


IERG5350 Reinforcement Learning
Week 11: Imitation Learning

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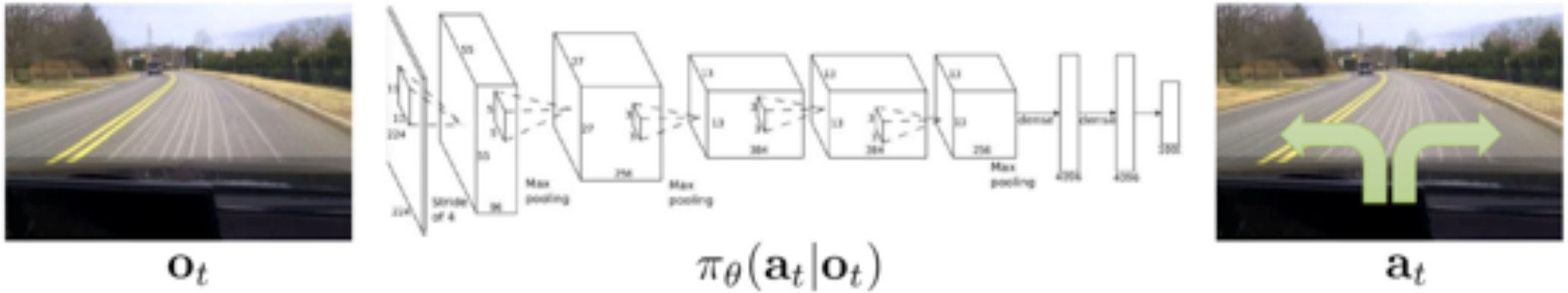
Some of the slides from Sergey Levine's RL lecture

Today’s Outline

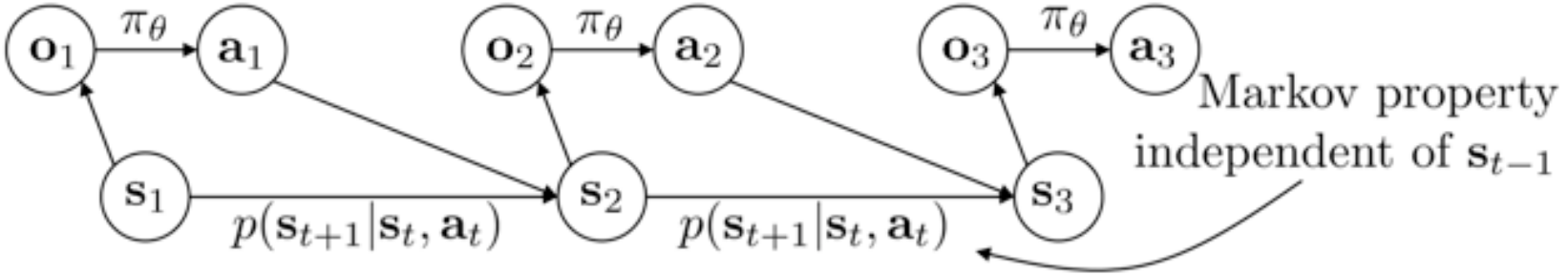
- Introduction on Imitation Learning
- Behavioral cloning and DAGGER
- Brief look on Inverse RL and GAIL
- Improving the model of the imitation learning
- Unifying imitation learning and reinforcement learning
- Case studies

Introduction on Imitation Learning

Supervised learning of the policy network

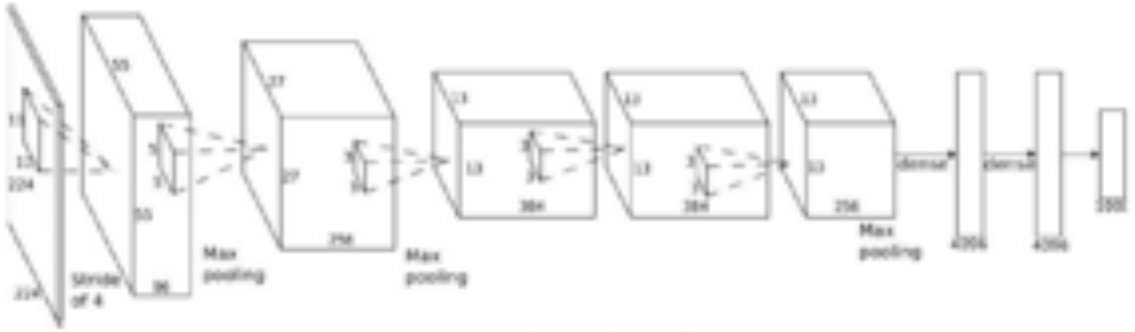


Action ground-truth is provided



Introduction on Imitation Learning

$\mathbf{o}_t$

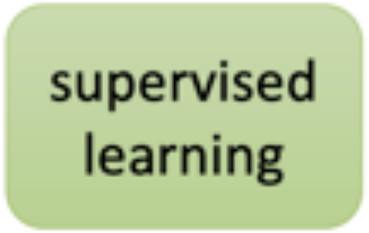


$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$

$\mathbf{a}_t$

$\mathbf{o}_t$

$\mathbf{a}_t$



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

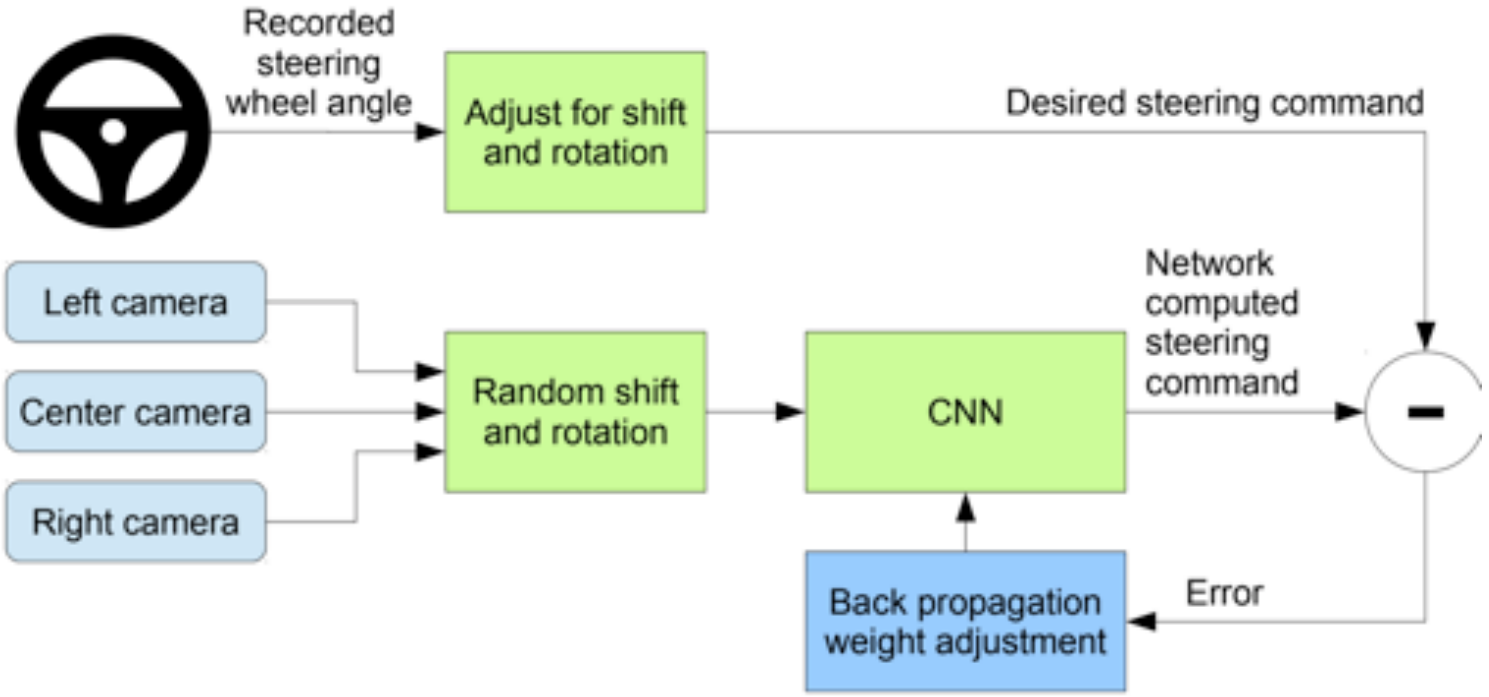
Behavioral cloning (BC)

Case Study: End to End Learning for Self-Driving Cars

- DAVER-2 System By Nvidia: It works to some degree!

Case Study: End to End Learning for Self-Driving Cars

- 72 hours of driving data as training data



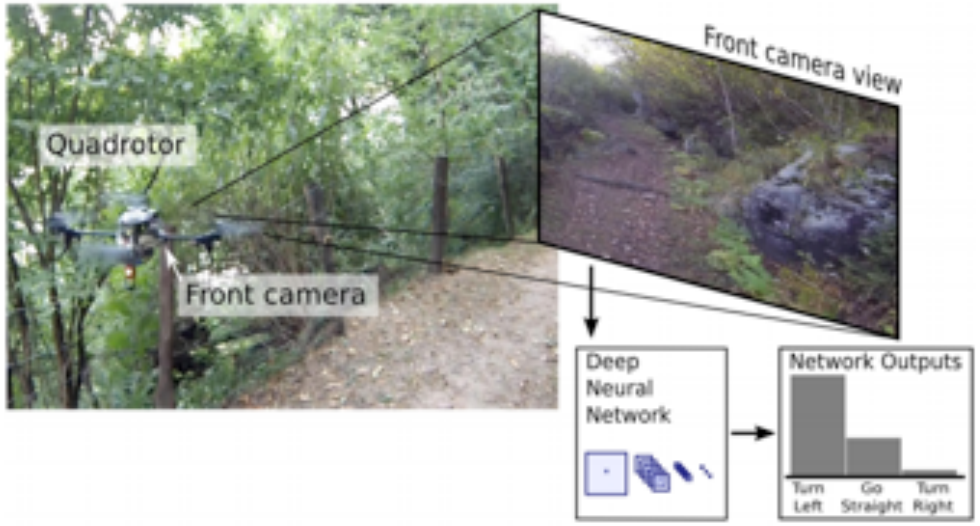
End-to-End Deep Learning for Self-Driving Cars
Mariusz Bojarski, Ben Firner, Beat Flepp, Larry Jackel, Urs Muller, Karol Zieba and Davide Del Testa | August 17, 2016

Example code of behavior clone: https://github.com/Az4z3l/CarND-Behavioral-Cloning

https://www.youtube.com/watch?feature=oembed&v=Rmv643N3-yM

Case Study: Trail following as a classification

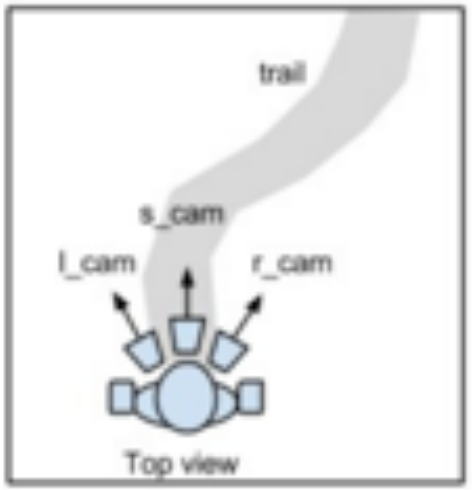
How to train a drone to fly

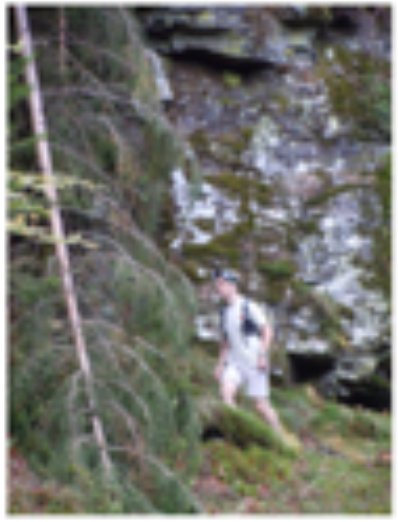


A. Giusti, et al. A Machine Learning Approach to Visual Perception of Forest Trails for Mobile Robot. IEEE trans on Robotics and Automation

