Advanced Imitation Learning Challenges and Open Problems

CS 294-112: Deep Reinforcement Learning

Sergey Levine

Imitation Learning

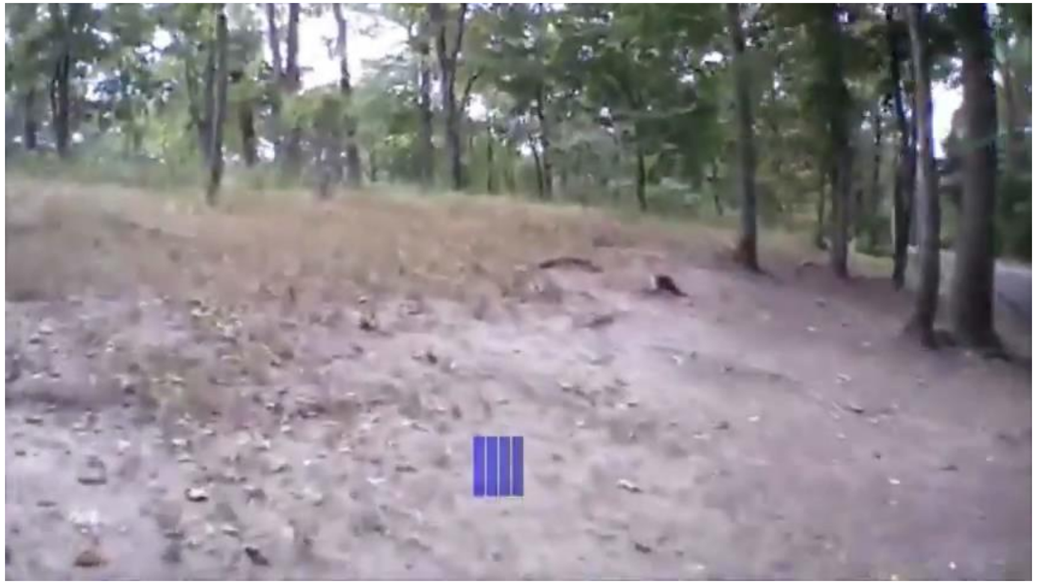
$\mathbf{o}_t$

$\mathbf{a}_t$

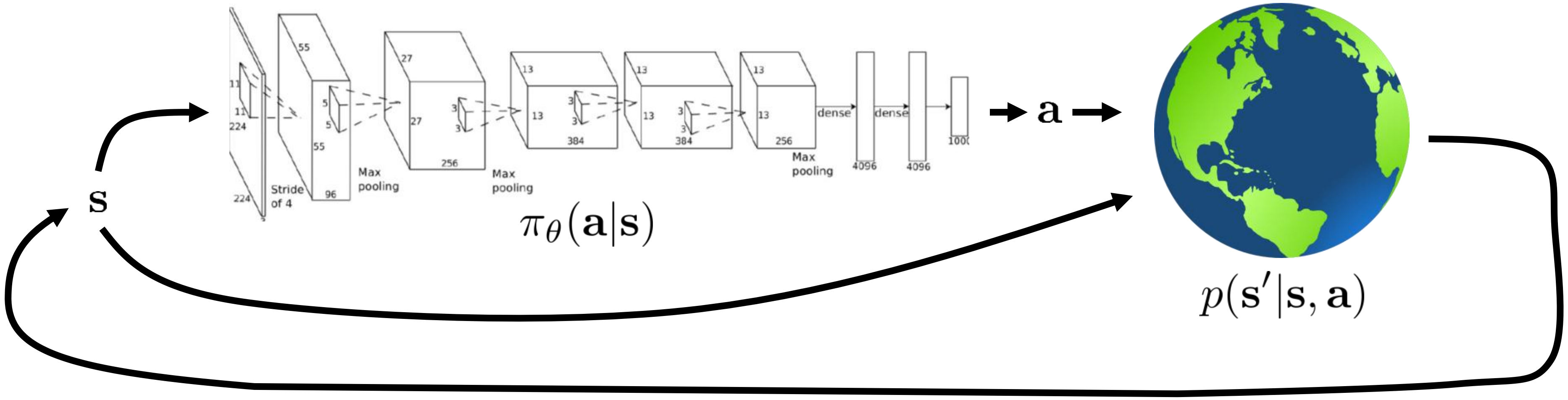
training data

supervised learning

$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$



Reinforcement Learning



Imitation vs. Reinforcement Learning

imitation learning

- Requires demonstrations
- Must address distributional shift
- Simple, stable supervised learning
- Only as good as the demo

