Challenges and Open Problems

CS 285

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UC Berkeley

Challenges in Deep Reinforcement Learning

What’s the problem?

Challenges with **core algorithms**:

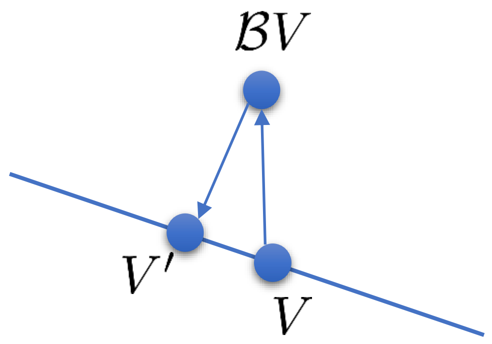
- Stability: does your algorithm converge?
- Efficiency: how long does it take to converge? (how many samples)
- Generalization: after it converges, does it generalize?

Challenges with **assumptions**:

- Is this even the right problem formulation?
- What is the source of *supervision*?

Stability and hyperparameter tuning

- Devising stable RL algorithms is very hard
- Q-learning/value function estimation
  - Fitted Q/fitted value methods with deep network function estimators are typically not contractions, hence no guarantee of convergence
  - Lots of parameters for stability: target network delay, replay buffer size, clipping, sensitivity to learning rates, etc.
- Policy gradient/likelihood ratio/REINFORCE
  - Very high variance gradient estimator
  - Lots of samples, complex baselines, etc.
  - Parameters: batch size, learning rate, design of baseline
- Model-based RL algorithms
  - Model class and fitting method
  - Optimizing policy w.r.t. model non-trivial due to backpropagation through time
  - More subtle issue: policy tends to *exploit* the model



The challenge with hyperparameters

- Can’t run hyperparameter sweeps in the real world
    - How representative is your simulator? Usually the answer is “not very”
- Actual sample complexity = time to run algorithm x number of runs to sweep
    - In effect stochastic search + gradient-based optimization
- Can we develop more stable algorithms that are less sensitive to hyperparameters?

What can we do?

- Algorithms with favorable improvement and convergence properties
  - Trust region policy optimization [Schulman et al. ‘16]
  - Safe reinforcement learning, High-confidence policy improvement [Thomas ‘15]
- Algorithms that adaptively adjust parameters
  - Q-Prop [Gu et al. ‘17]: adaptively adjust strength of control variate/baseline

- More research needed here!
- Not great for beating benchmarks, but absolutely essential to make RL a viable tool for real-world problems

Sample Complexity

gradient-free methods
(e.g. NES, CMA, etc.)

10x

fully online methods
(e.g. A3C)

10x

policy gradient methods
(e.g. TRPO)

10x

replay buffer value estimation methods
(Q-learning, DDPG, NAF, SAC, etc.)

10x

model-based deep RL
(e.g. PETS, guided policy search)

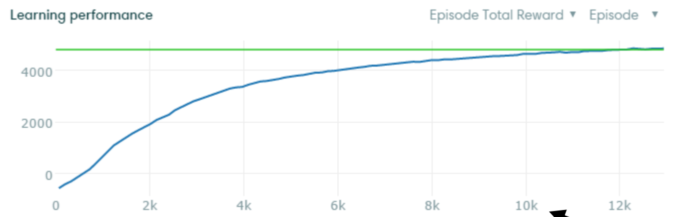
10x

model-based "shallow" RL
(e.g. PILCO)

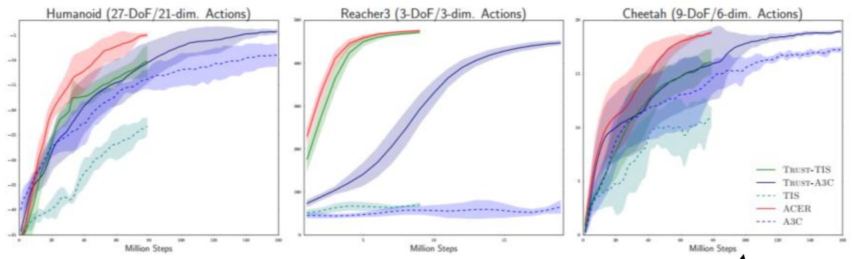
Evolution Strategies as a Scalable Alternative to Reinforcement Learning

Tim Salimans[1] Jonathan Ho[1] Xi Chen[1] Ilya Sutskever[1]

half-cheetah (slightly different version)



TRPO+GAE (Schulman et al. '16)

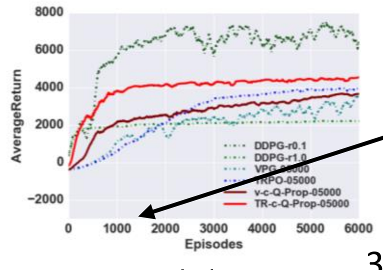


Wang et al. '17

100,000,000 steps
(100,000 episodes)
(~ 15 days real time)

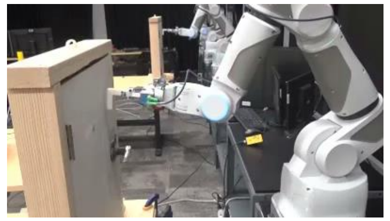
10,000,000 steps
(10,000 episodes)
(~ 1.5 days real time)

half-cheetah

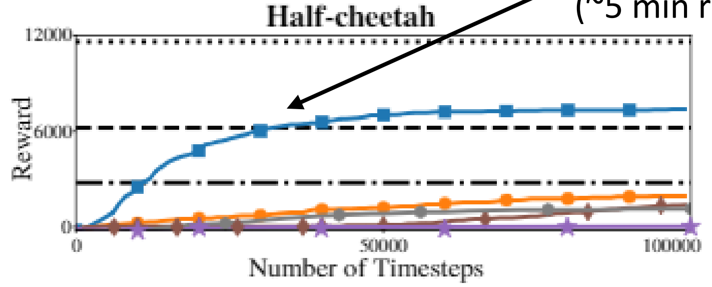


Gu et al. '16

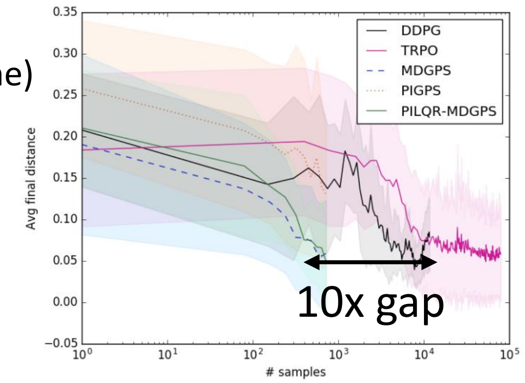
1,000,000 steps
(1,000 episodes)
(~3 hours real time)