Case Study: Trail following as a classification

Human walking data





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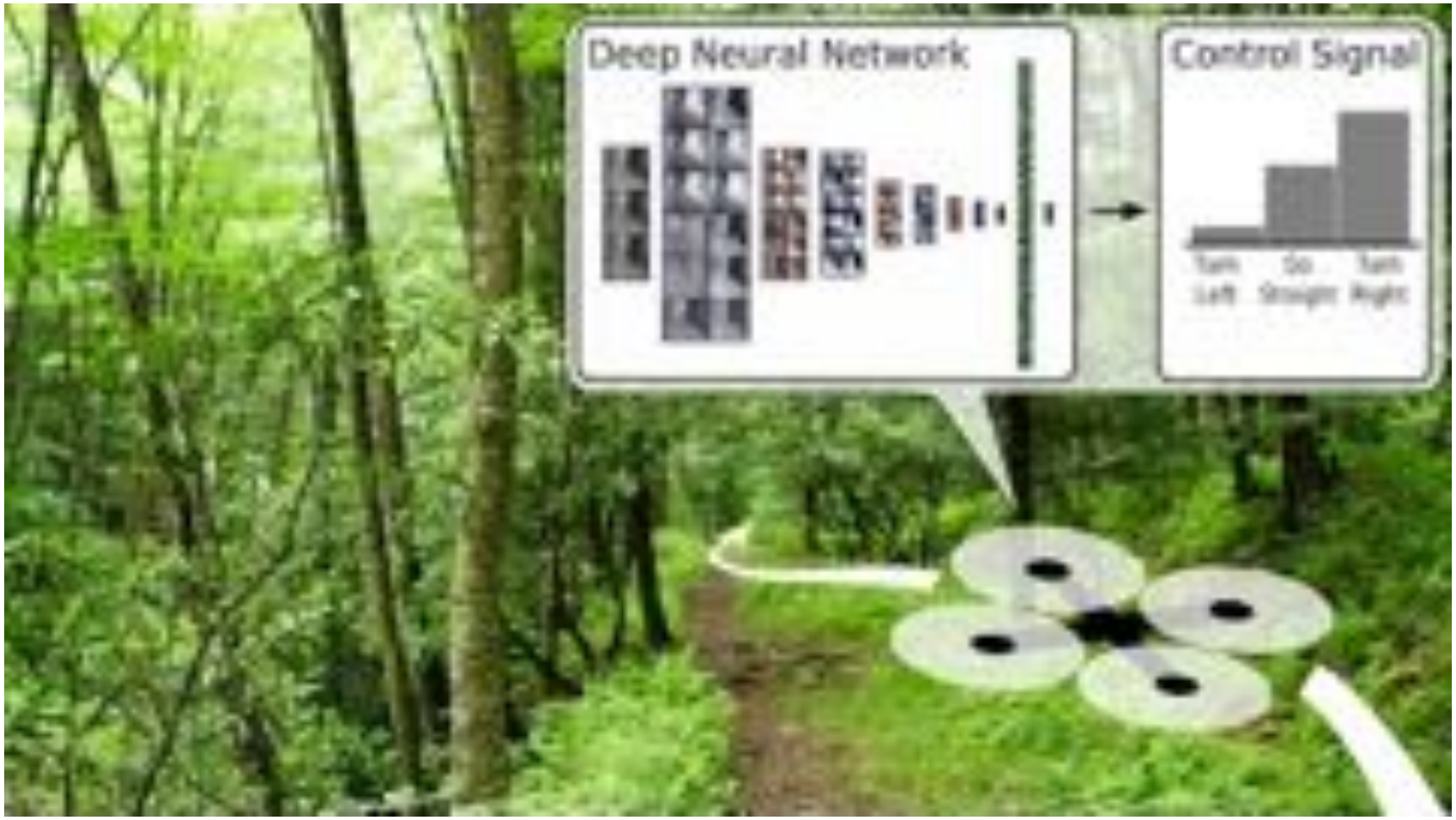
Case Study: Trail following as a classification



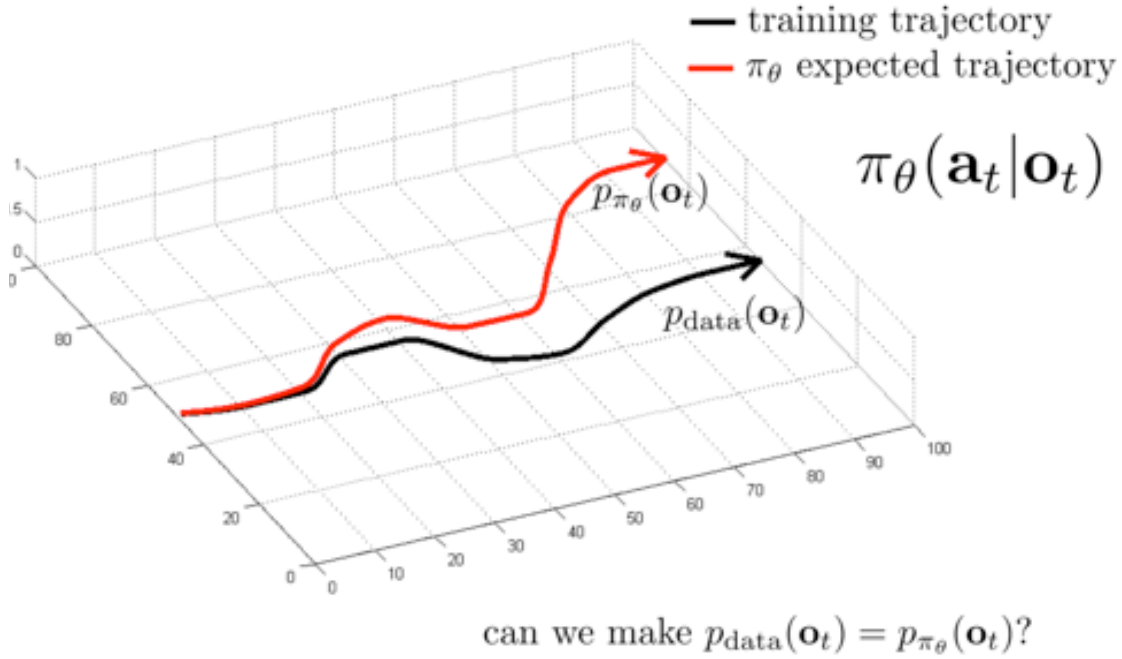
https://youtu.be/umRdt3zGgpU

Limitations of Supervised Imitation Learning

- The trained policy run into the off-course situations
- Mistakes grow quadratically in T: don't learn how to recover from failure

$$\mathbf{J}(\hat{\pi}_{\mathbf{sup}}) \leq \mathbf{T}^2 \varepsilon$$

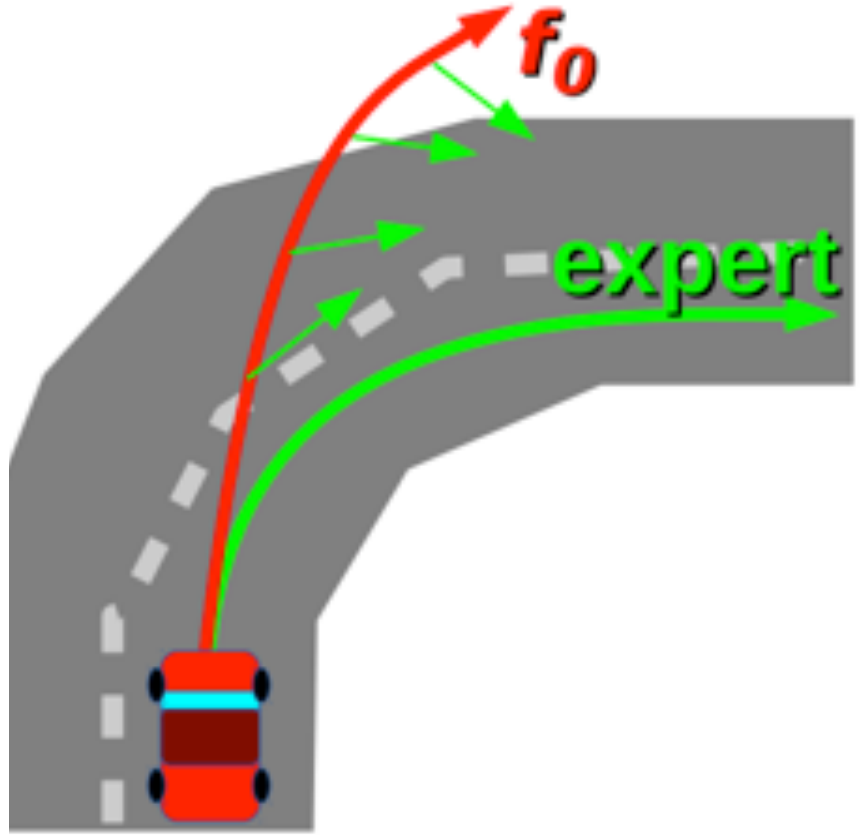
[Ross 2012]



Annotating More On-Policy Data Iteratively

We can collect more training samples for those off-expert situations.

- run our current policy and observe.
- Then ask the human experts to label the possible actions again.
- This allows us to collect samples that we miss when we deploy the policy.



DAgger: Dataset Aggregation

can we make $p_{\text{data}}(\mathbf{o}_t) = p_{\pi_\theta}(\mathbf{o}_t)$?

idea: instead of being clever about $p_{\pi_\theta}(\mathbf{o}_t)$, be clever about $p_{\text{data}}(\mathbf{o}_t)$!

DAgger: Dataset Aggregation

goal: collect training data from $p_{\pi_\theta}(\mathbf{o}_t)$ instead of $p_{\text{data}}(\mathbf{o}_t)$

how? just run $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$

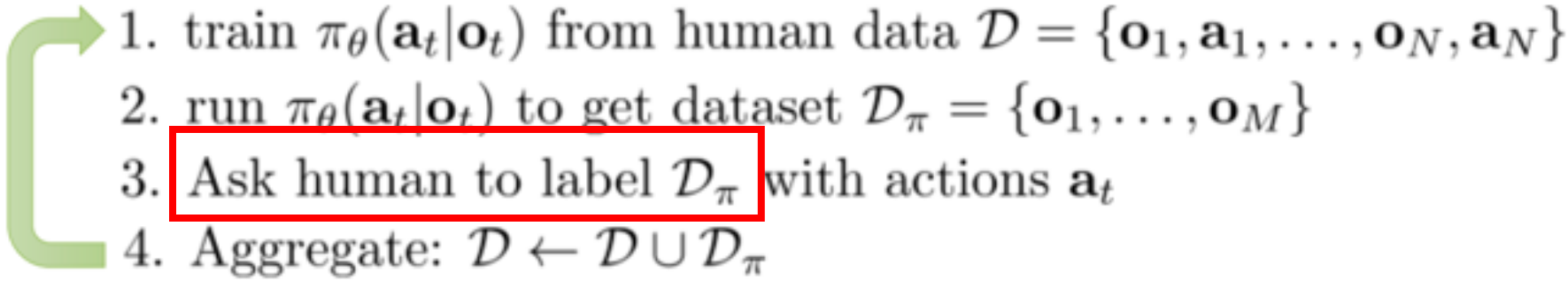
but need labels $\mathbf{a}_t$!

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

Ross, Gordon, and Bagnell 2011

Limitation with DAgger

- Need to query expert many times during the training
- Very expansive if it is human expert



DAgger with Other Expert Algorithms

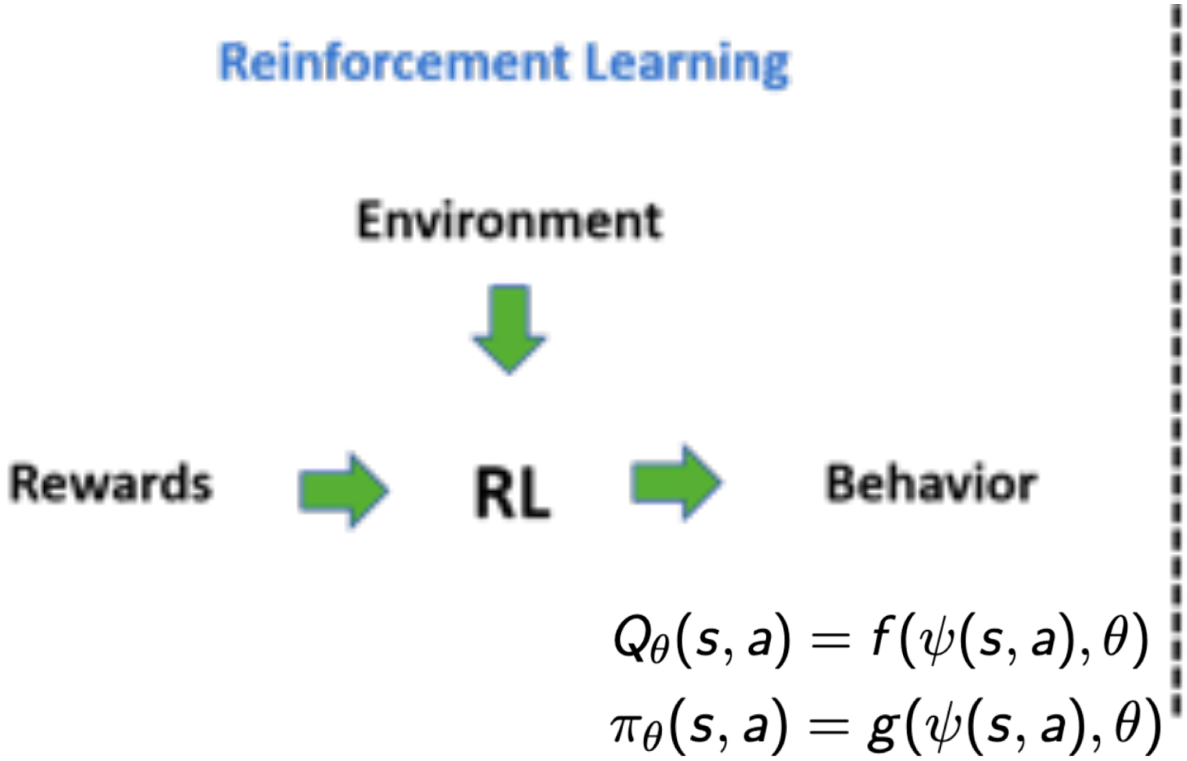
- Learn (quickly) to imitate other slow algorithms
- Game playing: we can compute suboptimal expert behavior with brute-force search offline, then use it during training time for a policy function to approximate
- Discrete optimizers: Many discrete optimization problems such as shortest path are very slow. Then use imitation learning to try to build shortest path optimizers that will run sufficiently efficiently in real time.