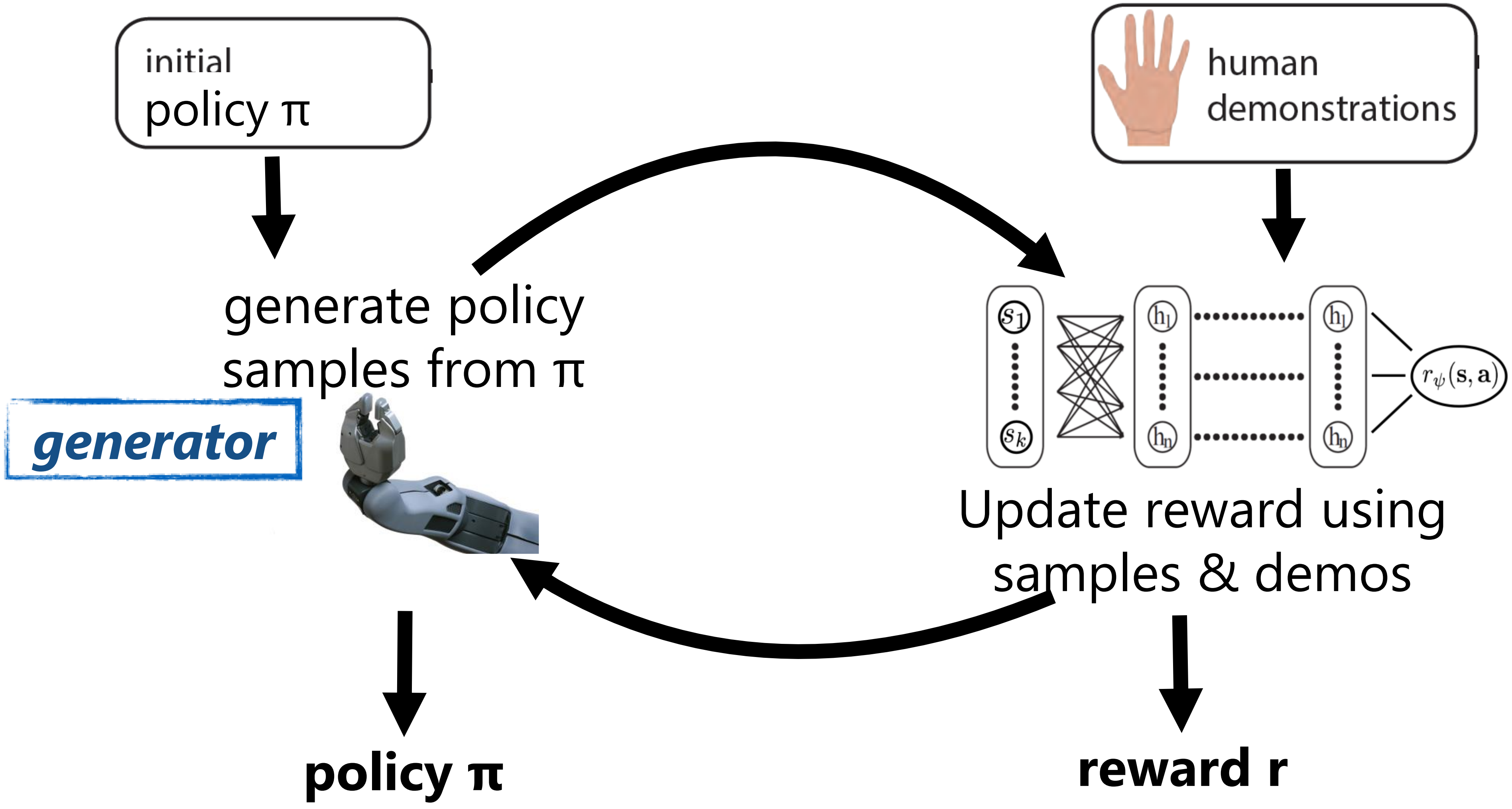
reinforcement learning

- Requires reward function
- Must address exploration
- Potentially non-convergent RL
- Can become arbitrarily good

Can we get the best of both?

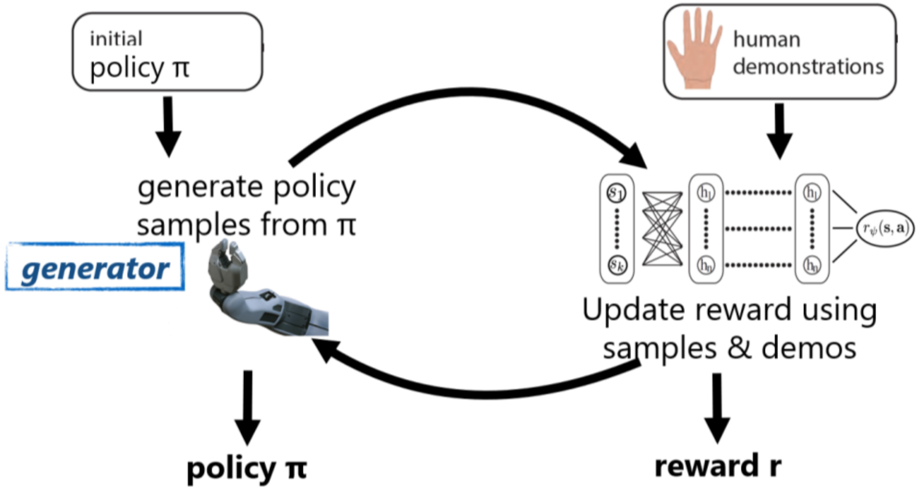
e.g., what if we have demonstrations *and* rewards?

Addressing distributional shift with RL?



Addressing distributional shift with RL?

IRL *already* addresses distributional shift via RL



this part is regular "forward" RL

But it doesn't use a known reward function!

Simplest combination: pretrain & finetune

- Demonstrations can overcome exploration: show us how to do the task
- Reinforcement learning can improve beyond performance of the demonstrator
- Idea: initialize with imitation learning, then finetune with reinforcement learning!

1. collected demonstration data $(\mathbf{s}_i, \mathbf{a}_i)$
2. initialize π_θ as $\max_\theta \sum_i \log \pi_\theta(\mathbf{a}_i|\mathbf{s}_i)$
3. run π_θ to collect experience
4. improve π_θ with any RL algorithm

Simplest combination: pretrain & finetune

Muelling et al. '13

Simplest combination: pretrain & finetune

Pretrain & finetune

1. collected demonstration data $(\mathbf{s}_i, \mathbf{a}_i)$
2. initialize π_θ as $\max_\theta \sum_i \log \pi_\theta(\mathbf{a}_i|\mathbf{s}_i)$
3. run π_θ to collect experience
4. improve π_θ with any RL algorithm

vs. DAgger

1. train $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ from human data $\mathcal{D} = \{\mathbf{o}_1, \mathbf{a}_1, \dots, \mathbf{o}_N, \mathbf{a}_N\}$
2. run $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ to get dataset $\mathcal{D}_\pi = \{\mathbf{o}_1, \dots, \mathbf{o}_M\}$
3. Ask human to label $\mathcal{D}_\pi$ with actions $\mathbf{a}_t$
4. Aggregate: $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_\pi$

What's the problem?

Pretrain & finetune

1. collected demonstration data $(\mathbf{s}_i, \mathbf{a}_i)$
2. initialize π_θ as $\max_\theta \sum_i \log \pi_\theta(\mathbf{a}_i|\mathbf{s}_i)$
3. run π_θ to collect experience ← can be very bad (due to distribution shift)
4. improve π_θ with any RL algorithm ← first batch of (very) bad data can destroy initialization

Can we avoid forgetting the demonstrations?

Off-policy reinforcement learning

- Off-policy RL can use any data
- If we let it use demonstrations as off-policy samples, can that mitigate the exploration challenges?
  - Since demonstrations are provided as data in every iteration, they are never forgotten
  - But the policy can still become *better* than the demos, since it is not forced to mimic them

off-policy policy gradient (with importance sampling)

off-policy Q-learning

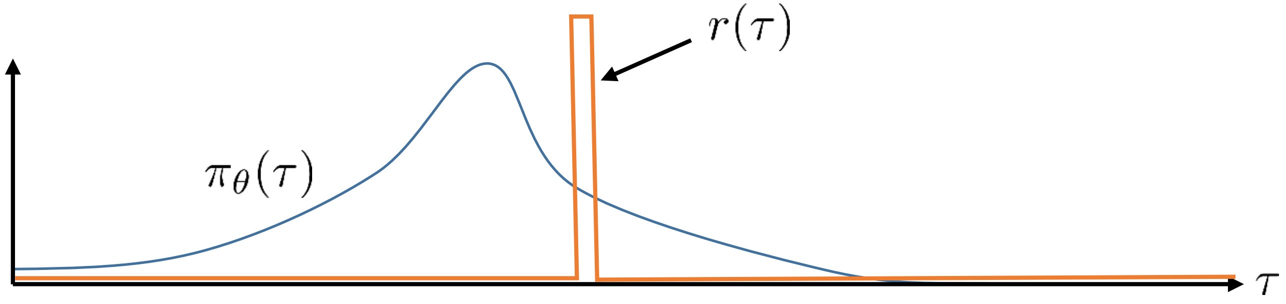
Policy gradient with demonstrations

$$\nabla_\theta J(\theta) = \sum_{\tau \in \mathcal{D}} \left[\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) \left(\prod_{t'=1}^{t} \frac{\pi_\theta(\mathbf{a}_{t'}|\mathbf{s}_{t'})}{q(\mathbf{a}_{t'}|\mathbf{s}_{t'})} \right) \left(\sum_{t'=t}^{T} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \right) \right]$$

includes demonstrations *and* experience

Why is this a good idea? Don't we want on-policy samples?