30,000 steps
(30 episodes)
(~5 min real time)



Chua et a. '18: Deep Reinforcement Learning in a Handful of Trials



about 20 minutes of experience on a real robot

Chebotar et al. '17 (note log scale)

The challenge with sample complexity

- Need to wait for a long time for your homework to finish running
- Real-world learning becomes difficult or impractical
- Precludes the use of expensive, high-fidelity simulators
- Limits applicability to real-world problems

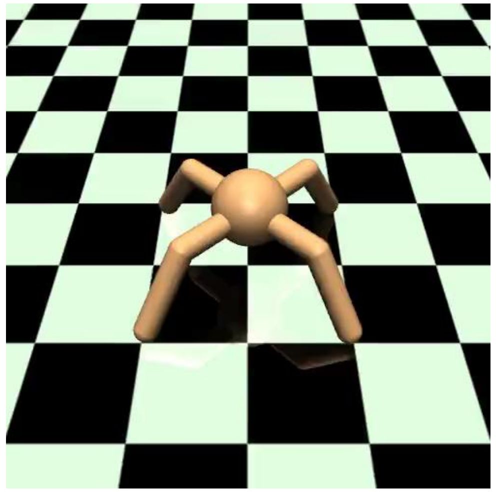
What can we do?

- Better model-based RL algorithms
- Design faster algorithms
  - Addressing Function Approximation Error in Actor-Critic Algorithms (Fujimoto et al. ‘18): simple and effective tricks to accelerate DDPG-style algorithms
  - Soft Actor-Critic (Haarnoja et al. ‘18): very efficient maximum entropy RL algorithm
- Reuse prior knowledge to accelerate reinforcement learning
  - RL2: Fast reinforcement learning via slow reinforcement learning (Duan et al. ‘17)
  - Learning to reinforcement learning (Wang et al. ‘17)
  - Model-agnostic meta-learning (Finn et al. ‘17)

Scaling & Generalization

Scaling up deep RL & generalization

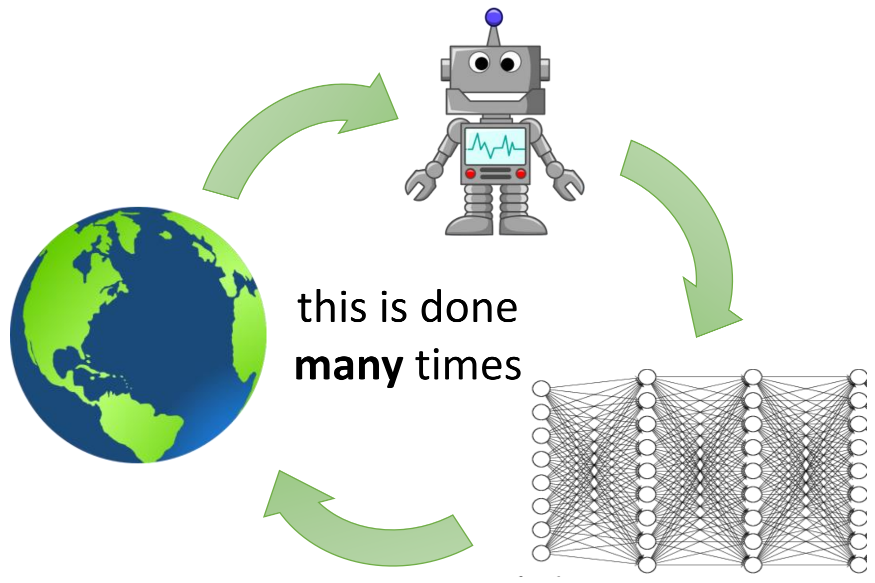
- Large-scale
- Emphasizes diversity
- Evaluated on generalization



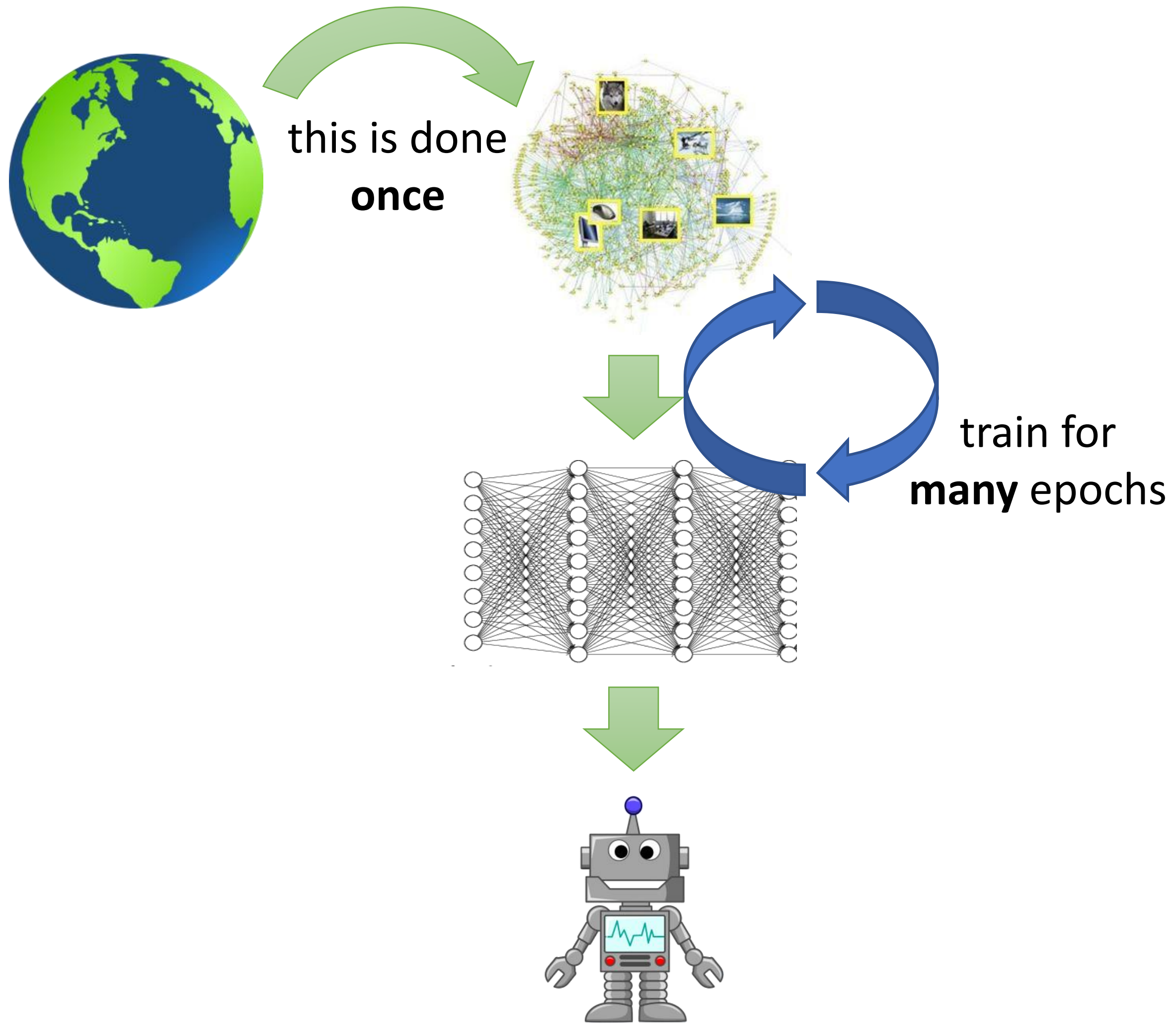
- Small-scale
- Emphasizes mastery
- Evaluated on performance
- Where is the generalization?

