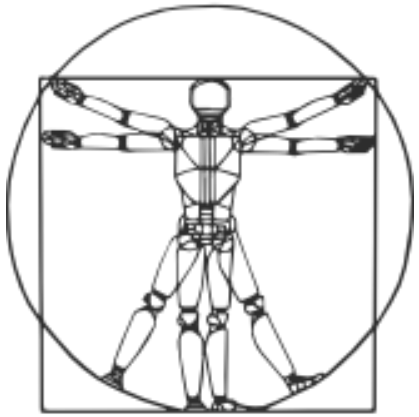


CSC2626
Imitation Learning for Robotics

Florian Shkurti

Week 9: Imitation Learning Combined with RL and Planning.
Imitating Long-Horizon Tasks.

Today's agenda

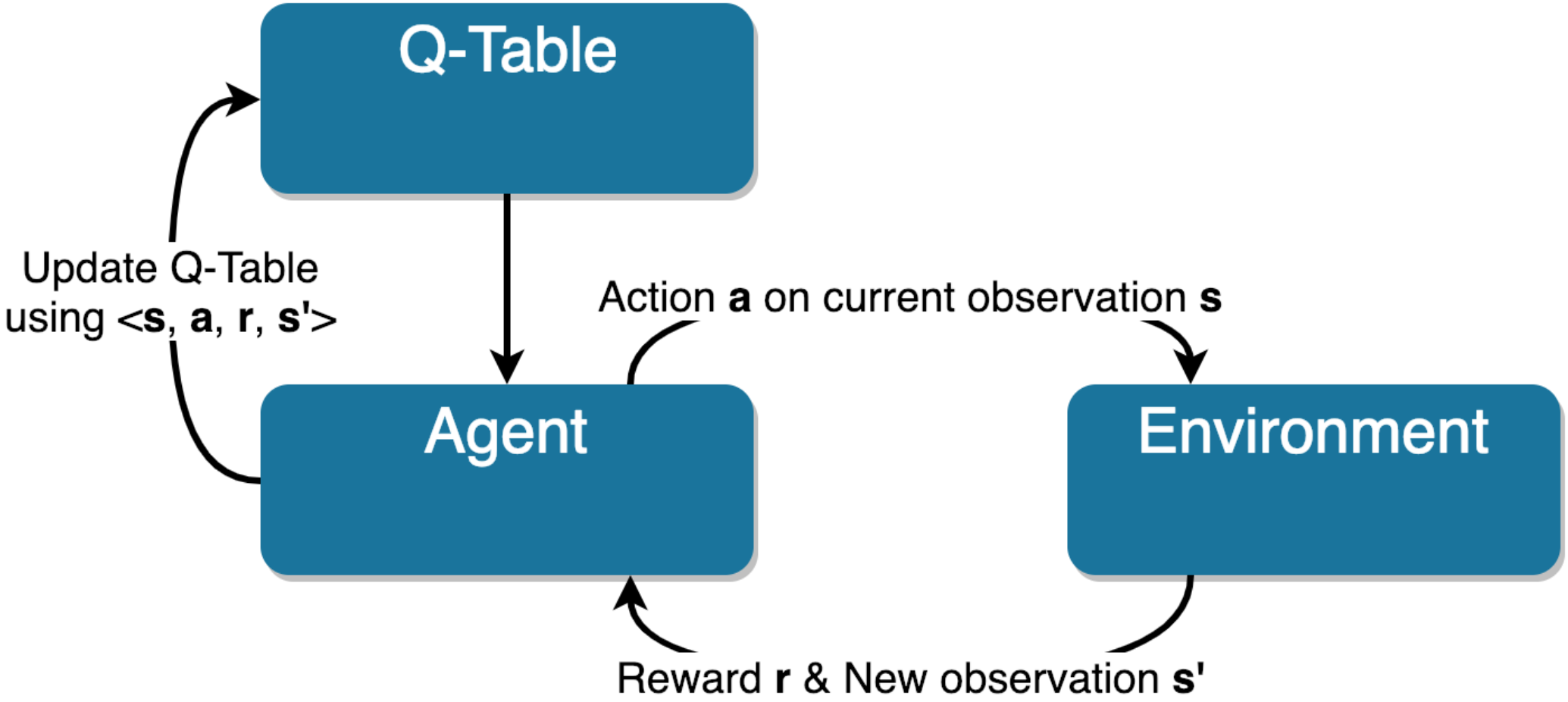
- Respecting demonstrations by a large margin (DQN with demonstrations)
- Conditional imitation learning
- End-to-end neural motion planner
- DeepMimic
- Learning dexterous manipulation with RL + demonstrations
- Relay Policy Learning

Acknowledgments
Today's slides are based on student presentations from 2019 by: Bryan Chan, Chandripal Budnarain, Renato Fereira, David Acuna, Brenna Li, Wei Cui

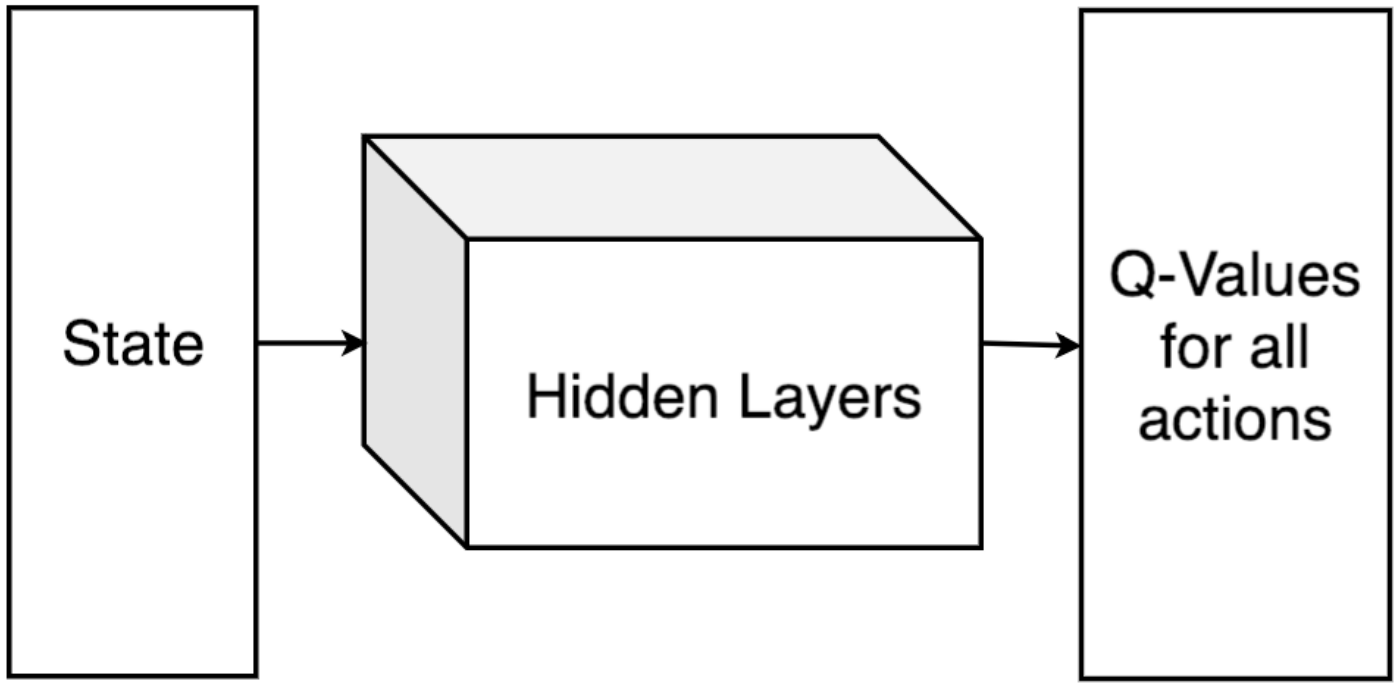
Deep Q-Learning from Demonstrations (DQfD)

Bryan Chan & Chandripal Budnarain

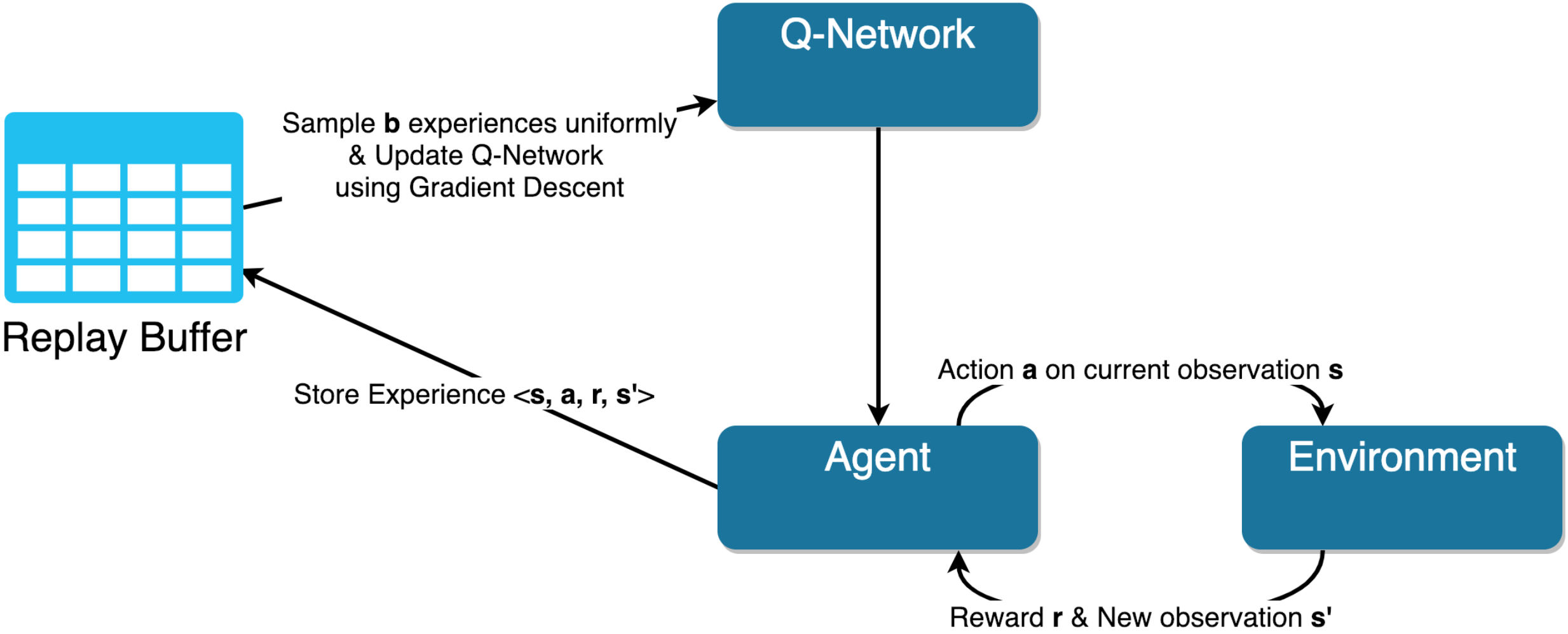
Q-Learning Algorithm



Q-Function Approximator



DQN Algorithm



How to Combine Demonstration Data with DQN?

Loss Function

- Recall that the loss function for Q-Learning is:

$$J_{\mathrm{DQN}}(\phi) = E_{\mathbf{s}\sim d^{\pi_\beta}(\mathbf{s}),\, \mathbf{a}\sim\pi_\beta(\mathbf{a}|\mathbf{s})}\left[\left(Q_\phi(\mathbf{s},\mathbf{a}) - (r(\mathbf{s},\mathbf{a}) + \gamma \mathrm{max}_{a'} Q_{\bar{\phi}}(\mathbf{s}^{'},\mathbf{a}^{'}))\right)^2\right]$$

- Given demonstration data, we want the agent to learn from it
- **Issue:** Demonstration data only covers a small subset of the state space and does not consider a lot of actions
- **Issue:** Some values correspond to state-action pairs not observed during training and the Q-Network would propagate these values in the Bellman recursion

Large-Margin Classification Loss

- Push the values of other actions to be at least a margin lower than the demonstrator's action. The loss function:

$$J_E(\phi) = \max_a \left(Q_\phi(s,a) + l(a,a_E)\right) - Q_\phi(s,a_E)$$

where $l(a, a_E)$ is a margin function that is 0 when $a = a_E$ and some positive value otherwise, and a_E is the demonstrator's action

- In this paper, $l(a, a_E) = 0$ if $a = a_E$, and 0.8 otherwise

Overall Loss Function

$$J(\phi) = J_{\text{DQN}}(\phi) + \lambda_1 J_n(\phi) + \lambda_2 J_E(\phi) + \lambda_3 J_{\text{reg}}(\phi)$$

where λ's control the weighting between the losses,

$J_n(\phi)$ is the n-step TD-loss

$J_{\text{reg}}(\phi)$ is the L2 regularization loss

Tradeoff between following demonstration data and finding optimal Q-values

Prioritized Experience Replay

- In DQN, we sample experiences from the replay buffer uniformly
- What if we focus on addressing large mistakes first?
- We can prioritize what tuples we sample by looking at the TD-error corresponding to a tuple (s, a, r, s')

$$\delta = (r(s,a) + \gamma \max_{a'} Q_{\bar{\phi}}(s^{'}, a^{'})) - Q_{\phi}(s,a)$$

Prioritized Experience Replay

- Priority of experience i: $P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$ where $p_i = |\delta_i| + \epsilon$

- α (hyperparameter) decides how much prioritization is used.

  If $\alpha = 0$, we are sampling uniformly

- **Issue:** Sampling with priority introduces bias and changes the behavior distribution

Prioritized Experience Replay

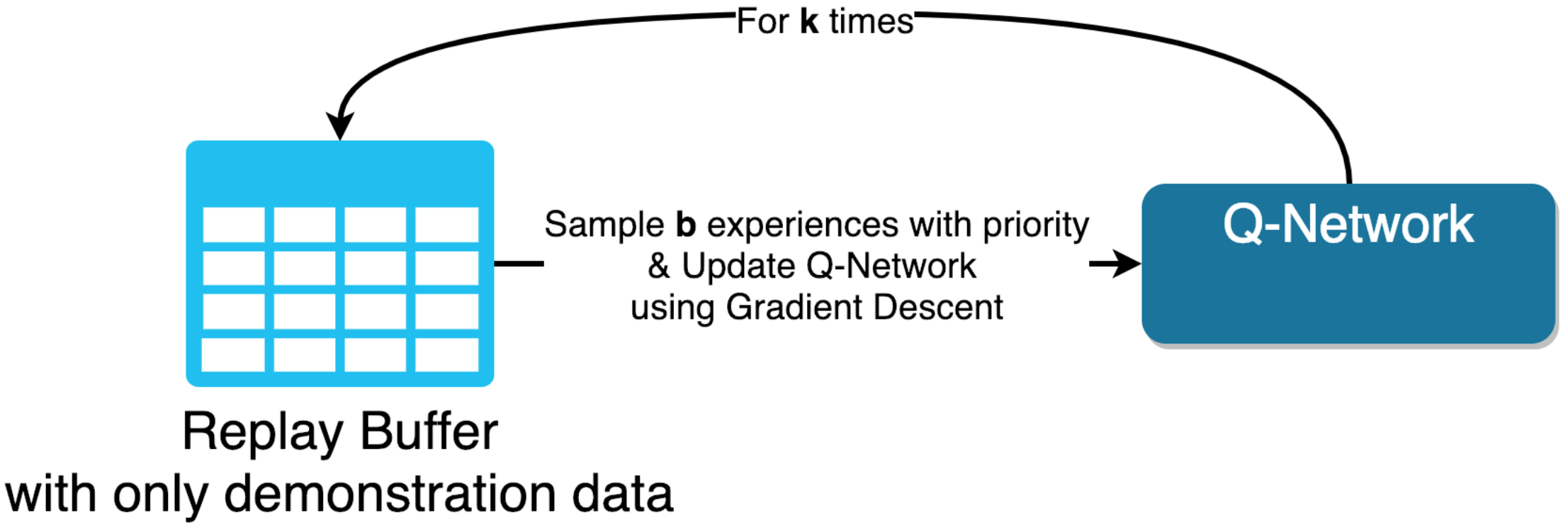
- **Solution:** Correct using weighted importance-sampling with weights $w_i = (\frac{1}{N}\frac{1}{P(i)})^{\beta}$, where N is number of samples

- β (hyperparameter) decides how much we should compensate for the non-uniform probabilities $P(i)$. If $\beta = 1$, we fully compensate.

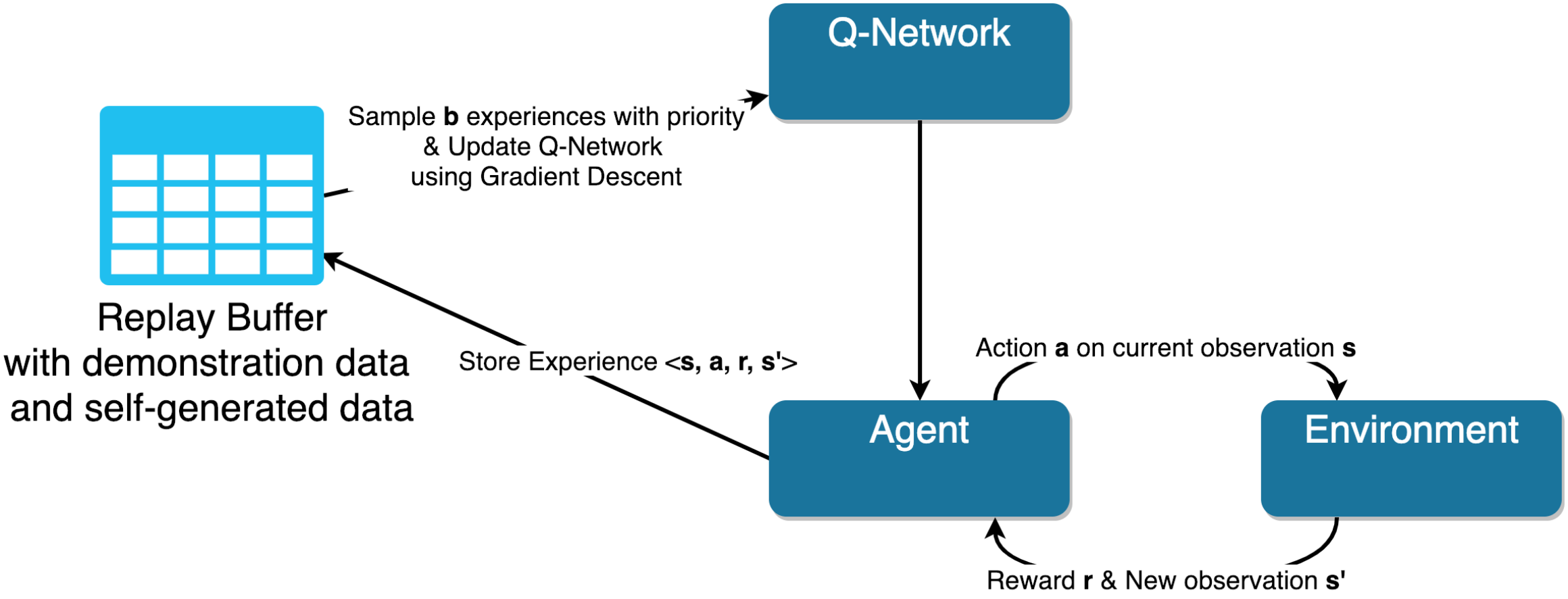
- In general, α and β change together as time goes on. The idea is that we first sample close to uniformly, then slowly sample with priority.