best sampling distribution should have high reward!



optimal importance sampling

say we want $E_{p(x)}[f(x)]$

$E_{p(x)}[f(x)] \approx \frac{1}{N} \sum_i \frac{p(x_i)}{q(x_i)} f(x_i)$

which $q(x)$ gives lowest variance?

answer: $q(x) \propto p(x)|f(x)|$

Policy gradient with demonstrations

$$\nabla_\theta J(\theta) = \sum_{\tau \in \mathcal{D}} \left[\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) \left(\prod_{t'=1}^{t} \frac{\pi_\theta(\mathbf{a}_{t'}|\mathbf{s}_{t'})}{q(\mathbf{a}_{t'}|\mathbf{s}_{t'})} \right) \left(\sum_{t'=t}^{T} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \right) \right]$$

How do we construct the sampling distribution?

problem 1: which distribution did the demonstrations come from?

option 1: use supervised behavior cloning to approximate π_{demo}

option 2: assume Diract delta: $\pi_{\text{demo}}(\tau) = \frac{1}{N}\delta(\tau \in \mathcal{D})$

this works best with self-normalized importance sampling

standard IS

$$E_{p(x)}[f(x)] \approx \frac{1}{N} \sum_i \frac{p(x_i)}{q(x_i)} f(x_i)$$

self-normalized IS

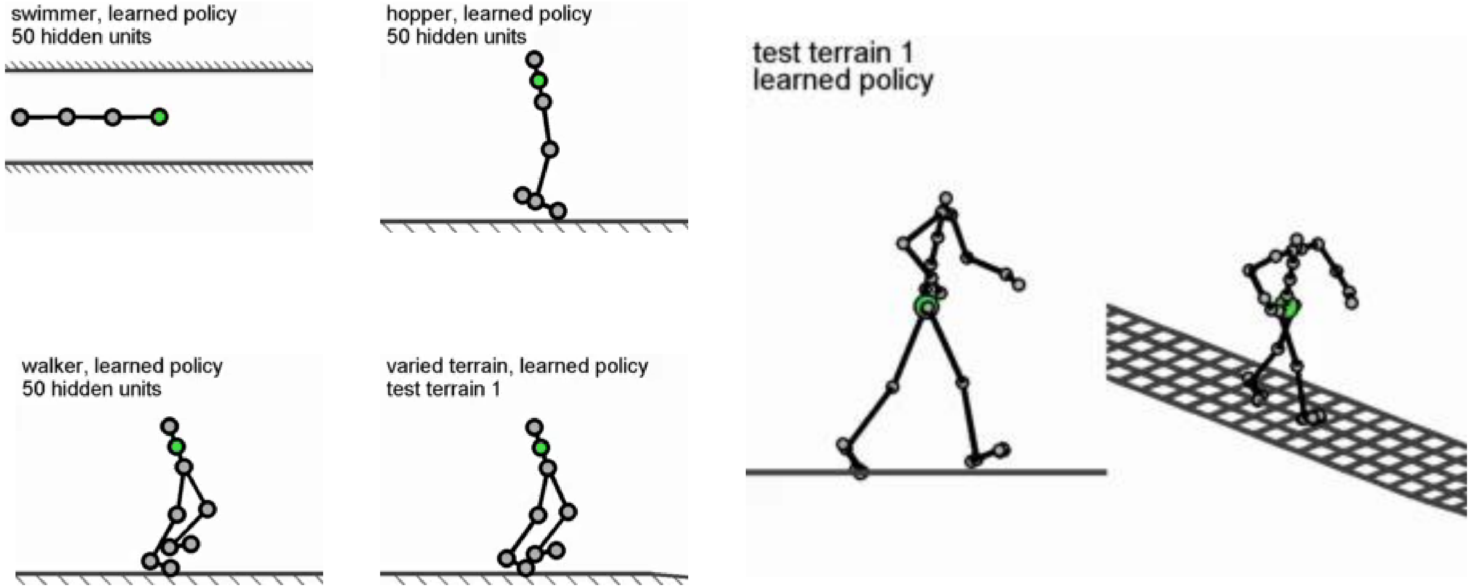
$$E_{p(x)}[f(x)] \approx \frac{1}{\sum_j \frac{p(x_j)}{q(x_j)}} \sum_i \frac{p(x_i)}{q(x_i)} f(x_i)$$

problem 2: what to do if we have multiple distributions?

fusion distribution: $q(x) = \frac{1}{M} \sum_i q_i(x)$

Example: importance sampling with demos

$$\nabla_\theta J(\theta) = \sum_{\tau \in \mathcal{D}} \left[\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) \left(\prod_{t'=1}^{t} \frac{\pi_\theta(\mathbf{a}_{t'}|\mathbf{s}_{t'})}{q(\mathbf{a}_{t'}|\mathbf{s}_{t'})} \right) \left(\sum_{t'=t}^{T} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \right) \right]$$



Levine, Koltun ’13. “Guided policy search”

Q-learning with demonstrations

- Q-learning is *already* off-policy, no need to bother with importance weights!
- Simple solution: drop demonstrations into the replay buffer

full Q-learning with replay buffer:

