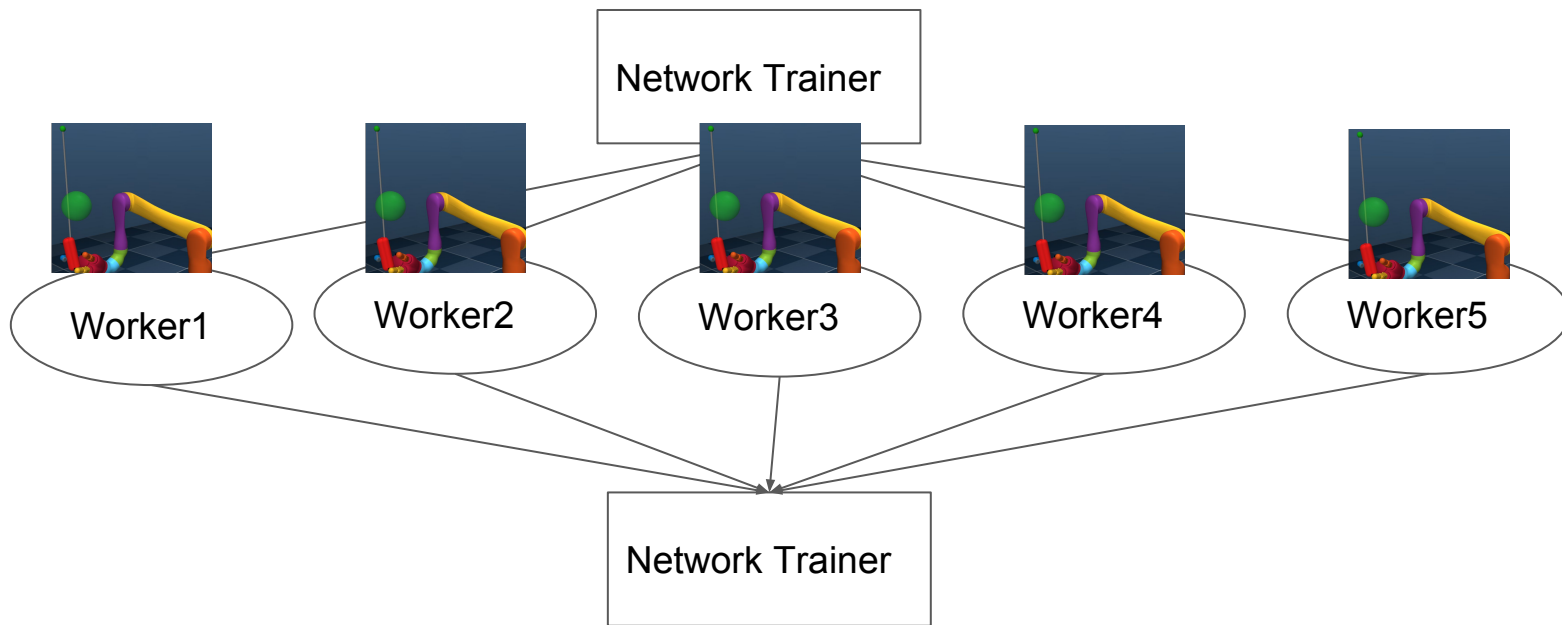
Topics: Manipulation

- State Representation



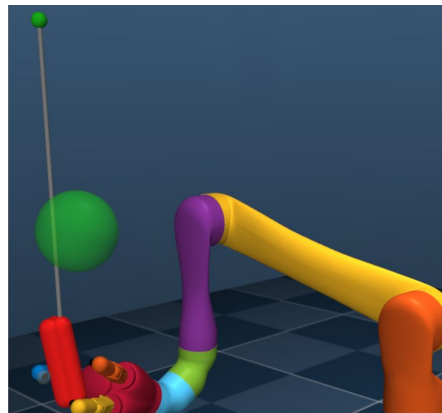
Topics: Manipulation

- Asynchronous NAF



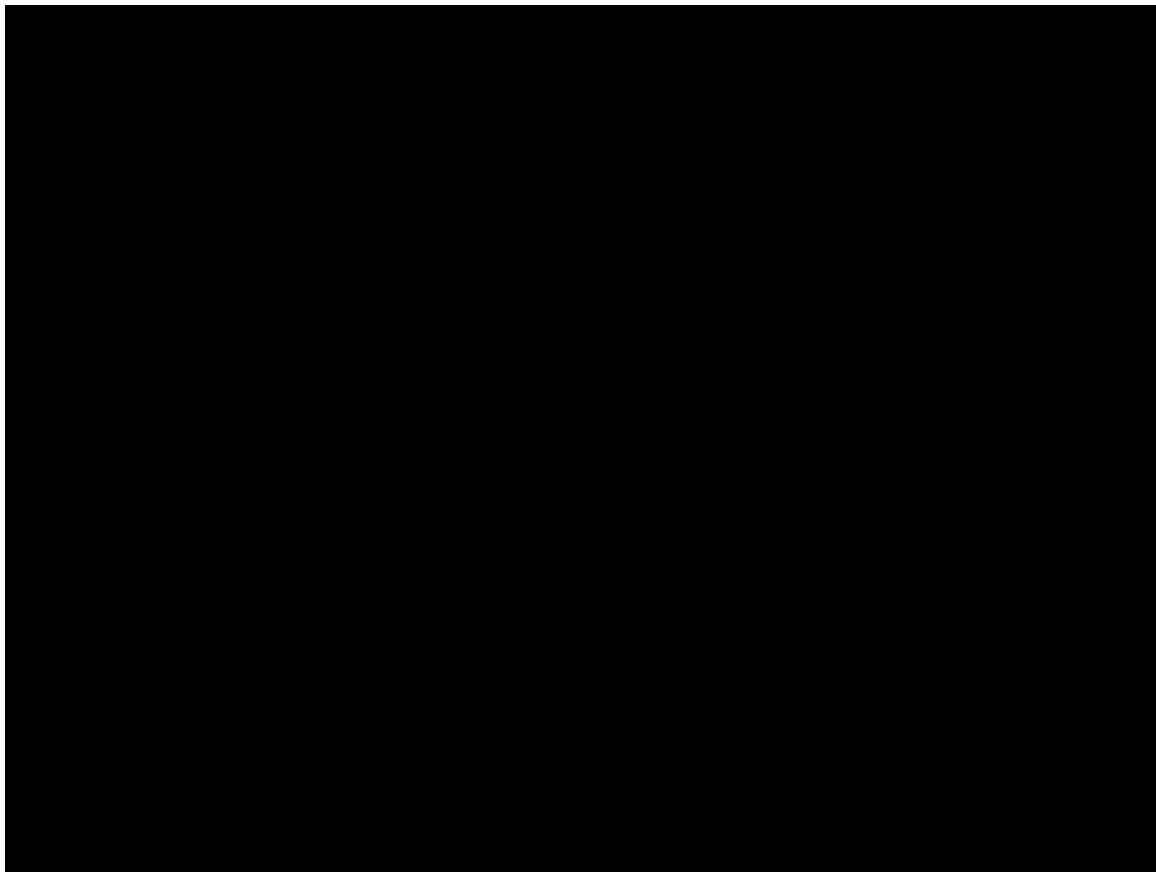
Topics: Manipulation

- Safety Constraints
 - Joint Position Limits:
 - Maximum commanded velocity allowed per joint
 - Strict position limits for each joint
 - Bounding sphere for end-effector position



Very important for training from scratch on real systems!

Topics: Manipulation



Topics: Manipulation

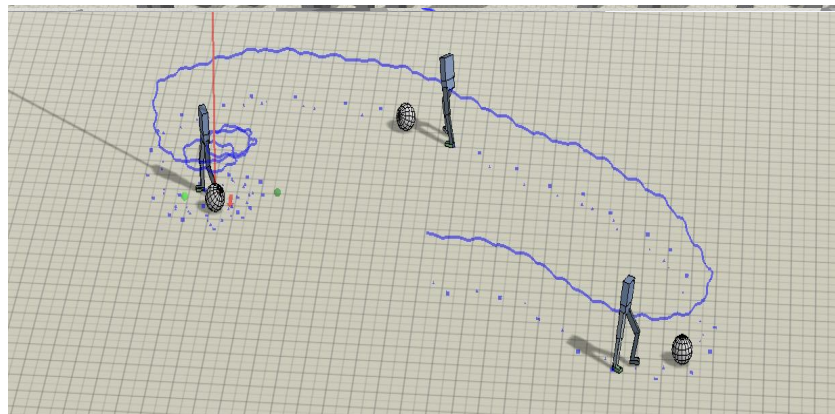