- In this paper, $\alpha = 0.4$ and $\beta = 0.6$ (Fixed)

DQfD Pre-Training



DQfD Post-Training



DQfD Replay Buffer Tweak

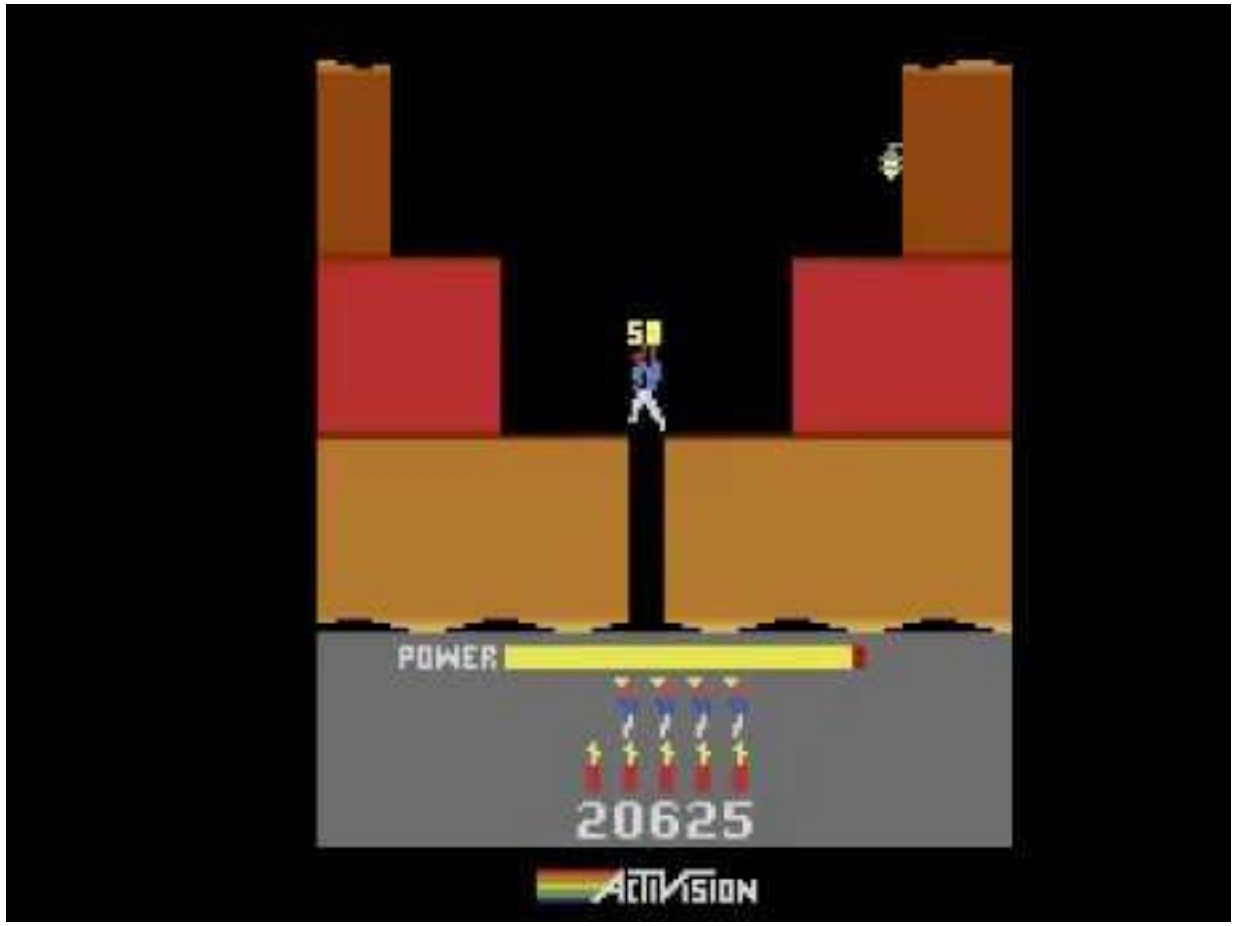
- We give more priority on demonstration data (by having a higher ϵ)
- In this paper, $\epsilon_a = 0.001$ (self-generated) and $\epsilon_d = 1.0$ (demonstration)

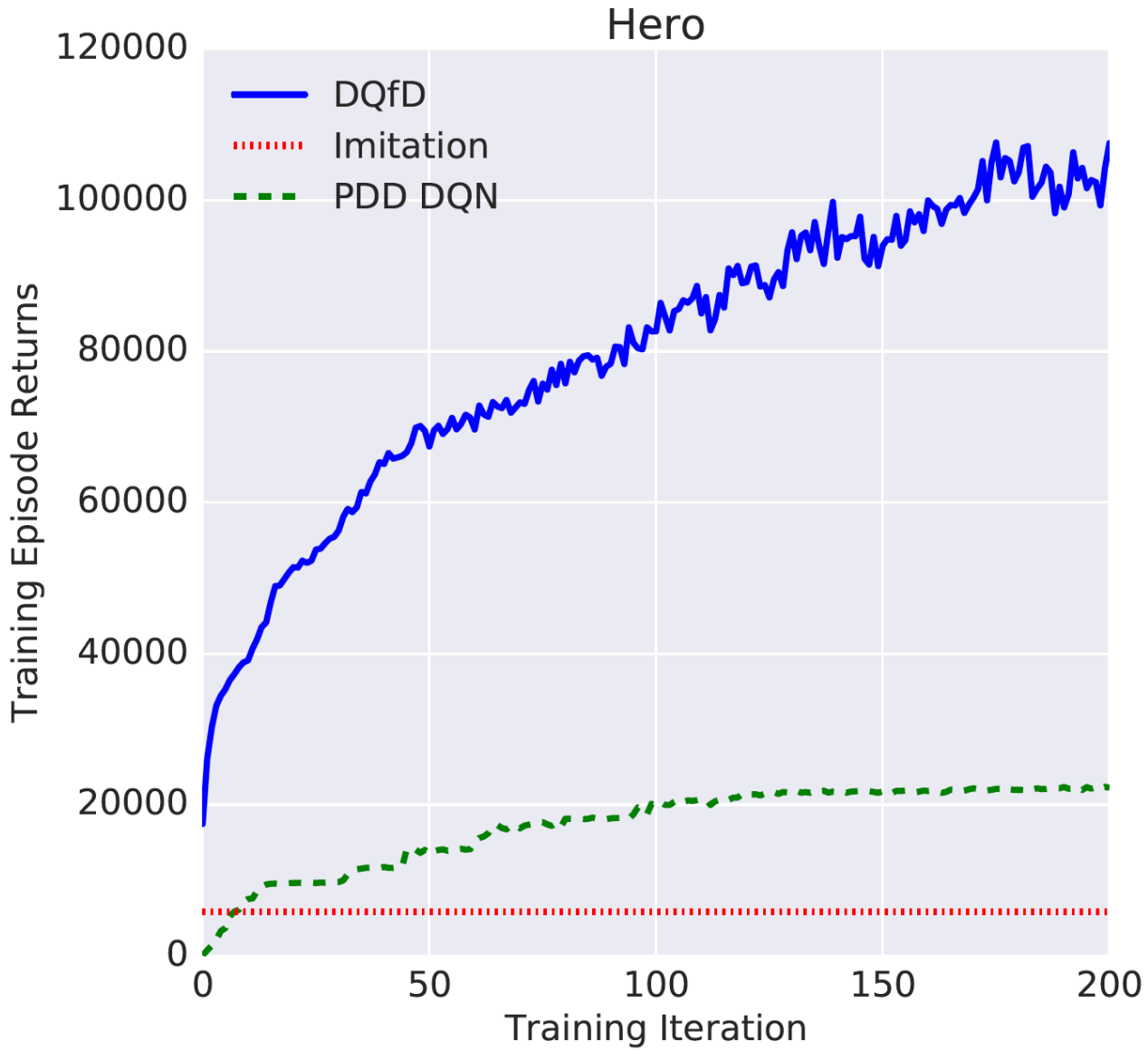
- **Problem:** What if the replay buffer is full?

- 1) We want to make sure the agent does not go too far from demonstrator unless some other action is optimal: **keep demonstration data**

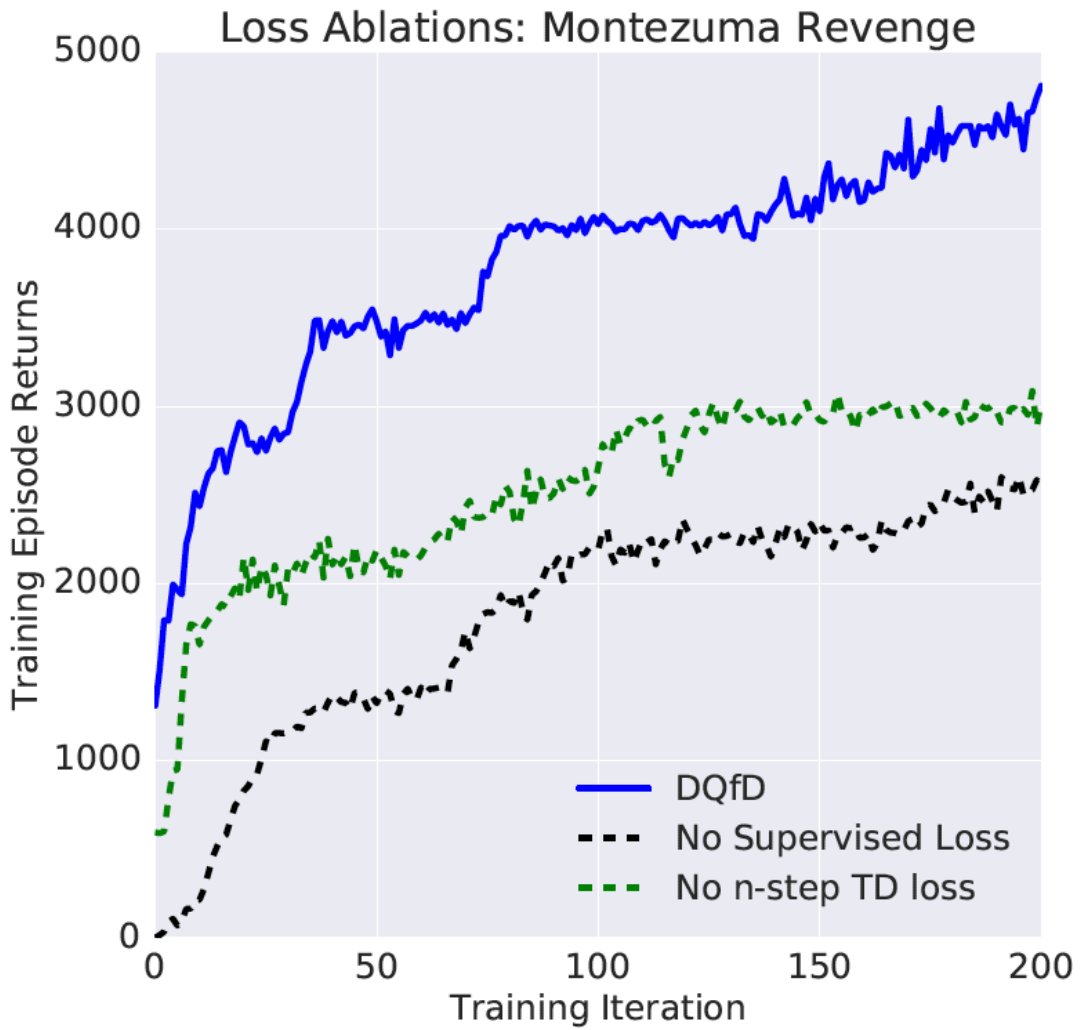
- 2) Old experience tuples are out-of-date: **remove oldest self-generated data**

Experiment


POWER
20625
ACTIVISION


Hero
DQfD
Imitation
PDD DQN
Training Episode Returns
Training Iteration
0
20000
40000
60000
80000
100000
120000
0
50
100
150
200

Removing Supervised Loss



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End-to-end Driving via Conditional Imitation Learning

Wei Cui

Electrical & Computer Engineering
University of Toronto

Feb 1st 2019

Brief Overview of the Paper

- This paper focuses on the task of self-driving, while allowing users to interact with high-level navigation commands.
- As the conventional imitation learning is not sufficient, the agent solves the task through conditional imitation learning.

▸ Link


FPS
Speed
Gear
18 km/h
1
4x

Problem Formulation

- The main task : given specified sensory inputs, the agent achieves self-driving through computing controller outputs, while following navigational guidance.
- **Sensory Inputs** (Observation **o**) :

&

Measurements (i.e. Speed)

- **Controller Outputs** :

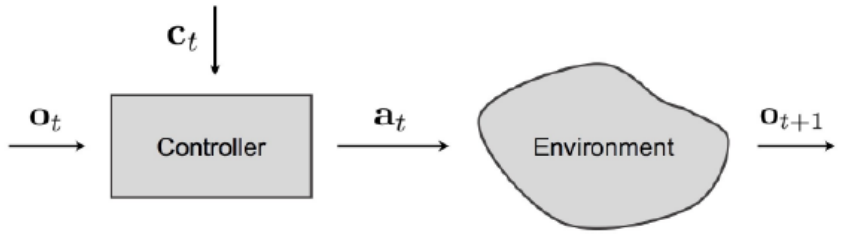
$$\mathbf{a} = [s, \alpha] \tag{1}$$

  - s : steering angle
  - α : acceleration

Conditional Imitation Learning

- Conditional Imitation Learning : for both training and testing, the agent receives additional input : **c** (navigation command).
- The formulation for Conditional Imitation Learning :

$$\min_{\theta} \sum_{i} \mathcal{L}(F(\mathbf{o}_i, \mathbf{c}_i; \theta), \mathbf{a}_i) \tag{2}$$

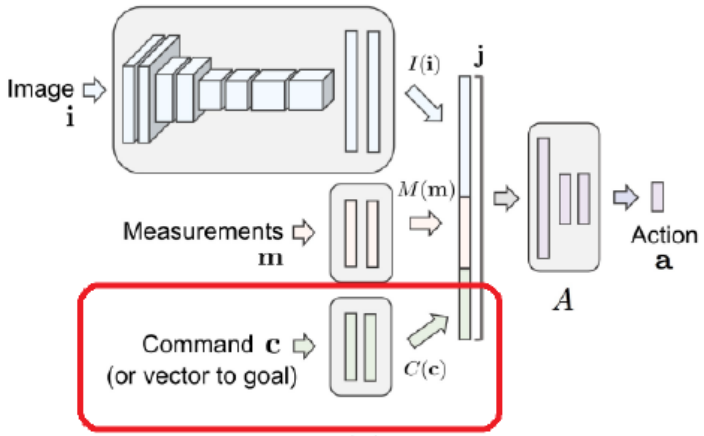


- The high level commands explored for this paper :

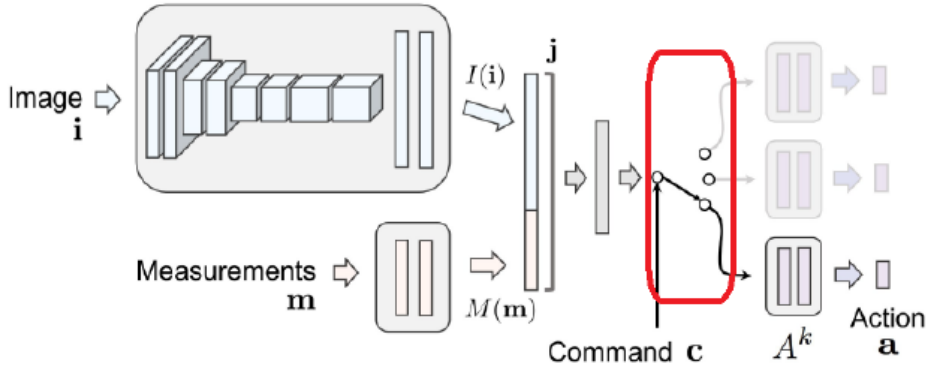
$$\mathbf{c} \in \{\text{continue, left, straight, right}\} \tag{3}$$

Network Architecture

- Two models are explored :
  - ***command input*** model
  - ***branched*** model



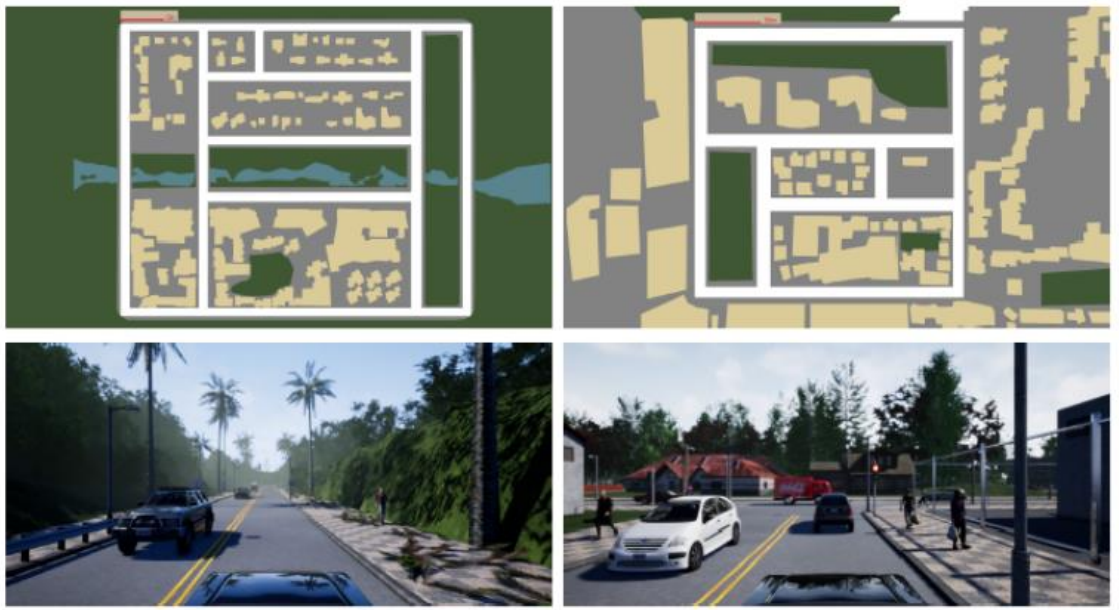
(a)



(b)

System Setup

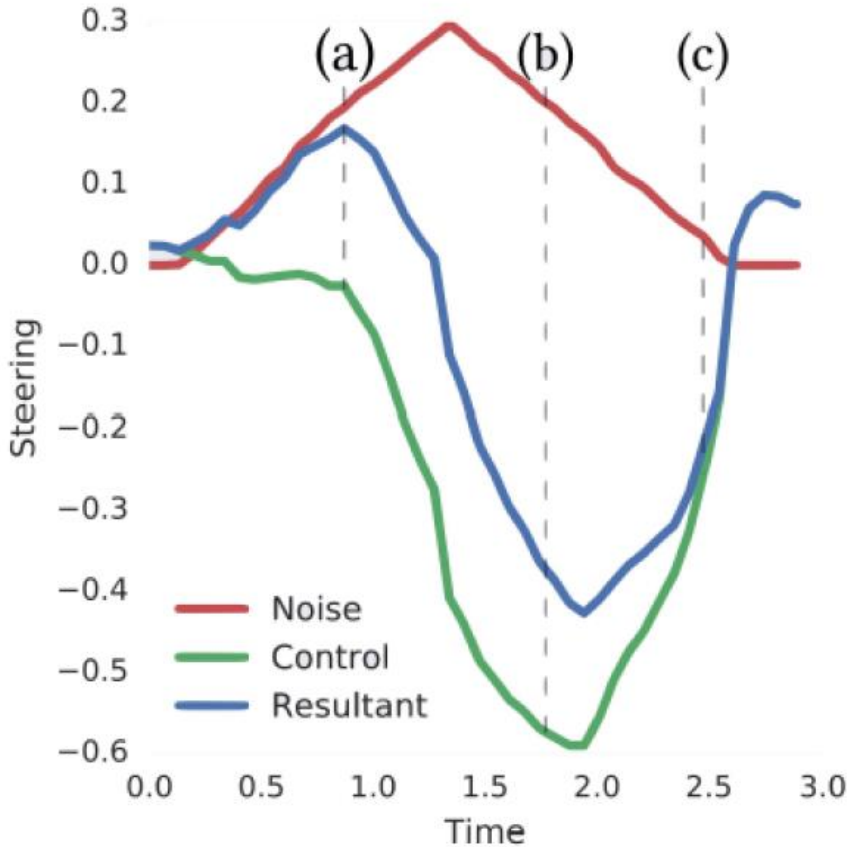
- Two systems : a simulated urban environment and a physical system.
- **Simulated Environment :** an urban driving simulator, CARLA.
- Town 1 for training ; Town 2 for exclusive testing.