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

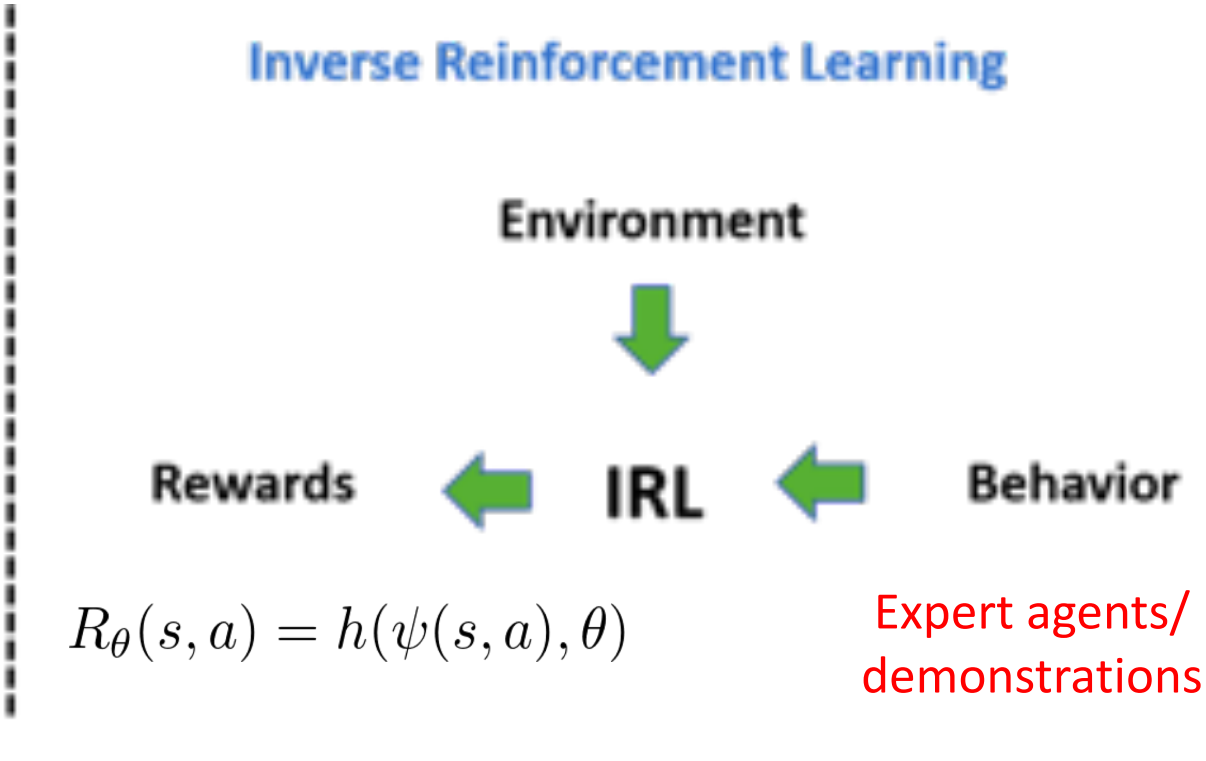
Ask other algorithm!

Inverse Reinforcement Learning (IRL)

- Sometimes it is easier to provide expert data rather than define reward
- Learn a cost/reward function that could explain the expert behaviors



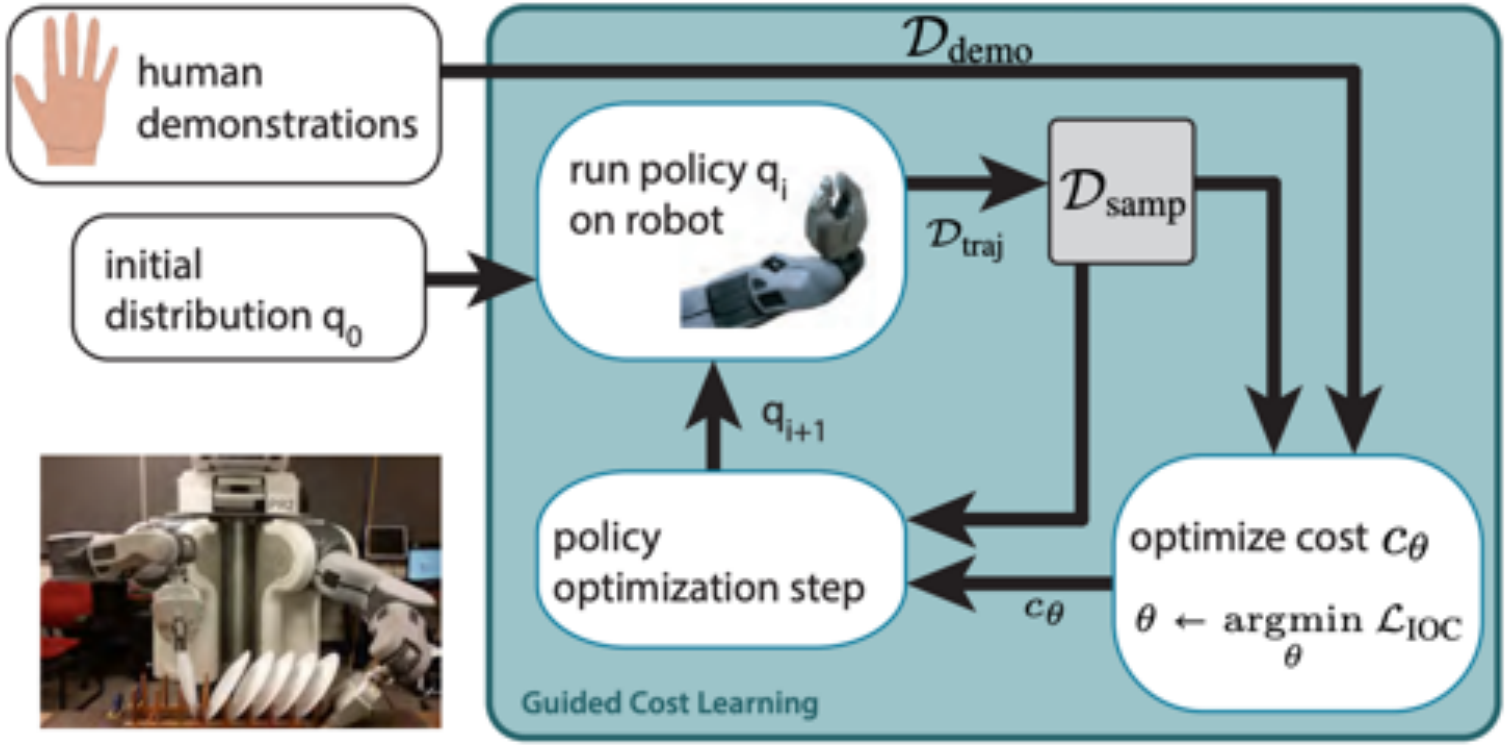
$$Q_\theta(s,a) = f(\psi(s,a),\theta)$$
$$\pi_\theta(s,a) = g(\psi(s,a),\theta)$$



$$R_\theta(s,a) = h(\psi(s,a),\theta)$$

Expert agents/ demonstrations

Guided Cost Learning



$$\mathcal{L}_{\text{IOC}}(\theta) = \frac{1}{N} \sum_{\tau_i \in \mathcal{D}_{\text{demo}}} c_\theta(\tau_i) + \log Z$$

$$\approx \frac{1}{N} \sum_{\tau_i \in \mathcal{D}_{\text{demo}}} c_\theta(\tau_i) + \log \frac{1}{M} \sum_{\tau_j \in \mathcal{D}_{\text{samp}}} \frac{\exp(-c_\theta(\tau_j))}{q(\tau_j)},$$

Finn, et al, ICML'16. https://arxiv.org/pdf/1603.00448.pdf

Generative Adversarial Imitation Learning(GAIL)

- Like inverse RL, GANs learn an objective function for generative modeling

Zhu et al. '17

Arjovsky et al. '17

Isola et al. '17

GAIL		GANs
trajectory τ	$\longleftrightarrow$	sample x
policy $\pi \sim q(\tau)$	$\longleftrightarrow$	generator G
reward r	$\longrightarrow$	discriminator D

Ho and Ermon,NIPS'16. https://arxiv.org/pdf/1606.03476.pdf

Slides adapted from Levine.

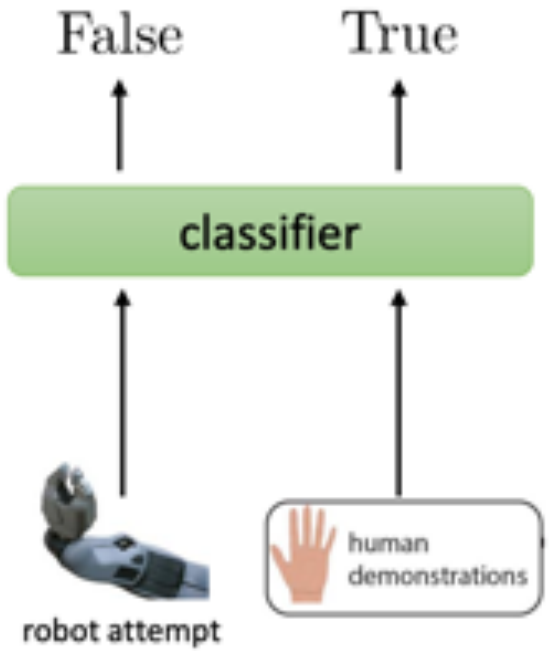
Connection between IRL and GAIL

Guided Cost Learning
Finn, et al. ICML'16

learns distribution $p(\tau)$ such that demos have max likelihood

$p(\tau) \propto \exp(r(\tau))$ (MaxEnt model)

GAIL
Ho & Ermon, NIPS'16



$D(\tau)$ = probability τ is a demo

use $\log D(\tau)$ as "reward"

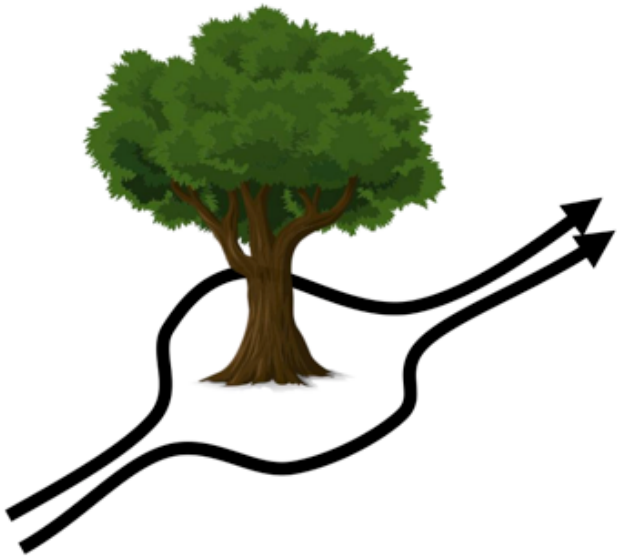
Finn, Christiano, et al. A connection between GANs, Inverse RL, and Energy-based Models. https://arxiv.org/pdf/1611.03852.pdf

Slides adapted from Levine.

Improving the Supervised Imitation Learning

How can we improve the policy model?