What have we learned from this?

- Efficiency is important for real robots
- Safety is important for real robots
- It is possible to apply DeepRL on real robots to accomplish complex tasks

Complex Task?

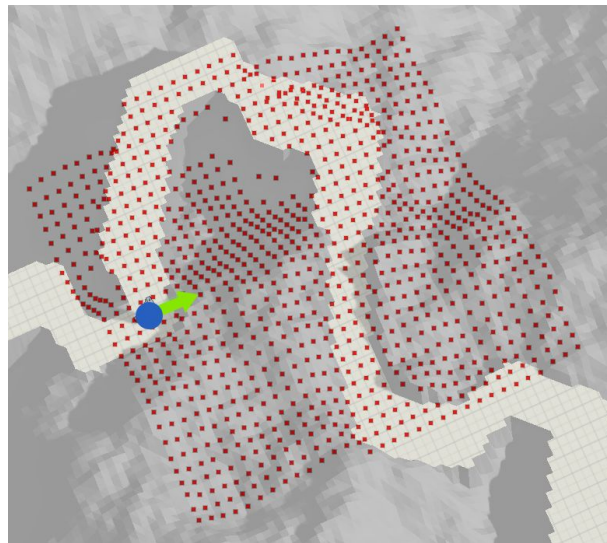
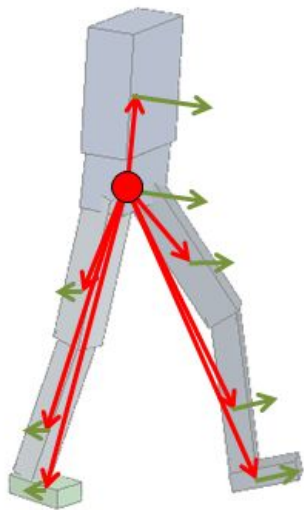
Topics: Locomotion

DeepLoco: Dynamic Locomotion Skills Using Hierarchical Deep Reinforcement Learning: Peng et al, 2017



Topics: Locomotion

DeepLoco: Dynamic Locomotion Skills Using Hierarchical Deep Reinforcement Learning: Peng et al, 2017