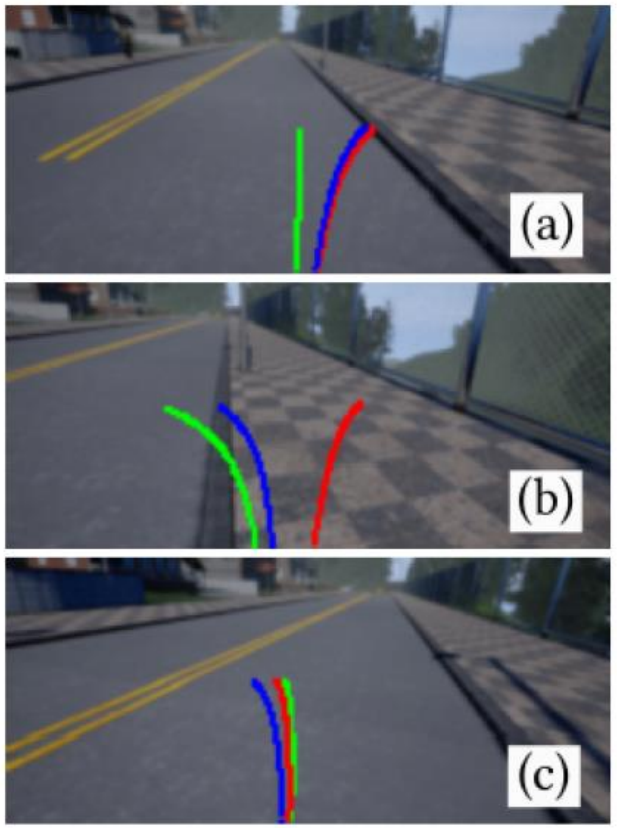


Town 1 (training) Town 2 (testing)

Training Data Preparation

- Firstly, additional state-action pairs are collected through injecting noise into expert's control, and let the expert to respond. This method is an alternative to DAgger (not used in the paper).





Training Data Preparation (Cont'd)

- The authors further augment the data through applying random transformations to the images as inputs to the agent.

- The types of transformations include :
  - Change in contrast, brightness, and tone.
  - Adding Gaussian blur, Gaussian noise, salt-and-pepper noise (sparse white and black pixels).
  - Region dropout (masking out a random set of rectangles of roughly 1% of image area)

Training Details

- **Some normalization used :** 50% dropout after fully-connected hidden layers, and 20% dropout after convolutional layers.
- **Loss Function :** As mentioned before, each action contains a tuple of signals : $\mathbf{a} = [s, \alpha]$.
  With model's action $\mathbf{a}$ and expert's action $\mathbf{a}_e$, the per-sample loss function :

$$\mathcal{L}(\mathbf{a}, \mathbf{a}_e) = ||s - s_e||^2 + \lambda_a ||\alpha - \alpha_e||^2 \tag{4}$$

- Different than DAgger, the agent's parameters are optimized once after all the data is collected, without iterative loops.
- For the command-conditional models, minibatches were constructed to contain an equal number of samples with each command.

Testing Methods : Simulation Environment

- **Baseline Method :**
  - Standard Imitation Learning : $\mathbf{a} = \mathcal{F}(\mathbf{o})$
- **Variations on the current model :** Investigate on the importance of each component.
  - The ***command input*** model.
  - The ***branched*** model trained without noise-injected data.
  - The ***branched*** model trained without data augmentation.
  - The ***branched*** model implemented with a shallower network.

Testing Results : Simulation Environment

Model	Success rate		Km per infraction	
	Town 1	Town 2	Town 1	Town 2
Non-conditional	20%	26%	5.76	0.89
Ours branched	**88%**	**64%**	2.34	1.18
Ours cmd. input	78%	52%	3.97	1.30
Ours no noise	56%	22%	1.31	0.54
Ours no aug.	80%	0%	4.03	0.36
Ours shallow net	46%	14%	0.96	0.42

Testing Methods & Results : Physical System

- The authors picked only 3 competitive methods in simulation environment testing for this comparison :
  - The ***command input*** model.
  - The ***branched*** model trained without noise-injected data.
  - The ***branched*** model trained without data augmentation.
- The results still support the necessity for each of the model's component :

Model	Missed turns	Interventions	Time
Ours branched	**0%**	**0.67**	**2:19**
Ours cmd. input	11.1%	2.33	4:13
Ours no noise	24.4%	8.67	4:39
Ours no aug.	73%	39	10:41

Appendix A : Network Architecture Details

- For both architectures explored as shown above, the individual modules are identical.
- **The image module :**
  - Consists of 8 convolutional and 2 fully connected layers.
  - The convolution kernel size is 5 in the first layer and 3 in the following layers. The first, third, and fifth convolutional layers have a stride of 2.
  - The number of channels increases from 32 in the first convolutional layer to 256 in the last.
  - Fully-connected layers contain 512 units each.
- **Other modules :**
  - Implemented as standard multilayer perceptrons, with ReLU nonlinearities after all hidden layers.

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Main idea

Jointly optimize perception and planning

End-to-end Interpretable Neural Motion Planner

Wenyuan Zeng[1,2*] Wenjie Luo[1,2*]
Simon Suo[1,2] Abbas Sadat[1] Bin Yang[1,2] Sergio Casas[1,2] Raquel Urtasun[1,2]
[1]Uber Advanced Technologies Group [2]University of Toronto
{wenyuan,wenjie,suo,abbas,byang10,sergio.casas,urtasun}@uber.com

Abstract

In this paper, we propose a neural motion planner for learning to drive autonomously in complex urban scenarios that include traffic-light handling, yielding, and interactions with multiple road-users. Towards this goal, we design a holistic model that takes as input raw LIDAR data and a HD map and produces interpretable intermediate representations in the form of 3D detections and their future trajectories, as well as a cost volume defining the goodness of each position that the self-driving car can take within the planning horizon. We then sample a set of diverse physically possible trajectories and choose the one with the minimum learned cost. Importantly, our cost volume is able to naturally capture multi-modality. We demonstrate the effectiveness of our approach in real-world driving data captured in several cities in North America. Our experiments show that the learned cost volume can generate safer planning than all the baselines.

due to the nature of self-driving control being a sequential decision problem, and requires massive amounts of data to generalize. Furthermore, interpretability is difficult to obtain for analyzing the mistakes of the network. It is also hard to incorporate sophisticated prior knowledge about the scene, e.g. that vehicles should not collide.

In contrast, most self-driving car companies, utilize a *traditional engineering stack*, where the problem is divided into subtasks: perception, prediction, motion planning and control. Perception is in charge of estimating all actors' positions and motions, given the current and past evidences. This involves solving tasks such as 3D object detection and tracking. Prediction[1], on the other hand, tackles the problem of estimating the future positions of all actors as well as their intentions (e.g., changing lanes, parking). Finally, motion planning takes the output from previous stacks and generates a safe trajectory for the SDV to execute via a control system. This framework has interpretable intermediate representations by construction, and prior knowledge can be easily exploited, for example in the form of high definition

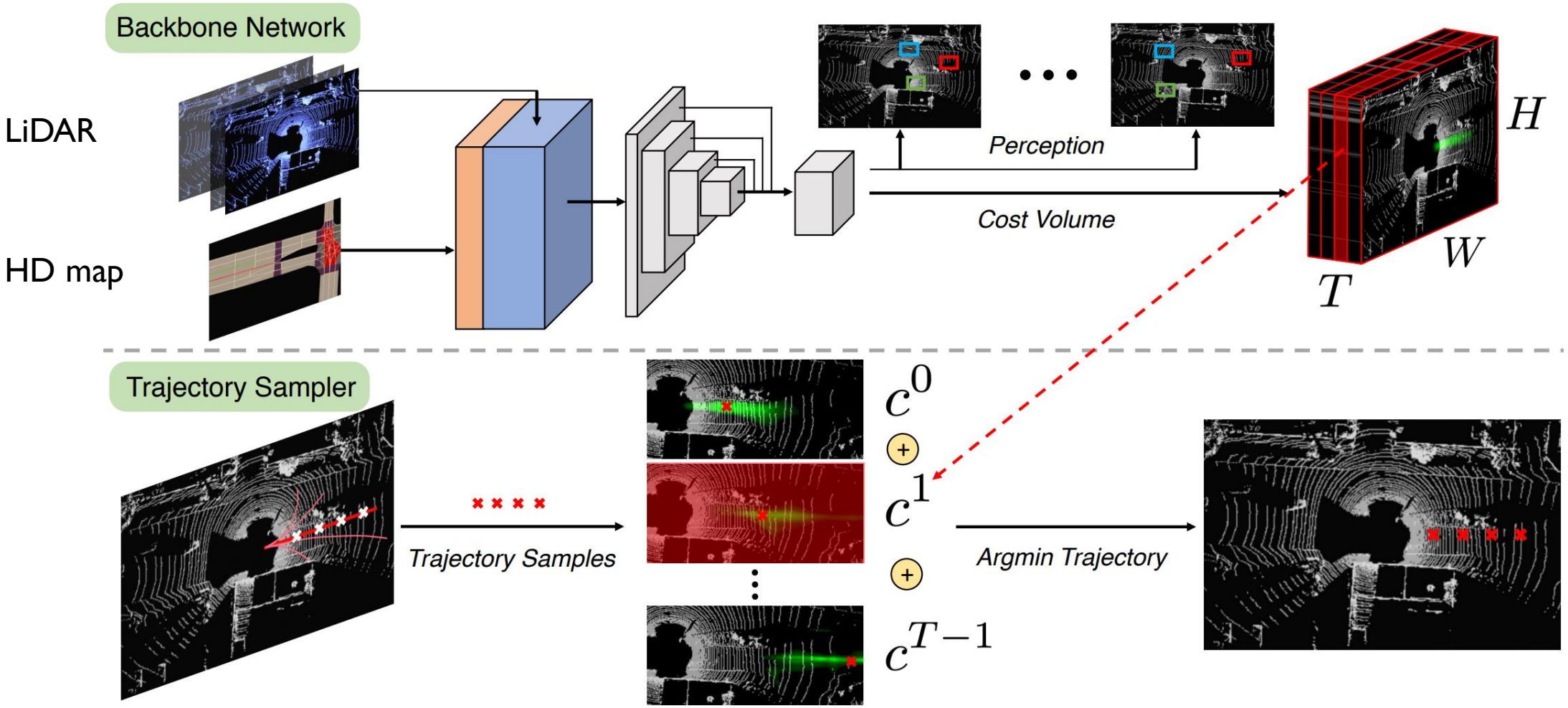

Figure 1. Our end-to-end interpretable neural motion planner. Backbone network takes LiDAR data and maps as inputs, and outputs bounding boxes of other actors for future timesteps (perception), as well as a cost volume for planning with T filters. Next, for each trajectory proposal from the sampler, its cost is indexed from different filters of the cost volume and summed together. The trajectory with the minimal cost will be our final planning.

Perception and planning loss functions

Perception Loss: Our perception loss includes classification loss, for distinguishing a vehicle from the background, and regression loss, for generating precise object bounding boxes. For each predefined anchor box, the network outputs a classification score as well as several regression targets. This classification score $p^k_{i,j}$ indicates the probability of existence of a vehicle at this anchor. We employ a cross-entropy loss for the classification defined as

$$\mathcal{L}_{cla} = \sum_{i,j,k} \left(q^k_{i,j} \log p^k_{i,j} + (1 - q^k_{i,j}) \log(1 - p^k_{i,j}) \right), \quad (6)$$

where $q^k_{i,j}$ is the class label for this anchor (i.e., $q^k_{i,j} = 1$ for vehicle and 0 for background). The regression outputs include information of position, shape and heading angle at each time frame t, namely

Planning Loss: Learning a reasonable cost volume is challenging as we do not have ground-truth. To overcome this difficulty, we minimize the max-margin loss where we use the ground-truth trajectory as a positive example, and randomly sampled trajectories as negative examples. The intuition behind is to encourage the ground-truth trajectory to have the minimal cost, and others to have higher costs. More specifically, assume we have a ground-truth trajectory $\{(x^t, y^t)\}$ for the next T time steps, where (x^t, y^t) is the position of our vehicle at the t time step. Define the cost volume value at this point (x^t, y^t) as $\hat{c}^t$. Then, we sample N negative trajectories, the i^{th} among which is $\{(x^t_i, y^t_i)\}$ and the cost volume value at these points are c^t_i. The sampling procedure for negative trajectories is similar as we described in Section. 3.2, except there is 0.8 probability that the negative sample doesn't obey SDV's initial states, e.g. we randomly sample a velocity to replace SDV's initial velocity. This will provide easier negative examples for the model to start with. The overall max-margin loss is defined as

$$\mathcal{L}_{\text{planning}} = \sum_{\{(x^t, y^t)\}} \left(\max_{1 \le i \le N} \left(\sum_{t=1}^{T} \left[\hat{c}^t - c^t_i + d^t_i + \gamma^t_i \right]_+ \right) \right)$$

Results

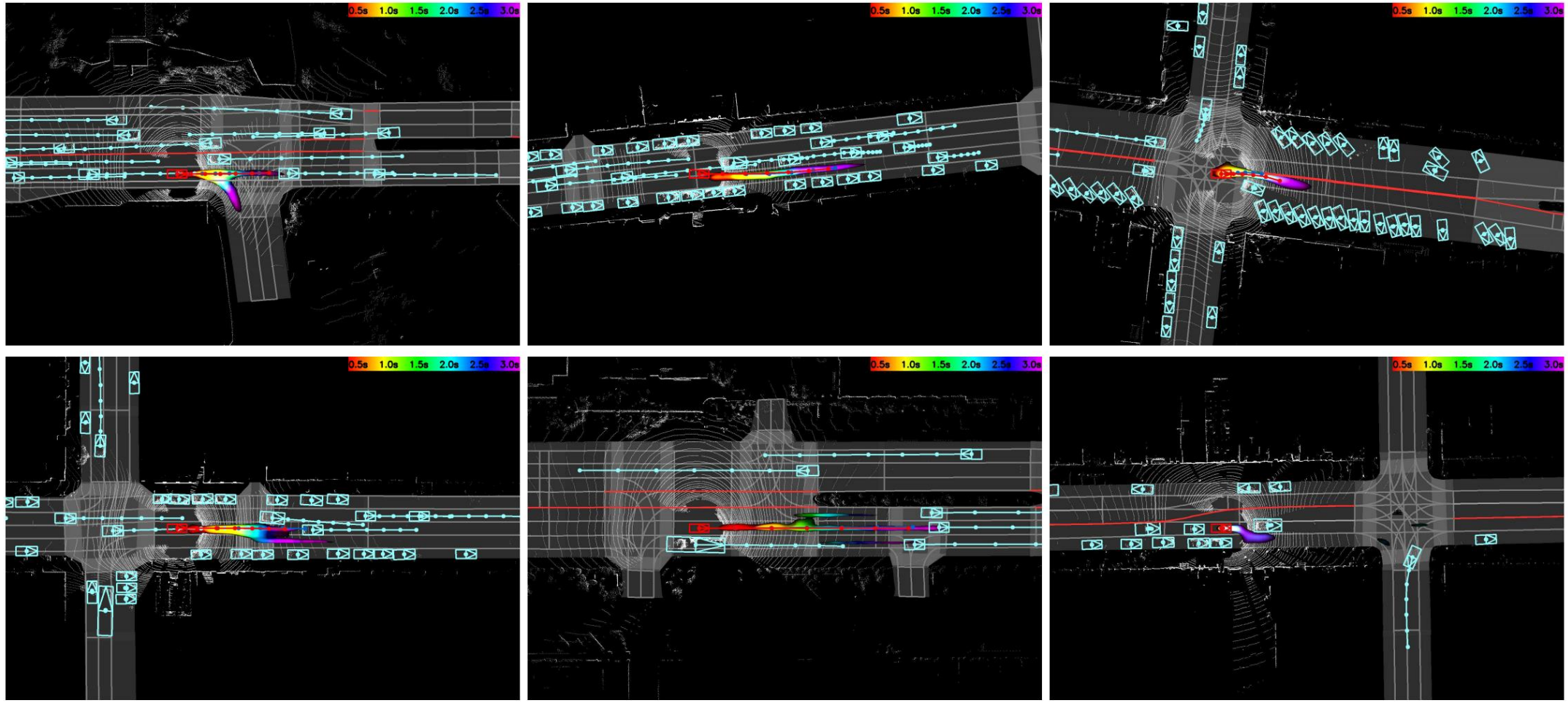

Figure 3. **Cost Volume across Time** We shown planned trajectory in red and ground-truth in blue. We overlay lower cost region for different timesteps in the same figure, using different colors (indicated by legend). Detection and corresponding prediction results are in cyan. (best view in color)

