Forsvarets forskningsinstitutt

Deep Learning for Control in Robotics

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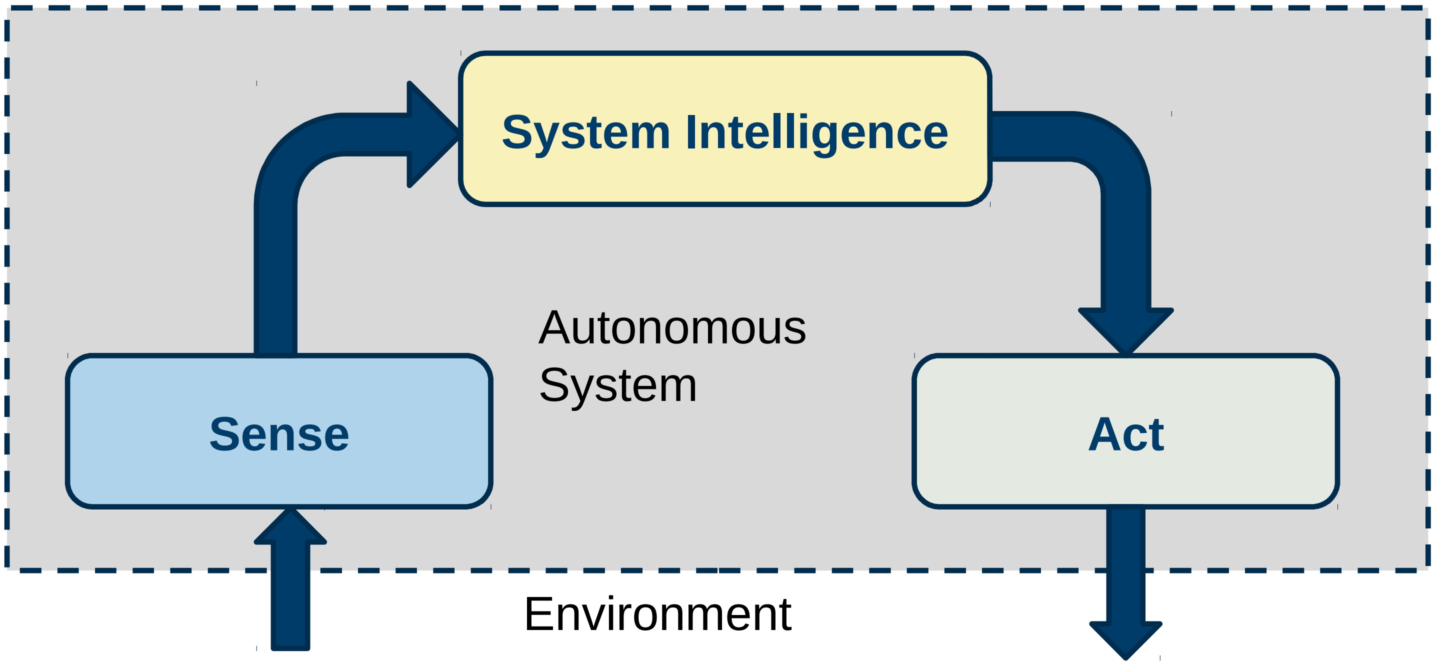
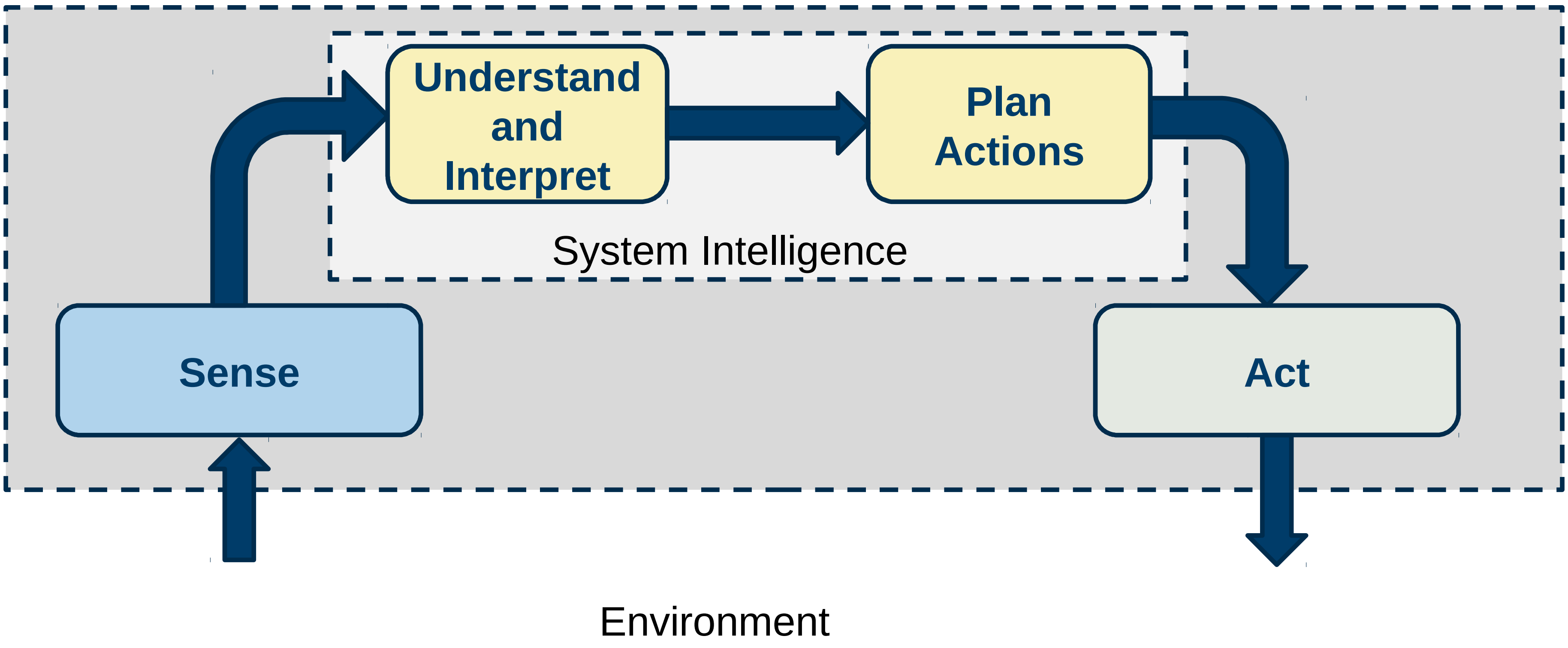
Robotics = Physical Autonomous Systems

- An autonomous system is a system that can automatically perform a predefined set of tasks under real world conditions
- Examples:
  - Autonomous vehicles (navigation)
  - Autonomous manipulator systems (manipulation)