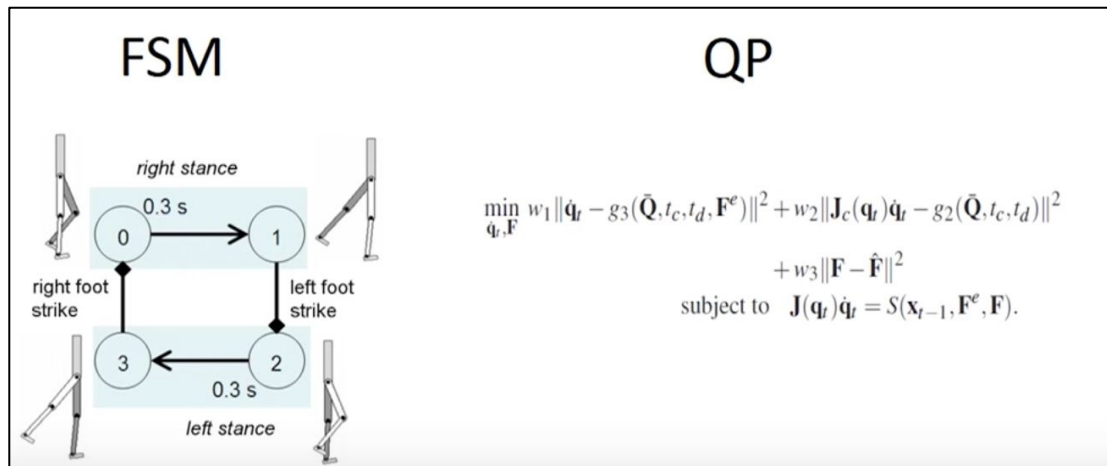


Topics: Locomotion

- Highlight:

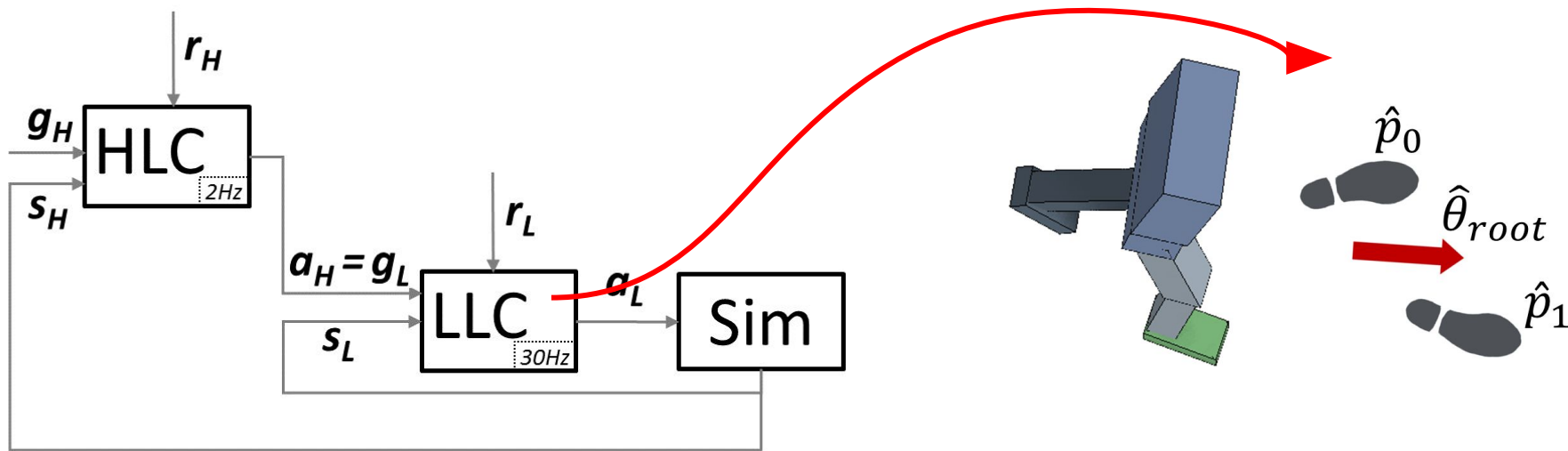
Less prior knowledge

Hierarchical RL



Topics: Locomotion

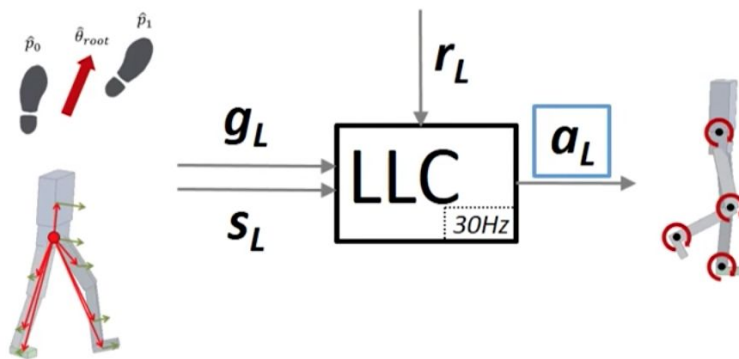
DeepLoco: Dynamic Locomotion Skills Using Hierarchical Deep Reinforcement Learning: Peng et al.



Topics: Locomotion

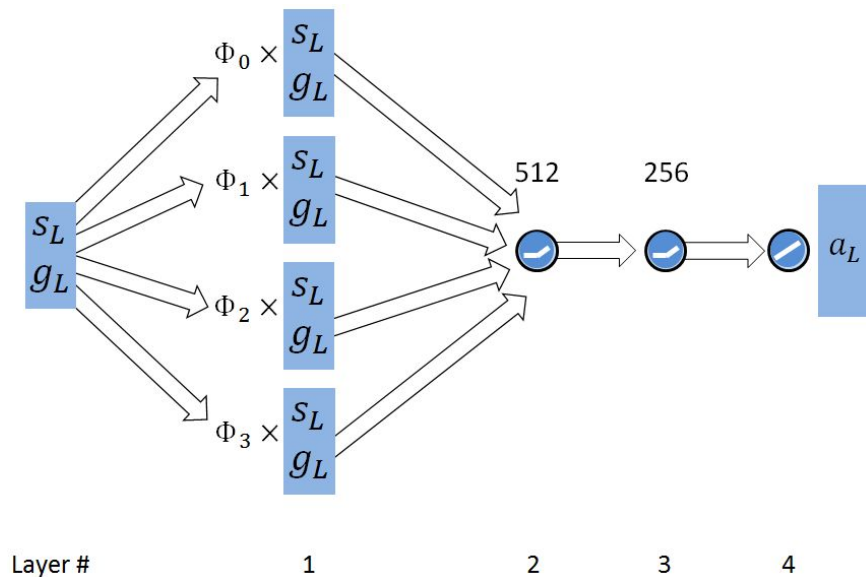
DeepLoco: Dynamic Locomotion Skills Using Hierarchical Deep Reinforcement Learning: Peng et al.