- Multimodal behavior
- Non-Markovian behavior

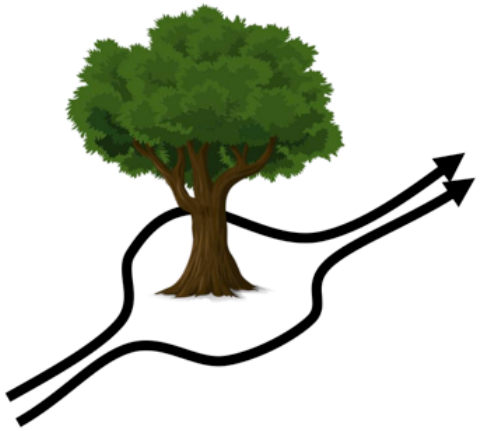


$$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$$

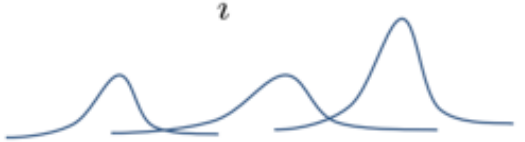
behavior depends only on current observation

Improving the Supervised Imitation Learning

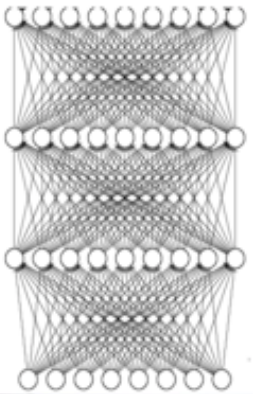
- Handling multimodal behavior
  - Output mixture of Gaussians
  - Latent variable models
  - Autoregressive discretization



$$\pi(\mathbf{a}|\mathbf{o}) = \sum_i w_i \mathcal{N}(\mu_i, \Sigma_i)$$



$$w_1, \mu_1, \Sigma_1, \ldots, w_N, \mu_N, \sigma_N$$



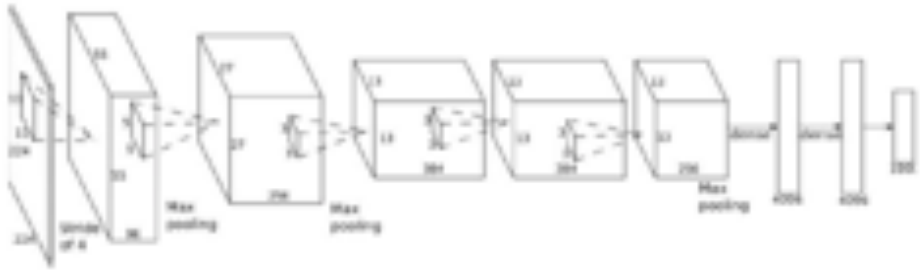
Modeling the whole history

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

behavior depends only on current observation

$$\pi_\theta(\mathbf{a}_t|\mathbf{o}_1, ..., \mathbf{o}_t)$$

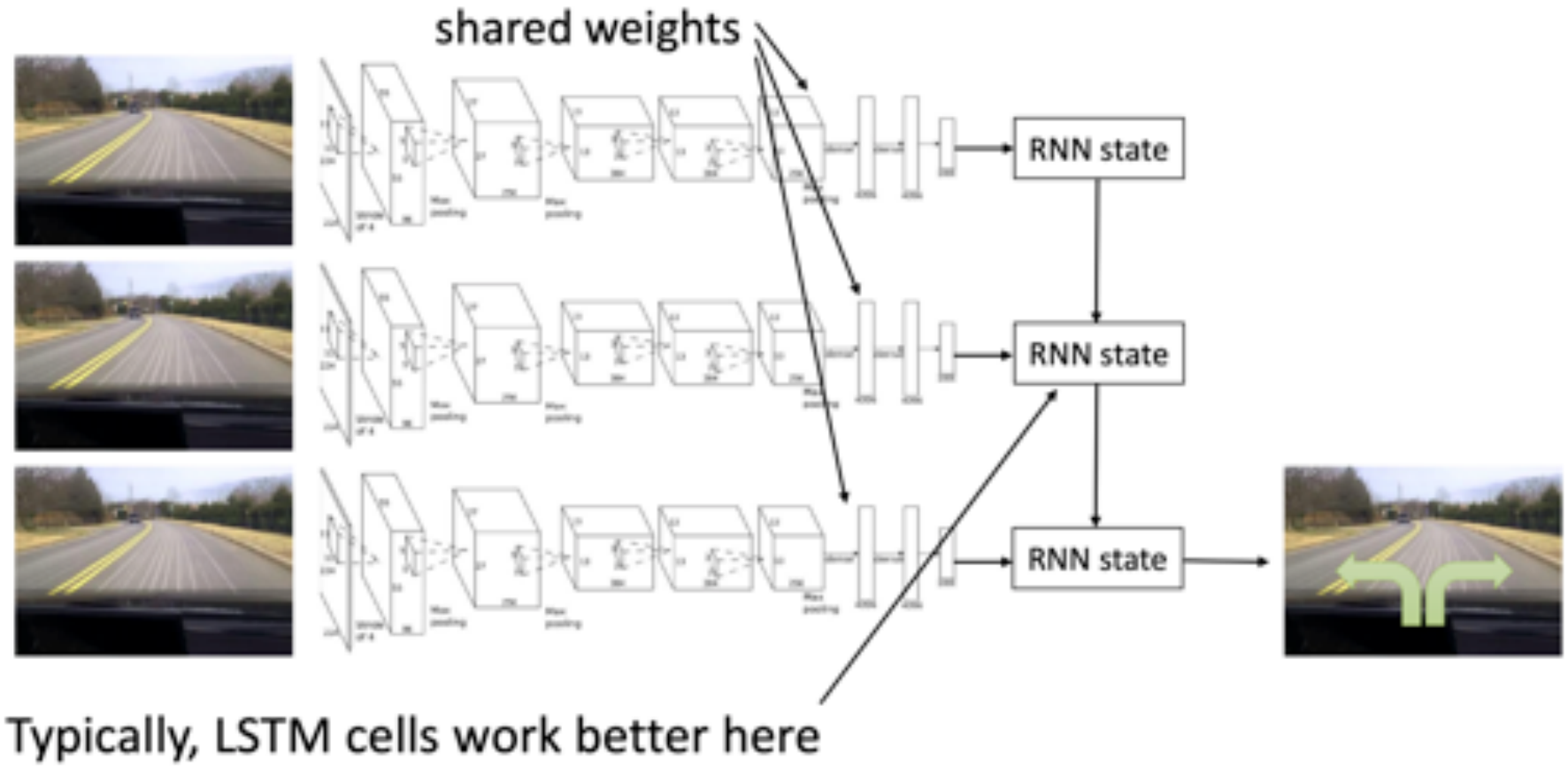
behavior depends on all past observations



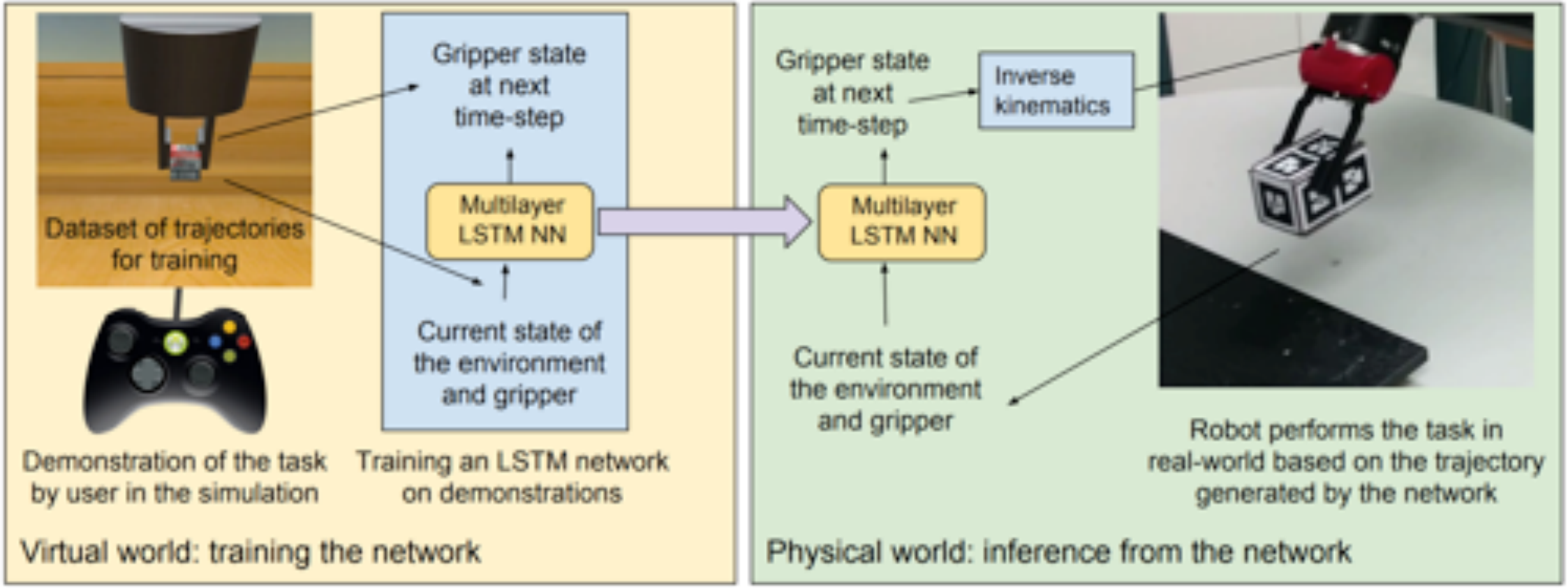
variable number of frames, too many weights

Modeling the whole history

- We can use a LSTM sequential model to encode the history

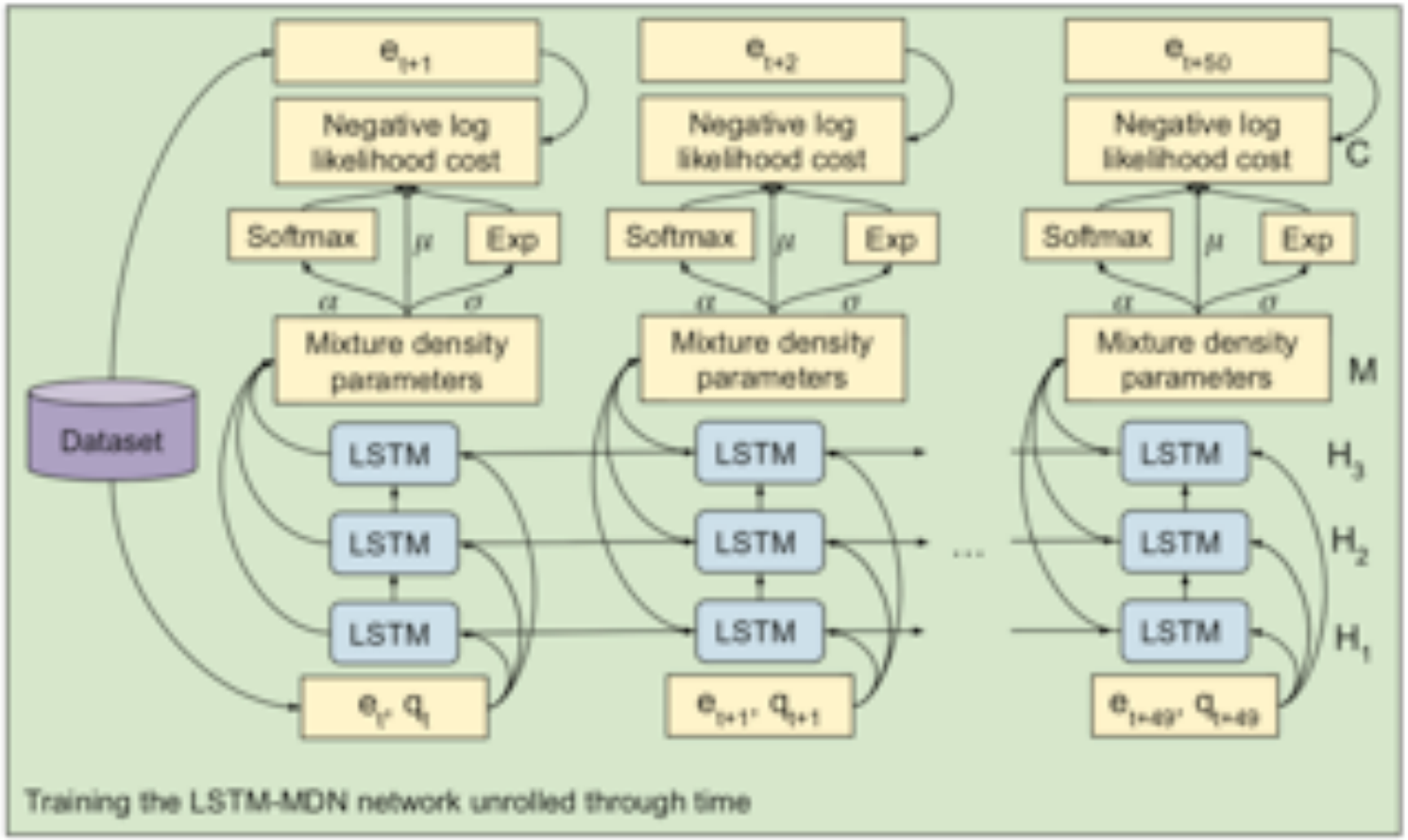


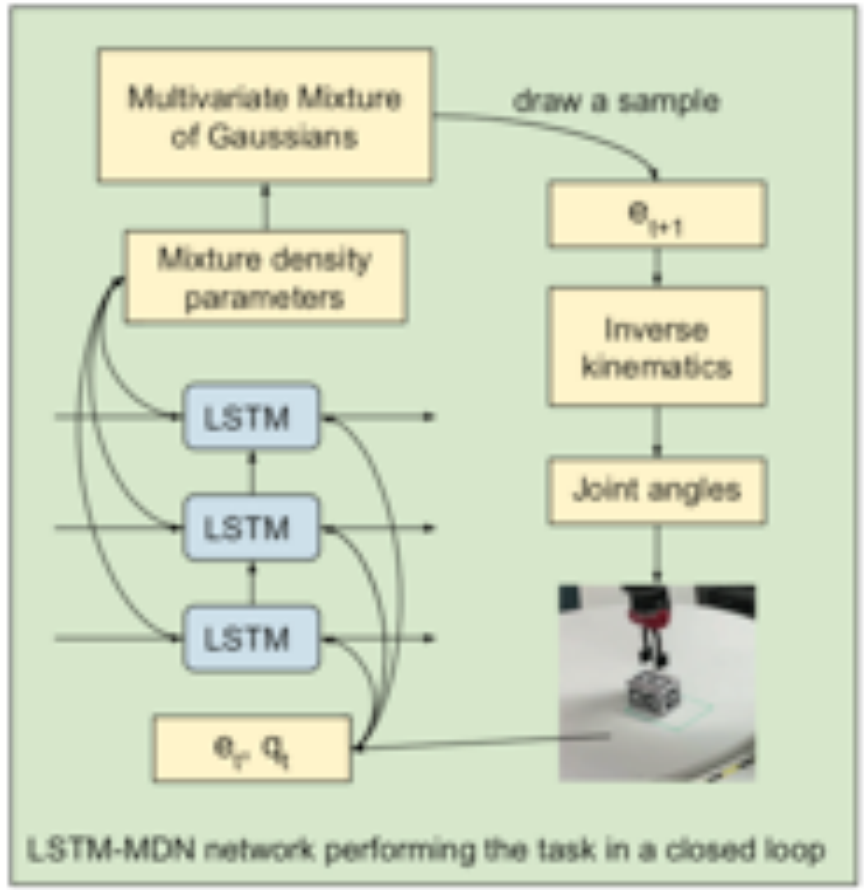
Case Study: Learning from demonstration using LSTM