RL has a **big** problem

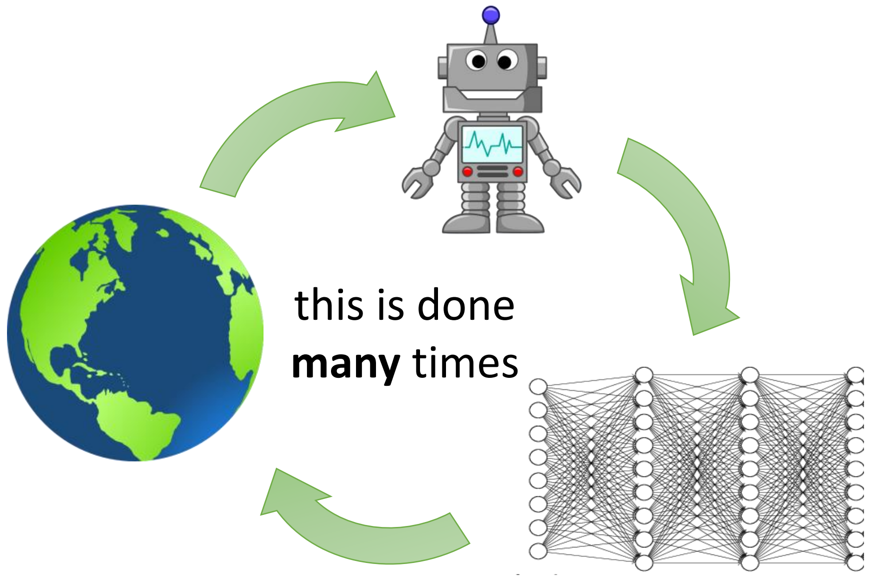
reinforcement learning

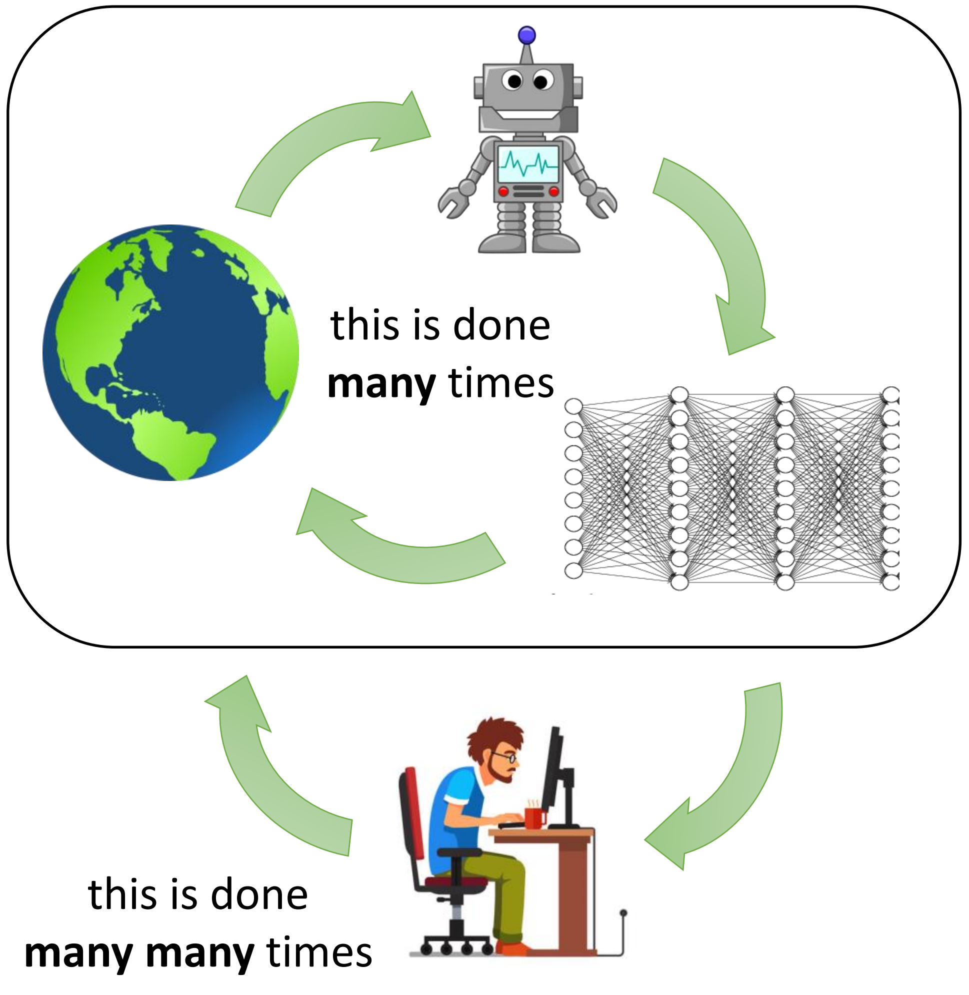