$$\| \text{leg}_L - \text{leg}_R \|^2 + \| \text{foot}_L - \text{foot}_R \|^2$$



Topics: Locomotion

LLC (Low Level Controller):

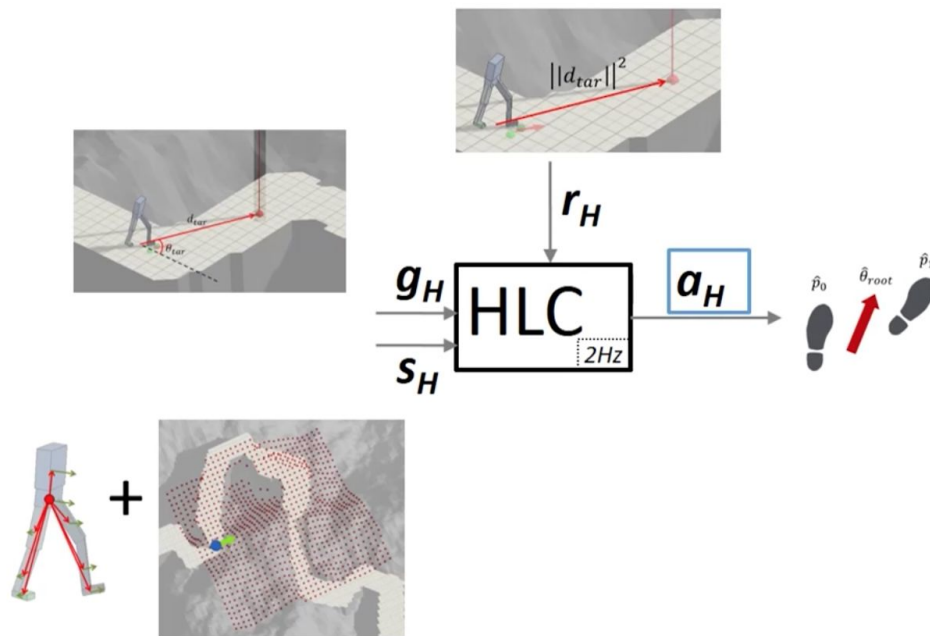


- State
- Action
- Goal
- Reward

$$r_L = w_{pose}r_{pose} + w_{vel}r_{vel} + w_{root}r_{root} + w_{com}r_{com} + w_{end}r_{end} + w_{heading}r_{heading}$$

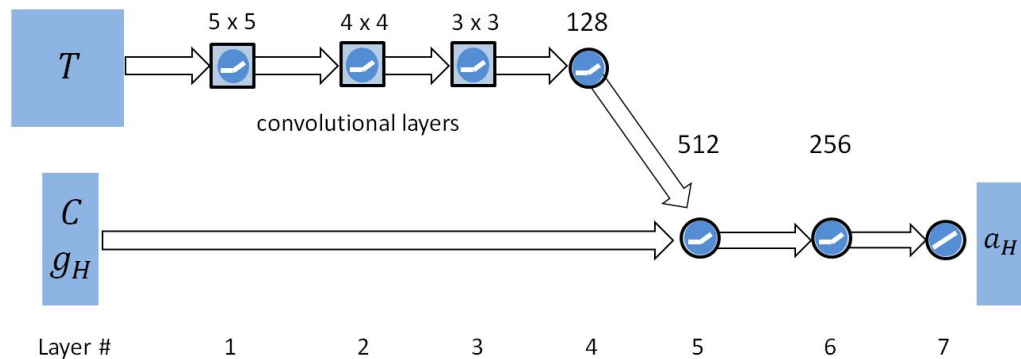
Topics: Locomotion

HLC (High Level Controller):