Rahmatizadeh et al. Learning real manipulation tasks from virtual demonstrations using LSTM. AAAI 2018

Case Study: Learning from demonstration using LSTM

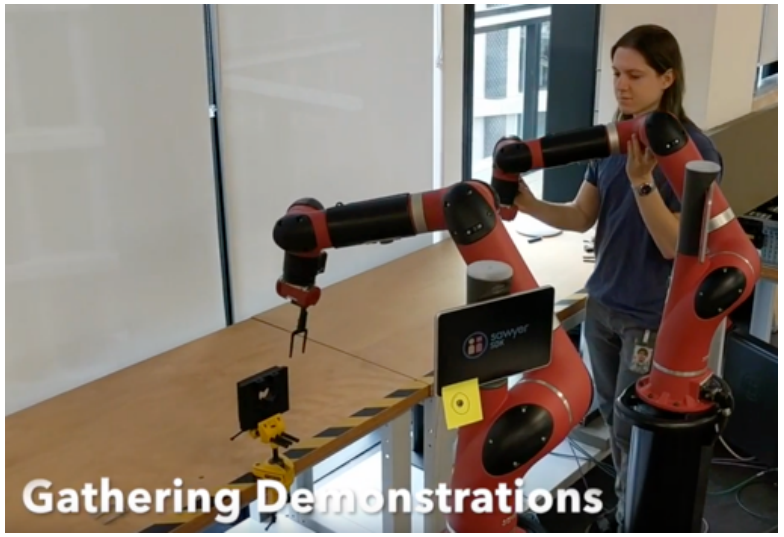




Rahmatizadeh et al. Learning real manipulation tasks from virtual demonstrations using LSTM. AAAI 2018

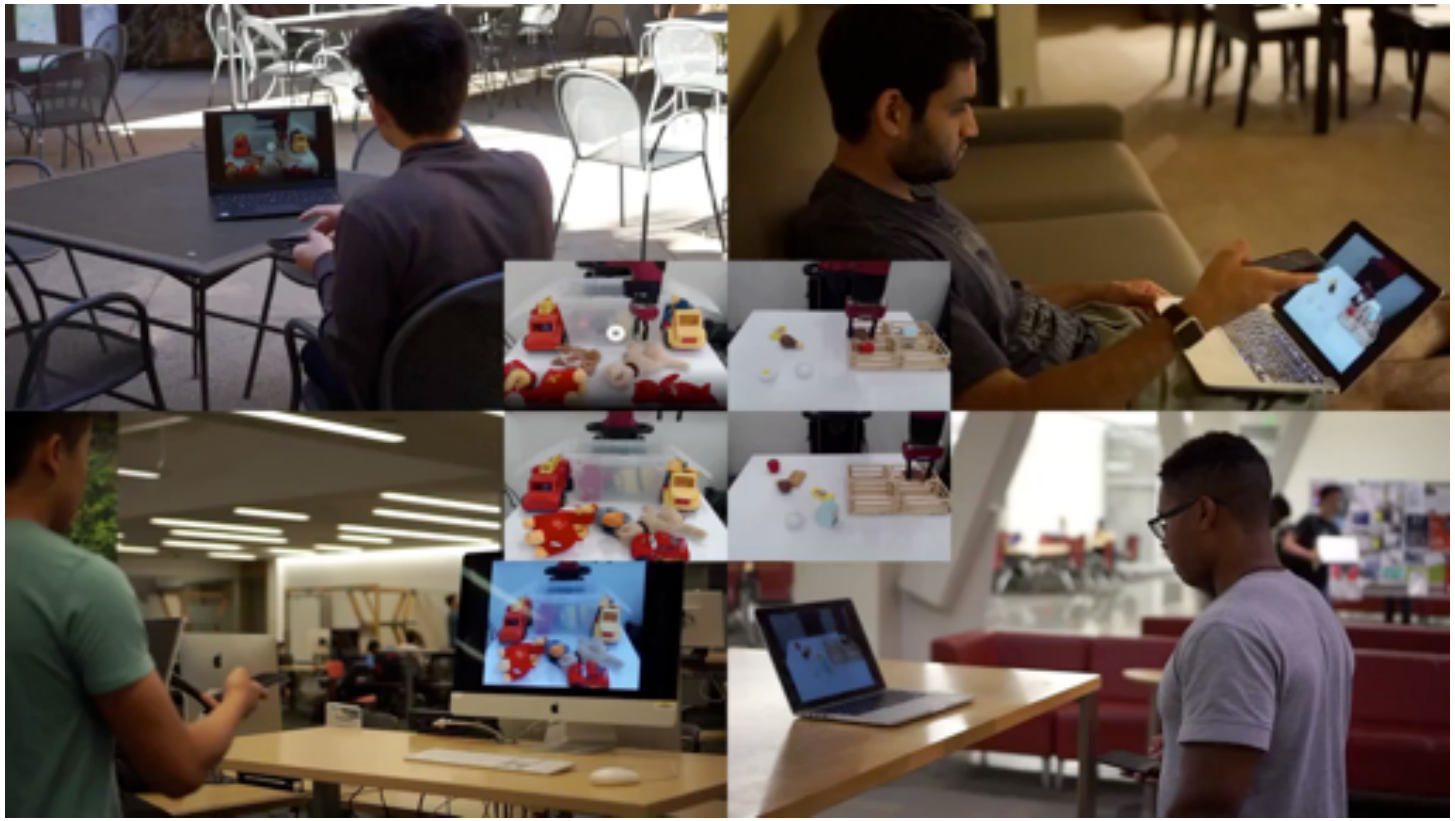
Scale up the data collection of human demonstration?

- Rahmatizadeh et al manually collected 650 demonstrations for Pick and place, and 1614 for Push to pose
- Make it like how we collect ImageNet through Crowd-sourcing!



RoboTurk: Crowdsourcing Robotic Demonstrations

- RoboTurk is a crowdsourcing platform that is collecting human demonstrations of tasks such as “picking” and “assembly”;

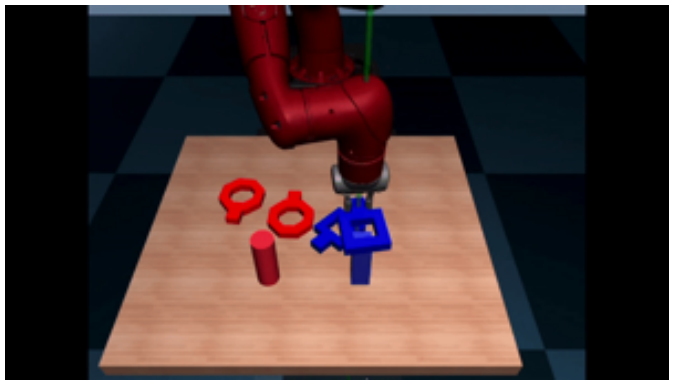


Stanford Fei-Fei Li’s Team

http://roboturk.stanford.edu/

RoboTurk: Crowdsourcing Robotic Demonstrations

- 137.5 hours of demonstration for two tasks
- 1071 successful picking demonstrations and 1147 assembly demonstrations



Quantitative Results

	Number of Demonstrations				
Task	**0**	**1**	**10**	**100**	**1000**
Bin Picking (Can)	0±0	278±351	273±417	385±466	**641±421**
Assembly (Round)	0±0	381±467	663±435	575±470	**775±388**

Stanford Fei-Fei Li's Team

http://roboturk.stanford.edu/

Problems with Imitation Learning

- Humans need to provide data, which is typically in a limited amount
- Humans are not good at providing some kinds of actions
- Human can learn autonomously (unsupervised learning)

Imitation Learning vs. Reinforcement Learning

Imitation Learning

- Requires demonstrations
- Issue of distributional shift
- Simple stable supervised learning
- Only as good as the demo

Reinforcement Learning

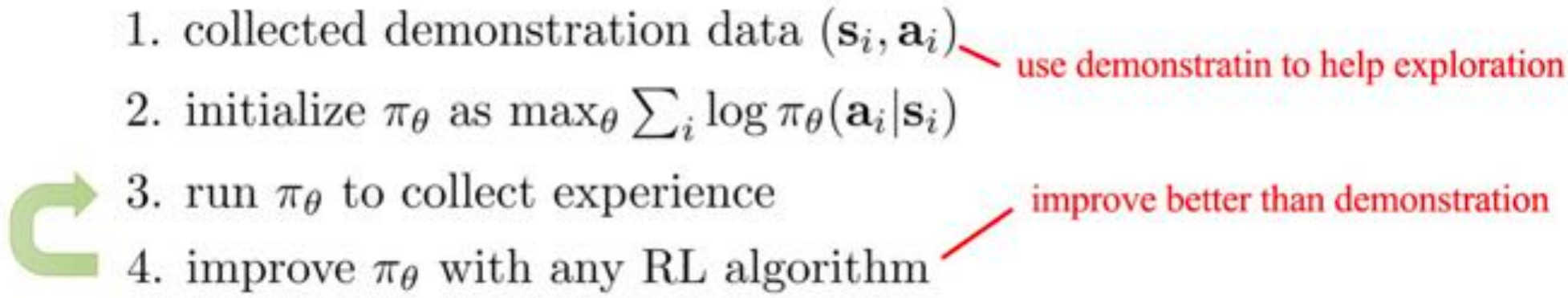
- Requires reward function
- Must address exploration
- Potentially non-convergent
- Can become superhuman good

Can we get the best of both worlds?

What if we can have both demonstrations and rewards

Simplest Combination: Pretrain & Finetune

- Use the expert demonstration to initialize a policy (overcome exploration)
- Then apply RL to improve the policy and learn to deal with those off-course scenarios and go beyond performance of the demonstrator



Simplest Combination: Pretrain & Finetune

Pretrain & finetune

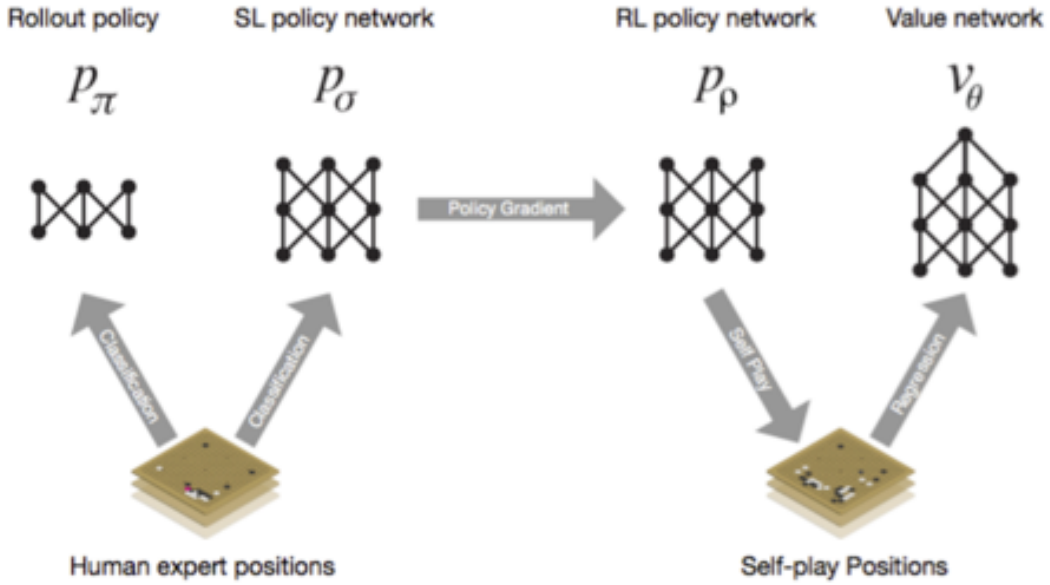
1. collected demonstration data $(\mathbf{s}_i, \mathbf{a}_i)$
2. initialize π_θ as $\max_\theta \sum_i \log \pi_\theta(\mathbf{a}_i|\mathbf{s}_i)$
3. run π_θ to collect experience
4. improve π_θ with any RL algorithm

vs. DAgger

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

Pretrain & Finetune for AlphaGo

- SL Policy Network: Train the policy network on 30 million moves from games played by human experts (could predict the human move 57% of the time)
- RL Policy Network: Then finetune the weights with policy gradients



David Silver, et al. Mastering the ancient game of Go with Machine Learning. Nature 2016