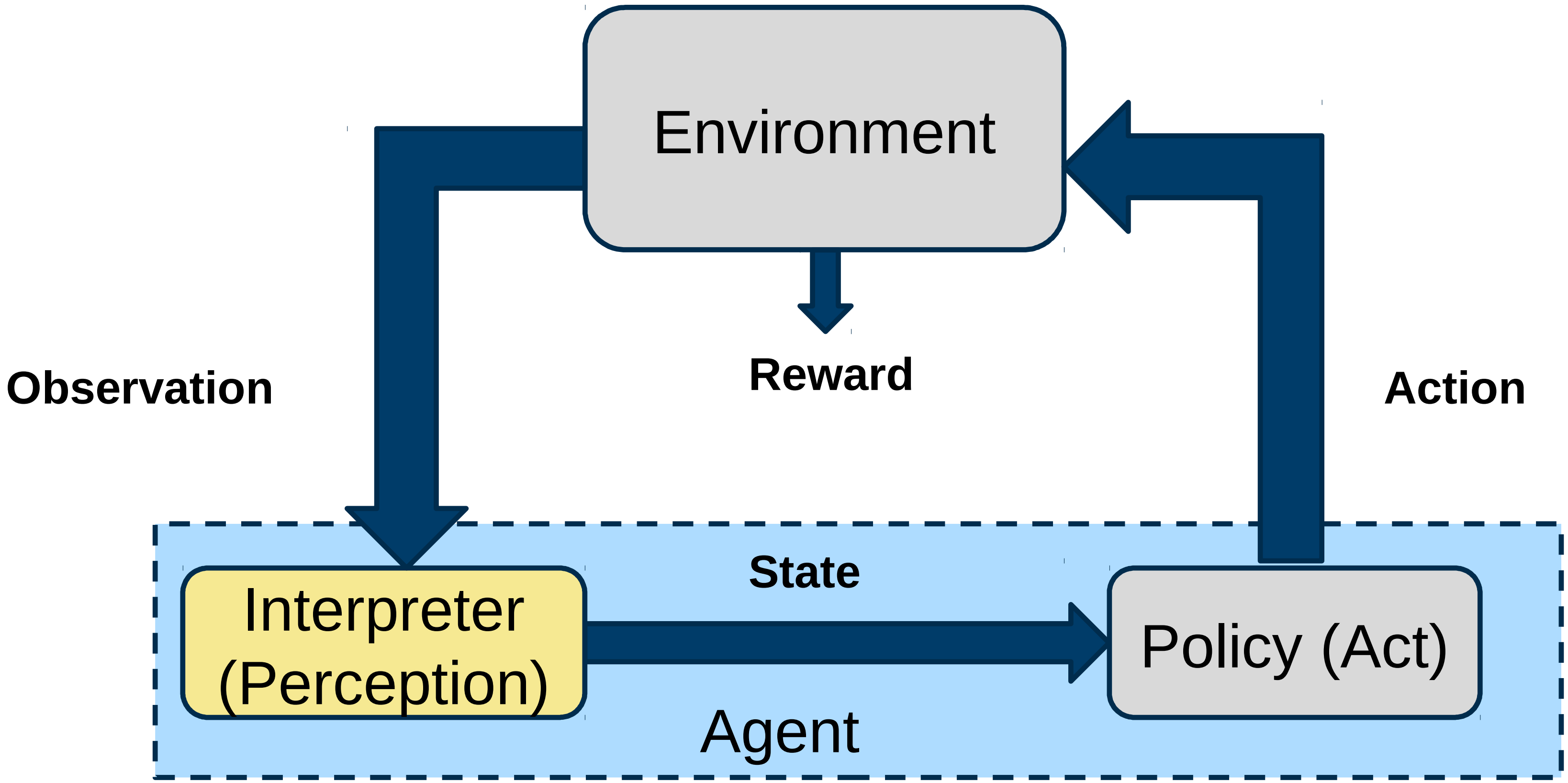
Designing Autonomous System Intelligence

- Main components
  - Understand/Interpret the sensor signals
  - Plan appropriate actions
- Going from manual design to automatic learning