supervised machine learning

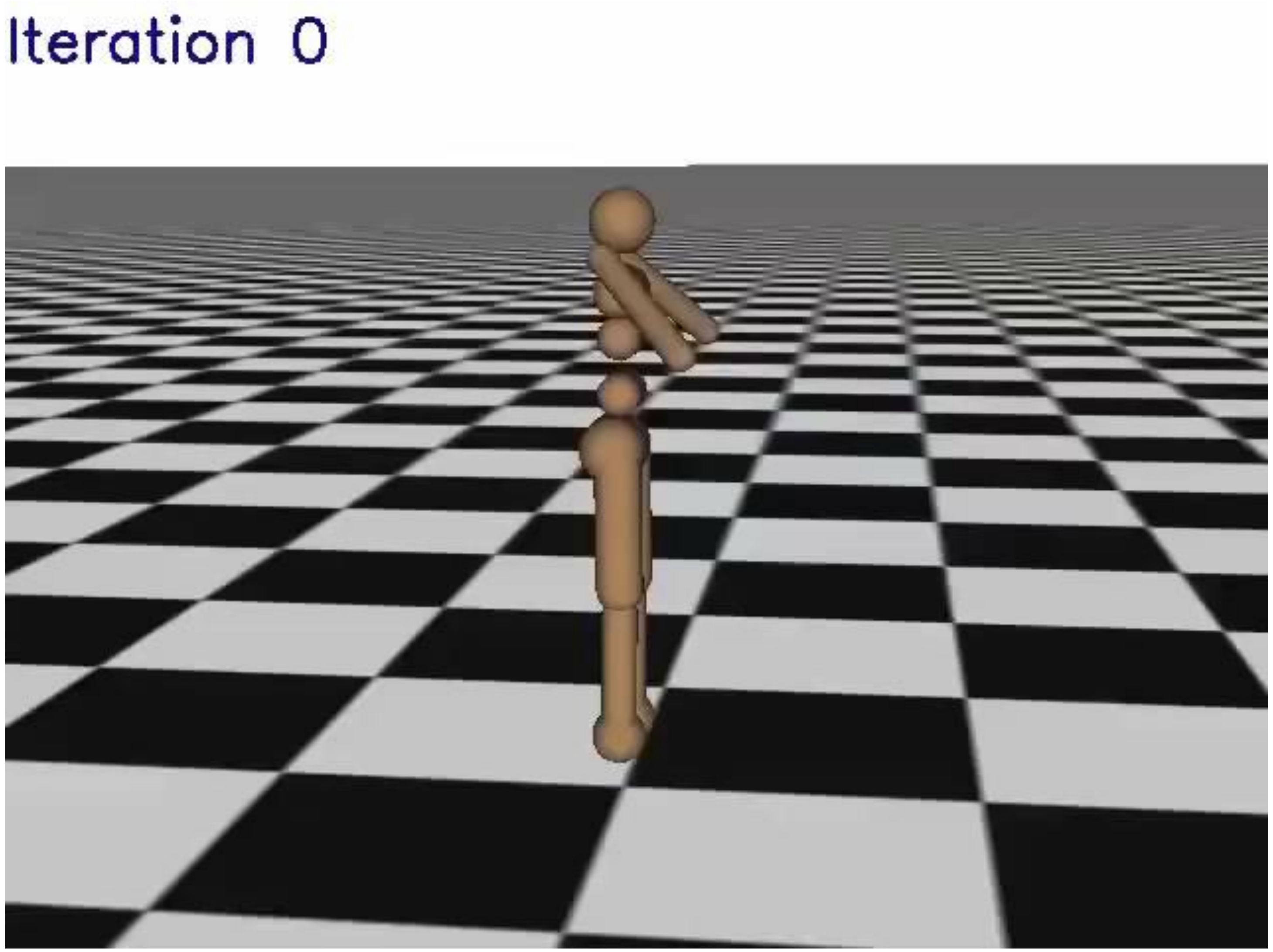


RL has a **big** problem





How bad is it?