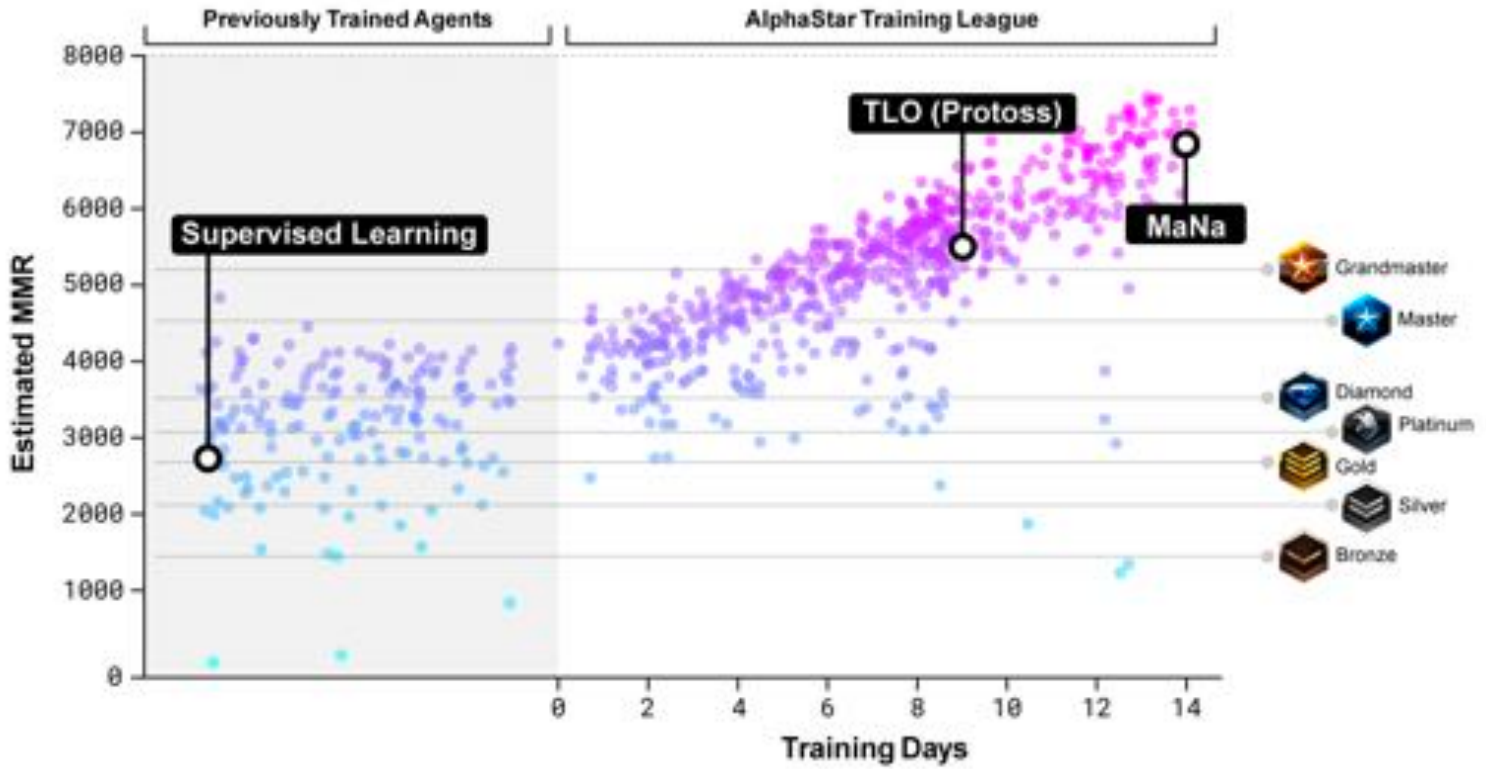
Pretrain & Finetune for Starcraft2

- Supervised learning from anonymised human games released by Blizzard.
- This allowed AlphaStar to learn, by imitation, the basic micro and macro-strategies used by players on the StarCraft ladder.
- This initial agent defeated the built-in “Elite” level AI - around gold level for a human player - in 95% of games.

https://deepmind.com/blog/alphastar-mastering-real-time-strategy-game-starcraft-ii/

Pretrain & Finetune for Starcraft2

- Population-based and multi-agent reinforcement learning



https://deepmind.com/blog/alphastar-mastering-real-time-strategy-game-starcraft-ii/

Problem with the 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?

Solution: Off-policy Reinforcement Learning

- Off-policy RL can use any data
- We can use demonstrations as off-policy samples
  - Since demonstrations are provided as data in every iteration, they are never forgotten
  - 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

- Importance sampling on policy gradient

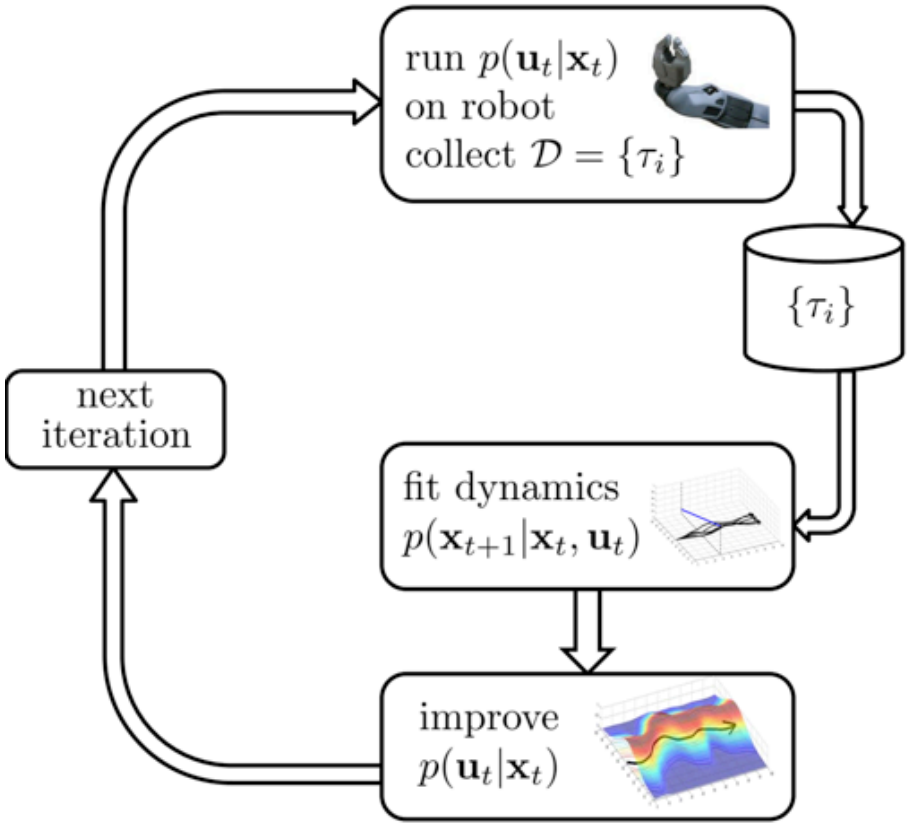
$$\nabla_\theta J(\theta) = \sum_{\tau \in \mathcal{D}} \left[\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) \left(\prod_{t'=1}^{t} \frac{\pi_\theta(\mathbf{a}_{t'}|\mathbf{s}_{t'})}{q(\mathbf{a}_{t'}|\mathbf{s}_{t'})} \right) \left(\sum_{t'=t}^{T} r(\mathbf{s}_{t'}, \mathbf{a}_{t'})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

from experience and demonstration

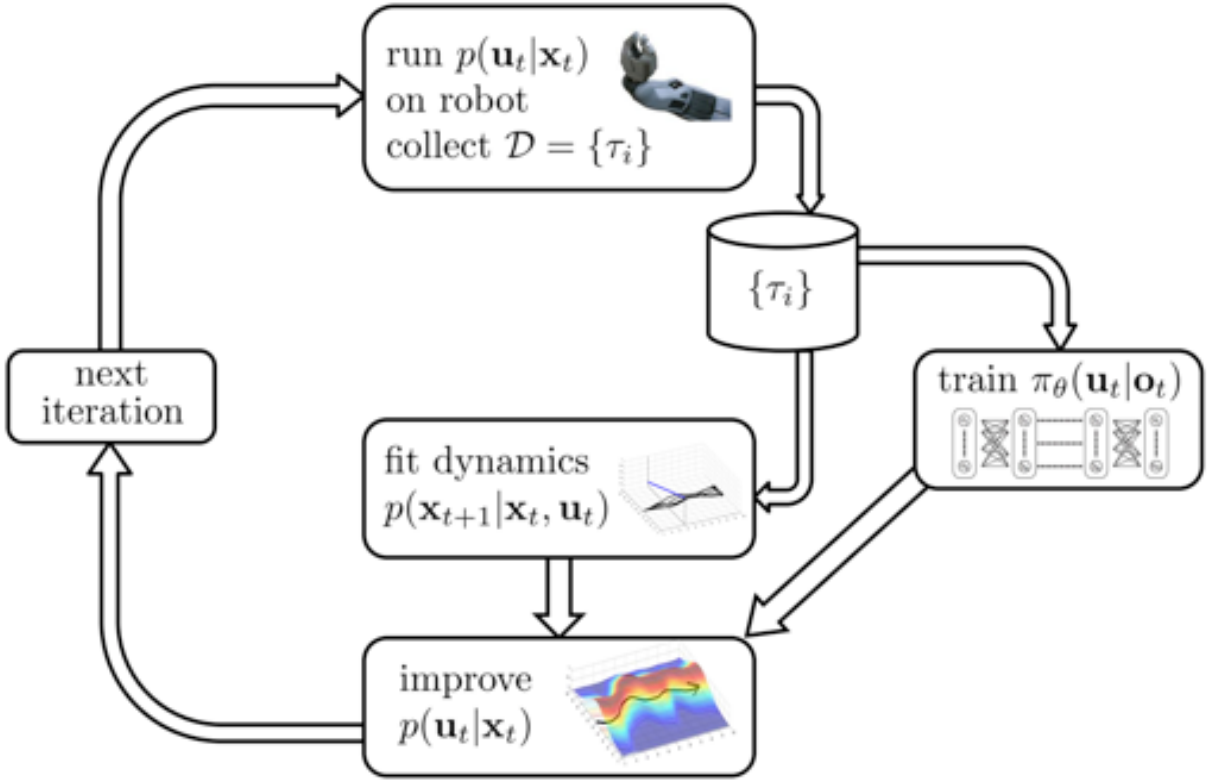
- Problem: which distribution did the demonstrations come from?
- Option 1: use supervised behavior cloning to approximate π_{demo}
- Option 2: assume Diract delta: $\pi_{demo}(\tau) = \frac{1}{N}\delta(\tau \in \mathcal{D})$

Guided Policy Search

Optimal control for trajectory optimization



Guide the training of policy network

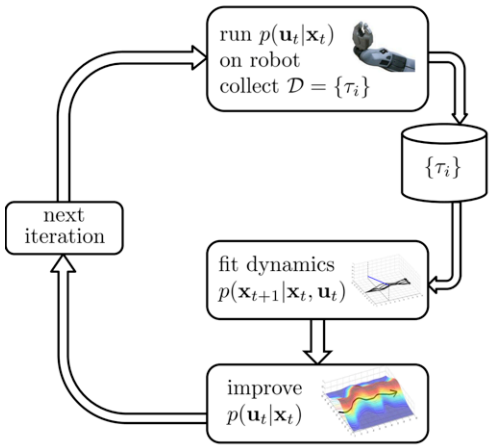


Review on model-based RL

- Optimal control for trajectory optimization (f is given)

$$\min_{u_1,\ldots,u_t} \sum_{t=1}^{T} c(x_t, u_t) \text{ s.t. } x_t = f(x_{t-1}, u_{t-1})$$

- If f is not given, we learn locally linear models and use these models to solve for a time-varying linear Gaussian controller

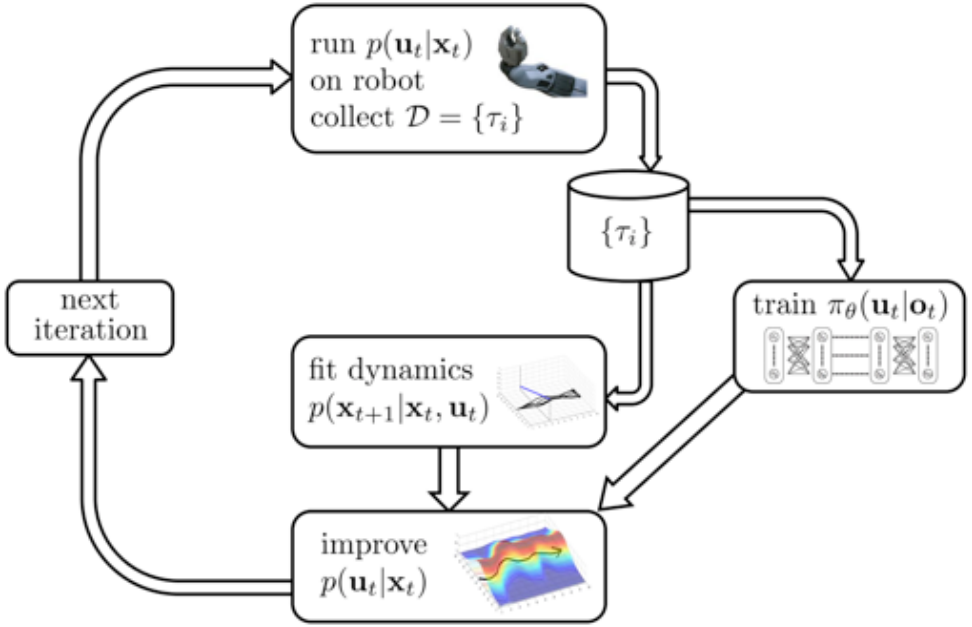


$$p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t) = \mathcal{N}(f(\mathbf{x}_t, \mathbf{u}_t))$$
$$f(\mathbf{x}_t, \mathbf{u}_t) = \mathbf{A}_t\mathbf{x}_t + \mathbf{B}_t\mathbf{u}_t$$