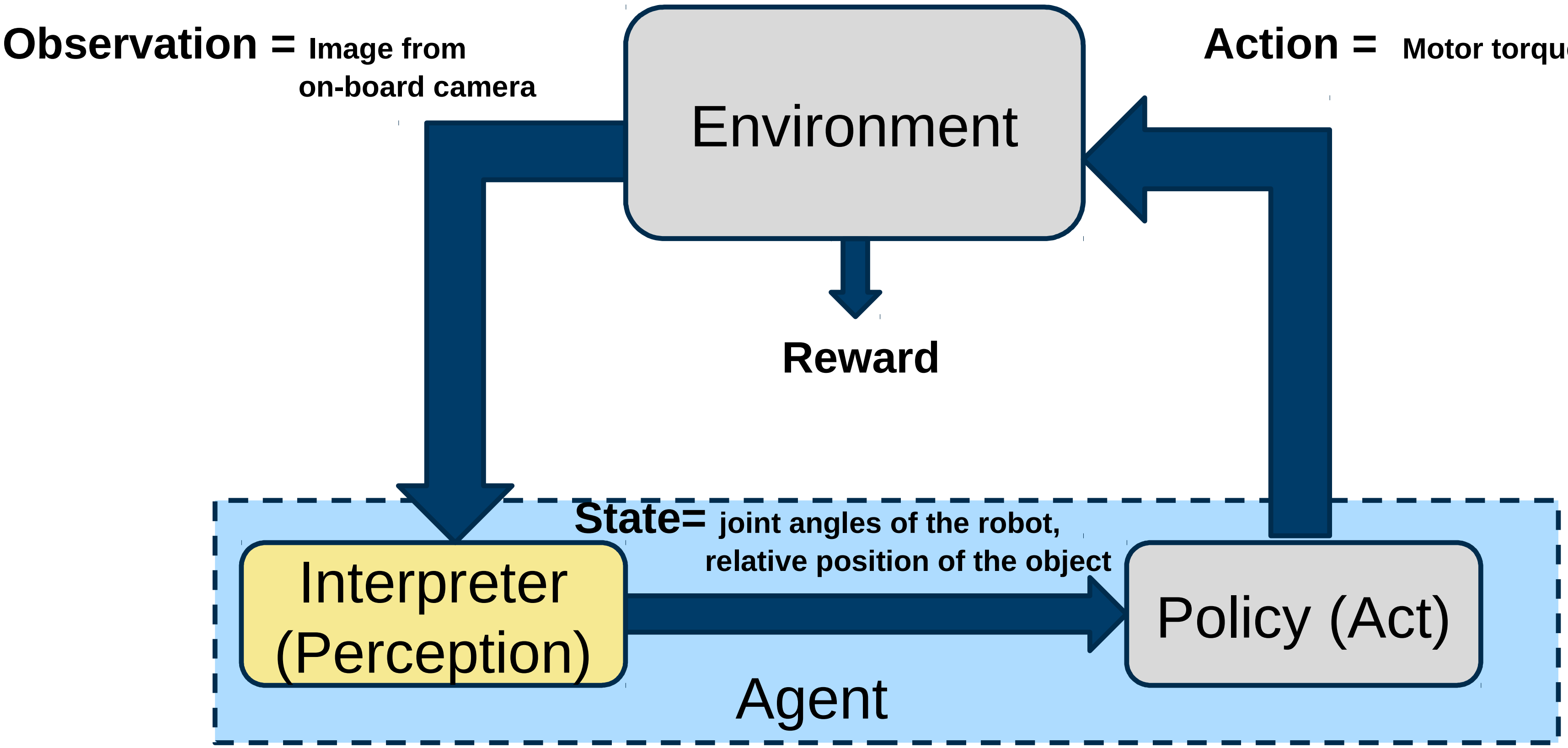
Reinforcement Learning

- We can cast the learning problem as a reinforcement learning problem



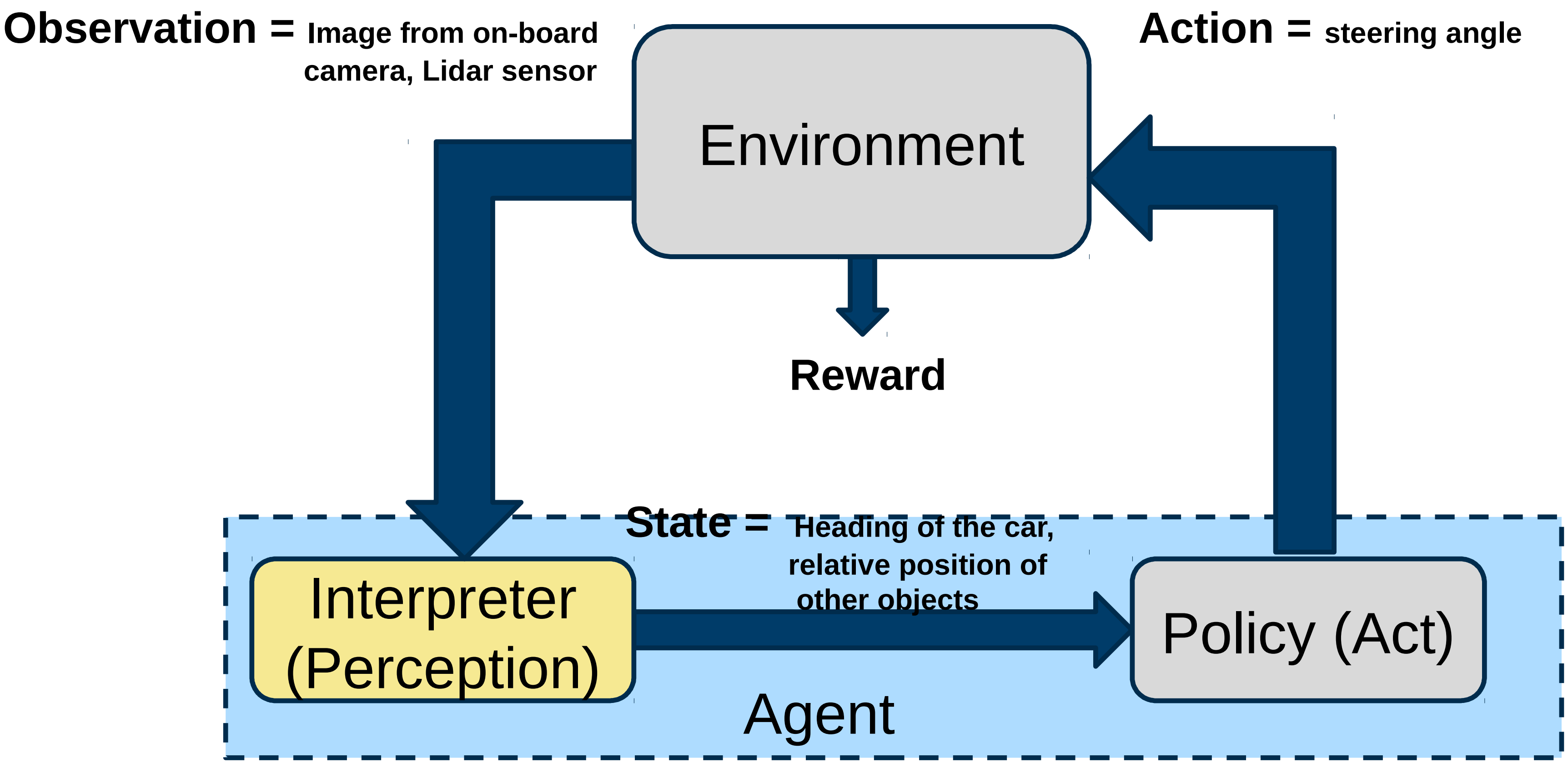
Example 1 (Manipulation)

- Controlling robotic arm



Example 2 (Navigation)

- Controlling an autonomous car



Learnable Modules

- Policy/Control (state-to-action)
- Perception (observations-to-state)
- Policy+Perception (observations-to-action)
- Environment model (action+ current state -to- next state)
- Reward function (action+ current state -to- reward/cost)
- Expected rewards (Value functions Q, V)

Learning Perception vs Control

- Data distribution
  - Perception learning uses iid assumption and it is reasonable
  - Control learning cannot use iid assumption, because data are correlated.
    - Errors can grow: **compounding errors**
- Supervision signal
  - Perception learning can be based on supervised learning
  - Control learning with direct supervision is not straight-forward.
- Data collection
  - Perception learning can use offline data
  - Control learning with offline data is difficult
    - Simulators
    - an lead to realty gap

Weaknesses of Reinforcement Learning

- Learning through mostly trial and error
  - High cost in terms of time and resources
- Need a suitable reward function (manually designed)
  - In many cases designing reward function difficult

Try to exploit other information in learning in addition to reinforcement learning

- Expert demonstrations
- Control theory

Main Approaches

- Manual design of actions (Learn perception only)
  - Mediated perception
  - Direct perception
- Learn actions (policy)
  - Pure reinforcement learning
    - DQN, DDPG,NAF,A3C,TRPO, PPO, ACKTR etc.
  - Optimal control and reinforcement learning
    - GPS (Guided Policy Search)
  - Pure expert demonstration based learning
    - Behavior cloning (Behavior reflex)
  - Combined expert demonstration and reinforcement learning
    - Maximum entropy inverse reinforcement learning
    - Guided Cost Learning (CGL)
    - Generative Adversarial Imitation Learning (GAIL)

Learn Perception, Manually Design Actions/Policy

Mediated Perception

Input Image

- Segmentation and detection
- Depth and 3D understanding
- Estimating your posistion and orientation (pose)
- Tracking and re-identification