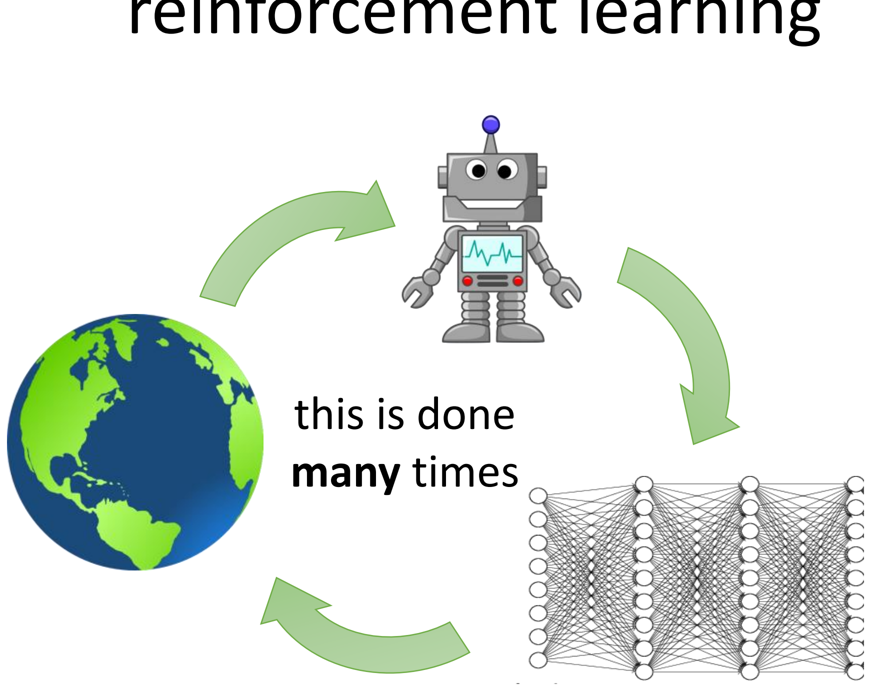


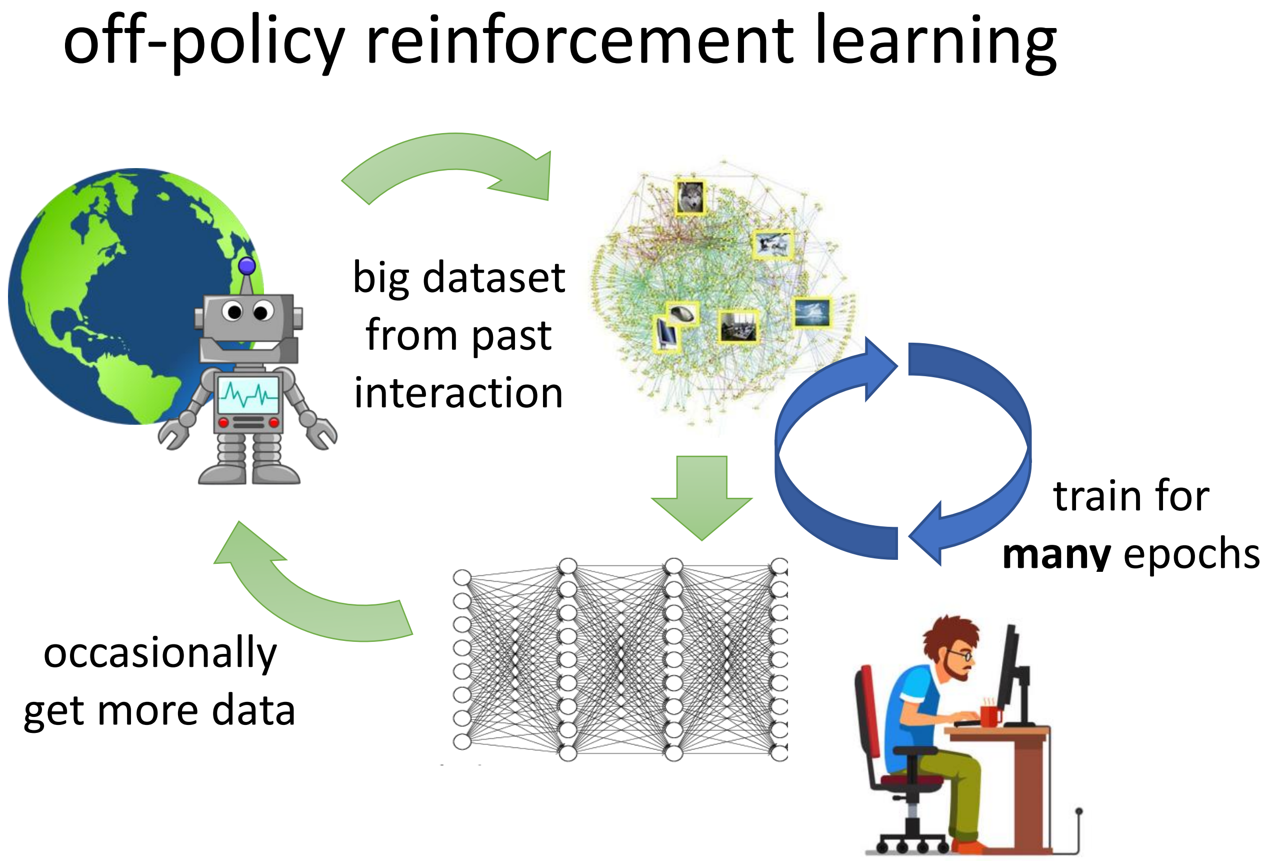
- This is quite cool
- It takes 6 days of real time (if it was real time)
- ...to run on an infinite flat plane

The real world is not so simple!

Schulman, Moritz, L., Jordan, Abbeel ’16

Off-policy RL?





Not just robots!

autonomous driving

language & dialogue
(structured prediction)

finance

What’s the problem?

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Challenges with **assumptions**:

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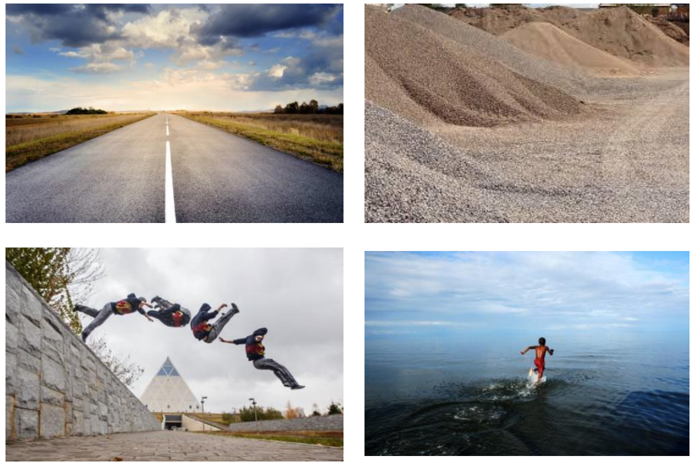
Problem Formulation

Single task or multi-task?