Guided policy search (GPS) formulation

$$\min_{u_1,\ldots,u_t} \sum_{t=1}^{T} c(x_t, u_t) \text{ s.t. } x_t = f(x_{t-1}, u_{t-1}) \text{ s.t. } u_t = \pi_\theta(x_t)$$

$$\min_{p(\tau)} \sum_{t=1}^{T} E_{p(\mathbf{x}_t,\mathbf{u}_t)}[c(\mathbf{x}_t, \mathbf{u}_t) + \mathbf{u}_t^T \lambda_t + \rho_t D_{KL}(p(\mathbf{u}_t|\mathbf{x}_t) \| \pi_\theta(\mathbf{u}_t|\mathbf{x}_t))]$$

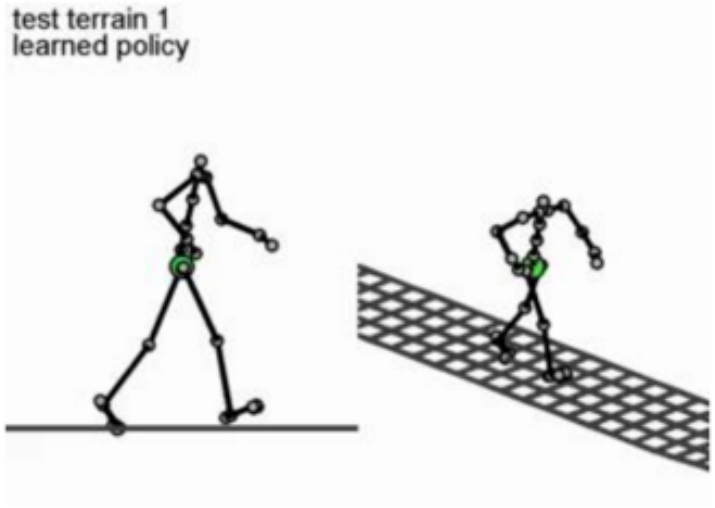


Dual gradient descend

1. Start with some initial choice of λ (by λ, we include λ_t corresponding to each time step)
2. Assign $\tau \leftarrow \arg\min_\tau \mathcal{L}(\tau, \theta, \lambda)$.
3. Assign $\theta \leftarrow \arg\min_\theta \mathcal{L}(\tau, \theta, \lambda)$.
4. Compute $\frac{dg}{d\lambda} = \frac{d\mathcal{L}}{d\lambda}(\tau, \theta, \lambda)$. Take a gradient step $\lambda \leftarrow \lambda + \alpha \frac{dg}{d\lambda}$
5. Repeat steps 2-4.

Guided policy search (GPS) Applications

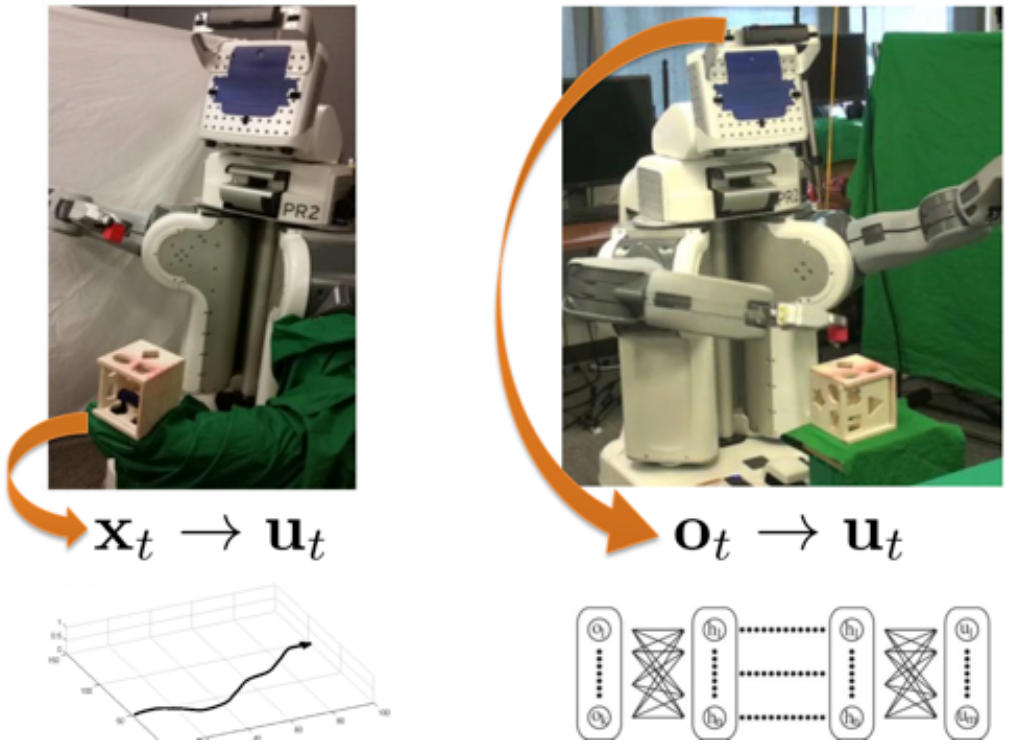
First demo of GPS:



http://graphics.stanford.edu/projects/gpspaper/humanoid.mp4
http://graphics.stanford.edu/projects/gpspaper/video.mp4

Levine and Koltun. ICML'13

End-to-End Training of Deep Visuomotor Policies



Sergey Levine, Chelsea Finn, Trevor Darrell, Pieter Abbeel. JMLR'16

Q-learning with demonstrations

- Q-learning is already off-policy, no need to bother with importance weighting
- Simple solution: throw demonstrations into the replay buffer

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

$K\times$

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 $\mathcal{B}$
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

https://youtu.be/WGJwLfeVN9w

Vecerik et al., ‘17, “Leveraging Demonstrations for Deep Reinforcement Learning on Robotics Problems with Sparse Rewards

Imitation learning as an auxiliary loss function

- Hybrid objective: we can combine RL and imitation learning objective

$$\underbrace{E_{\pi_\theta}[r(\mathbf{s},\mathbf{a})]}_{\text{RL}} + \lambda \underbrace{\sum_{(\mathbf{s},\mathbf{a})\in\mathcal{D}_{\text{demo}}} \log \pi_\theta(\mathbf{a}|\mathbf{s})}_{\text{Imitation learning}}$$

Issue: The weight needs careful tuning

Hybrid policy gradient

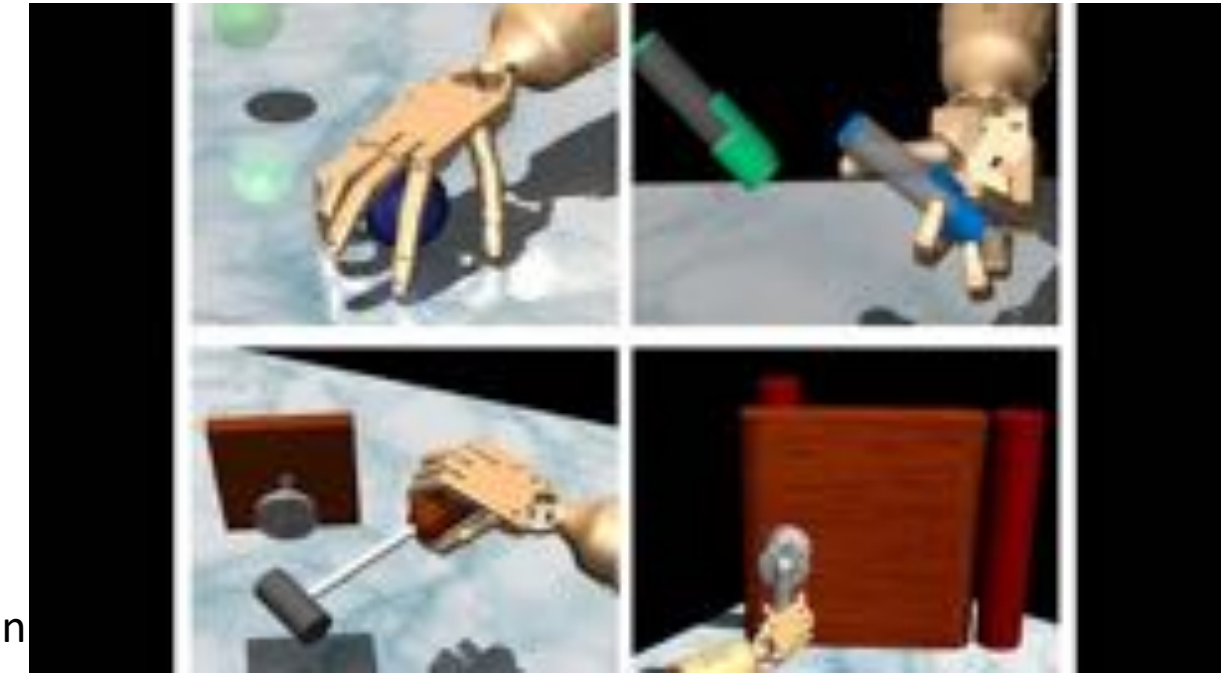
$$g_{aug} = \sum_{(s,a)\in\rho_\pi} \nabla_\theta \ln \pi_\theta(a|s) A^\pi(s,a) + \sum_{(s,a^*)\in\rho_D} \nabla_\theta \ln \pi_\theta(a^*|s) w(s,a^*)$$

policy gradient

make policy closer to demonstrations

weighting function

$$w(s,a) = \lambda_0 \lambda_1^k \max_{(s',a')\in\rho_\pi} A^\pi(s',a') \quad \forall (s,a) \in \rho_D$$



Rajeswaran et al., ‘17, “Learning Complex Dexterous Manipulation with Deep Reinforcement Learning and Demonstrations”

Hybrid Q-Learning

- Leverages a small set of demonstration data to massively accelerate the learning process

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

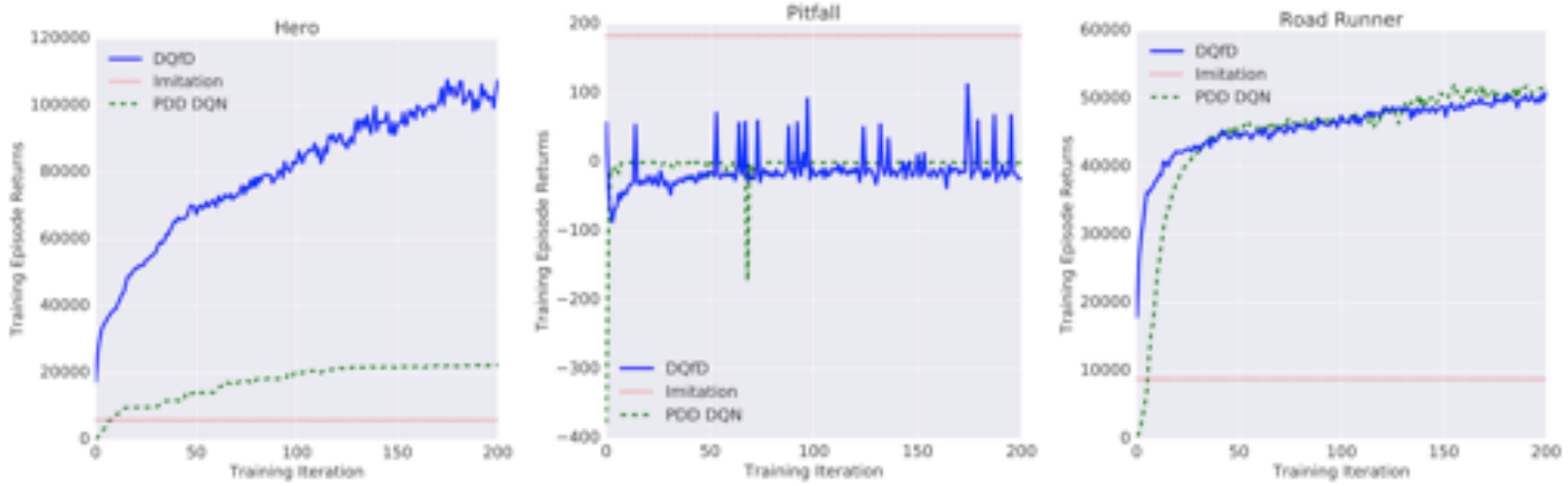
regularization loss

Q-learning loss

n-step Q-learning loss

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

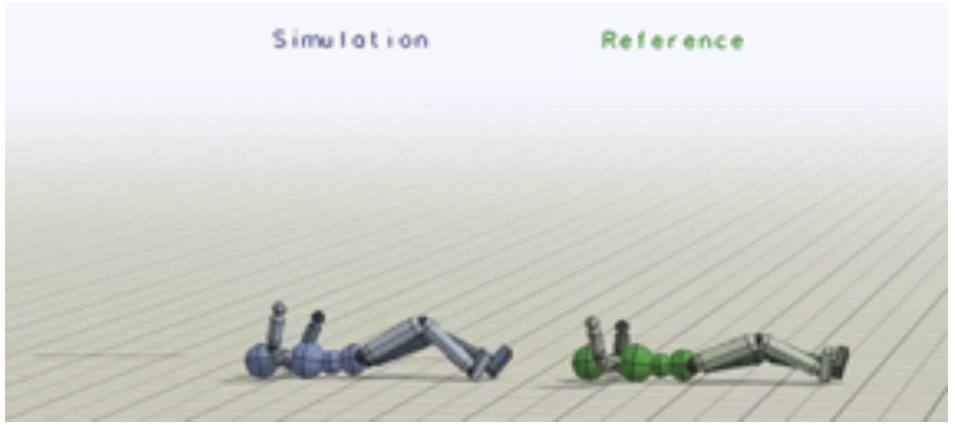
(marginal loss on example action)