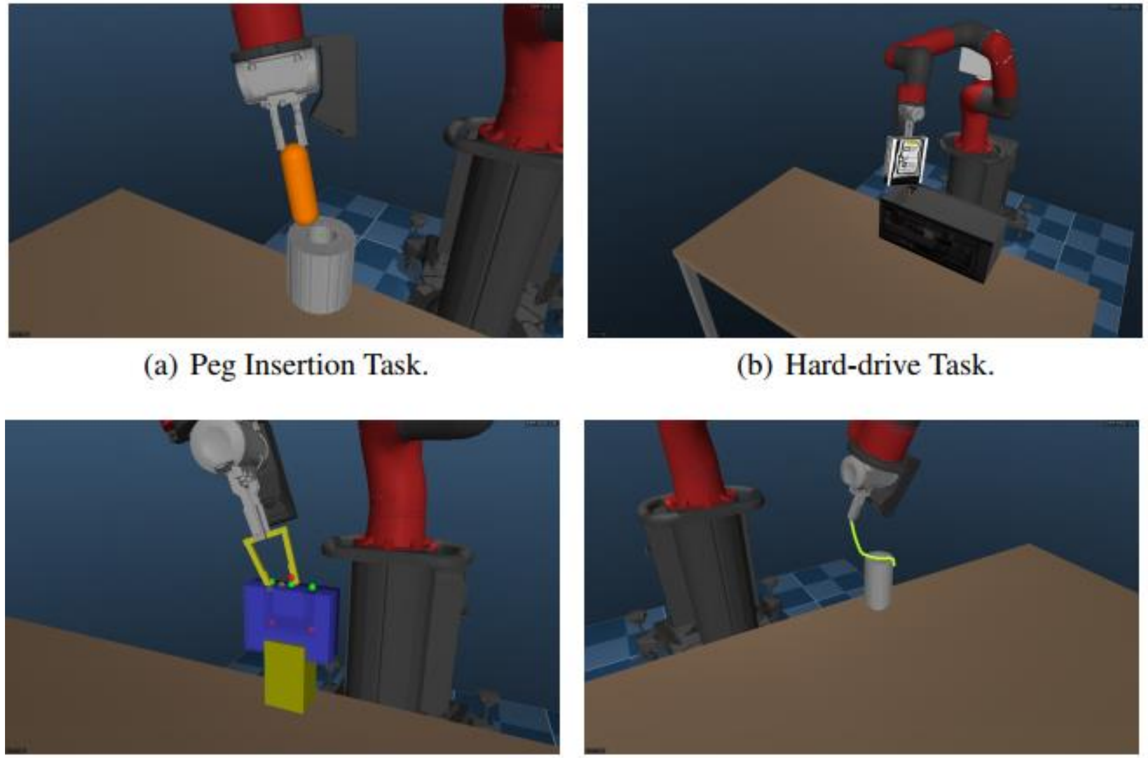
initialize $\mathcal{B}$ to contain the demonstration data

1. collect dataset $\{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)\}$ using some policy, add it to $\mathcal{B}$
   2. sample a batch $(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)$ from $\mathcal{B}$

   $K\times$

   3. $\phi \leftarrow \phi - \alpha \sum_i \frac{dQ_\phi}{d\phi}(\mathbf{s}_i, \mathbf{a}_i)(Q_\phi(\mathbf{s}_i, \mathbf{a}_i) - [r(\mathbf{s}_i, \mathbf{a}_i) + \gamma \max_{\mathbf{a}'} Q_\phi(\mathbf{s}'_i, \mathbf{a}'_i)])$

Q-learning with demonstrations

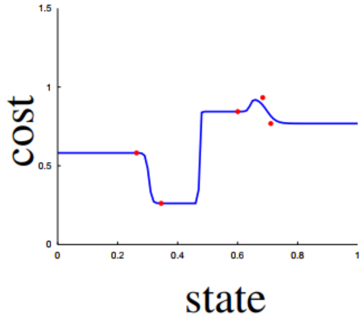


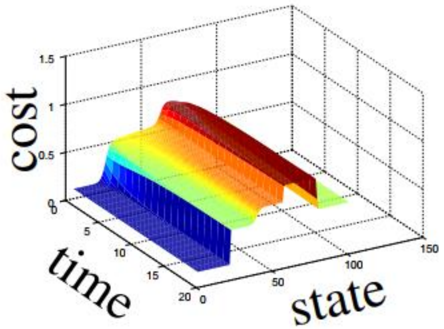
(a) Peg Insertion Task. (b) Hard-drive Task. (c) Clip Insertion Task (d) Cable Insertion Task.

Vecerik et al., ‘17, “Leveraging Demonstrations for Deep Reinforcement Learning…”

What's the problem?

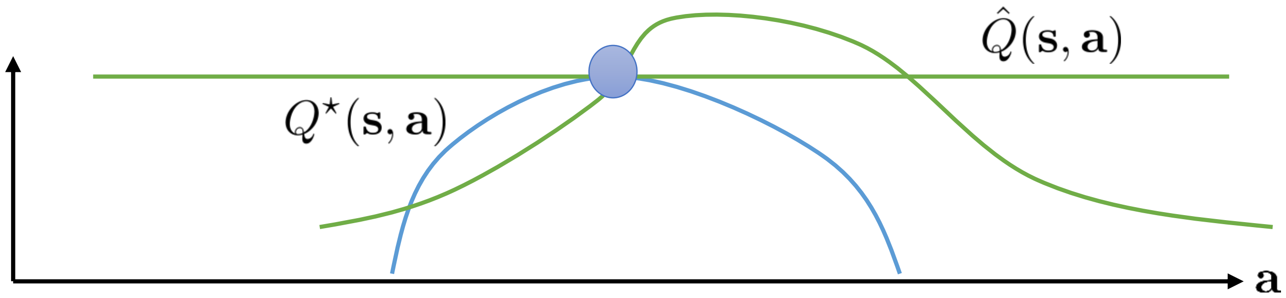
Importance sampling: recipe for getting stuck





$$\nabla_\theta J(\theta) = \sum_{\tau \in \mathcal{D}} \left[\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) \left(\prod_{t'=1}^{t} \frac{\pi_\theta(\mathbf{a}_{t'}|\mathbf{s}_{t'})}{q(\mathbf{a}_{t'}|\mathbf{s}_{t'})} \right) \left(\sum_{t'=t}^{T} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) \right) \right]$$

Q-learning: just good data is not enough



So far...

- Pure imitation learning
  - Easy and stable supervised learning
  - Distributional shift
  - No chance to get better than the demonstrations
- Pure reinforcement learning
  - Unbiased reinforcement learning, can get arbitrarily good
  - Challenging exploration and optimization problem
- Initialize & finetune
  - Almost the best of both worlds
  - ...but can forget demo initialization due to distributional shift
- Pure reinforcement learning, with demos as off-policy data
  - Unbiased reinforcement learning, can get arbitrarily good
  - Demonstrations don’t always help
- Can we strike a compromise? A little bit of supervised, a little bit of RL?