Deep Learning

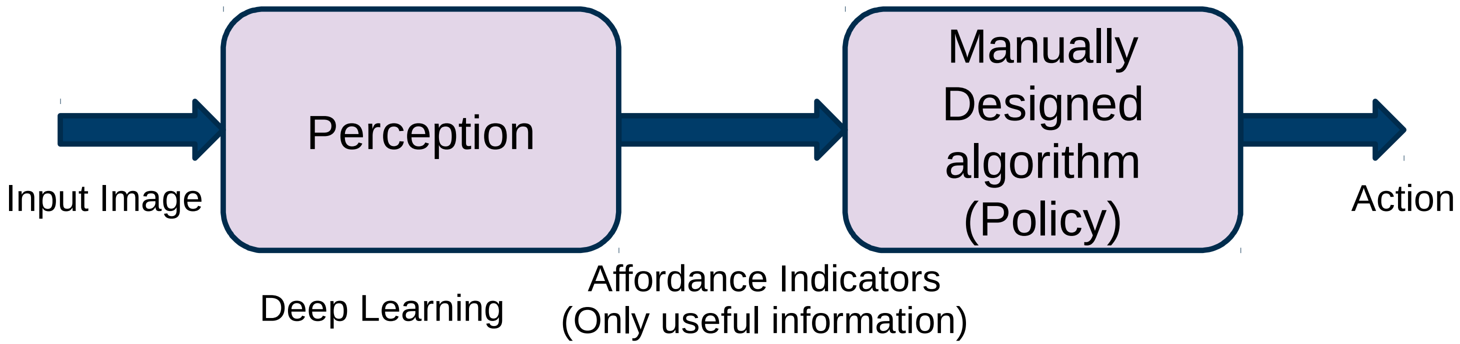
World Model
(Represents whole scene)

Manually designed algorithm (policy)

Action

Direct Perception

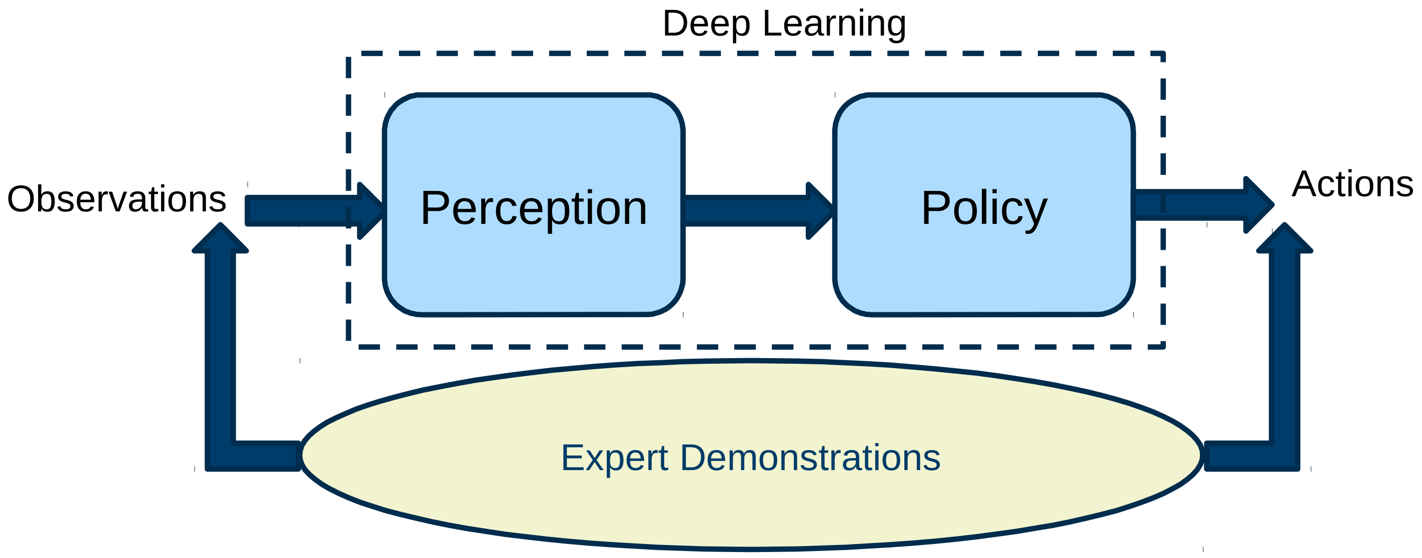
- Learn «Affordance Indicators» from input image
  - Eg: Distance to the left lane/right lane, distance to the next car
- Use a manually designed algorithm to convert affordance indicators to actions.



Learn Perception and Actions
(Expert Demonstrations only)

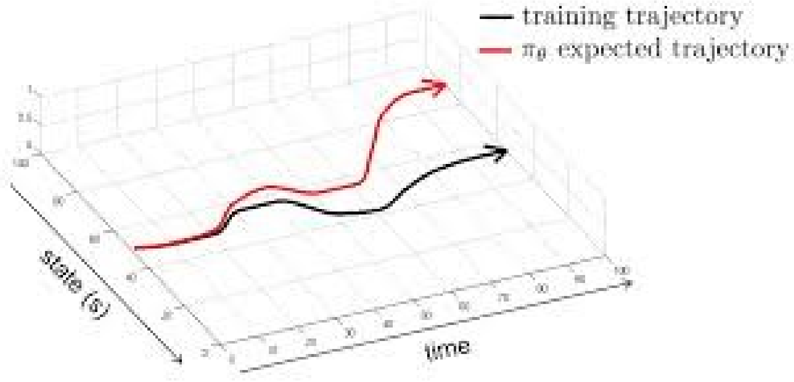
Behavior Cloning

- A type of imitation learning
- Direct learning of the mapping between input observations and actions
- Supervised learning problem with training data given by the expert demonstrations
- Mostly applied in controlling autonomous vehicles



Issues of Behavior Cloning

- Weaknesses
  - Compounding Errors
  - Reactive Policies
- Reasons
  - Assumption of iid samples
  - Distribution mismatch between training and testing
  - Ignore temporal dependencies (long term goals are not considered)
  - Blind imitation of expert demonstrations