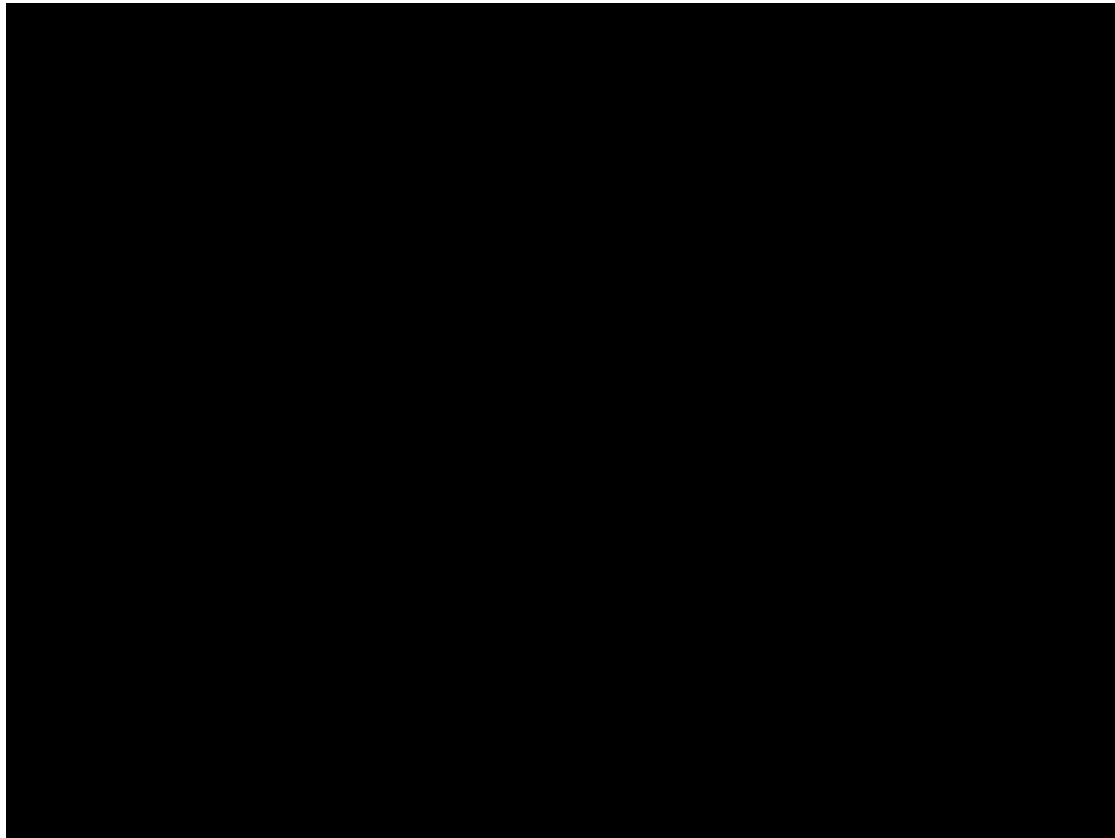
Topics: Locomotion

HLC (High Level Controller):



- State
- Training

Topics: Locomotion



Topics: Locomotion

What have we learned from this?

- Identify hierarchical structure is important.
- State representation for different hierarchies are important.

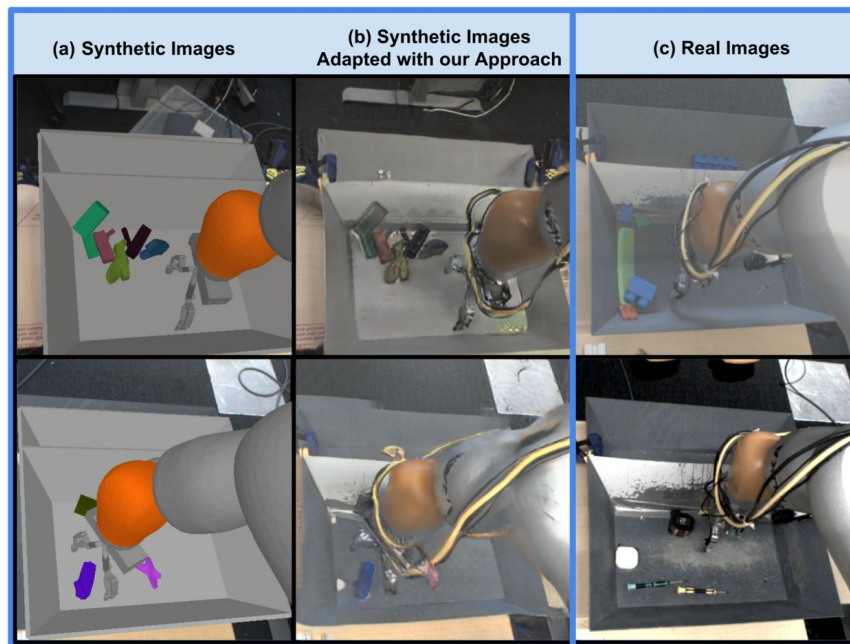
Can we do better?

- Current topic: identify the internal hierarchical structure automatically.

Are we ready?

Topics: Sim2Real

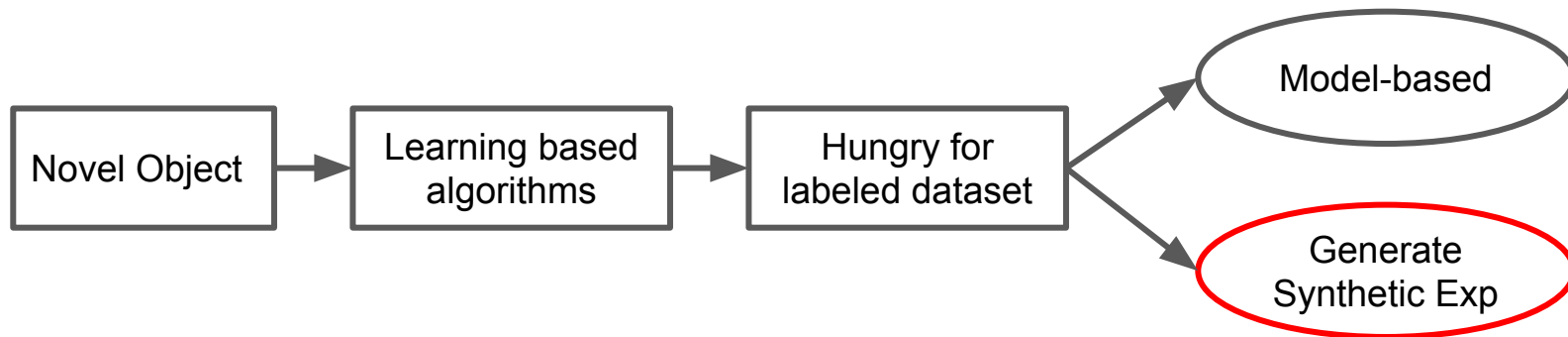
Using Simulation and Domain Adaptation to Improve Efficiency of Deep Robotic Grasping: Bousmalis et al, 2017