Imitation as an auxiliary loss function

imitation objective: $\sum_{(\mathbf{s},\mathbf{a})\in\mathcal{D}_{\mathrm{demo}}} \log \pi_\theta(\mathbf{a}|\mathbf{s})$ (or some variant of this)

RL objective: $E_{\pi_\theta}[r(\mathbf{s},\mathbf{a})]$ (or some variant of this)

hybrid objective: $E_{\pi_\theta}[r(\mathbf{s},\mathbf{a})] + \lambda \sum_{(\mathbf{s},\mathbf{a})\in\mathcal{D}_{\mathrm{demo}}} \log \pi_\theta(\mathbf{a}|\mathbf{s})$

need to be careful in choosing this weight

Example: hybrid policy gradient

standard policy gradient

$$g_{aug} = \sum_{(s,a)\in\rho_\pi} \nabla_\theta \ln \pi_\theta(a|s) A^\pi(s,a) + \sum_{(s,a^*)\in\rho_D} \nabla_\theta \ln \pi_\theta(a^*|s) w(s,a^*)$$

increase demo likelihood

Rajeswaran et al., '17, "Learning Complex Dexterous Manipulation…"

Example: hybrid Q-learning

$$J(Q) = J_{DQ}(Q) + \lambda_1 J_n(Q) + \lambda_2 J_E(Q) + \lambda_3 J_{L2}(Q).$$

regularization loss

because why not…

Q-learning loss

n-step Q-learning loss

$$J_E(Q) = \max_{a \in A}[Q(s,a) + l(a_E, a)] - Q(s, a_E)$$

margin-based loss on example action

Hester et al., ‘17, “Learning from Demonstrations…”

What’s the problem?

hybrid objective: $E_{\pi_\theta}[r(\mathbf{s}, \mathbf{a})] + \lambda \sum_{(\mathbf{s},\mathbf{a}) \in \mathcal{D}_{\text{demo}}} \log \pi_\theta(\mathbf{a}|\mathbf{s})$

- Need to tune the weight
- The design of the objective, esp. for imitation, takes a lot of care
- Algorithm becomes problem-dependent

- Pure imitation learning
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  - Distributional shift
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- Initialize & finetune
  - Almost the best of both worlds
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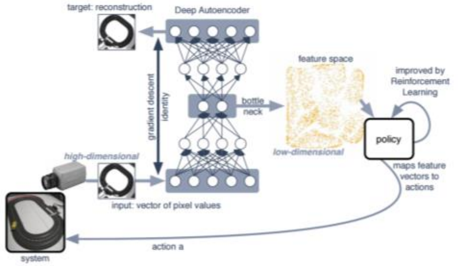
- Pure reinforcement learning, with demos as off-policy data
  - Unbiased reinforcement learning, can get arbitrarily good
  - Demonstrations don't always help
- Hybrid objective, imitation as an "auxiliary loss"
  - Like initialization & finetuning, almost the best of both worlds
  - No forgetting
  - But no longer pure RL, may be biased, may require lots of tuning

Break

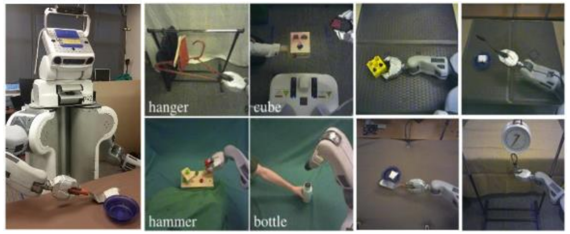
Challenges in Deep Reinforcement Learning

Some recent work on deep RL

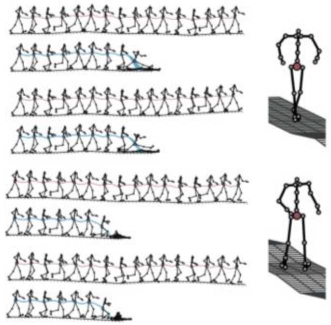
stability | efficiency | scale



RL on raw visual input
Lange et al.
2009

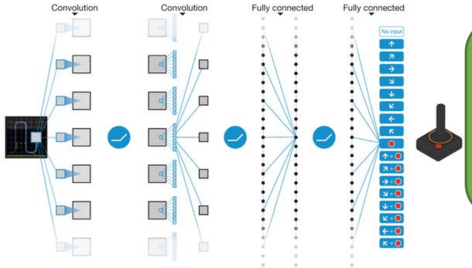


End-to-end visuomotor policies
Levine*, Finn* et al.
2015

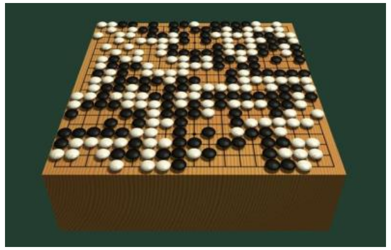


Guided policy search
Levine et al.
2013

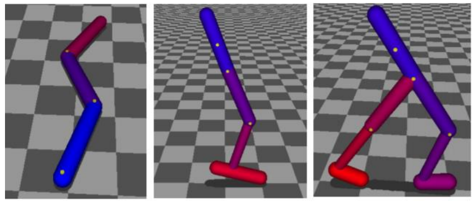
Deep deterministic policy gradients
Lillicrap et al.
2015



Deep Q-Networks
Mnih et al.
2013



AlphaGo
Silver et al.
2016

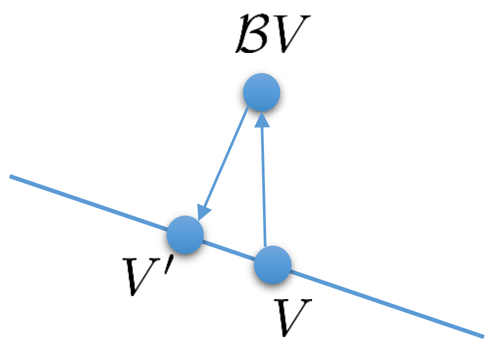


Trust region policy optimization
Schulman et al.
2015

Supersizing self-supervision
Pinto & Gupta
2016

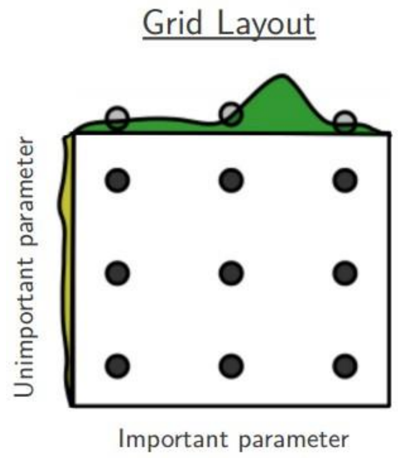
Stability and hyperparameter tuning

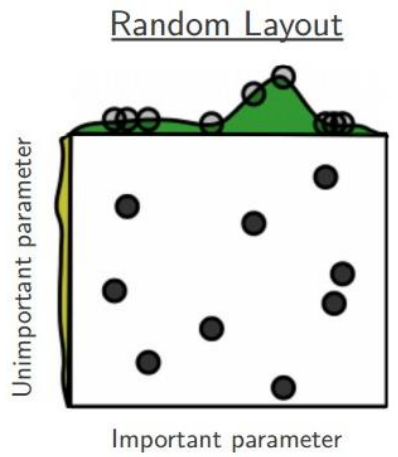
- Devising stable RL algorithms is very hard
- Q-learning/value function estimation
  - Fitted Q/fitted value methods with deep network function estimators are typically not contractions, hence no guarantee of convergence
  - Lots of parameters for stability: target network delay, replay buffer size, 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