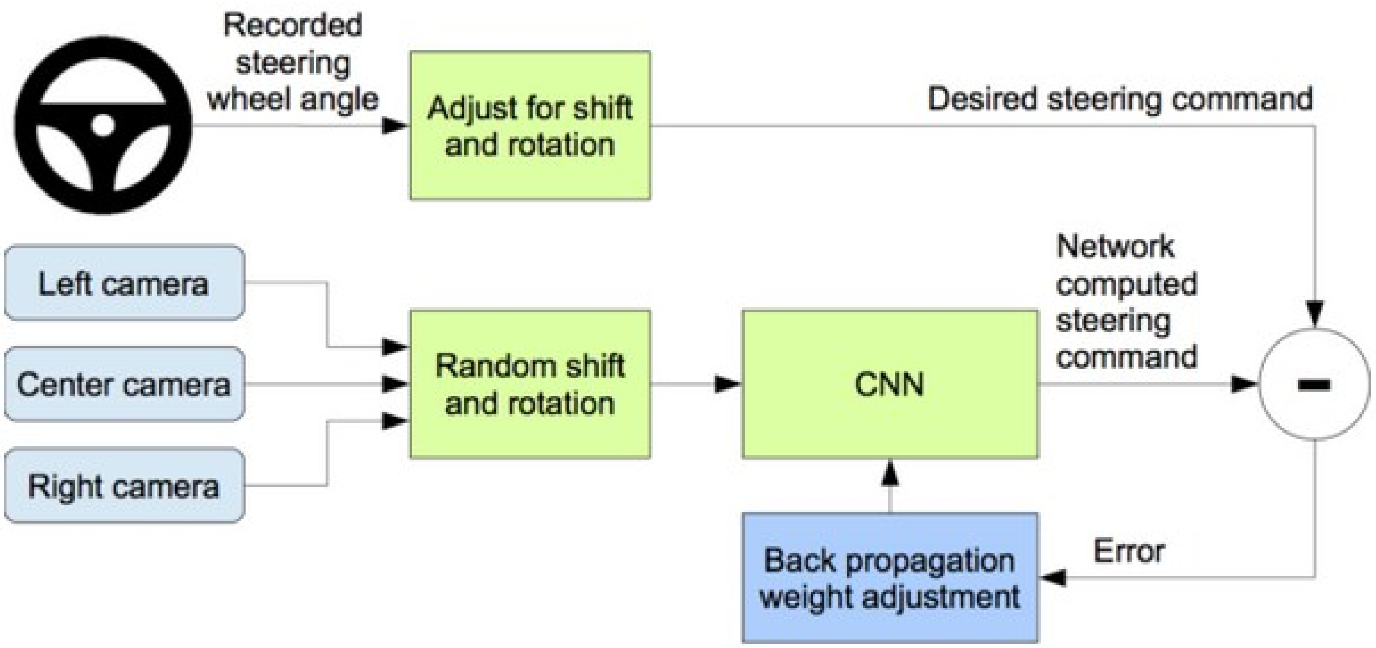
http://rail.eecs.berkeley.edu/deeprlcourse-fa17/f17docs/lecture_2_behavior_cloning.pdf

DAgger (Dataset Aggegation)

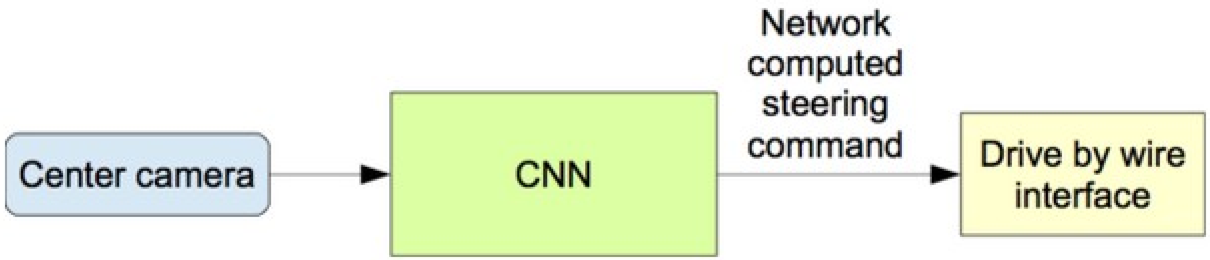
- Algorithm proposed to combat «compounding errors»
- Iteratively interleaves execution and training.

1. Use the expert demonstrations to train a policy
2. Use the policy to gather data
3. Label data using the expert
4. Add new data to the dataset
5. Train a new policy on new data (supervised learning)
6. Repeat from step 2

NVIDIA Deep Driving (Training)

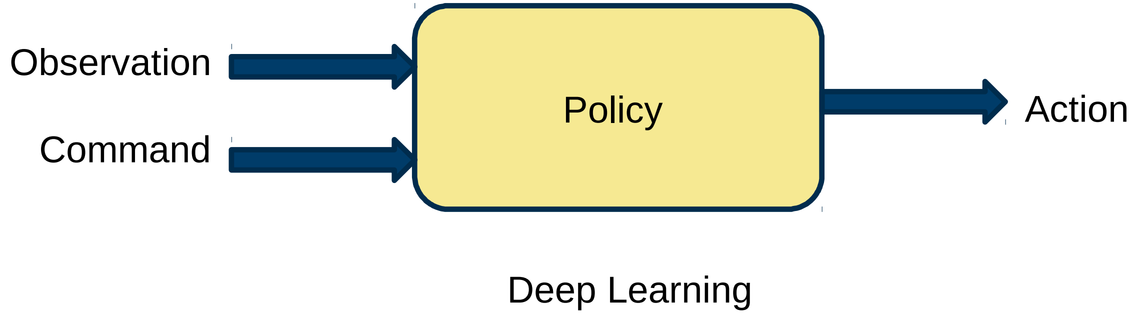


NVIDIA Deep Driving (Testing)



CARLA- Car Learning to Act

- Conditional Imitation Learning.
- More than driving straight
- Supervised training with expert demonstrations
  - Observertion = Forward Camera Image
  - Command = follow the lane, straight, left, right
  - Action= Steering parameters



Learn Perception and Actions
(Expert Demonstrations + Reinforcement Learning)

Inverse Reinforcement Learning (IRL)

- Motivation
  - In reinforcement learning, we assume that a reward/cost function is known (Manually designed reward function).
  - However, in many real world applications the reward structure is unclear.
  - In inverse reinforcement learning, we learn the reward function based on expert demonstrations.

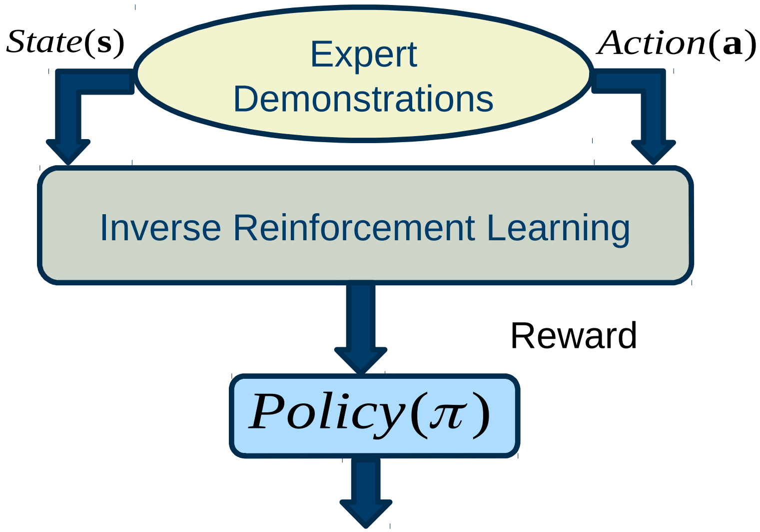
IRL vs. RL

- Reinforcement Learning (RL)
  - States $\boldsymbol{x}$ and actions $\boldsymbol{u}$ are drawn from a given set
  - Direct interaction with the environment or an environment model is known. $p(\boldsymbol{x}_{t+1}|\boldsymbol{x}_t, \boldsymbol{u}_t)$
  - Reward function $r_\psi(\boldsymbol{x}, \boldsymbol{u})$ is known
  - Learn the optimal policy $\pi^\star(\boldsymbol{u}|\boldsymbol{x})$

- Inverse Reinforcement Learning (IRL)
  - States and actions are drawn from a given set
  - Direct interaction with the environment or an environment model is known
  - Expert demonstrations (state-action pairs generated by an expert) are given $\tau_i = [\mathbf{x}_1, \boldsymbol{u}_1, \boldsymbol{x}_2, \boldsymbol{u}_2, \boldsymbol{x}_3, \boldsymbol{u}_3, \ldots, \boldsymbol{x}_T, \boldsymbol{u}_T]$
  - Assume expert demonstrations are samples from an optimal policy
  - Learn the reward function $r_\psi(\boldsymbol{x}, \boldsymbol{u})$ and then optimal policy $\pi^\star(\boldsymbol{u}|\boldsymbol{x})$.