Results

Method	L2 along trajectory (m)				L2 across trajectory (m)				L1 (m)				L2 (m)			
	0s	1s	2s	3s	0s	1s	2s	3s	0s	1s	2s	3s	0s	1s	2s	3s
FaF[18]	0.29	0.49	0.87	1.52	0.16	0.23	0.39	0.58	0.45	0.72	1.31	2.14	0.37	0.60	1.11	1.82
IntentNet[5]	0.23	0.42	0.79	1.27	0.16	0.21	0.32	0.48	0.39	0.61	1.09	1.79	0.32	0.51	0.93	1.52
Ours	**0.21**	**0.37**	**0.69**	**1.15**	**0.12**	**0.16**	**0.25**	**0.37**	**0.34**	**0.54**	**0.94**	**1.52**	**0.28**	**0.45**	**0.80**	**1.31**

Table 2. Motion Forecasting Metric

Method	Detection mAP @ IoU (pts $\geq$ 1)				
	0.5	0.6	0.7	0.8	0.9
MobileNet[13]	86.1	78.3	60.4	27.5	1.1
FaF[18]	89.8	82.5	68.1	35.8	2.5
IntentNet[5]	**94.4**	89.4	75.4	43.5	3.9
Pixor[32]	93.4	89.4	78.8	52.2	**7.6**
Ours	94.2	**90.8**	**81.1**	**53.7**	7.1

Table 4. Detection mAP Result

LiDAR 3D object detection

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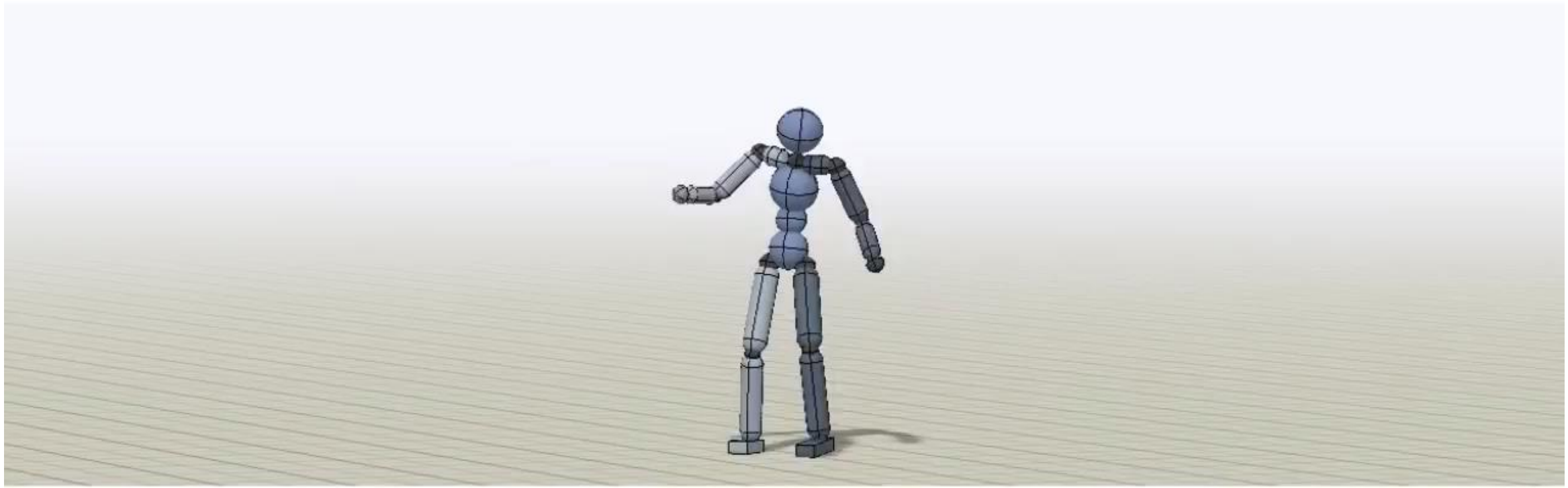
DeepMimic: Example-Guided Deep Reinforcement Learning of Physics-Based Character Skills



Xue Bin Peng[1], Pieter Abbeel[1], Sergey Levine[1], Michiel van de Panne[2]

[1] University of California Berkeley

[2] University of British Columbia

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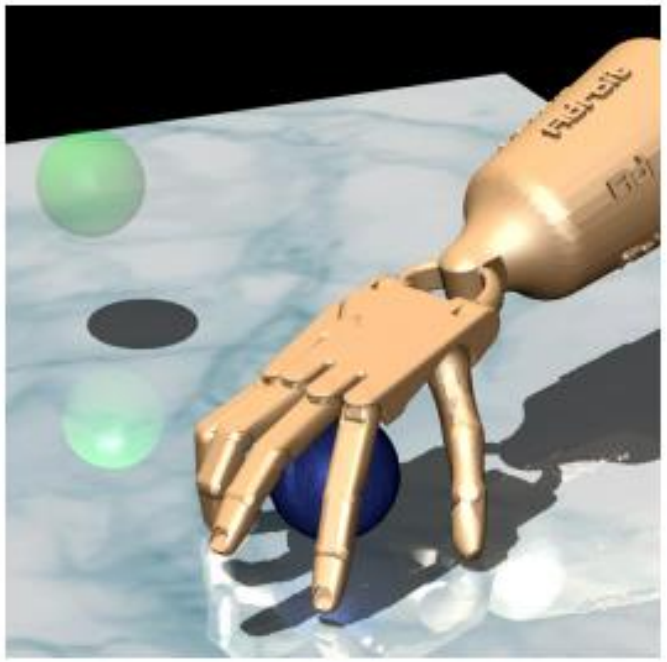
Learning Complex Dexterous Manipulation with Deep Reinforcement Learning and Demonstrations

Aravind Rajeswaran , Vikash Kumar , Abhishek Gupta, Giulia Vezzani , John Schulman , Emanuel Todorov , Sergey Levine

Jason Rebello
UTIAS

Motivation

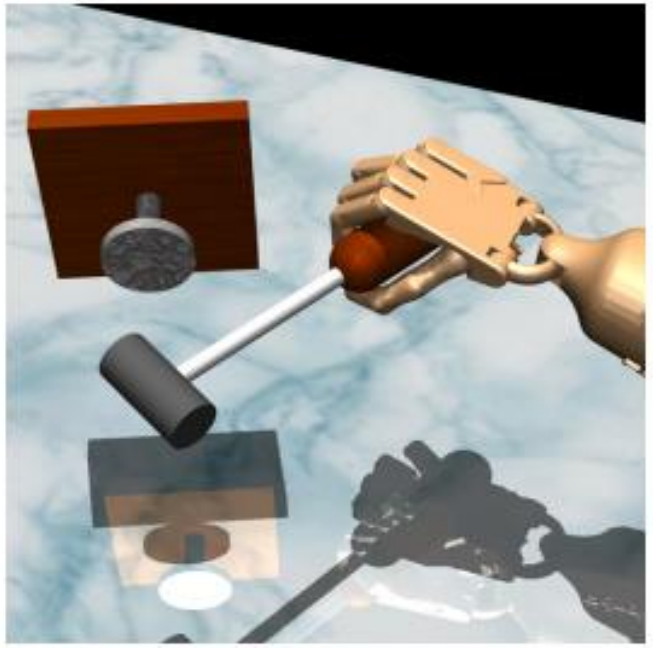
- Dexterous multi-fingered hands are ***extremely versatile***
- ***Control*** is challenging due to high dimensionality, complex contact patterns
- Previous methods require ***reward shaping***
- DRL limited to ***simpler manipulators and simple tasks***
- Lack of physical systems due to ***sample inefficiency***



Object relocation task

Contributions

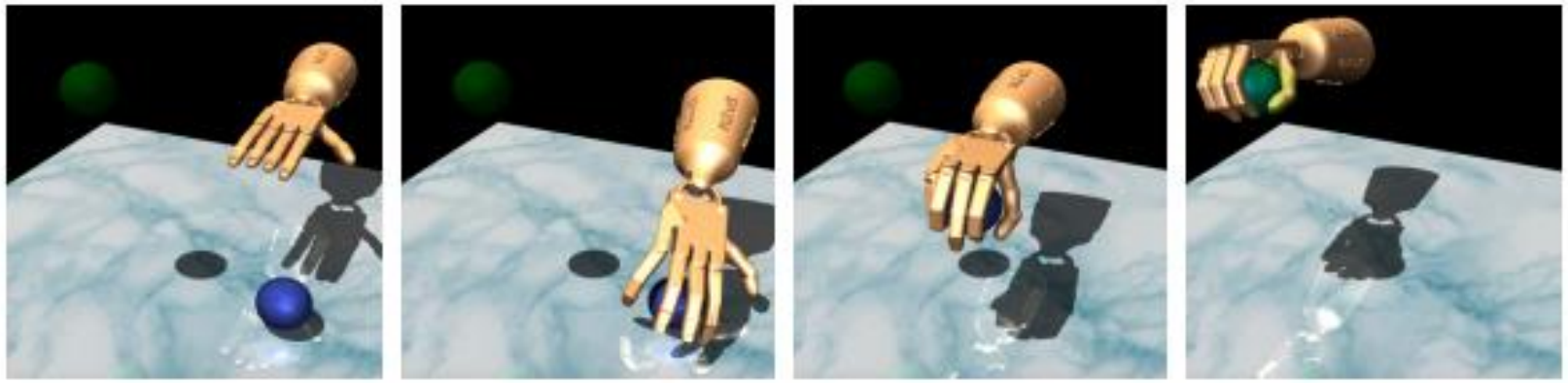
- Manipulation with ***24-DOF*** hand
- ***Model Free*** DRL
- Used in ***complex tasks with variety of tools***
- Small number of ***human demonstrations*** reduces sample complexity
- ***Reduces learning time***
- ***Robust*** and natural movements



Tool use task

Manipulation Task 1

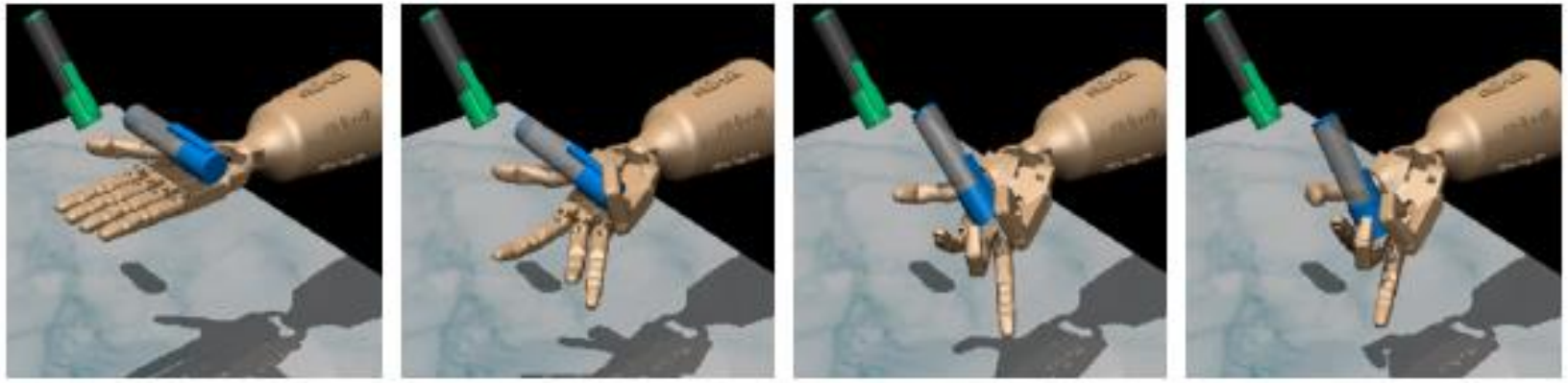
Object Relocation



- Move Blue ball to green position
- Task complete when ball is epsilon ball away from target
- Positions of ball and target are randomized
- Main challenge is exploration (reach object, grab and move to target location)

Manipulation Task 2

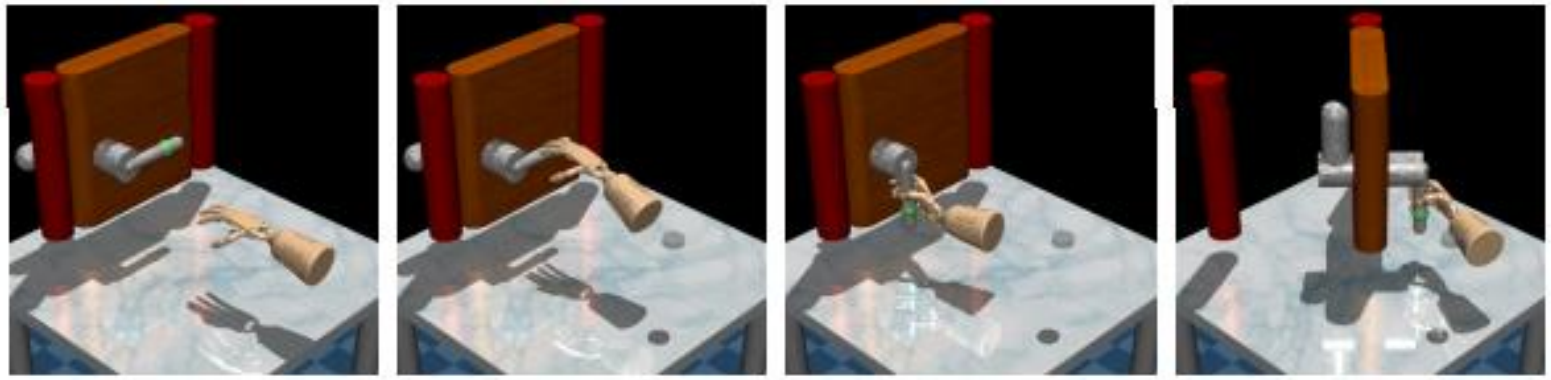
In-hand Manipulation



- Reposition blue pen to match orientation of green target
- Task complete when orientation is achieved
- Base of hand is fixed
- Large number of contacts with complex solutions
- Used a well shaped reward for training an expert

Manipulation Task 3

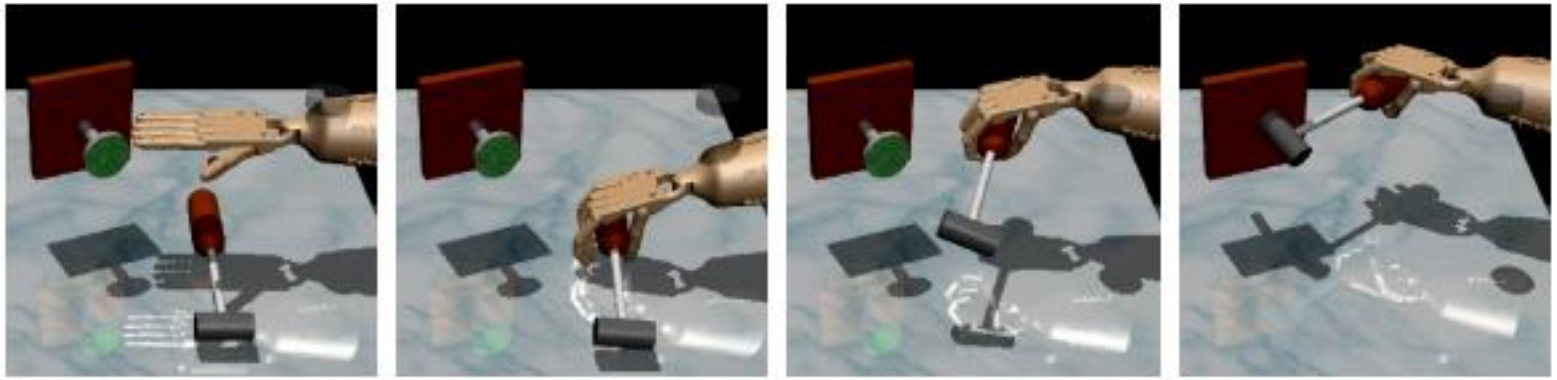
Door Opening



- Undo latch and swing door open
- Task complete when door touches door stopper
- No information of latch explicitly provided
- A lot of hidden sub-tasks
- Position of door is randomized

Manipulation Task 4

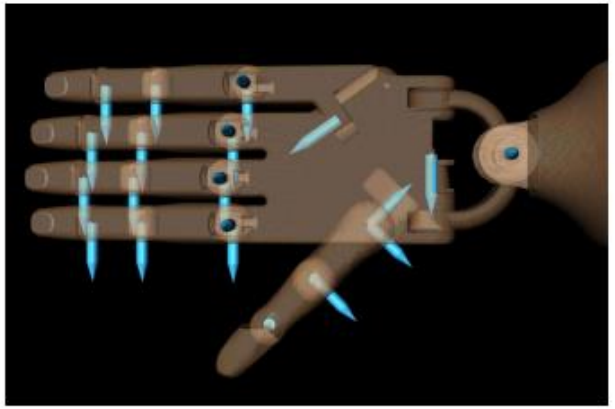
Tool Use



- Pickup and hammer nail
- Task complete when entire nail is inside the board
- Use tool instead of just relocation
- Multiple steps in task

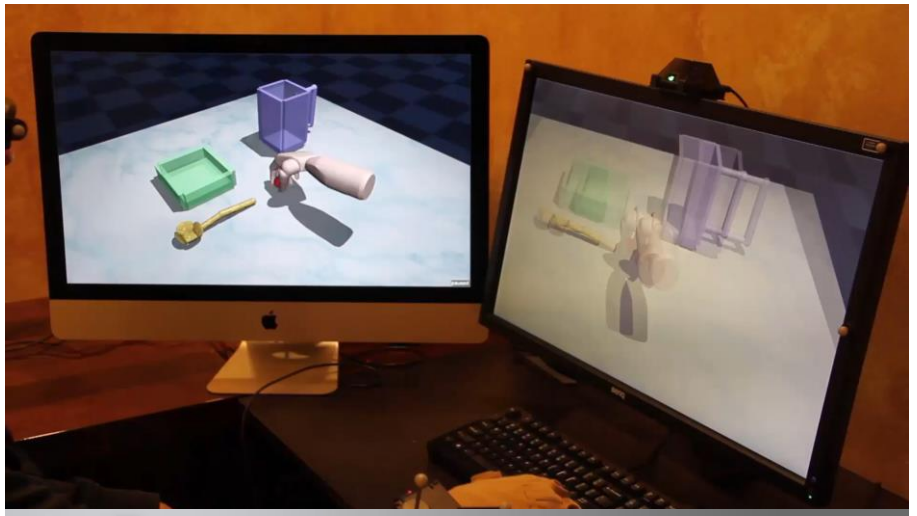
Experimental Setup

ADROIT hand



HTC headset

HAPTIX Simulator



CyberGlove 3

- 24-DOF hand
- First, middle, ring – 4 DOF each
- Little finger, thumb – 5 DOF each
- Wrist – 2 DOF
- Actuated with position control and has joint angle sensor
- MuJoCo physics simulation with friction
- 25 demonstrations for each task