Tuning hyperparameters

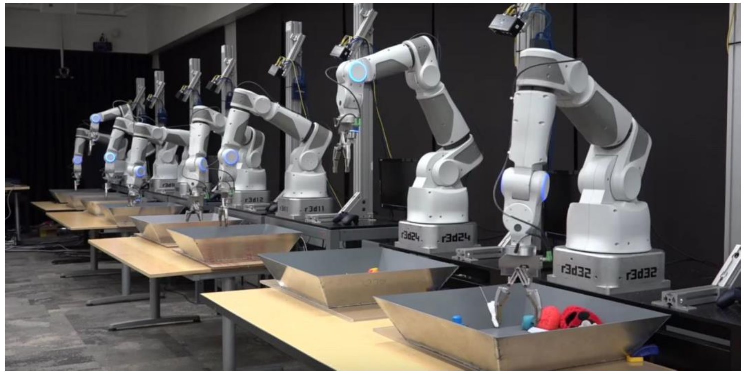
- Get used to running multiple hyperparameters
  - `learning_rate = [0.1, 0.5, 1.0, 5.0, 20.0]`
- Grid layout for hyperparameter sweeps OK when sweeping 1 or 2 parameters
- Random layout generally more optimal, the only viable option in higher dimensions
- Don’t forget the random seed!
  - RL is self-reinforcing, very likely to get local optima
  - Don’t assume it works well until you test a few random seeds
  - Remember that random seed is not a hyperparameter!





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, etc.)

10x

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

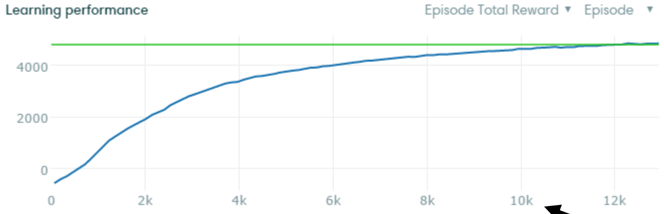
10x

model-based “shallow” RL
(e.g. PILCO)

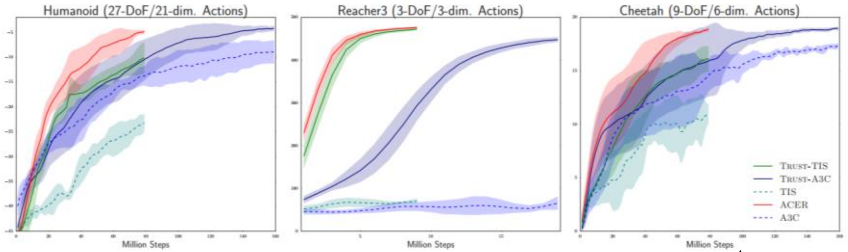
Evolution Strategies as a Scalable Alternative to Reinforcement Learning

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

half-cheetah (slightly different version)



TRPO+GAE (Schulman et al. ‘16)

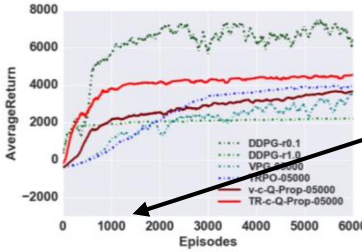


Wang et al. ‘17

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

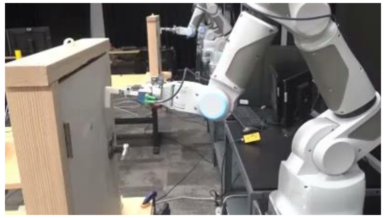
10,000,000 steps
(10,000 episodes)
(~ 1.5 days real time)

half-cheetah

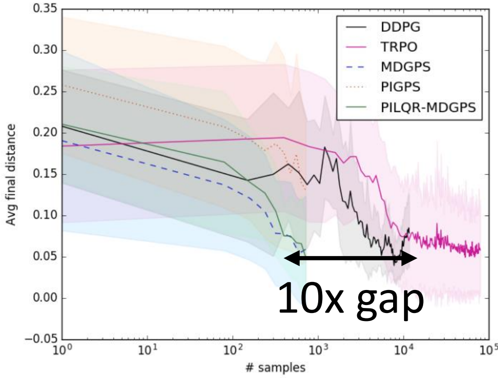


Gu et al. ‘16

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



	cart-pole	cart-double-pole	unicycle
state space	$\mathbb{R}^4$	$\mathbb{R}^6$	$\mathbb{R}^{12}$
# trials	≤ 10	20–30	≈ 20
experience	$\approx 20\,$s	$\approx 60\,$s–$90\,$s	$\approx 20\,$s–$30\,$s
parameter space	$\mathbb{R}^{305}$	$\mathbb{R}^{1816}$	$\mathbb{R}^{28}$

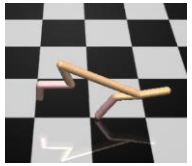


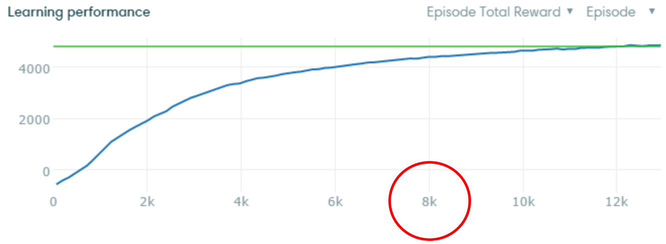
about 20 minutes of experience on a real robot

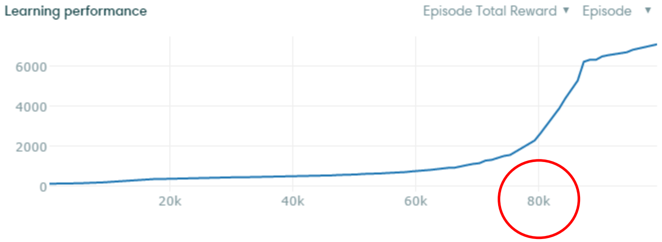
Chebotar et al. ’17 (note log scale)