Challenges of IRL

- Ill-defined problem
- Expert demonstrations are not drawn from the optimal policy



Maximum Entropy IRL

- Trajectory $\tau_i = [\mathbf{x}_1^i, \boldsymbol{u}_1^i, \boldsymbol{x}_2^i, \boldsymbol{u}_2^i, \boldsymbol{x}_3^i, \boldsymbol{u}_3^i, \ldots, \boldsymbol{x}_T^i, \boldsymbol{u}_T^i]$
- Expert demonstrations $\mathcal{D} = \{\tau_i\}$
- Reward $R_\psi(\tau) = \sum_t r_\psi(\boldsymbol{x}_t, \boldsymbol{u}_t)$

- Define the probability of a given trajectory as

$$p(\tau) = \frac{1}{Z} \exp(R_\psi(\tau))$$

where
$$Z = \sum_{\tau \in \mathcal{D}_{all}} \exp(R_\psi(\tau))$$

- Objective of maximum entropy IRL is to maximize the probability of expert demonstrations with respect to ψ

$$\mathcal{L}(\psi) = \sum_{\tau \in \mathcal{D}} \log p_{r_\psi}(\tau)$$

Maxent IRL Optimization with Dynamic Programming

$$\begin{aligned}
\max_{\psi} \mathcal{L}(\psi) &= \sum_{\tau \in \mathcal{D}} \log p_{r_\psi}(\tau) \\
&= \sum_{\tau \in \mathcal{D}} \log \frac{1}{Z} \exp(R_\psi(\tau)) \\
&= \sum_{\tau \in \mathcal{D}} R_\psi(\tau) - M \log Z \\
&= \sum_{\tau \in \mathcal{D}} R_\psi(\tau) - M \log \sum_{\tau} \exp(R_\psi(\tau))
\end{aligned}$$

$$\nabla_\psi \mathcal{L}(\psi) = \sum_{\tau \in \mathcal{D}} \frac{dR_\psi(\tau)}{d\psi} - M \frac{1}{\sum_\tau \exp(R_\psi(\tau))} \sum_{\tau} \exp(R_\psi(\tau)) \frac{dR_\psi(\tau)}{d\psi}$$

Maxent IRL Optimization with Dynamic Programming

$$\nabla_\psi \mathcal{L}(\psi) = \sum_{\tau \in \mathcal{D}} \frac{dR_\psi(\tau)}{d\psi} - M \frac{1}{\sum_\tau \exp(R_\psi(\tau))} \sum_\tau \exp(R_\psi(\tau)) \frac{dR_\psi(\tau)}{d\psi}$$

- But by definition $$\frac{1}{\sum_\tau \exp(R_\psi(\tau))} \exp(R_\psi(\tau)) = p(\tau)$$

- Therefore the second term becomes $$-M \sum_\tau p(\tau) \frac{dR_\psi(\tau)}{d\psi}$$

- We can compute this at the state level, rather than at the trajectory level

$$-M \sum_{\boldsymbol{x}} p(\boldsymbol{x}) \frac{dr_\psi(\boldsymbol{x})}{d\psi}$$

- We can use dynamic programming to calculate $p(\boldsymbol{x})$

Maxent IRL Optimization with Dynamic Programming

- We calculate $p(\boldsymbol{x})$ = probability of visiting state $\boldsymbol{x}$
- Assume probability of visiting state $\boldsymbol{x}$ at t=t is $p(\boldsymbol{x}, t) = \mu_t(\boldsymbol{x})$
- Then by the rules of dynamic programming

$$\mu_{t+1}(\boldsymbol{x}') = \sum_{\boldsymbol{u}} \sum_{\boldsymbol{x}} \mu_t(\boldsymbol{x}) \pi(\boldsymbol{u}|\boldsymbol{x}) p(\boldsymbol{x}'|\boldsymbol{x}, \boldsymbol{u})$$

- Then $p(\boldsymbol{x}') = \frac{1}{T} \sum_t \mu_t(\boldsymbol{x}')$

- This procedure is expensive if the number of states of the system is large.

Maxent IRL Optimization with Dynamic Programming

- The whole algorithm
  1. Gather demonstrations $\mathcal{D}$
  2. Initialize ψ
  3. Find the optimal policy $\pi(\boldsymbol{u}|\boldsymbol{x})$ with the reward function r_ψ (standard RL)
  4. Find state visitation frequency $p(\boldsymbol{x})$ (dynamic programming procedure)
  5. Compute gradient $\nabla_\psi \mathcal{L} = \sum_{\tau \in \mathcal{D}} \frac{dR_\psi}{d\psi}(\tau) - M \sum_{\boldsymbol{x}} p(\boldsymbol{x}) \frac{dr_\psi}{d\psi}(\boldsymbol{x})$
  6. Update ψ with gradient ascent
  7. Repeat from step 3

Maxent IRL Optimization with Sampling

- Dynamic programming approach not suitable for
  - Large state-spaces
  - Unknown dynamics

- The problem is the denominator (Partition function) Z

$$p(\tau) = \frac{1}{Z} \exp(R_\psi(\tau))$$

$$Z = \sum_{\tau \in \mathcal{D}_{all}} \exp(R_\psi(\tau))$$

- Use sampling to estimate Z instead of exact calculation: Guided Cost Learning (GCL).

Guided Cost Learning (GCL)

- Start with the log likelihood (per trajectory) of the expert trajectories

$$\mathcal{L}(\psi) = \frac{1}{N} \sum_{\tau \in \mathcal{D}} \log p_{r_\psi}(\tau)$$

- Substituting $p(\tau) = \frac{1}{Z} \exp(R_\psi(\tau))$ we get $\mathcal{L}(\psi) = \frac{1}{N} \sum_{\tau \in \mathcal{D}} R_\psi(\tau) + \log Z$

- In notation used in paper ($\psi = \theta$ and $R = -c$), $\mathcal{L}_{\text{IOC}}(\theta) = \frac{1}{N} \sum_{\tau_i \in \mathcal{D}_{\text{demo}}} c_\theta(\tau_i) + \log Z$

- Partition function Z is given by $Z = \sum_{\tau \in \mathcal{D}_{all}} \exp(-c_\theta(\tau)) = \sum_{\tau \in \mathcal{D}_{all}} \exp(-c_\theta(\tau)) p(\tau)$

  where $p(\tau)$ is a uniform distribution.