MDP definition: $\mathcal{M} = \{\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{T}, \rho_0, \gamma\}$

States — Rewards — Initial Probability distribution — Actions — Transition dynamics — Discount Factor

Value function: $V^{\pi}(s) = \mathbb{E}_{\pi,\mathcal{M}}\left[\sum_{t=0}^{\infty} \gamma^t r_t \mid s_0 = s\right]$

Q function: $Q^{\pi}(s,a) = \underbrace{\mathbb{E}_{\mathcal{M}}\left[\mathcal{R}(s,a)\right]}_{\text{Reward for taking action a in state s}} + \underbrace{\mathbb{E}_{s' \sim \mathcal{T}(s,a)}\left[V^{\pi}(s')\right]}_{\text{Expected reward in state s'}}$

Advantage function: $A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$

- Directly optimize parameters of policy to maximize objective

Sub-optimal

Vanilla Policy Gradient:

$$g = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(a_t^i | s_t^i) \hat{A}^\pi(s_t^i, a_t^i, t)$$

Fisher Information Matrix:

$$F_\theta = \frac{1}{NT} \sum_{i=1}^{N} \nabla_\theta \log \pi_\theta(a_t^i | s_t^i) \nabla_\theta \log \pi_\theta(a_t^i | s_t^i)^T$$

- Fisher information matrix measures the curvature (sensitivity) of policy relative to model parameters

- Fisher information matrix is related to the Hessian matrix

Methodology (NPG)

- Limit policy change based on parameter change
- Fisher information matrix maps between parameter space and policy space
- Generally use learning rate in optimization
- Poor step size leads to poor initialization
- Use Fisher information matrix to perform update

Gradient ascent update:

$$\theta_{k+1} = \theta_k + \sqrt{\frac{\delta}{g^T F_{\theta_k}^{-1} g}} F_{\theta_k}^{-1} g$$

Steepest Ascent direction

Normalized step-size

Methodology (Problems with RL)

- Challenges with using NPG
  - RL requires careful reward shaping
  - Impractical number of samples to learn (approx. 100 hours)
  - Unnatural movement
  - Not as robust to environmental variations
- Solution
  - Combine RL with demonstrations
  - Guide exploration and decrease sample complexity
  - Robust and natural looking behaviour
  - Demonstration Augmented Policy Gradient (DAPG)

Methodology (Pretraining with BC)

- Exploration in PG achieved with stochastic action distribution
- Poor initialization leads to slow exploration
- Behavioral Cloning (BC) guides exploration
- Reduces sample complexity

$$\underset{\theta}{\text{maximize}} \sum_{(s,a)\in\rho_D} \ln \pi_\theta(a|s)$$

- Mimic actions taken in demonstrations
- Does not guarantee effectiveness of policy due to distributional shift

Methodology (Fine-tuning with augmented loss)

- BC does not make optimal use of demonstrations
- Cannot learn subtasks (reaching, grasping, hammering)
- BC policy (only grasping)
- Capturing all data

Policy gradient

Behavioral cloning

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

Dataset from policy

Dataset from demonstrations

Weighting function

iteration

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

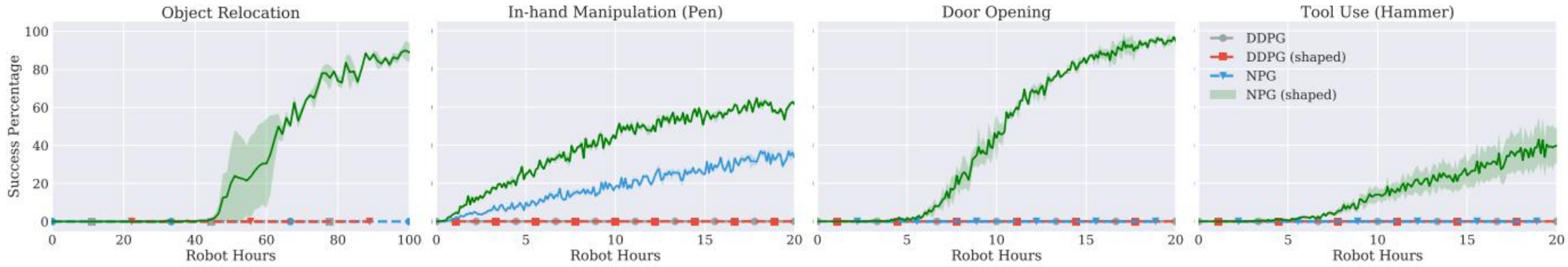
hyperparameters

Reinforcement learning from scratch

- Can RL cope with high dimensional manipulation tasks ?
- Is it robust to variations in environment ?
- Are movements safe and can they be used on real hardware ?

- Compare NPG vs DDPG (Deep Deterministic Policy Gradient)
- DDPG is a policy gradient actor-critic algorithm that is off-policy
- Stochastic policy for exploration, estimates deterministic policy
- Score based on percentage of successful trajectories (100 samples)
- Sparse Reward vs Reward shaping

Reinforcement learning from scratch



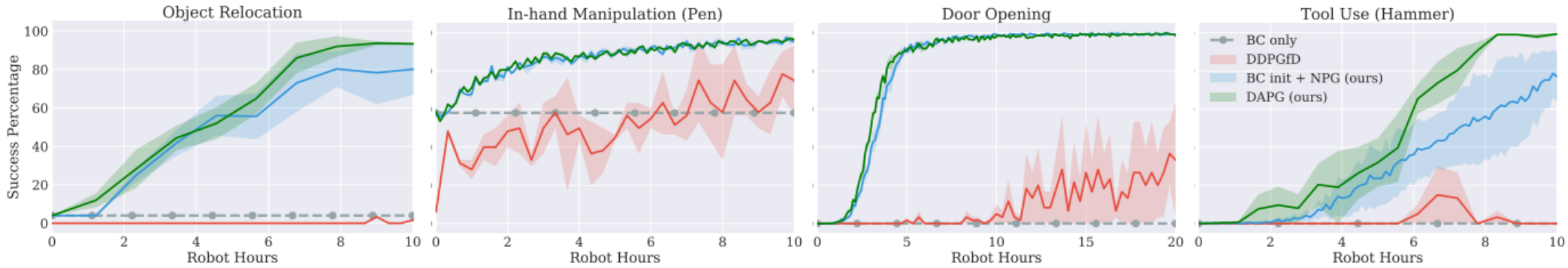
- NPG learns with reward shaping, DDPG fails to learn
- DDPG is sample efficient but sensitive to hyper-parameters
- Resulting policies have unnatural behaviors
- Poor sample efficiency, cant use on hardware
- Cannot generalize to unseen environment (weight and ball size change)

Reinforcement learning with demonstrations

- Does incorporating demonstrations reduce learning time?
- Comparison of DAPG vs DDPGfD (.. from Demonstrations)?
- Does it result in human like behaviour ?

- DDPGfD better version of DDPG (demonstrations in replay buffer, prioritized experience replay, n-step returns, regularization)
- Only use sparse rewards

Reinforcement learning with demonstrations



- DAPG outperforms DDPGfD
- DAPG requires few robot hours
- Can be used on real hardware
- Robust and human behavior
- Generalizes to unseen environment

RL iterations to achieve 90% success

Method	DAPG	(sp)	RL	(sh)	RL	(sp)
Task	N	Hours	N	Hours	N	Hours
Relocation	52	5.77	880	98	∞	∞
Hammer	55	6.1	448	50	∞	∞
Door	42	4.67	146	16.2	∞	∞
Pen	30	3.33	864	96	2900	322

NPG

Future Work

- Tests on real hardware
- Reduce sample complexity using novelty based exploration methods
- Learn policies from raw visual inputs and tactile sensing

Results

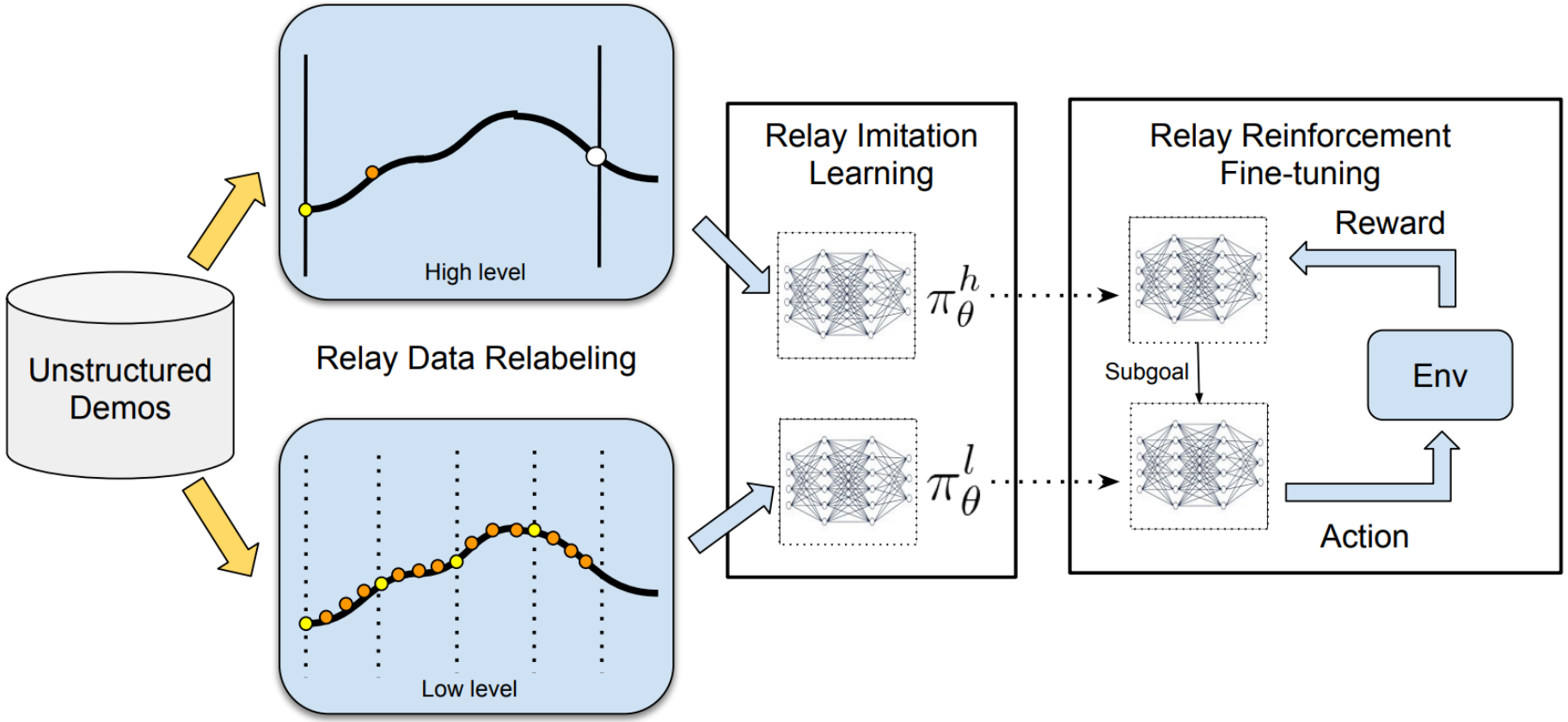

Leaning Complex Dexterous Manipulation
with
Deep Reinforcement Learning
& Demonstrations
Aravind Rajeswaran*, Vikash Kumar *, Abhishek Gupta, John Schulman,
Emanuel Todorov, Sergey Levine
OPENAI, UC BERKELEY, UW SEATTLE

Today's agenda

- Respecting demonstrations by a large margin (DQN with demonstrations)
- Conditional imitation learning
- End-to-end neural motion planner
- DeepMimic
- Learning dexterous manipulation with RL + demonstrations
- Relay Policy Learning

Acknowledgments
Today's slides are based on student presentations from 2019 by: Bryan Chan, Chandripal Budnarain, Renato Fereira, David Acuna, Brenna Li, Wei Cui

Overview: Relay Policy Learning



Relay Policy Architecture

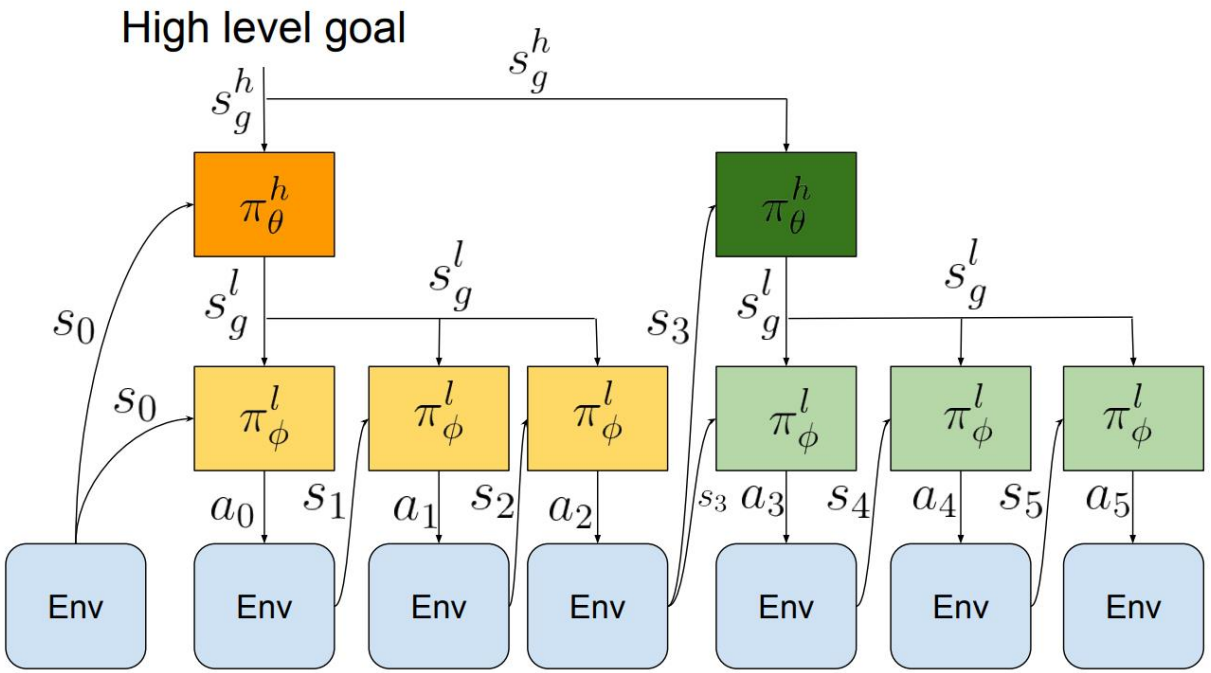


Figure 3: **Relay policy architecture:** A high level goal setter π_θ takes high level goal s_g^h and sets goals s_g^l for a lower level policy π_ϕ, which acts for a fixed time horizon before resampling s_g^l

Hierarchical Imitation Learning

Algorithm 2 Relay data relabeling for RIL low level

Require: Demonstrations $D = \{\tau_0, \tau_1, ...\tau_N\}$

for $n = 1...N$ **do**
  for $t = 1...t_n$ **do**
    for $w = 1...W_l$ **do**
      Add $(s_t^n, a_t^n, s_{t+w}^n)$ to D_l
    end for
  end for
end for

Algorithm 3 Relay data relabeling for RIL high level

Require: Demonstrations $D = \{\tau_0, \tau_1, ...\tau_N\}$

for $n = 1...N$ **do**
  for $t = 1...t_n$ **do**
    for $w = 1...W_h$ **do**
      Add $(s_t^n, s_{t+\min(w,W_l)}^n, s_{t+w}^n)$ to D_h
    end for
  end for
end for

Given these relay-data-relabeled datasets, we train π_θ^l and π_θ^h by maximizing the likelihood of the actions taken given the corresponding states and goals:

$$\max_{\phi,\theta} \mathbb{E}_{(s,a,s_g^l)\sim D_l}[\log \pi_\phi(a|s, s_g^l)] + \mathbb{E}_{(s,s_g^l,s_g^h)\sim D_h}[\log \pi_\theta(s_g^l|s, s_g^h)]. \quad (1)$$

This procedure gives us an initialization for both the low-level and the high-level policies, without the requirement for any explicit goal labeling from a human demonstrator. As we show in our

Algorithm 1 Relay Policy Learning

Require: Unstructured pool of demonstrations $D = \{\tau_0, \tau_1, ...\tau_N\}$

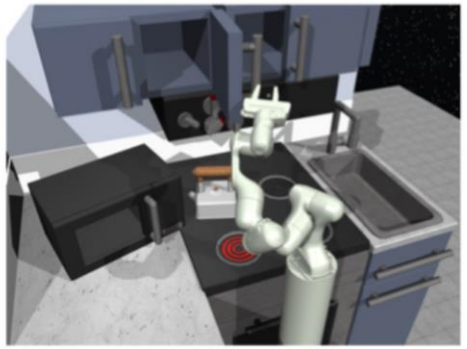
1: Relabel goals in demonstration trajectories using Algorithm 2, 3 to extract D_l, D_h
2: **Relay Imitation Learning:** Train π_θ^h and π_ϕ^l using Eqn 1
3: **while** not done **do**
4: Collect on-policy experience with π_θ^h and π_ϕ^l for high level goals different s_g^h
5: [Optional] Relabel this experience (Sec. 4.3), and add to D_l, D_h
6: Update the policy via policy gradient update using Eqn 2, 3.
7: **end while**
8: Distill fine-tuned policies into a single multi-goal policy

$$\nabla_\phi J_l = \mathbb{E}[\nabla_\phi \log \pi_\phi^l(a|s, s_g^l) \sum_t r_l(s_t, a_t, s_g^l)] + \lambda_l \mathbb{E}_{(s,a,s_g^l)\sim\mathcal{D}_l}[\nabla_\phi \log \pi_\phi^l(a|s, s_g^l)] \tag{2}$$

$$\nabla_\theta J_h = \mathbb{E}[\nabla_\theta \log \pi_\theta^h(s_g^l|s, s_g^h) \sum_t r_h(s_t, s_g^l, s_g^h)] + \lambda_h \mathbb{E}_{(s,s_g^l,s_g^h)\sim\mathcal{D}_h}[\nabla_\theta \log \pi_\theta^h(s_g^l|s, s_g^h)]. \tag{3}$$