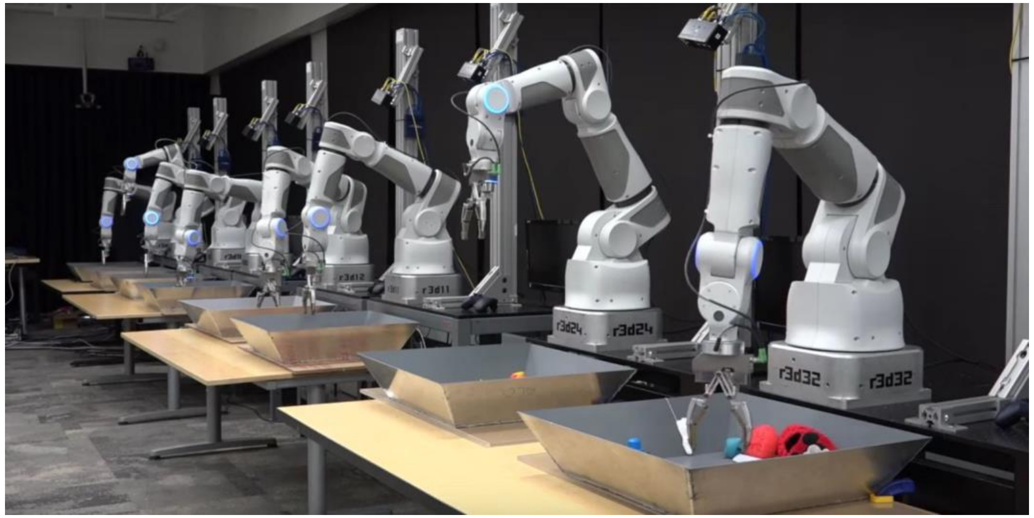
What about more realistic tasks?

- Big cost paid for dimensionality
- Big cost paid for using raw images
- Big cost in the presence of real-world diversity (many tasks, many situations, etc.)



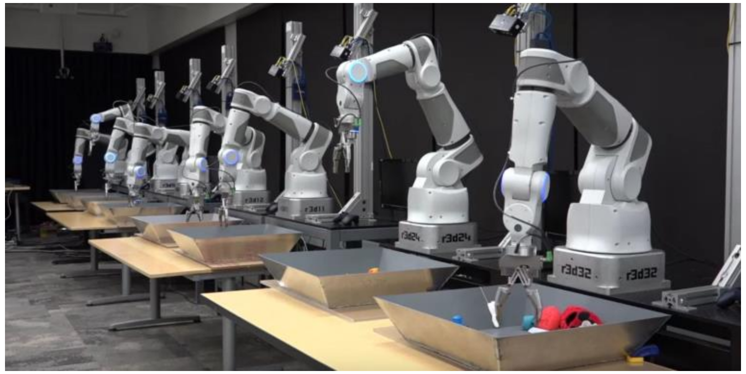






The challenge with sample complexity

- 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

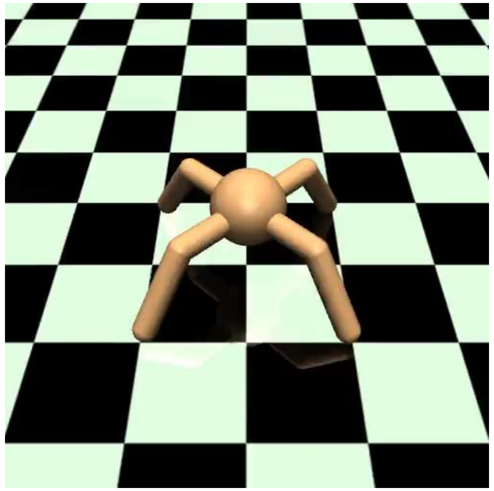


What can we do?

- Better model-based RL algorithms
- Design faster algorithms
  - Q-Prop (Gu et al. ‘17): policy gradient algorithm that is as fast as value estimation
  - Learning to play in a day (He et al. ‘17): Q-learning algorithm that is much faster on Atari than DQN
- 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 up deep RL & generalization

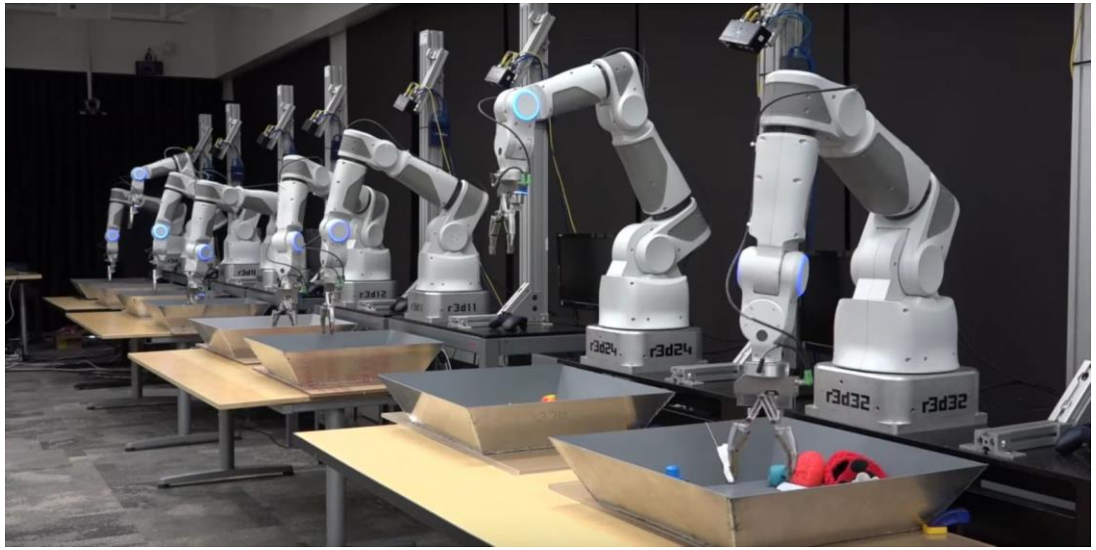
- Large-scale
- Emphasizes diversity
- Evaluated on generalization



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

Generalizing from massive experience

Pinto & Gupta, 2015



Levine et al. 2016

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)
  - many others…

Generalizing from prior knowledge & experience

- Can we get better generalization by leveraging off-policy data?
- Model-based methods: perhaps a good avenue, since the model (e.g. physics) is more task-agnostic
- What does it mean to have a "feature" of decision making, in the same sense that we have "features" in computer vision?
  - Options framework (mini behaviors)
    - Between MDPs and semi-MDPs: A framework for temporal abstraction in reinforcement learning (Sutton et al. '99)
    - The option-critic architecture (Bacon et al. '16)
  - Muscle synergies & low-dimensional spaces
    - Unsupervised learning of sensorimotor primitives (Todorov & Gahramani '03)

Reward specification

- 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?