Topics: Sim2Real

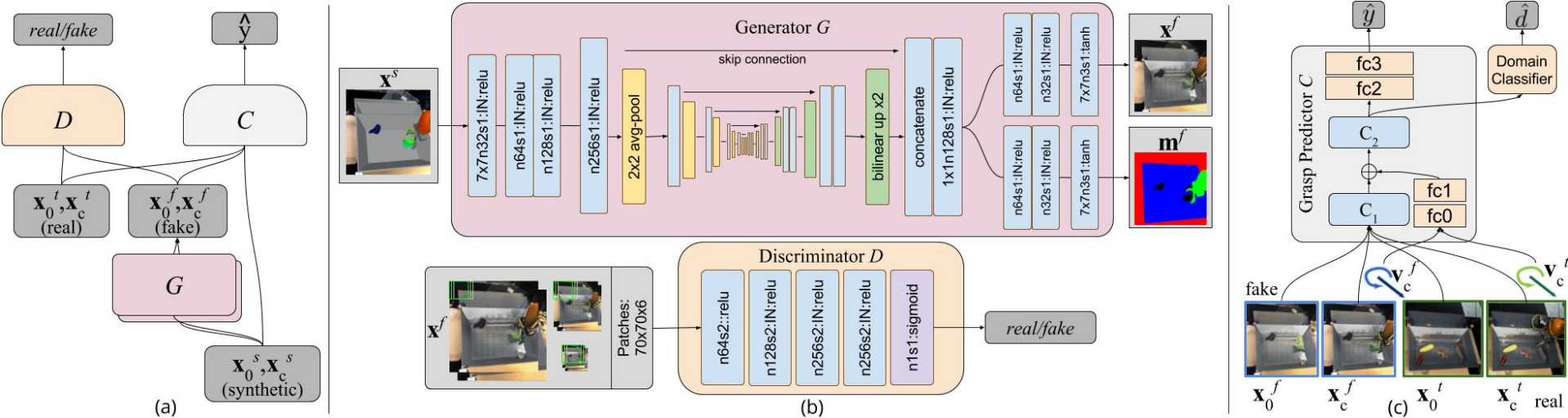
Why this is important?

- Grasping:



Topics: Sim2Real

Approach



How to get started?



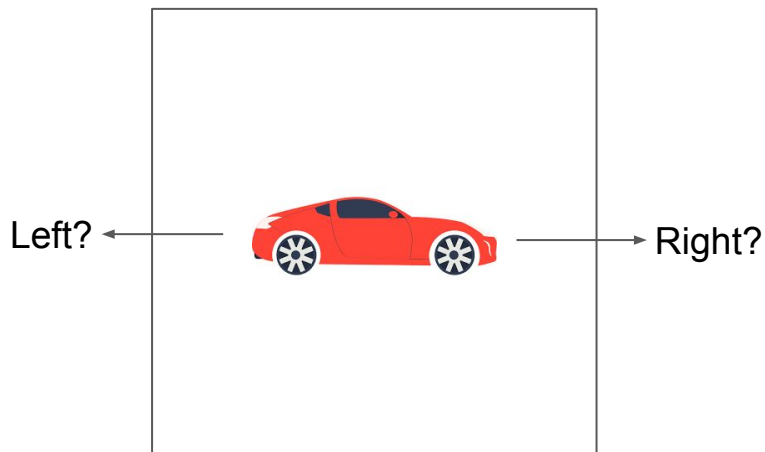
Algorithms

- Libraries:
 - Baselines (OpenAI): <https://github.com/openai/baselines>
 - Rllab (OpenAI): <https://github.com/rll/rllab>
 - Coach (Intel): <https://github.com/NervanaSystems/coach>
 - ...
- Implement your own:
 - Go back to the original paper
 - Use open-source code as reference
 - Start testing from toy examples

Algorithms

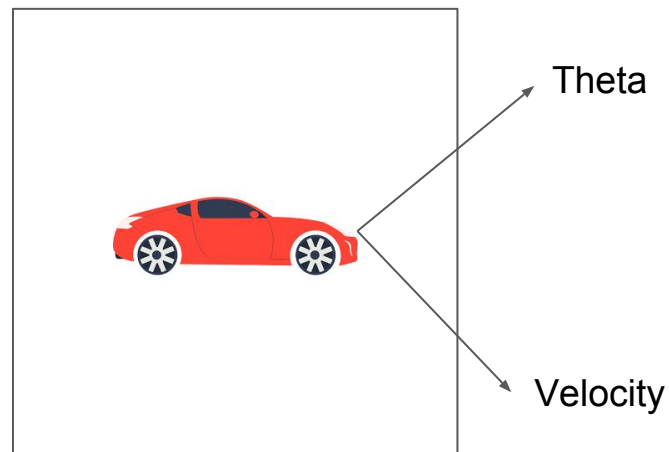
How to select an algorithm for your problem?

- Action space: continuous? Discrete?