Results

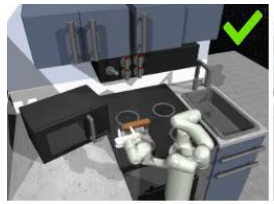
Microwave, Kettle, Light, Slider



Kettle, Bottom Burner, Slider, Cabinet

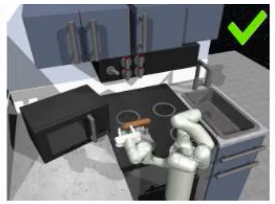
Top Burner, Bottom Burner, Slider, Cabinet

Microwave, Kettle, Top Burner, Light



M, K, TB, L

BB, TB, S, C



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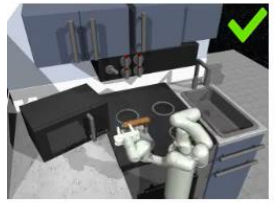

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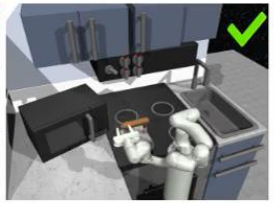
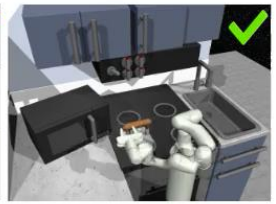
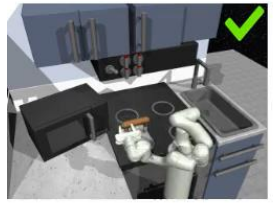


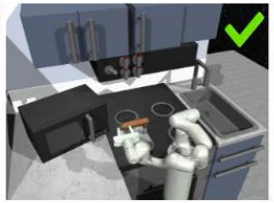
M, BB, L, S



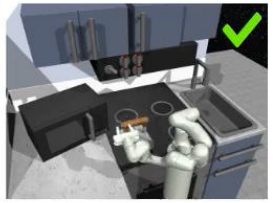
K, BB, TB, S



K, TB, L, S



M, L, S, C



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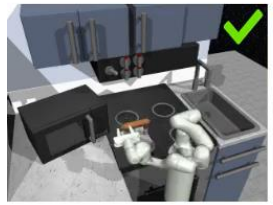
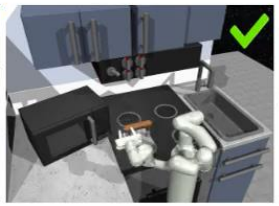
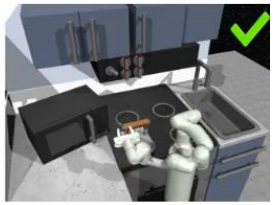


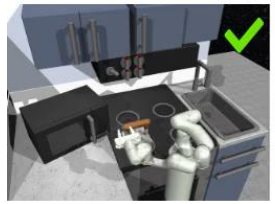
M, BB, TB,S



M, K, BB, C



M, BB, TB, C

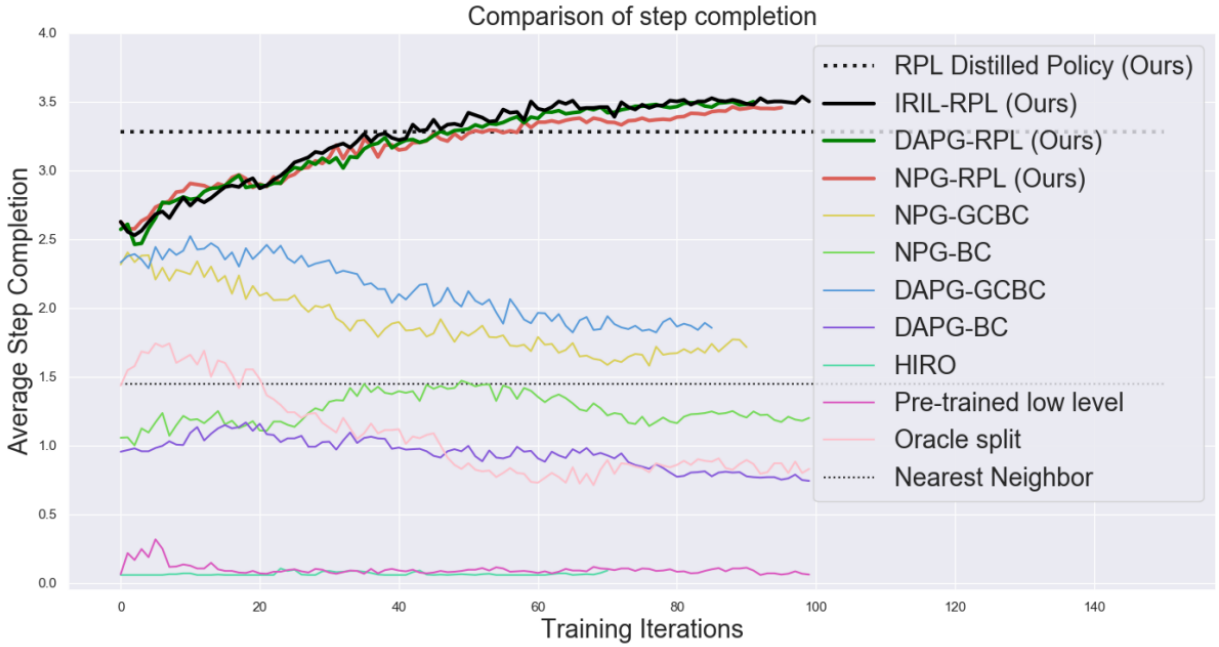


M, K, BB, S

Key

M = microwave
K = Kettle
BB = Bottom Burner
TB = Top Burner
L = Light
S = Slider
C = Hinge Cabinet

Results


Comparison of step completion
Average Step Completion
Training Iterations
RPL Distilled Policy (Ours)
IRIL-RPL (Ours)
DAPG-RPL (Ours)
NPG-RPL (Ours)
NPG-GCBC
NPG-BC
DAPG-GCBC
DAPG-BC
HIRO
Pre-trained low level
Oracle split
Nearest Neighbor


Comparison of success rate
Success Percentage
Training Iterations
RPL Distilled Policy (Ours)
IRIL-RPL (Ours)
DAPG-RPL (Ours)
NPG-RPL (Ours)
NPG-GCBC
NPG-BC
DAPG-GCBC
DAPG-BC
HIRO
Pre-trained low level
Oracle split
Nearest Neighbor

Appendix

Today's agenda

- Respecting demonstrations by a large margin (DQN with demonstrations)
- Demonstrating both actions and Q-values (AggreVaTe)
- Autonomous driving for high-speed racecars
- Conditional imitation learning
- End-to-end neural motion planner

Acknowledgments
Today's slides are based on student presentations from 2019 by: Bryan Chan, Chandripal Budnarain, Renato Fereira, David Acuna, Brenna Li, Wei Cui

AggreVaTe:

Reinforcement and Imitation Learning via Interactive No-Regret Learning

CSC 2621

Renato Ferreira Pinto Junior

Stéphane Ross & J. Andrew Bagnell (2014)

Pick one:

Main idea

- DAgger aims to minimize disagreement with expert
  - What if it's easier to imitate the expert in an *unsafe* situation than in *safe* ones?

Main idea

- DAgger aims to minimize disagreement with expert
  - What if it's easier to imitate the expert in an *unsafe* situation than in *safe* ones?
  - No consideration of *cost-to-go* of learned policy

Main idea

- DAgger aims to minimize disagreement with expert
  - What if it's easier to imitate the expert in an *unsafe* situation than in *safe* ones?
- Instead, AggreVaTe (*Aggregate Values to Imitate*):
  - Minimizes expert's *cost-to-go*

Algorithm

Algorithm 1 AGGREVATE: Imitation Learning with Cost-To-Go

Initialize $\mathcal{D} \leftarrow \emptyset$, $\hat{\pi}_1$ to any policy in Π.
for $i = 1$ **to** N **do**
  Let $\pi_i = \beta_i \pi^* + (1 - \beta_i)\hat{\pi}_i$ #Optionally mix in expert's own behavior.
  Collect m data points as follows:
  for $j = 1$ **to** m **do**
    Sample uniformly $t \in \{1, 2, \ldots, T\}$.
    Start new trajectory in some initial state drawn from initial state distribution
    Execute current policy π_i up to time $t - 1$.
    Execute some exploration action a_t in current state s_t at time t
    Execute expert from time $t + 1$ to T, and observe estimate of cost-to-go $\hat{Q}$ starting at time t
  end for
  Get dataset $\mathcal{D}_i = \{(s, t, a, \hat{Q})\}$ of states, times, actions, with expert's cost-to-go.
  Aggregate datasets: $\mathcal{D} \leftarrow \mathcal{D} \bigcup \mathcal{D}_i$.
  Train cost-sensitive classifier $\hat{\pi}_{i+1}$ on $\mathcal{D}$
    (*Alternately: use any online learner on the data-sets $\mathcal{D}_i$ in sequence to get $\hat{\pi}_{i+1}$*)
end for
Return best $\hat{\pi}_i$ on validation.

No-Regret Online Learners

Intuition: No matter what the distribution of input data, your online policy/classifier will do asymptotically as well as the best-in-hindsight policy/classifier.

$$r_N = \frac{1}{N}\sum_{i=1}^{N} l_i(\pi_i) - \min_{\pi \in \Pi}\left[\frac{1}{N}\sum_{i=1}^{N} l_i(\pi)\right]$$

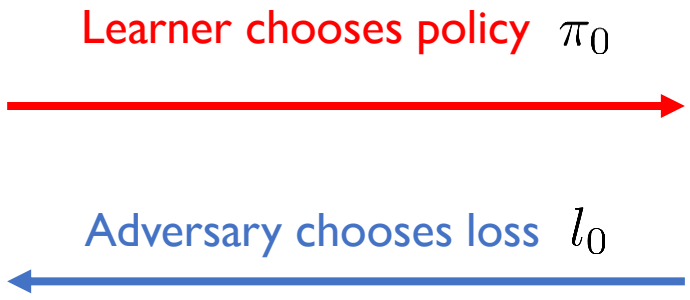
Policy has access to data up to round i

Policy has access to data up to round N

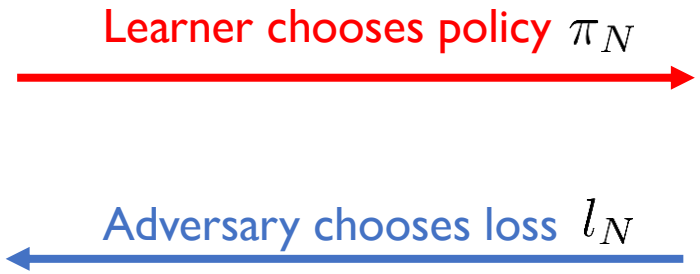
Loss function at round i

No-regret: $\lim_{N\to\infty} r_N = 0$

Online Learning



Learner / Policy Optimizer **Adversary**



Regret $r_N = \frac{1}{N}\sum_{i=1}^{N} l_i(\pi_i) - \min_{\pi\in\Pi}\left[\frac{1}{N}\sum_{i=1}^{N} l_i(\pi)\right]$

A no-regret online learning algorithm

Assume the learner has seen losses during rounds 0…t-1. What policy can the learner pick next?

Follow-The-Leader $\pi_t = \text{argmin}_{\pi \in \Pi} \left[\sum_{i=1}^{t-1} l_i(\pi) \right]$ (DAgger is equivalent to FTL)

Theorem (FTL): if Π is convex and the loss function l_i is strongly convex for all i, then we have:

$$r_N = \frac{1}{N} \sum_{i=1}^{N} l_i(\pi_i) - \min_{\pi \in \Pi} \left[\frac{1}{N} \sum_{i=1}^{N} l_i(\pi) \right] = O\left(\frac{\log N}{N} \right)$$

Analysis

- Classification regret: best in policy class compared to expert

$$\epsilon_{\text{class}} = \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^{N} \mathbb{E}_{t \sim U(1:T), s \sim d^t_{\pi_i}} [Q^*_{T-t+1}(s, a) - \min_a Q^*_{T-t+1}(s, a)]$$

$$a = \pi_i(s)$$

Analysis

- Classification regret: best in policy class compared to expert

$$\epsilon_{\text{class}} = \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^{N} \mathbb{E}_{t \sim U(1:T), s \sim d^t_{\pi_i}} [Q^*_{T-t+1}(s,a) - \min_a Q^*_{T-t+1}(s,a)]$$

- Online learning regret: learned policies compared to best in policy class

$$\epsilon_{\text{regret}} = \frac{1}{N} [\sum_{i=1}^{N} \ell_i(\hat{\pi}_i) - \min_{\pi \in \Pi} \sum_{i=1}^{N} \ell_i(\pi)]$$

$$\ell_i(\pi) = \mathbb{E}_{t \sim U(1:T), s \sim d^t_{\pi_i}} [Q^*_{T-t+1}(s, \pi)]$$

Analysis

- Classification regret: best in policy class compared to expert

$$\epsilon_{\text{class}} = \min_{\pi \in \Pi} \frac{1}{N} \sum_{i=1}^{N} \mathbb{E}_{t \sim U(1:T), s \sim d^t_{\pi_i}} [Q^*_{T-t+1}(s,a) - \min_a Q^*_{T-t+1}(s,a)]$$

- Online learning regret: learned policies compared to best in policy class

$$\epsilon_{\text{regret}} = \frac{1}{N} [\sum_{i=1}^{N} \ell_i(\hat{\pi}_i) - \min_{\pi \in \Pi} \sum_{i=1}^{N} \ell_i(\pi)]$$

$$\ell_i(\pi) = \mathbb{E}_{t \sim U(1:T), s \sim d^t_{\pi_i}} [Q^*_{T-t+1}(s, \pi)]$$

- Guarantee:

Theorem 2.1. *After N iterations of* AGGREVATE*:*

$$J(\hat{\pi}) \leq J(\overline{\pi}) \leq J(\pi^*) + T[\epsilon_{class} + \epsilon_{regret}] + O\left(\frac{Q_{\max} T \log T}{\alpha N}\right).$$

Thus if a no-regret online algorithm is used to pick the sequence of policies $\hat{\pi}_{1:N}$, then as the number of iterations $N \to \infty$:

$$\lim_{N \to \infty} J(\overline{\pi}) \leq J(\pi^*) + T\epsilon_{class}$$

Conclusion

- Optimizes for *cost-to-go* rather than naive imitation
  - Prefer actions in which it's possible to act optimally
  - Imitate expert *toward favourable situations*

Conclusion

- Optimizes for *cost-to-go* rather than naive imitation
  - Prefer actions in which it's possible to act optimally
  - Imitate expert *toward favourable situations*
- Limitations:
  - Expensive data collection (one data point per trajectory!)

Today's agenda

- Respecting demonstrations by a large margin (DQN with demonstrations)
- Demonstrating both actions and Q-values (AggreVaTe)
- Autonomous driving for high-speed racecars
- Conditional imitation learning
- End-to-end neural motion planner

Acknowledgments
Today's slides are based on student presentations from 2019 by: Bryan Chan, Chandripal Budnarain, Renato Fereira, David Acuna, Brenna Li, Wei Cui

Agile Autonomous Driving using End-to-End Deep Imitation Learning

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Presented by David Acuna and Brenna Li

Problem Formulation

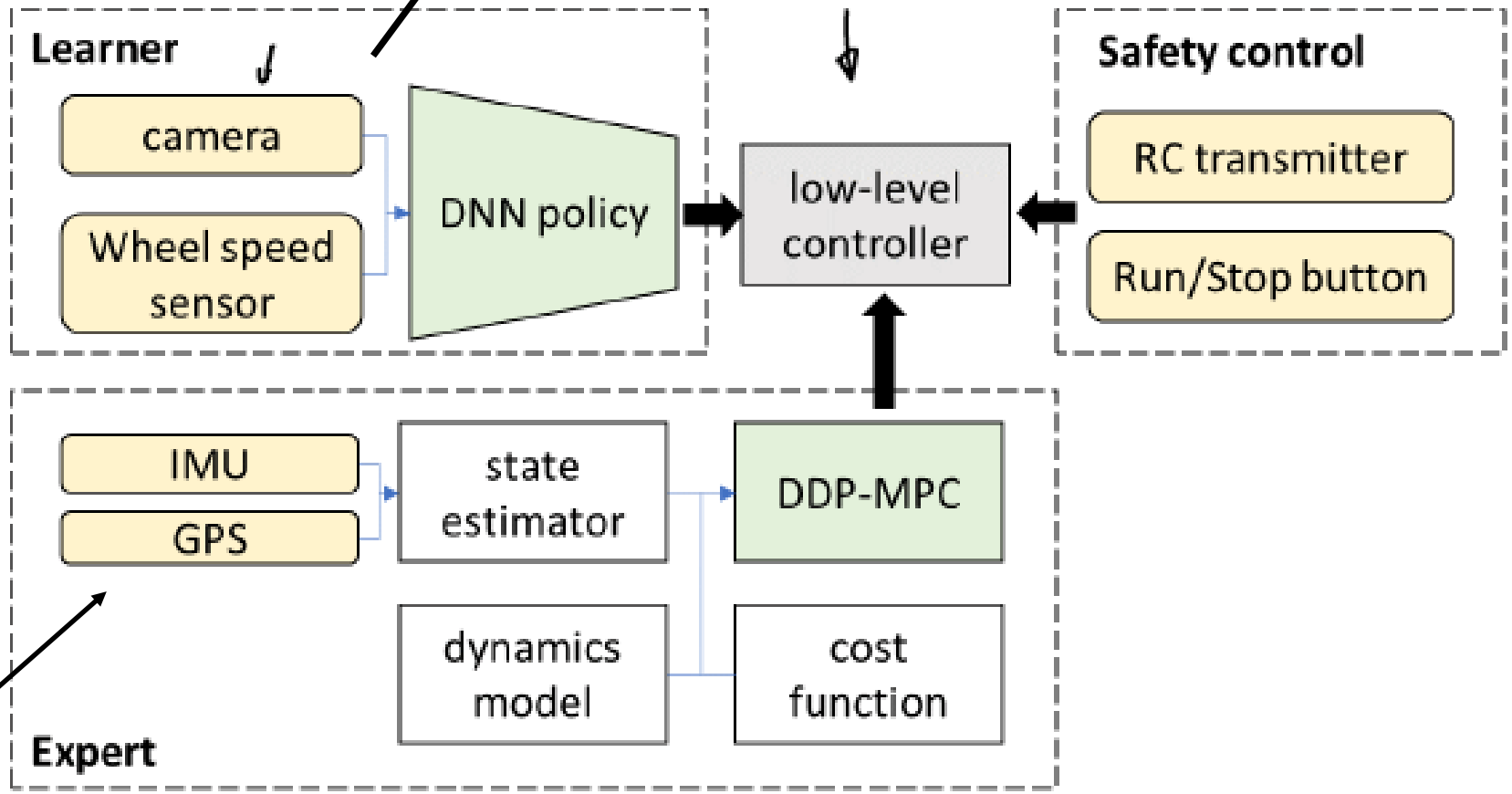
training/test track

off-the-road real-word scenario.
high-speed is a must

Auto-Rally car

Problem Formulation

cheap sensors. ~ $500
NN learns from raw images and speed sensor



expensive sensors
model predictive control
~ $6,000

IMU=Inertial Measurement Units
GPS=Global Positioning System

Formulation

$$\min_\pi J(\pi), \quad J(\pi) := \mathbb{E}_{\rho_\pi}\left[\sum_{t=0}^{T-1} c(s_t, a_t)\right],$$