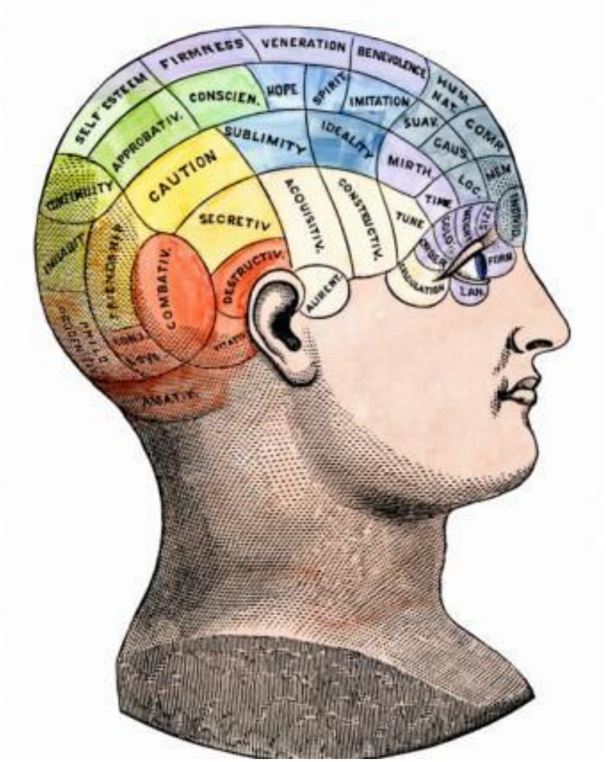
reward

Mnih et al. '15

reinforcement learning agent

what is the reward?

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

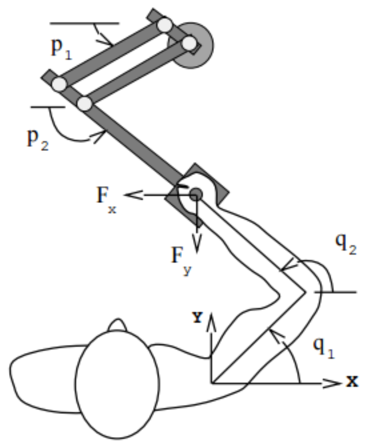
Deep models are what allow reinforcement learning algorithms to solve complex problems end to end!

What can deep learning & RL do well now?

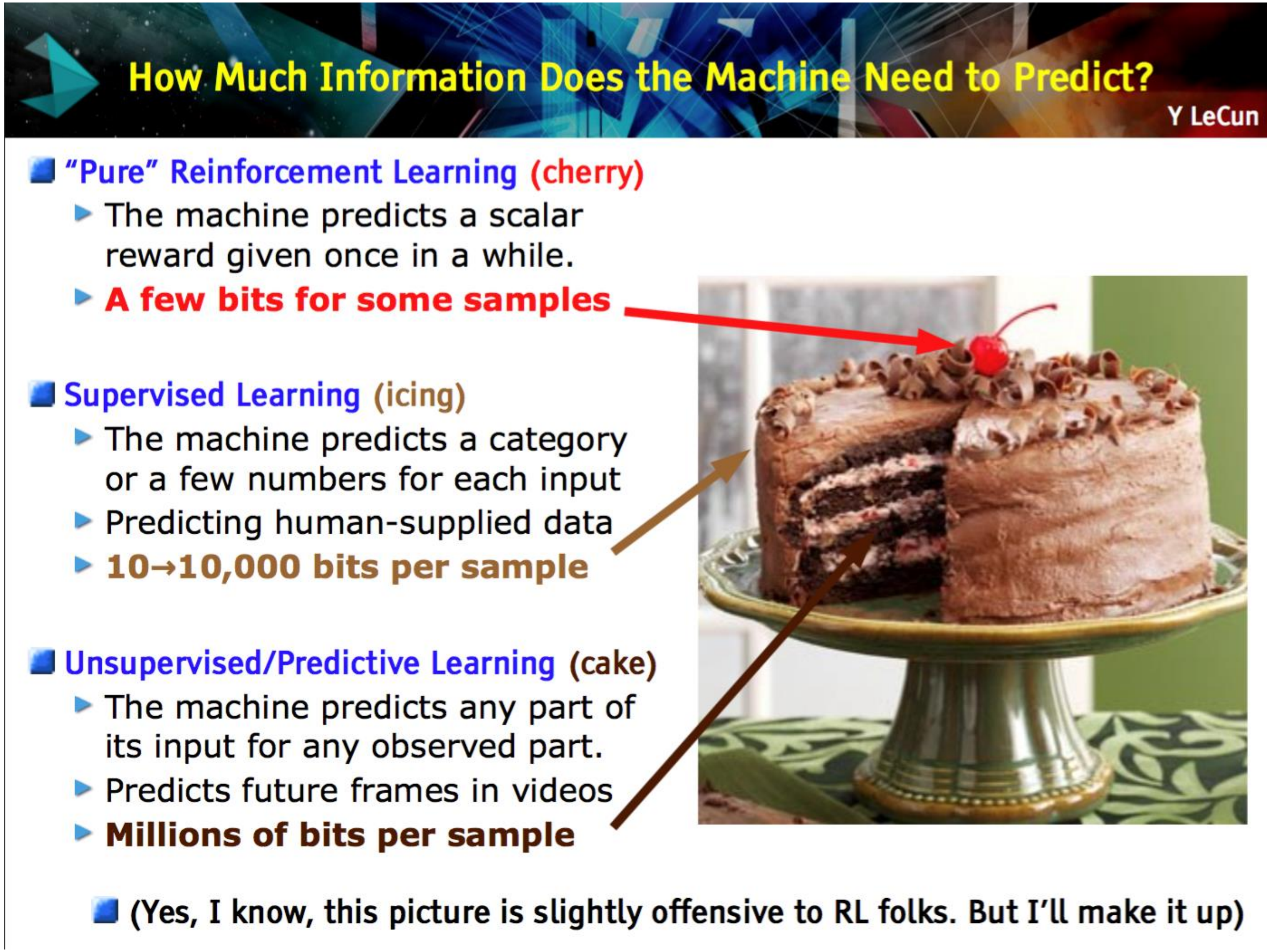
- Acquire high degree of proficiency in domains governed by simple, known rules
- Learn simple skills with raw sensory inputs, given enough experience
- Learn from imitating enough human-provided expert behavior

What has proven challenging so far?

- Humans can learn incredibly quickly
  - Deep RL methods are usually slow
- Humans can reuse past knowledge
  - Transfer learning in deep RL is an open problem
- Not clear what the reward function should be
- Not clear what the role of prediction should be



What is missing?



Where does the supervision 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
- Carefully understand the relationship between RL and other ML fields