Discrete

More often in Robotics

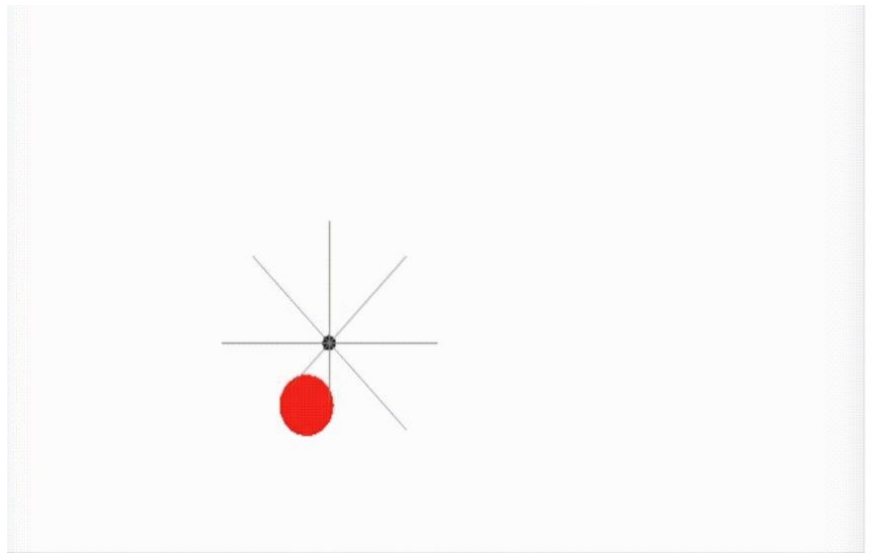


Continuous

Algorithms

How to select an algorithm for your problem?

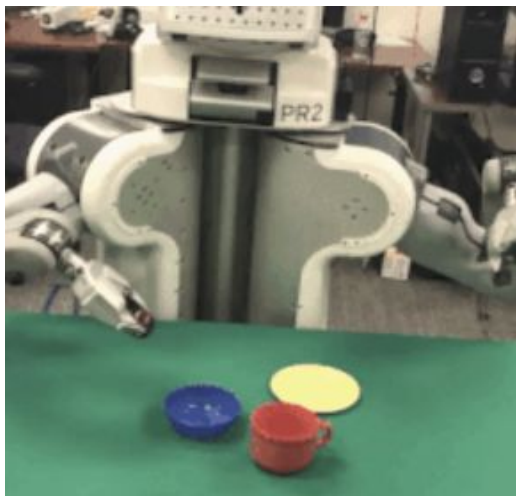
- Reduce your problem to toy example



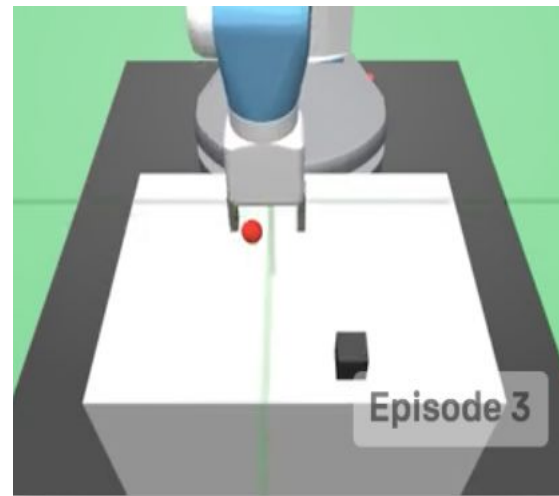
Algorithms

How to select an algorithm for your problem?

- Find similar task in “standard” problems



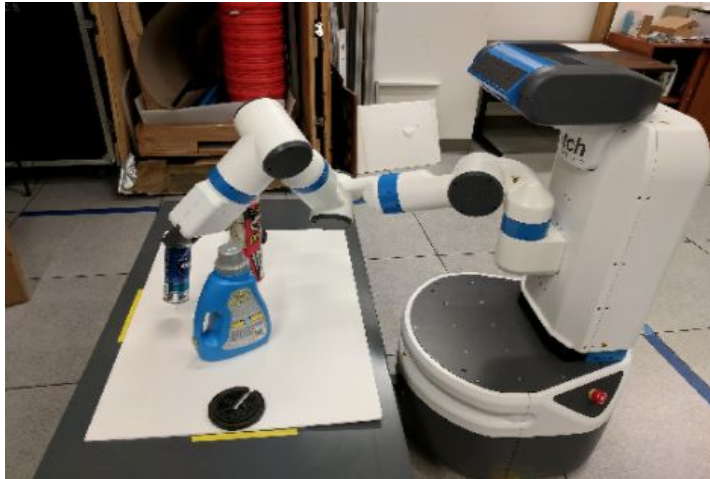
PR2 Robot (Huge robot, dual arm)