The real world is not so simple!

this is where generalization can come from…

maybe doesn't require any new assumption, but might merit additional treatment

pick MDP randomly in first state

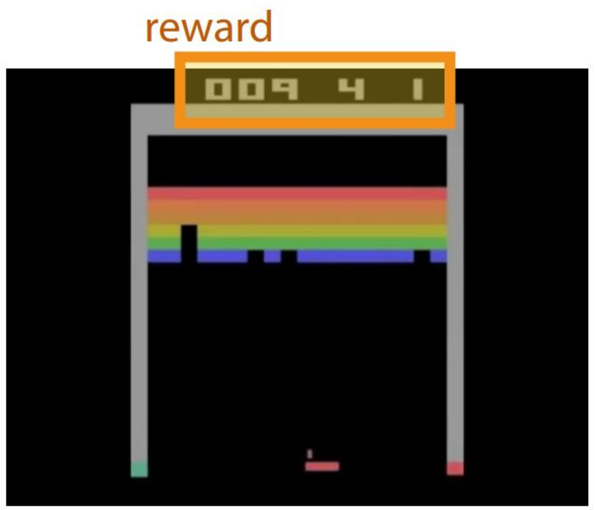
$$\begin{tikzcd}
 & \mathbf{s}_0 \arrow[r, "\pi(\mathbf{a}_0|\mathbf{s}_0)"] & \mathbf{s}_1 \arrow[r] & \text{etc.} & \text{MDP 0} \\
p(\mathbf{s}_0) \arrow[ur, dashed, "\text{sample}"] \arrow[r, dashed, "\text{sample}"] \arrow[dr, dashed, "\text{sample}"] & \mathbf{s}_0 \arrow[r, "\pi(\mathbf{a}_0|\mathbf{s}_0)"] & \mathbf{s}_1 \arrow[r] & \text{etc.} & \text{MDP 1} \\
 & \mathbf{s}_0 \arrow[r, "\pi(\mathbf{a}_0|\mathbf{s}_0)"] & \mathbf{s}_1 \arrow[r] & \text{etc.} & \text{MDP 2}
\end{tikzcd}$$

Generalizing from multi-task learning

- Train on multiple tasks, then try to generalize or finetune
  - Policy distillation (Rusu et al. ‘15)
  - Actor-mimic (Parisotto et al. ‘15)
  - Model-agnostic meta-learning (Finn et al. ‘17)
  - many others…
- Unsupervised or weakly supervised learning of diverse behaviors
  - Stochastic neural networks (Florensa et al. ‘17)
  - Reinforcement learning with deep energy-based policies (Haarnoja et al. ‘17)
  - See lecture on unsupervised information-theoretic exploration
  - many others…

Where does the **supervision** come from?

- If you want to learn from many different tasks, you need to get those tasks somewhere!
- Learn objectives/rewards from demonstration (inverse reinforcement learning)
- Generate objectives automatically?

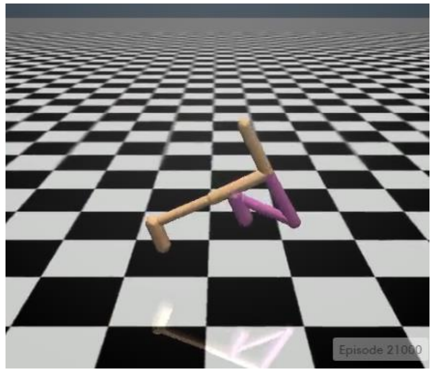


Mnih et al. '15

reinforcement learning agent

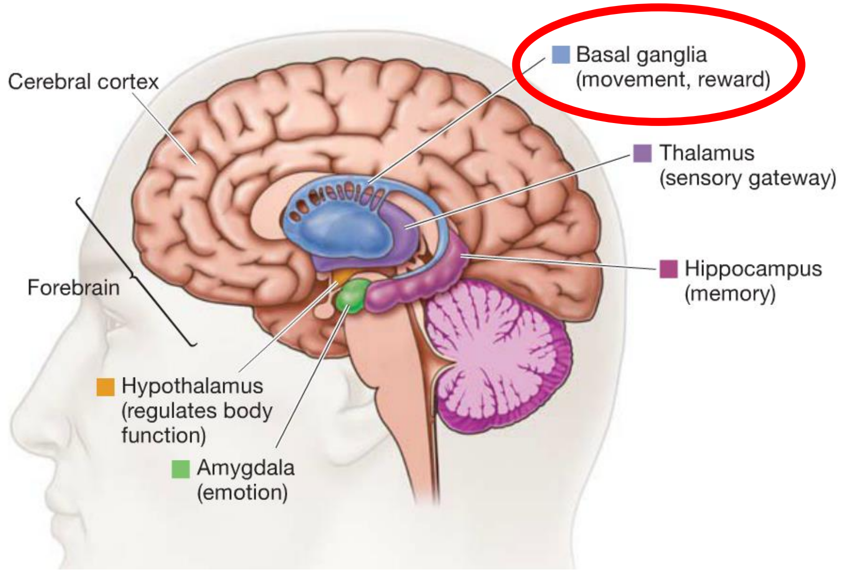
what is the reward?

What is the role of the reward function?



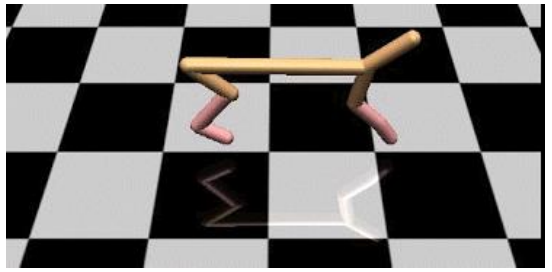
$$r(\mathbf{s},\mathbf{a}) = \begin{cases} 1 \text{ if walker is running} \\ 0 \text{ otherwise} \end{cases}$$

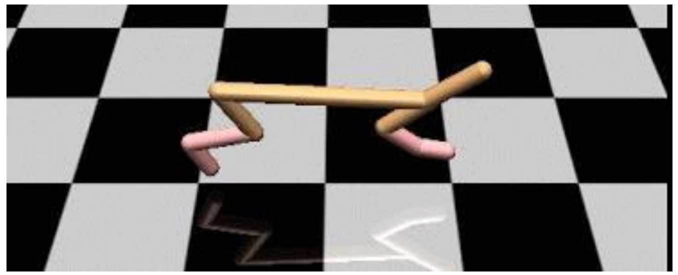
$$\begin{aligned} r(\mathbf{s},\mathbf{a}) = & w_1 v(\mathbf{s}) + \\ & w_2 \delta(|\theta_{\text{torso}}(\mathbf{s})| < \epsilon) + \\ & w_3 \delta(h_{\text{torso}}(\mathbf{s}) \geq h) \end{aligned}$$