- Z is an expectation and therefore, we approximate Z by using M samples drawn from a proposal distribution $q(\tau)$

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

Guided Cost Learning (GCL)

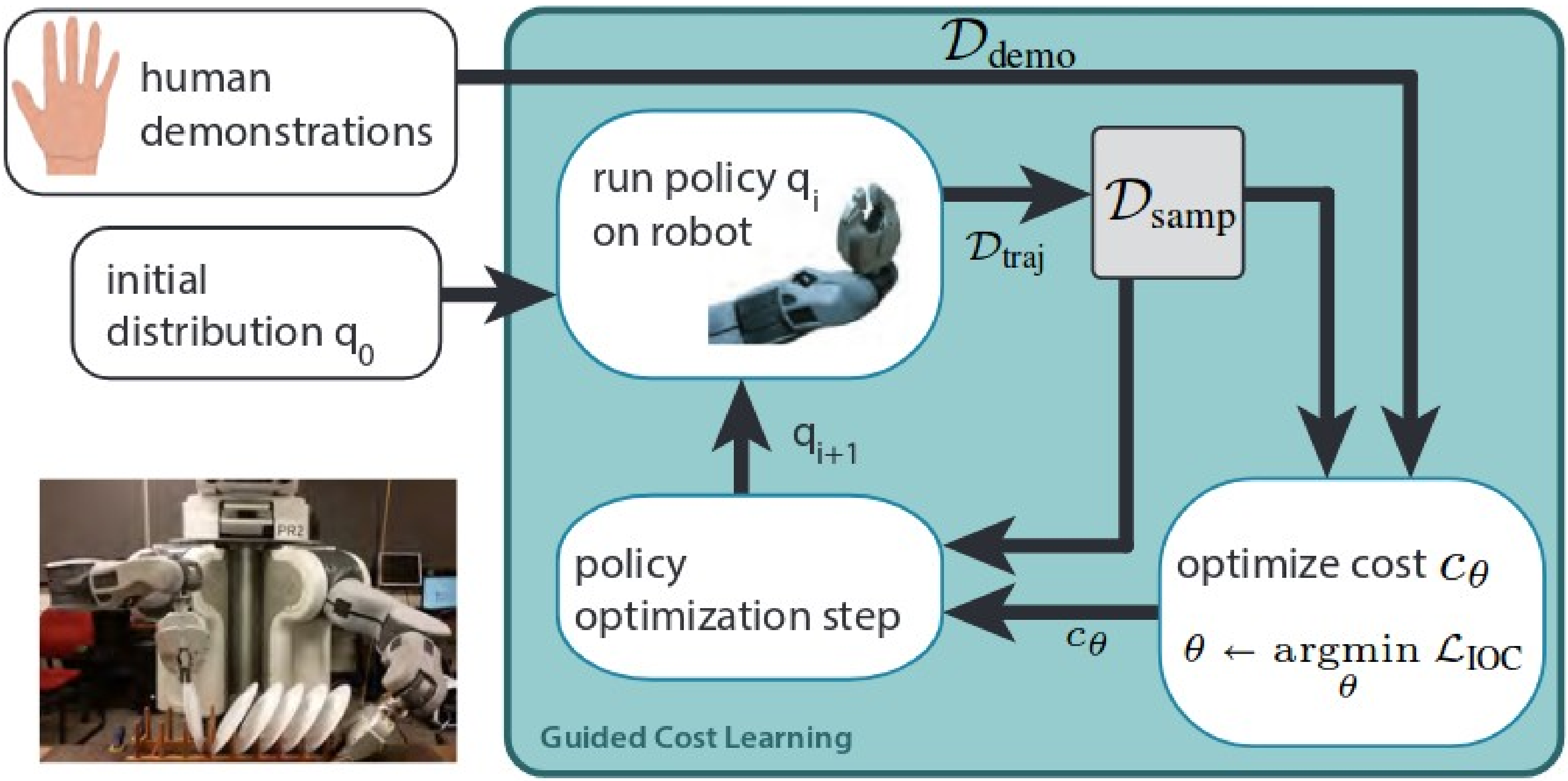
- We obtain gradients of $\mathcal{L}_{\text{IOC}}(\theta)$ wrt θ

$$\frac{d\mathcal{L}_{\text{IOC}}}{d\theta} = \frac{1}{N} \sum_{\tau_i \in \mathcal{D}_{\text{demo}}} \frac{dc_\theta}{d\theta}(\tau_i) - \frac{1}{Z} \sum_{\tau_j \in \mathcal{D}_{\text{samp}}} w_j \frac{dc_\theta}{d\theta}(\tau_j)$$

- Where $w_j = \frac{\exp(-c_\theta(\tau_j))}{q(\tau_j)}$ and $Z = \sum_j w_j$

- If $c_\theta(\tau)$ is implemented using a neural network we can back-propagate
  - $\frac{1}{N}$ If $\tau_i \in \mathcal{D}_{\text{demo}}$
  - $-\frac{w_j}{Z}$ If $\tau_i \in \mathcal{D}_{\text{samp}}$

Guided Cost Learning (GCL) Summary



Reference: https://arxiv.org/pdf/1603.00448.pdf

Guided Cost Learning (GCL) Summary

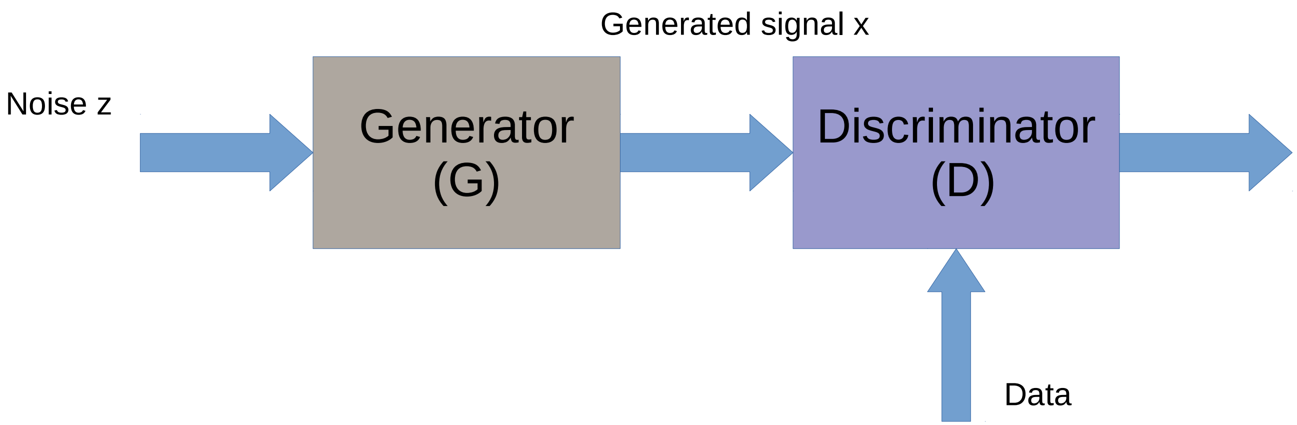
Algorithm 1 Guided cost learning

1: Initialize $q_k(\tau)$ as either a random initial controller or from demonstrations
2: **for** iteration $i = 1$ to I **do**
3: Generate samples $\mathcal{D}_{\text{traj}}$ from $q_k(\tau)$
4: Append samples: $\mathcal{D}_{\text{samp}} \leftarrow \mathcal{D}_{\text{samp}} \cup \mathcal{D}_{\text{traj}}$
5: Use $\mathcal{D}_{\text{samp}}$ to update cost c_θ using Algorithm 2
6: Update $q_k(\tau)$ using $\mathcal{D}_{\text{traj}}$ and the method from (Levine & Abbeel, 2014) to obtain $q_{k+1}(\tau)$
7: **end for**
8: **return** optimized cost parameters θ and trajectory distribution $q(\tau)$