- needs to account for high-speed
- involves a physical robot

$$J(\pi) = J(\pi') + \mathbb{E}_{s,t\sim d_\pi}\mathbb{E}_{a\sim\pi_s}[A^t_{\pi'}(s,a)]$$

$$A^t_{\pi'}(s,a) = Q^t_{\pi'}(s,a) - V^t_{\pi'}(s)$$

Advantage of taking action a at state s over what policy dictates

Formulation

$$J(\pi) - J(\pi^*)$$

expert

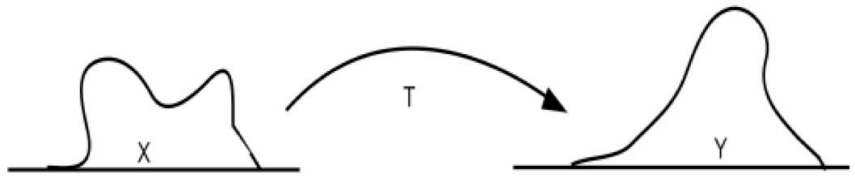
$$= \mathbb{E}_{s,t\sim d_\pi}\left[\mathbb{E}_{a\sim\pi_s}[Q^t_{\pi^*}(s,a)] - \mathbb{E}_{a^*\sim\pi^*_s}[Q^t_{\pi^*}(s,a^*)]\right]$$

Advantage of taking action a at state s over what expert's policy dictates

Wasserstein Distance

$$D_W(p,q) := \sup_{f:\mathrm{Lip}(f(\cdot))\leq 1} \mathbb{E}_{x\sim p}[f(x)] - \mathbb{E}_{x\sim q}[f(x)]$$

$$= \inf_{\gamma\in\Gamma(p,q)} \int_{\mathcal{M}\times\mathcal{M}} d(x,y)d\gamma(x,y),$$



Formulation

$$
\begin{aligned}
& J(\pi) - J(\pi^*) \\
& = \mathbb{E}_{s,t\sim d_\pi}\left[\mathbb{E}_{a\sim\pi_s}[Q^t_{\pi^*}(s,a)] - \mathbb{E}_{a^*\sim\pi^*_s}[Q^t_{\pi^*}(s,a^*)]\right] \\
& \leq C_{\pi^*}\mathbb{E}_{s,t\sim d_\pi}\left[D_W(\pi,\pi^*)\right] \\
& \leq C_{\pi^*}\mathbb{E}_{s,t\sim d_\pi}\mathbb{E}_{a\sim\pi_s}\mathbb{E}_{a^*\sim\pi^*_s}[\|a-a^*\|],
\end{aligned}
$$

learner policy expert's policy

$$
\min_\pi \mathbb{E}_{\rho_\pi}\left[\sum_{t=1}^T \hat{c}(s_t,a_t)\right] . \longrightarrow \hat{c}(s,a) = \mathbb{E}_{a^*\sim\pi^*_s}[\|a-a^*\|]
$$

Online Imitation Learning Problem (DAgger)

Online Imitation Learning

$$\min_\pi \mathbb{E}_{\rho_\pi}\left[\sum_{t=1}^{T} \hat{c}(s_t, a_t)\right] . \longrightarrow \hat{c}(s, a) = \mathbb{E}_{a^* \sim \pi_s^*}[\|a - a^*\|]$$

online IL problem

DAgger

Sequence of
Supervised Learning Problems

$$\pi_i = \arg\min_\pi \mathbb{E}_{\mathcal{D}}[\hat{c}(s_t, a_t)],$$

Batch Imitation Learning

Flipping the policies

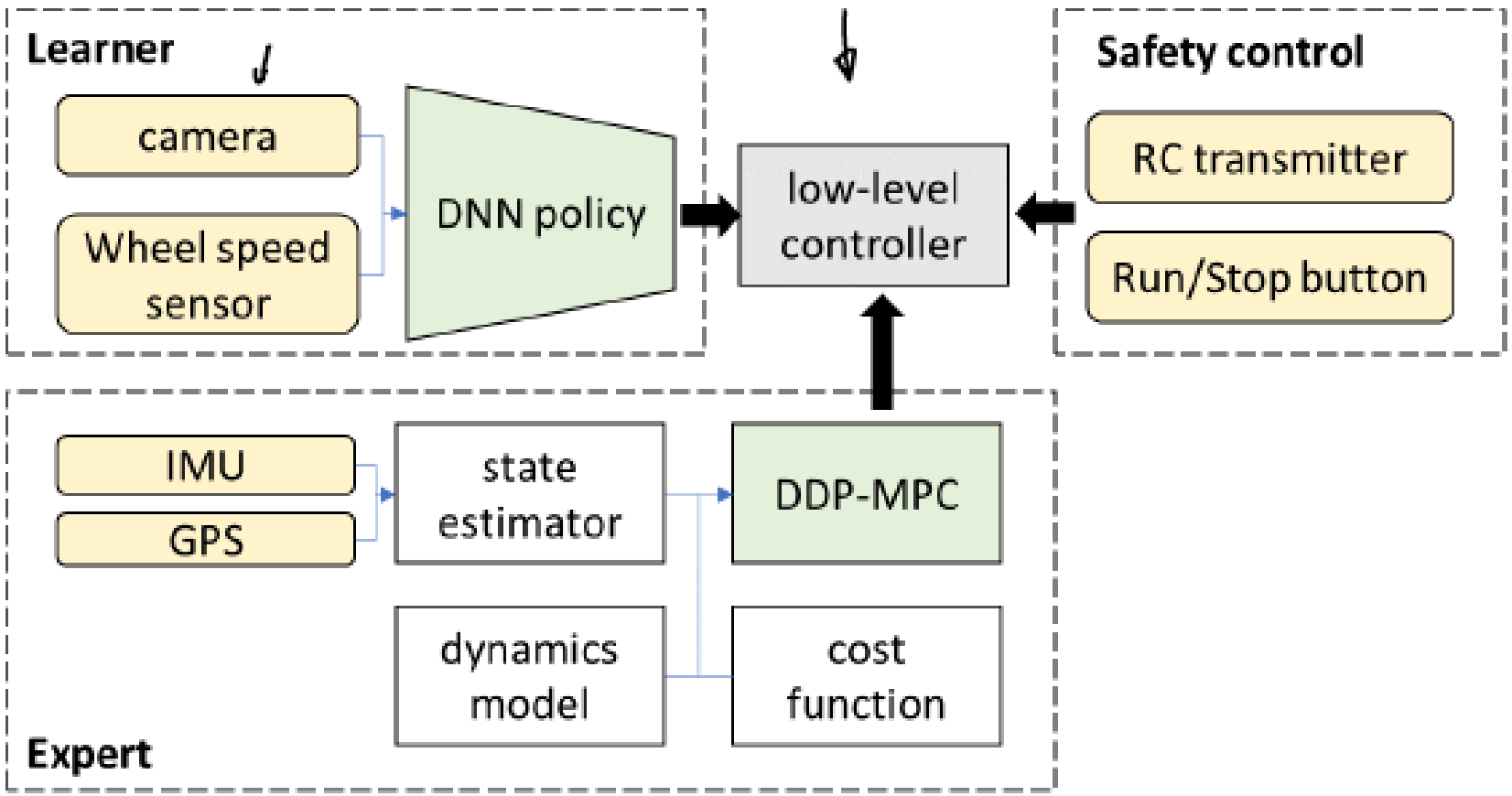
$$
\begin{aligned}
& J(\pi) - J(\pi^*) \\
& = \mathbb{E}_{s^*, t \sim d_{\pi^*}} \left[\mathbb{E}_{a \sim \pi_{s^*}} [Q_\pi^t(s^*, a)] - \mathbb{E}_{a^* \sim \pi^*_{s^*}} [Q_\pi^t(s^*, a^*)] \right] \\
& \leq \mathbb{E}_{s^*, t \sim d_{\pi^*}} \mathbb{E}_{a^* \sim \pi^*_{s^*}} \left[C_\pi^t(s^*) \tilde{c}_\pi(s^*, a^*) \right] . \qquad (8)
\end{aligned}
$$

expert policy expert policy

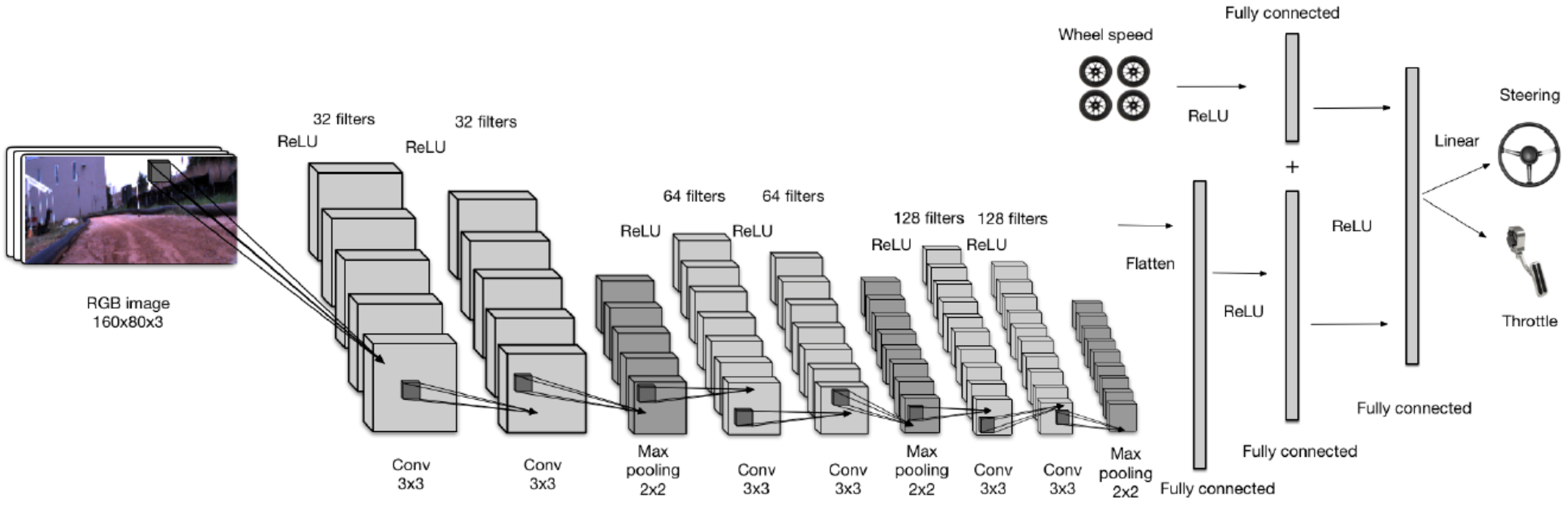
$$
\min_\pi \mathbb{E}_{\rho_{\pi^*}} \left[\sum_{t=1}^{T} \tilde{c}_\pi(s_t^*, a_t^*) \right]
$$

This corresponds to supervised learning (expectation is defined by a fixed policy)

System Diagram

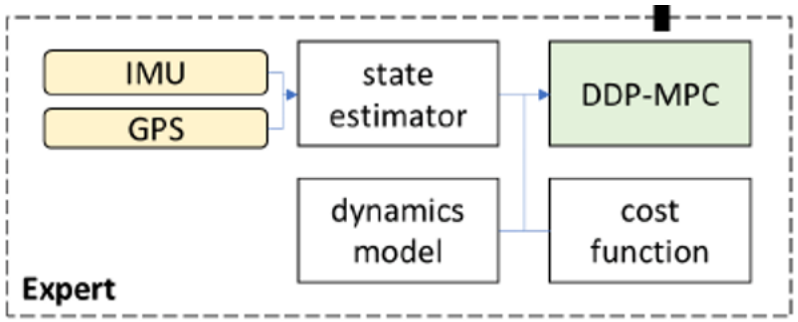


DNN Control Policy

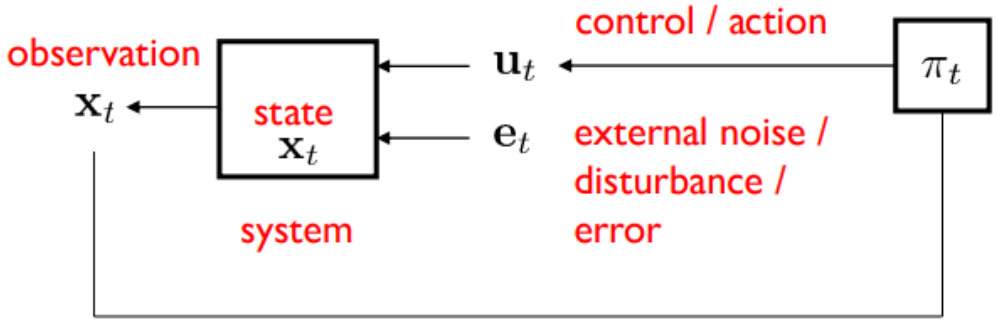


π

Expert – recall control



Optimal Control



$$\underset{\pi_0,\ldots,\pi_{T-1}}{\text{minimize}} \quad \mathbb{E}_{\mathbf{e}_t}\left[\sum_{t=0}^{T} c(\mathbf{x}_t, \mathbf{u}_t)\right]$$

$$\text{subject to} \quad \mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{u}_t, \mathbf{e}_t) \quad \text{known dynamics}$$

$$\mathbf{u}_t = \pi_t(\mathbf{x}_{0:t}, \mathbf{u}_{0:t-1})$$

control law / policy

Sparse Spectrum Gaussian Process

Expert – MPC

Differential Dynamic Program (DDP) ~ Recall iLQR

Given an initial sequence of states $\bar{\mathbf{x}}_0, \ldots, \bar{\mathbf{x}}_N$ and actions $\bar{\mathbf{u}}_0, \ldots, \bar{\mathbf{u}}_N$

Linearize dynamics $f(\mathbf{x}_t, \mathbf{u}_t) \approx \tilde{f}(\delta\mathbf{x}_t, \delta\mathbf{u}_t) = \underbrace{f(\bar{\mathbf{x}}_t, \bar{\mathbf{u}}_t)}_{\mathbf{b}_t} + \underbrace{\frac{\partial f}{\partial \mathbf{x}}(\bar{\mathbf{x}}_t, \bar{\mathbf{u}}_t)}_{A_t}\underbrace{(\mathbf{x}_t - \bar{\mathbf{x}}_t)}_{\delta\mathbf{x}_t} + \underbrace{\frac{\partial f}{\partial \mathbf{u}}(\bar{\mathbf{x}}_t, \bar{\mathbf{u}}_t)}_{B_t}\underbrace{(\mathbf{u}_t - \bar{\mathbf{u}}_t)}_{\delta\mathbf{u}_t}$

Taylor expand cost $c(\mathbf{x}_t, \mathbf{u}_t) \approx \tilde{c}(\delta\mathbf{x}_t, \delta\mathbf{u}_t) = c(\bar{\mathbf{x}}_t, \bar{\mathbf{u}}_t) + \underbrace{\nabla_{\mathbf{x}_t, \mathbf{u}_t} c(\bar{\mathbf{x}}_t, \bar{\mathbf{u}}_t)}_{\mathbf{h}_t} \begin{bmatrix} \mathbf{x}_t - \bar{\mathbf{x}}_t \\ \mathbf{u}_t - \bar{\mathbf{u}}_t \end{bmatrix} + 1/2 \begin{bmatrix} \mathbf{x}_t - \bar{\mathbf{x}}_t \\ \mathbf{u}_t - \bar{\mathbf{u}}_t \end{bmatrix}^T \underbrace{\nabla^2_{\mathbf{x}_t, \mathbf{u}_t} c(\bar{\mathbf{x}}_t, \bar{\mathbf{u}}_t)}_{H_t} \begin{bmatrix} \mathbf{x}_t - \bar{\mathbf{x}}_t \\ \mathbf{u}_t - \bar{\mathbf{u}}_t \end{bmatrix}$

Use LQR backward pass on the approximate dynamics $\tilde{f}(\delta\mathbf{x}_t, \delta\mathbf{u}_t)$ and cost $\tilde{c}(\delta\mathbf{x}_t, \delta\mathbf{u}_t)$

Do a forward pass to get $\delta\mathbf{u}_t$ and $\delta\mathbf{x}_t$ and update state and action sequence $\bar{\mathbf{x}}_0, \ldots, \bar{\mathbf{x}}_N$ and $\bar{\mathbf{u}}_0, \ldots, \bar{\mathbf{u}}_N$

Related works:

TABLE I: Comparison of our method to prior work on IL for autonomous driving

Methods	Tasks	Observations	Action	Algorithm	Expert	Experiment
[1]	On-road low-speed	Single image	Steering	Batch	Human	Real &simulated
[23]	On-road low-speed	Single image & laser	Steering	Batch	Human	Real &simulated
[24]	On-road low-speed	Single image	Steering	Batch	Human	Simulated
[20]	Off-road low-speed	Left & right images	Steering	Batch	Human	Real
[33]	On-road unknown speed	Single image	Steering + break	Online	Pre-specified policy	Simulated
Our Method	Off-road high-speed	Single image + wheel speeds	Steering + throttle	Batch & online	Model predictive controller	Real & simulated

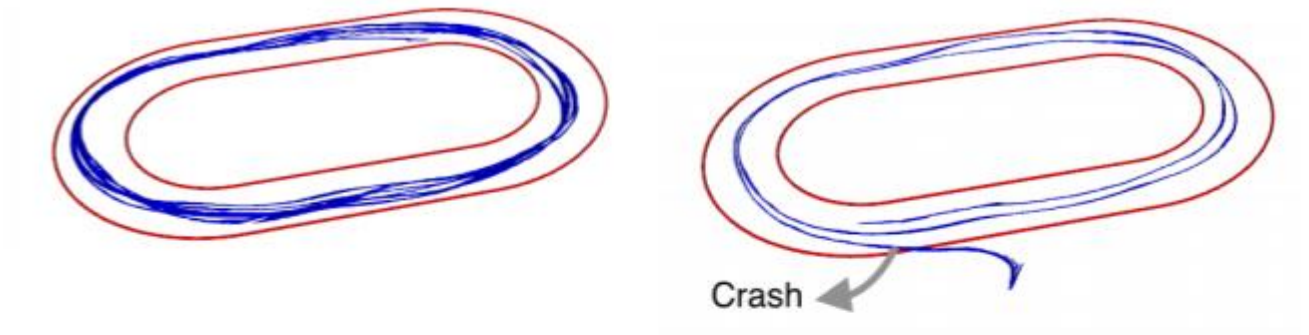
Experiment – Setup Experts

High Speed driving
at 7.5 m/s or 135 km / h

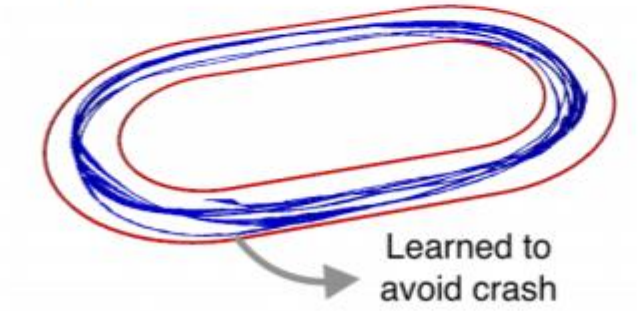
Cost for expert:

$$c(s_t, a_t) = \alpha_1 c_{\text{pos}}(s_t) + \alpha_2 c_{\text{spd}}(s_t) + \alpha_3 c_{\text{slip}}(s_t) + \alpha_3 c_{\text{act}}(a_t)$$

Experiment– learning trajectories



(a) MPC expert. (b) Batch IL.