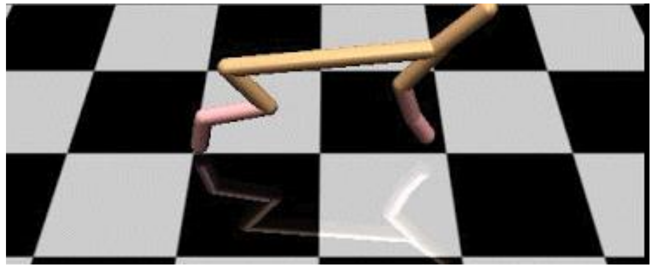

Cerebral cortex
Forebrain
Basal ganglia (movement, reward)
Thalamus (sensory gateway)
Hippocampus (memory)
Hypothalamus (regulates body function)
Amygdala (emotion)

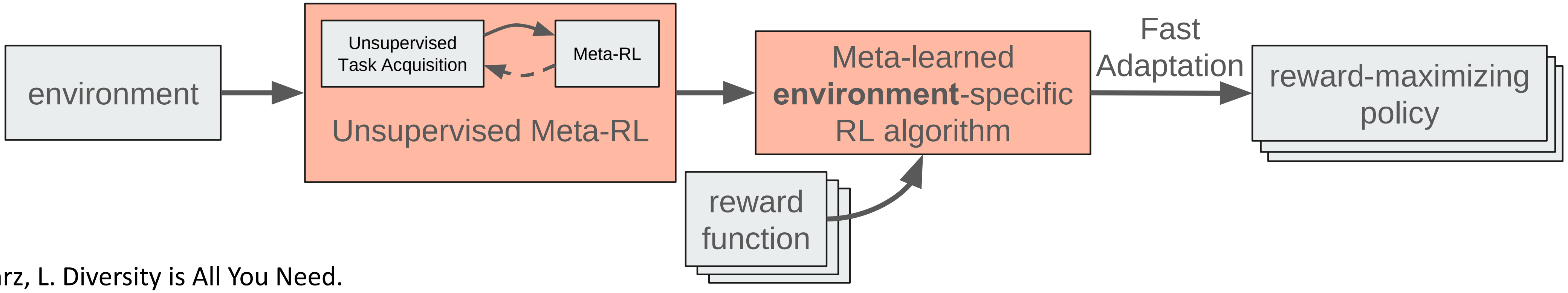
Unsupervised reinforcement learning?

1. Interact with the world, without a reward function
2. Learn *something* about the world (what?)
3. Use what you learned to quickly solve new tasks









Eysenbach, Gupta, Ibarz, L. Diversity is All You Need.

Gupta, Eysenbach, Finn, L. Unsupervised Meta-Learning for Reinforcement Learning.

Other sources of supervision

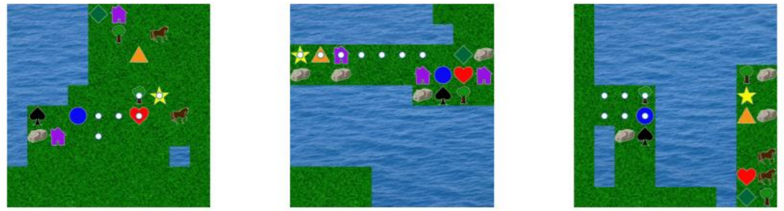
Should supervision tell us **what** to do or **how** to do it?

- Demonstrations
  - Muelling, K et al. (2013). Learning to Select and Generalize Striking Movements in Robot Table Tennis

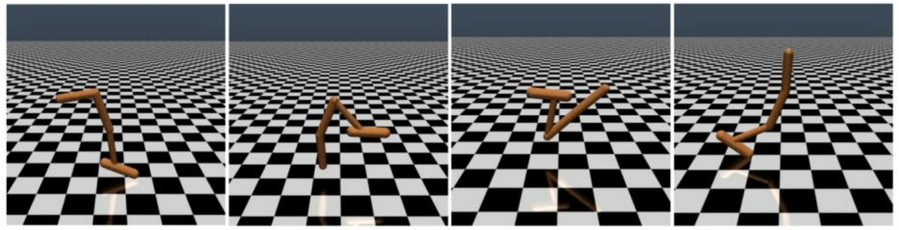
- Language
  - Andreas et al. (2018). Learning with latent language

Human description:
`move to the star`

Inferred description:
`reach the star cell`



- Human preferences
  - Christiano et al. (2017). Deep reinforcement learning from human preferences

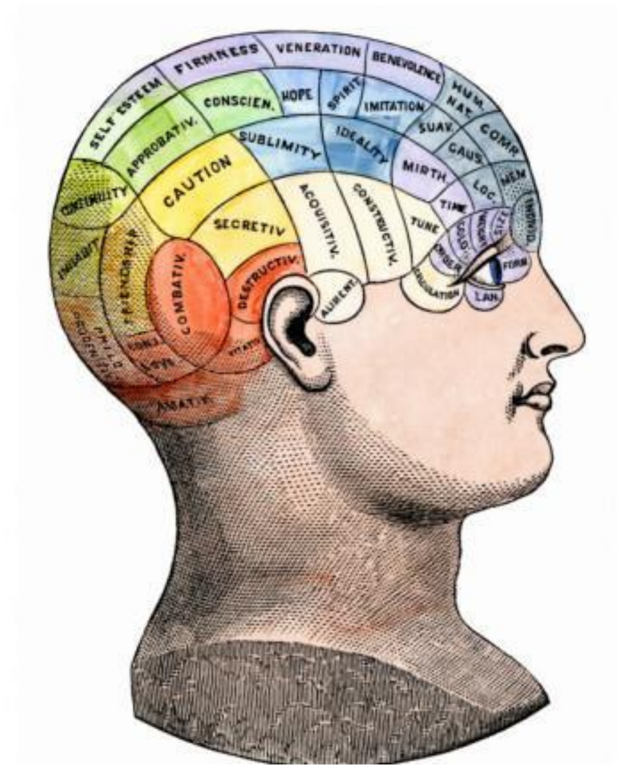


Rethinking the Problem Formulation

- How should we define a *control* problem?
  - What is the data?
  - What is the goal?
  - What is the supervision?
    - may not be the same as the goal…
- Think about the assumptions that fit your problem setting!
- Don’t assume that the basic RL problem is set in stone