Algorithm 2 Nonlinear IOC with stochastic gradients

1: **for** iteration $k = 1$ to K **do**
2: Sample demonstration batch $\hat{\mathcal{D}}_{\text{demo}} \subset \mathcal{D}_{\text{demo}}$
3: Sample background batch $\hat{\mathcal{D}}_{\text{samp}} \subset \mathcal{D}_{\text{samp}}$
4: Append demonstration batch to background batch: $\hat{\mathcal{D}}_{\text{samp}} \leftarrow \hat{\mathcal{D}}_{\text{demo}} \cup \hat{\mathcal{D}}_{\text{samp}}$
5: Estimate $\frac{d\mathcal{L}_{\text{IOC}}}{d\theta}(\theta)$ using $\hat{\mathcal{D}}_{\text{demo}}$ and $\hat{\mathcal{D}}_{\text{samp}}$
6: Update parameters θ using gradient $\frac{d\mathcal{L}_{\text{IOC}}}{d\theta}(\theta)$
7: **end for**
8: **return** optimized cost parameters θ

Similarity to Generative Adversarial Networks (GANs)



$$\mathcal{L}_{\text{discriminator}}(D) = \mathbb{E}_{\mathbf{x}\sim p}[-\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{x}\sim G}[-\log(1 - D(\mathbf{x}))]$$

$$\mathcal{L}_{\text{generator}}(G) = \mathbb{E}_{\mathbf{x}\sim G}[-\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{x}\sim G}[\log(1 - D(\mathbf{x}))]$$

Similarity to Generative Adversarial Networks (GANs)

GCL	GAN
Trajectory τ	Sample x
Policy π	Generator G
Reward $r = -c$	Discriminator D
Expert demonstrations	Real data (eg: real images)

- It can be proved that generator and discriminator loss functions for the GCL have a similar form to those of GAN

Generative Adversarial Imitation Learning (GAIL)

- Very similar to GCL
- But does not aim to learn a reward function, instead it uses a classifier (discriminator)
- Trajectory samples are drawn using the TRPO (Trust Region Policy Optimization) algorithm

Algorithm 1 Generative adversarial imitation learning

Input: Expert trajectories $\tau_E \sim \pi_E$, initial policy and discriminator parameters θ_0, w_0
for $i = 0, 1, 2, \dots$ **do**
  Sample trajectories $\tau_i \sim \pi_{\theta_i}$
  Update the discriminator parameters from w_i to w_{i+1} with the gradient

$$\hat{\mathbb{E}}_{\tau_i}[\nabla_w \log(D_w(s,a))] + \hat{\mathbb{E}}_{\tau_E}[\nabla_w \log(1 - D_w(s,a))] \tag{17}$$

  Take a policy step from θ_i to θ_{i+1}, using the TRPO rule with cost function $\log(D_{w_{i+1}}(s,a))$. Specifically, take a KL-constrained natural gradient step with

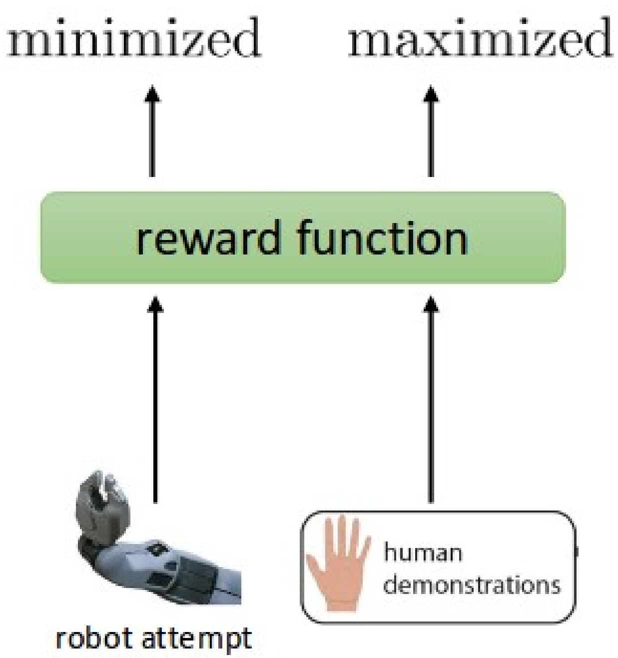
$$\begin{aligned} &\hat{\mathbb{E}}_{\tau_i}\left[\nabla_\theta \log \pi_\theta(a|s) Q(s,a)\right] - \lambda \nabla_\theta H(\pi_\theta), \\ &\text{where } Q(\bar{s},\bar{a}) = \hat{\mathbb{E}}_{\tau_i}[\log(D_{w_{i+1}}(s,a)) \,|\, s_0 = \bar{s}, a_0 = \bar{a}] \end{aligned} \tag{18}$$

end for

GCL vs GAIL

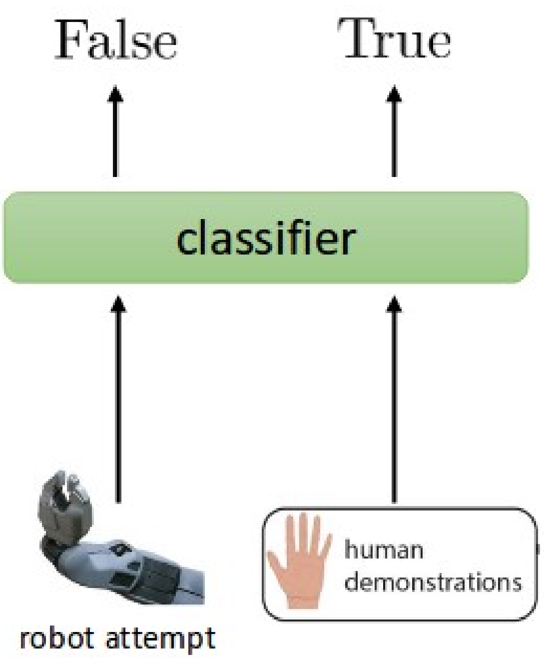
Guided Cost Learning

ICML 2016



Generative Adversarial Imitation Learning

Ho & Ermon, NIPS 2016



Reference: http://rail.eecs.berkeley.edu/deeprlcourse-fa17/f17docs/lecture_12_irl.pdf