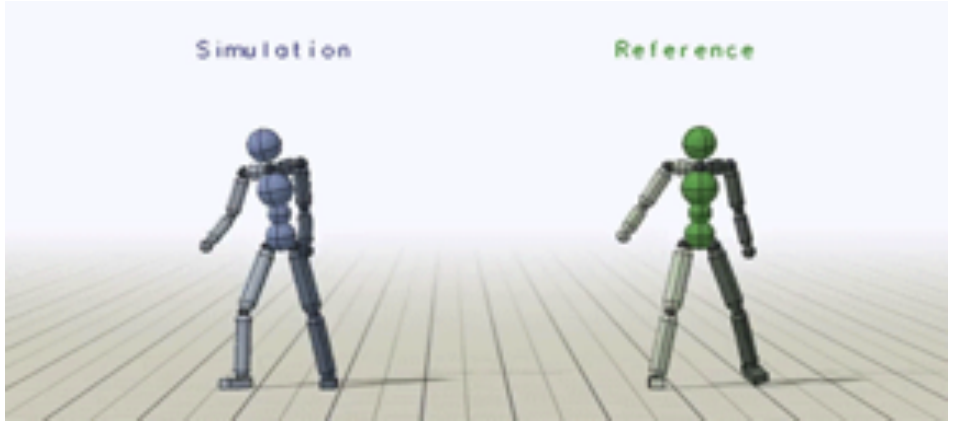


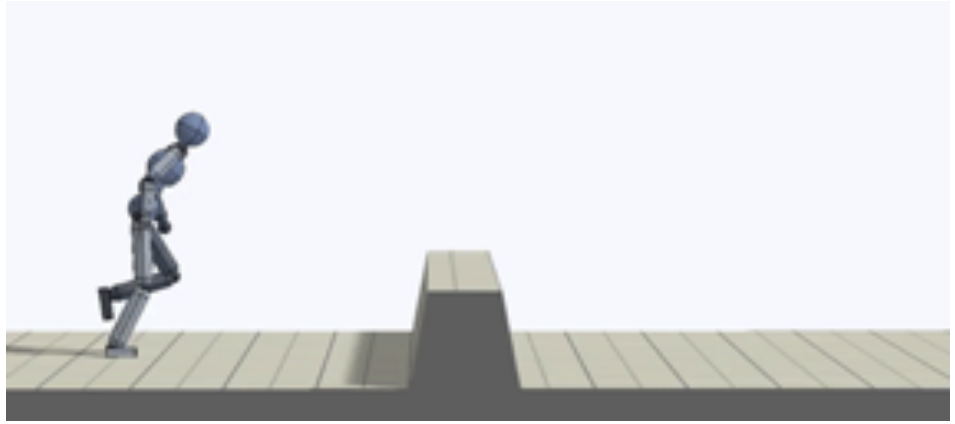
Hester et al., AAAI'18, "Deep Q-learning from Demonstrations"

Case Study: Motion Imitation

- To reproduce a given kinematic reference motion







Case Study: Motion Imitation

- Each reference motion is represented as a sequence of target poses

$$\hat{q}_0, \hat{q}_1, \cdots, \hat{q}_T,$$

- Reward function is defined as $r_t = \omega^I r_t^I + \omega^G r_t^G.$
- First term is imitation objective (imitate the reference motion), second term is task dependent
- Train with PPO

Peng et al. SIGGRAPH'18. DeepMimic: Example-Guided Deep Reinforcement Learning of Physics-Based Character Skills https://xbpeng.github.io/projects/DeepMimic/index.html

Case Study: Motion Imitation

- Imitation reward is carefully designed

$$r_t = \exp\left(-2\|\hat{q}_t - q_t\|^2\right).$$

$$r_t^I = w^p r_t^p + w^v r_t^v + w^e r_t^e + w^c r_t^c$$

$$w^p = 0.65, w^v = 0.1, w^e = 0.15, w^c = 0.1$$

$$r_t^p = \exp\left[-2\left(\sum_j \|\hat{q}_t^j \ominus q_t^j\|^2\right)\right]. \quad r_t^v = \exp\left[-0.1\left(\sum_j \|\hat{\dot{q}}_t^j - \dot{q}_t^j\|^2\right)\right]. \quad r_t^e = \exp\left[-40\left(\sum_e \|\hat{p}_t^e - p_t^e\|^2\right)\right]. \quad r_t^c = \exp\left[-10\left(\|\hat{p}_t^c - p_t^c\|^2\right)\right].$$

Peng et al. SIGGRAPH'18. DeepMimic: Example-Guided Deep Reinforcement Learning of Physics-Based Character Skills https://xbpeng.github.io/projects/DeepMimic/index.html

Case Study: Motion Imitation

Peng et al. SIGGRAPH'18. DeepMimic: Example-Guided Deep Reinforcement Learning of Physics-Based Character Skills https://xbpeng.github.io/projects/DeepMimic/index.html

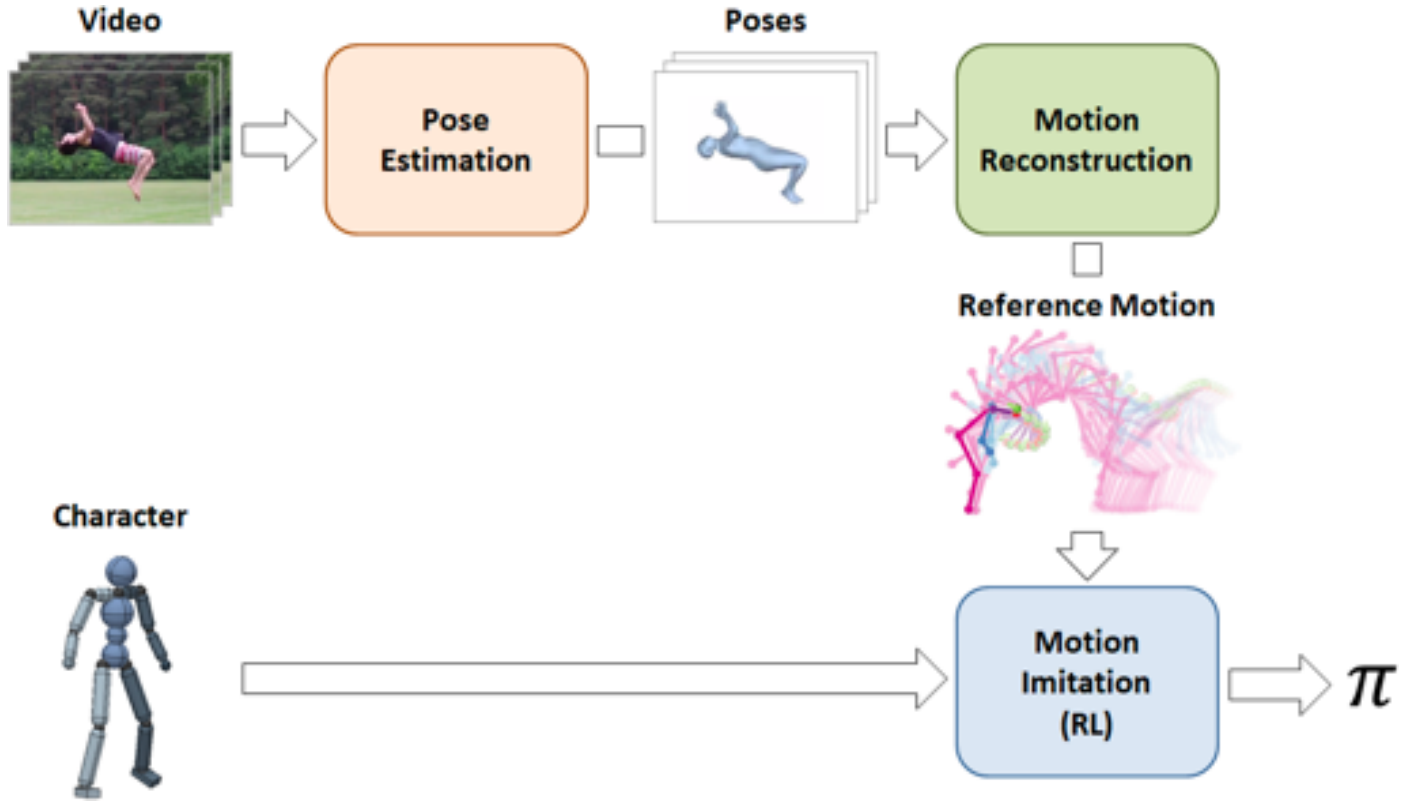
Case Study: Motion Imitation

- Follow-up work: how to get rid of MoCap data

Peng, et al. SFV: Reinforcement Learning of Physical Skills from Videos Transactions on Graphics (Proc. ACM SIGGRAPH Asia 2018) https://bair.berkeley.edu/blog/2018/10/09/sfv/

Case Study: Motion Imitation

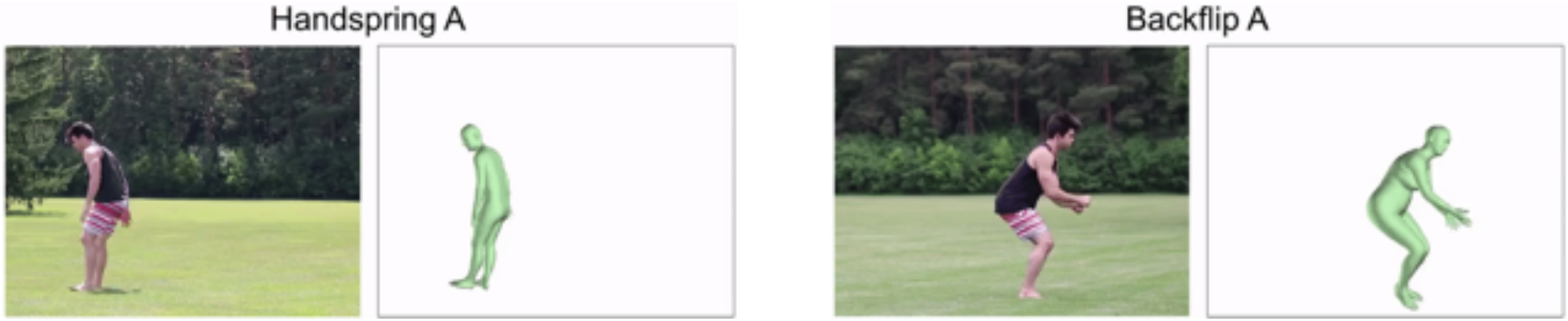
- Learning dynamics from videos



Peng, et al. SFV: Reinforcement Learning of Physical Skills from Videos Transactions on Graphics (Proc. ACM SIGGRAPH Asia 2018) https://bair.berkeley.edu/blog/2018/10/09/sfv/

Case Study: Motion Imitation

Vision-based pose estimator



Peng, et al. SFV: Reinforcement Learning of Physical Skills from Videos Transactions on Graphics (Proc. ACM SIGGRAPH Asia 2018) https://bair.berkeley.edu/blog/2018/10/09/sfv/

Case Study: Motion Imitation

- Learning dynamics from videos

https://bair.berkeley.edu/blog/2018/10/09/sfv/

Peng, et al. SFV: Reinforcement Learning of Physical Skills from Videos Transactions on Graphics (Proc. ACM SIGGRAPH Asia 2018) https://bair.berkeley.edu/blog/2018/10/09/sfv/

Two Major Problems in Imitation Learning

- How to collect expert demonstrations
  - Crowdsourcing
  - Guided policy search or optimal control for trajectory optimization
- How to optimize the policy for off-course situations
  - Simulate those situations to collect new labels
  - Use off-policy learning with the already collected samples
  - Combine IL and RL

Summary on Imitation Learning

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

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

Conclusion

- Imitation learning is an important research topic to bridge machine learning and human demonstration
  - Robot learning (learn from few samples)
  - Inverse reinforcement learning
  - Active learning
  - etc
- Recent survey: An Algorithmic Perspective on Imitation Learning: https://arxiv.org/pdf/1811.06711.pdf