Back to the Bigger Picture

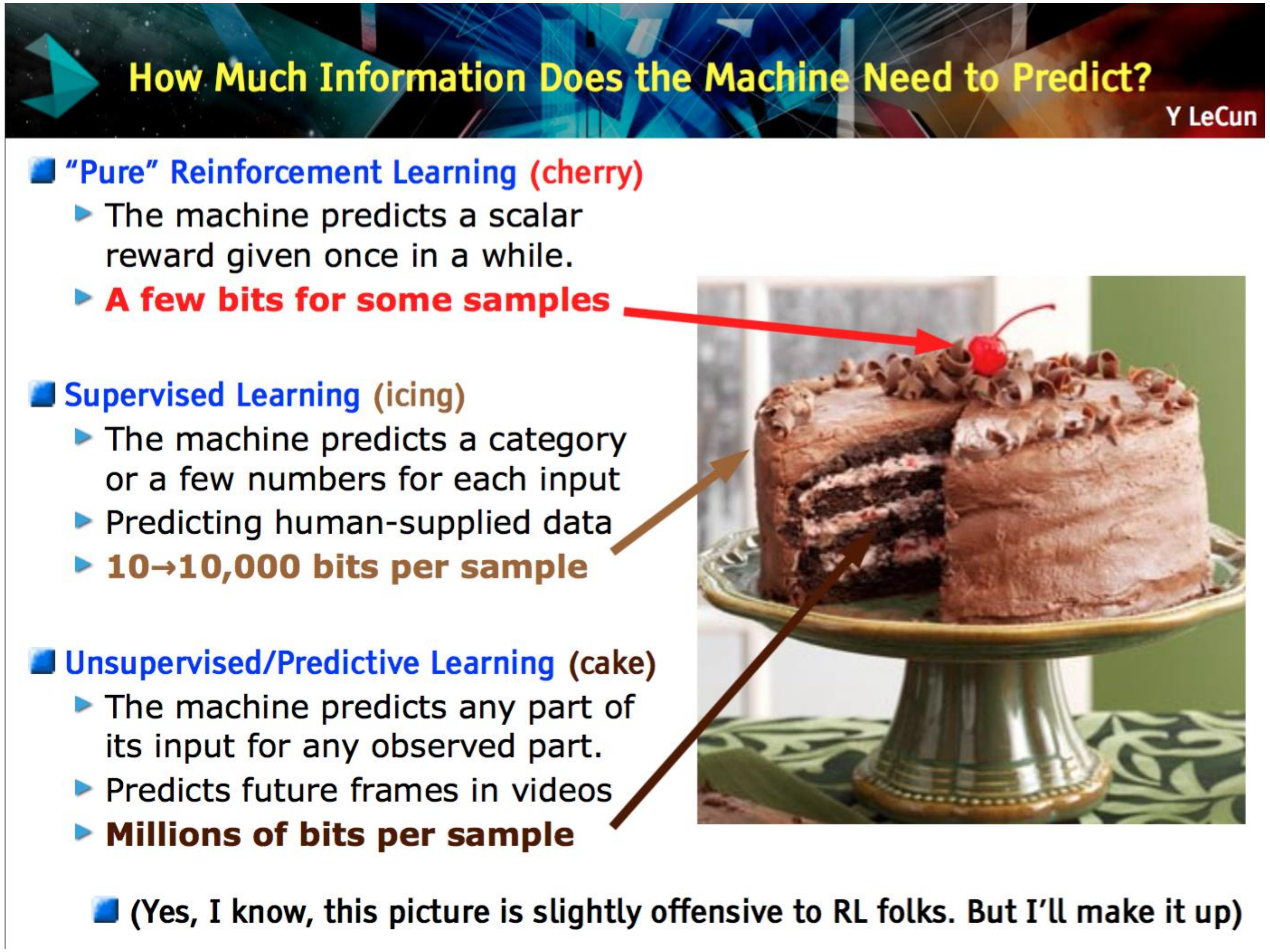
Learning as the basis of intelligence



- Reinforcement learning = can reason about decision making
- Deep models = allows RL algorithms to learn and represent complex input-output mappings

Deep models are what allow reinforcement learning algorithms to solve complex problems end to end!

What is missing?



How Much Information Does the Machine Need to Predict?

Y LeCun

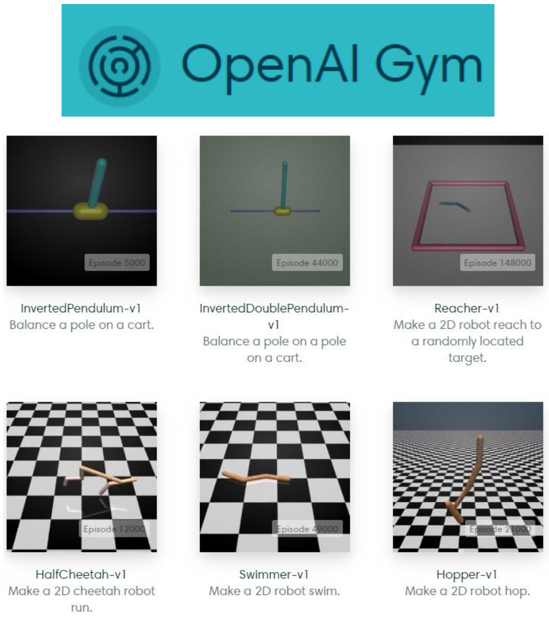
- **"Pure" Reinforcement Learning (cherry)**
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- **Supervised Learning (icing)**
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- **Unsupervised/Predictive Learning (cake)**
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**
- (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)

Where does the *signal* come from?

- Yann LeCun’s cake
    - Unsupervised or self-supervised learning
    - Model learning (predict the future)
    - Generative modeling of the world
    - Lots to do even before you accomplish your goal!
- Imitation & understanding other agents
    - We are social animals, and we have culture – for a reason!
- The giant value backup
    - All it takes is one +1
- All of the above

How should we answer these questions?

- Pick the right problems!
- Pay attention to generative models, prediction, etc., not just RL algorithms
- Carefully understand the relationship between RL and other ML fields


OpenAI Gym
InvertedPendulum-v1
Balance a pole on a cart.
InvertedDoublePendulum-v1
Balance a pole on a pole on a cart.
Reacher-v1
Make a 2D robot reach to a randomly located target.
HalfCheetah-v1
Make a 2D cheetah robot run.
Swimmer-v1
Make a 2D robot swim.
Hopper-v1
Make a 2D robot hop.