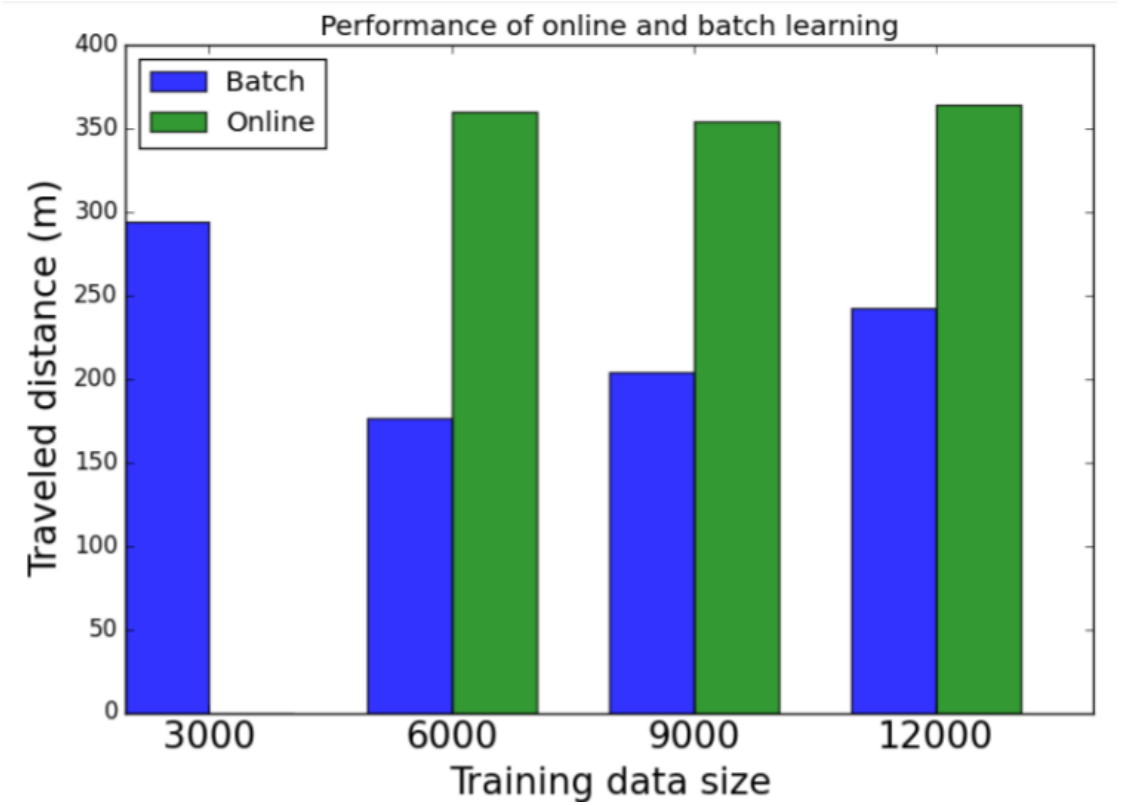


(c) Online IL.

Comparing – Loss (to expert)

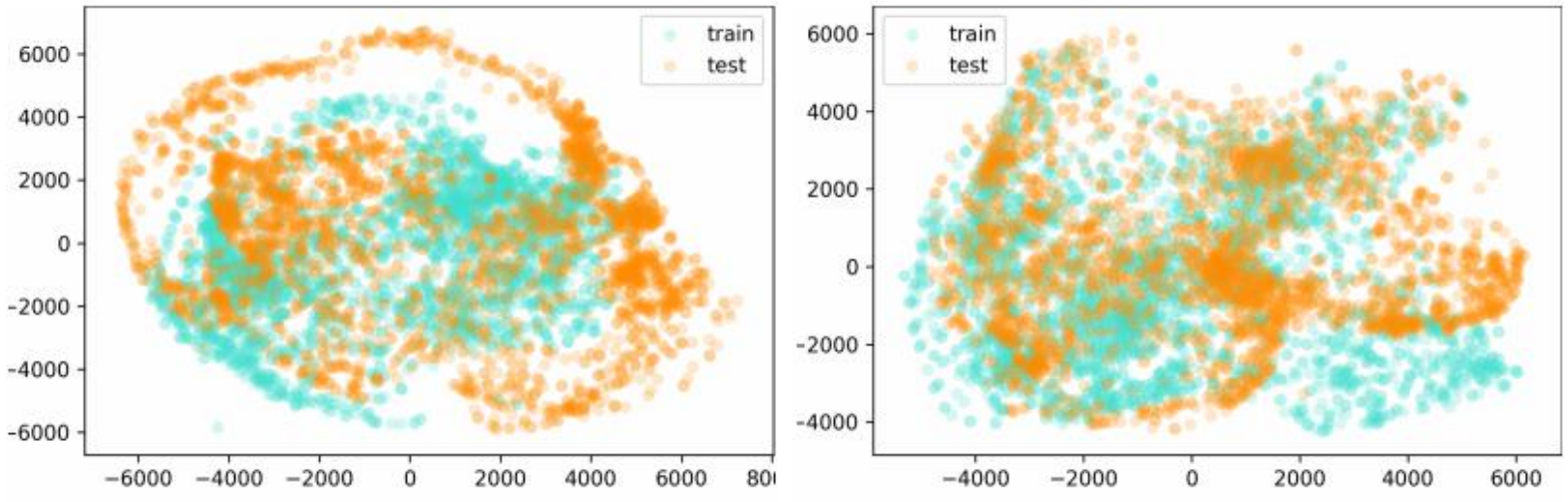
Policy	Avg. speed	Top speed	Training data	Completion ratio	Total loss	Steering/Throttle loss
Expert	6.05 m/s	8.14 m/s	N/A	100 %	0	0
Batch	4.97 m/s	5.51 m/s	3000	100 %	0.108	0.092/0.124
Batch	6.02 m/s	8.18 m/s	6000	51 %	0108	0.162/0.055
Batch	5.79 m/s	7.78 m/s	9000	53 %	0.123	0.193/0.071
Batch	5.95 m/s	8.01 m/s	12000	69 %	0.105	0.125/0.083
Online (1 iter)	6.02 m/s	7.88 m/s	6000	100 %	0.090	0.112/0.067
Online (2 iter)	5.89 m/s	8.02 m/s	9000	100 %	0.075	0.095/0.055
Online (3 iter)	6.07 m/s	8.06 m/s	12000	100 %	0.064	0.073/0.055

Comparing – distance travelled



Comparing – generalizability

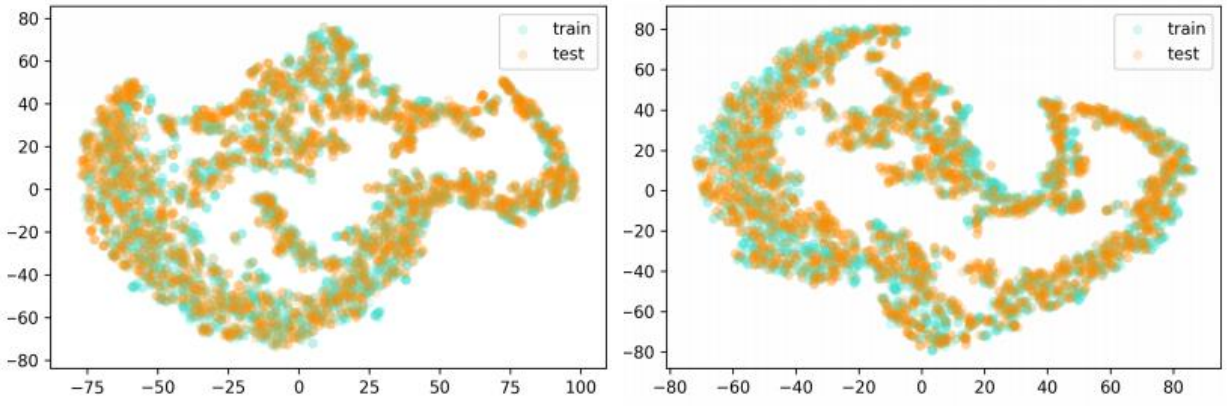
t-Distributed Stochastic Neighbor Embedding (t-SNE)



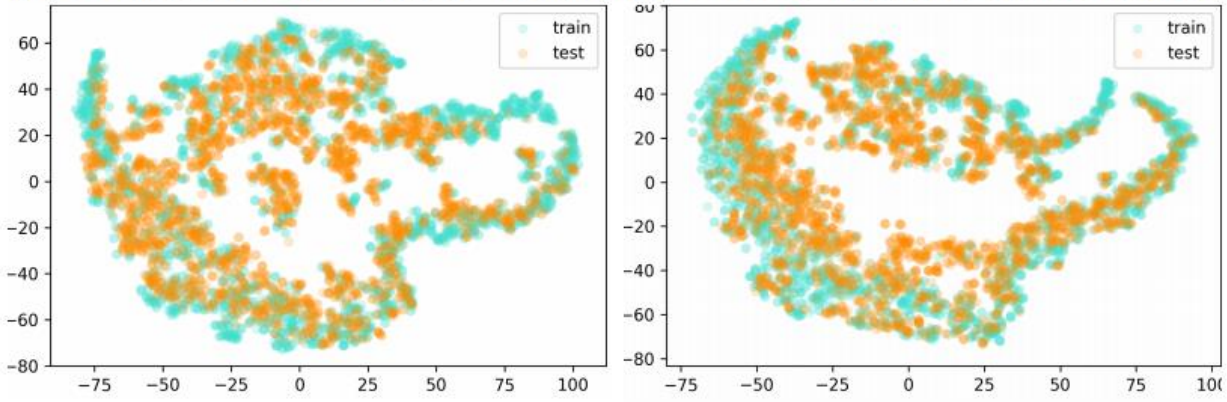
(a) Batch raw image

(b) Online raw image

Comparing – generalizability

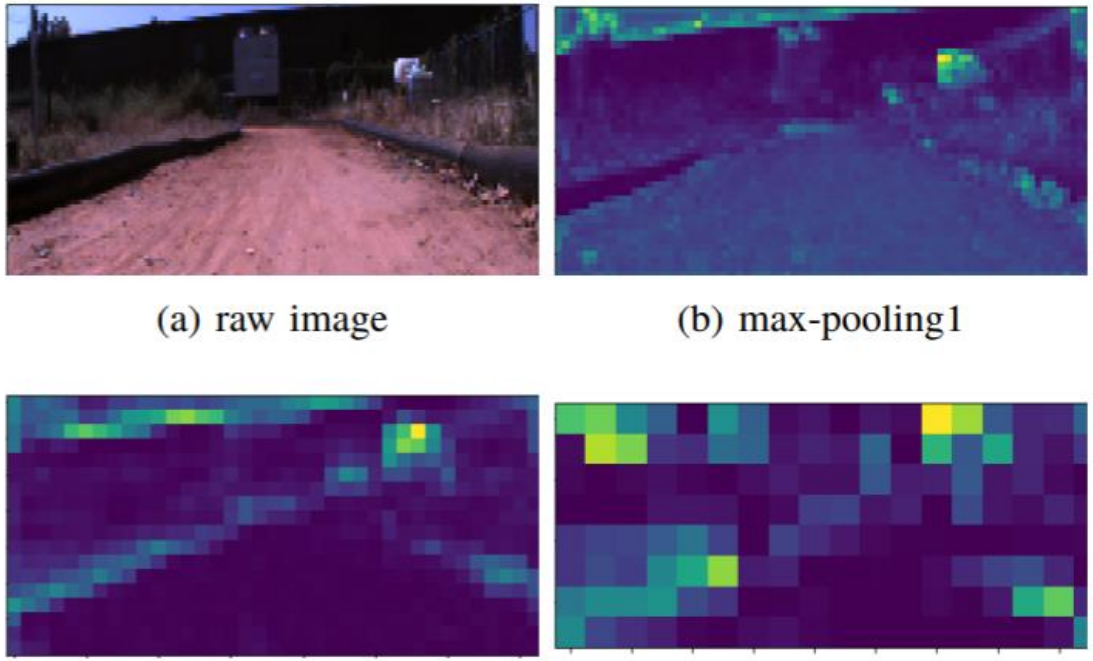


(a) Batch data wrt online model (b) Online data wrt online model



(c) Batch data wrt batch model (d) Online data wrt batch model

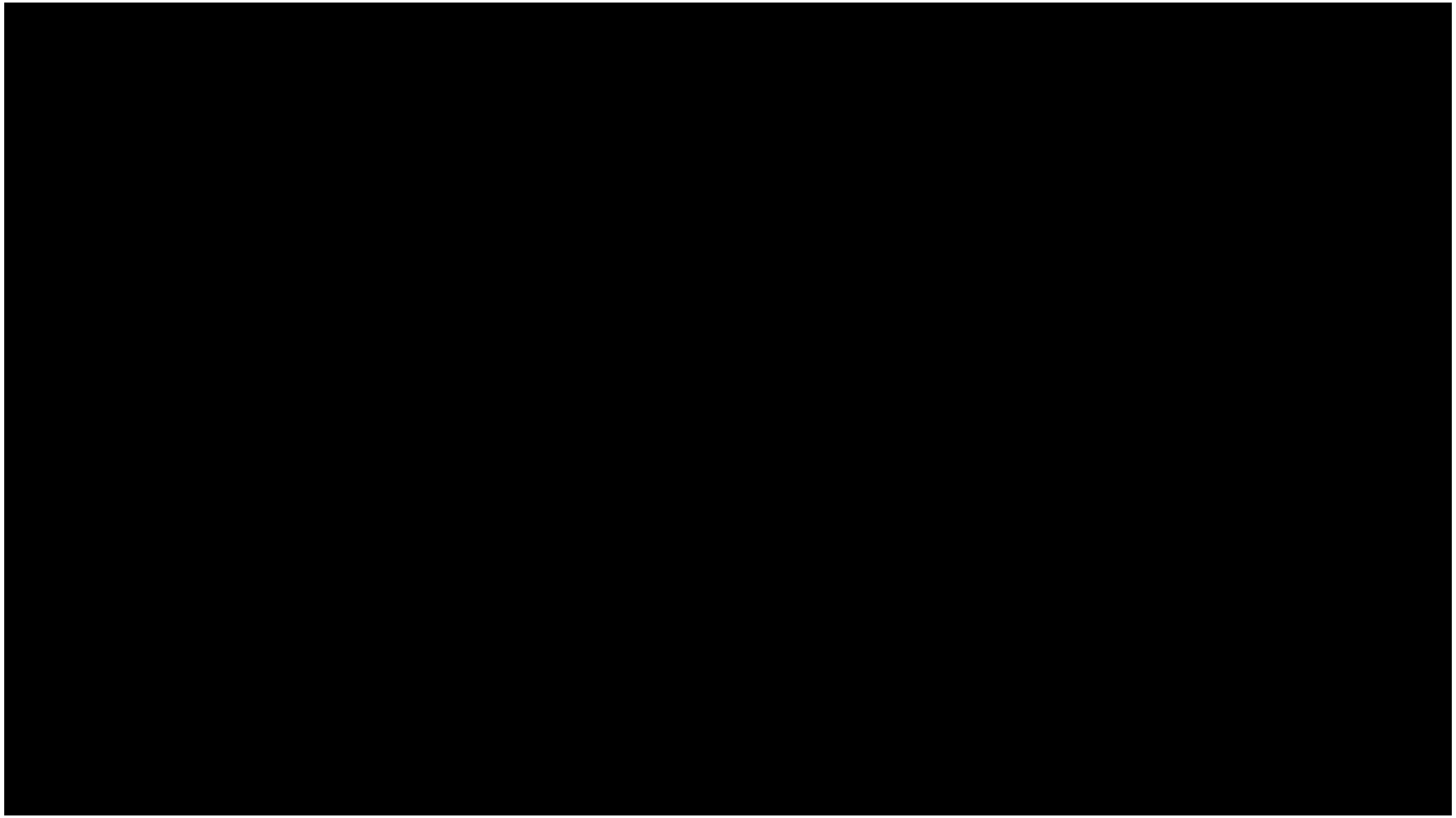
DNN – high and low capture



(a) raw image (b) max-pooling1

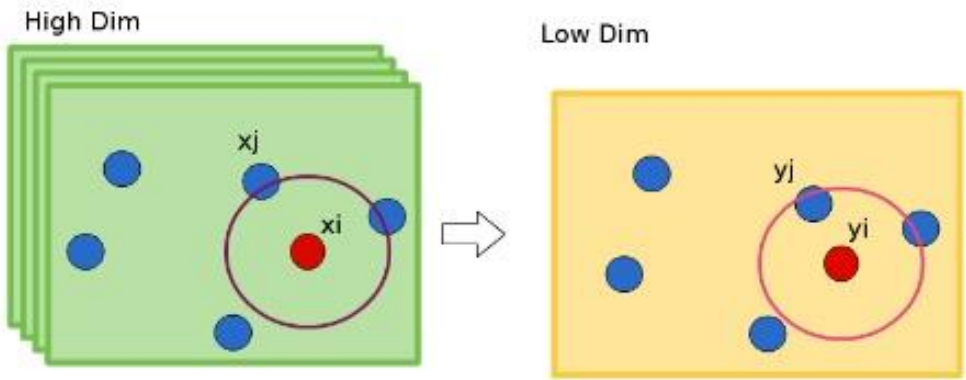
(c) max-pooling2 (d) max-pooling3

Fig. 9: The input RGB image and the averaged feature maps for each max-pooling layer.



Introduction

Measure pairwise similarities between high-dimensional and low-dimensonal objects



$$p_{j|i} = \frac{exp(-||x_i - x_j||^2/2\sigma_i^2)}{\sum_{k \neq i} exp(-||x_i - x_k||^2/2\sigma_i^2)}$$