Fetch simulation in gym

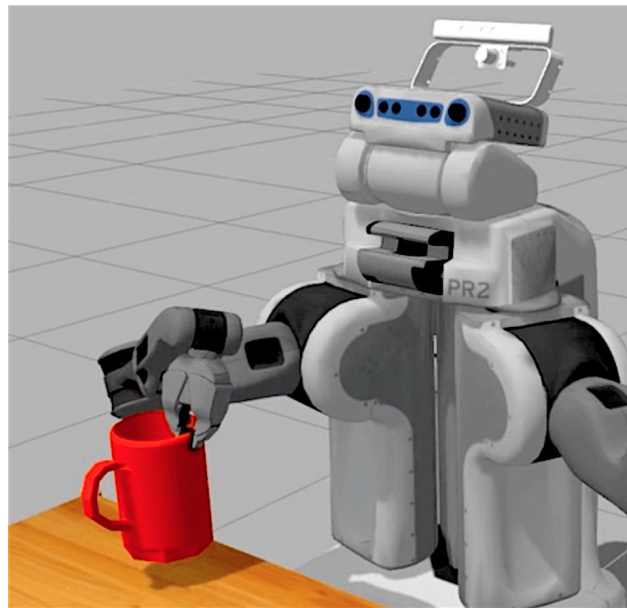
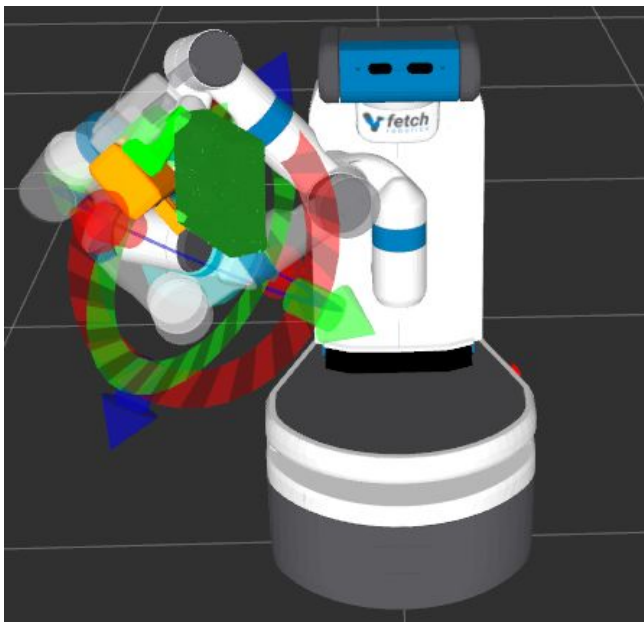
Environment

- Hardware robot
- Simulation

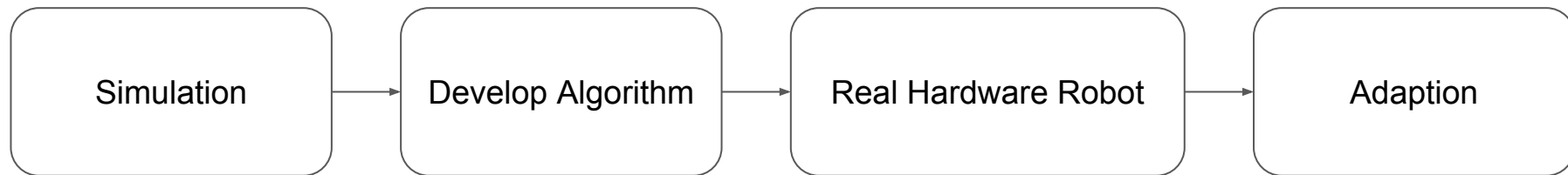


Environment

- Hardware robot
- Simulation



Environment



What is the problem of starting from real robot?

- **Expensive**
- **Safety**

Simulator

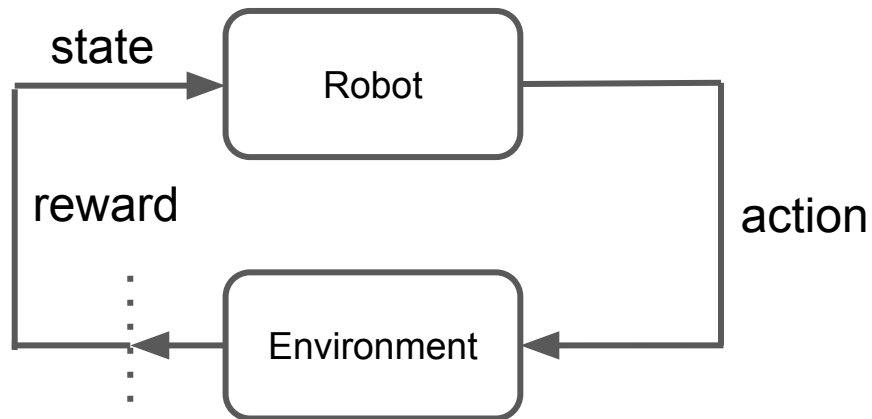
- Simulation Environment

- OpenAI Gym
- MuJoCo-py
- PyBullet
- Gazebo
- V-rep
- Roboschool
- Dart
-

- Dynamics Engine

- Box2D
- Bullet
- ODE
- ...

RL in Robotics: problems



- Reward?
- Structure?
- Exploration?
- Stability?

Future Directions

- Efficient RL
- Long Horizon Reasoning
- Hierarchical RL
- Meta-RL
- Reward Function
- Multi-model
- Lifelong Learning
- Simulation to Real
- ...

References

- [1] <https://gym.openai.com/>
- [2] Mnih, Volodymyr, et al. "Human-level control through deep reinforcement learning." Nature 518.7540 (2015): 529.
- [3] Silver, David, et al. "Mastering the game of Go with deep neural networks and tree search." nature 529.7587 (2016): 484-489.
- [4] Rajeswaran, Aravind, et al. "Learning complex dexterous manipulation with deep reinforcement learning and demonstrations." arXiv preprint arXiv:1709.10087 (2017).
- [5] Roboschool: <https://blog.openai.com/roboschool/>
- [6] Yan, Duan. "Meta Learning for Control." PhD Thesis (2017).
- [7] Gu, Shixiang, et al. "Deep reinforcement learning for robotic manipulation with asynchronous off-policy updates." Robotics and Automation (ICRA), 2017 IEEE International Conference on. IEEE, 2017.

References

- [8] Peng, Xue Bin, et al. "Deeploco: Dynamic locomotion skills using hierarchical deep reinforcement learning." ACM Transactions on Graphics (TOG) 36.4 (2017): 41.
- [9] Bousmalis, Konstantinos, et al. "Using simulation and domain adaptation to improve efficiency of deep robotic grasping." arXiv preprint arXiv:1709.07857 (2017).
- [10] Finn, Chelsea, et al. "One-shot visual imitation learning via meta-learning." arXiv preprint arXiv:1709.04905 (2017).

Thank you!