Project

- Project report:
  - 4-page summary of your project
  - Due Apr. 20, on CourSys

- Project presentation:
  - Apr. 1, 3, 5 – 10 minutes per person
  - Project does not need to be finished at this point
  - Summarize what you have done, and what remains to be done

Imitation Learning

CMPT 882

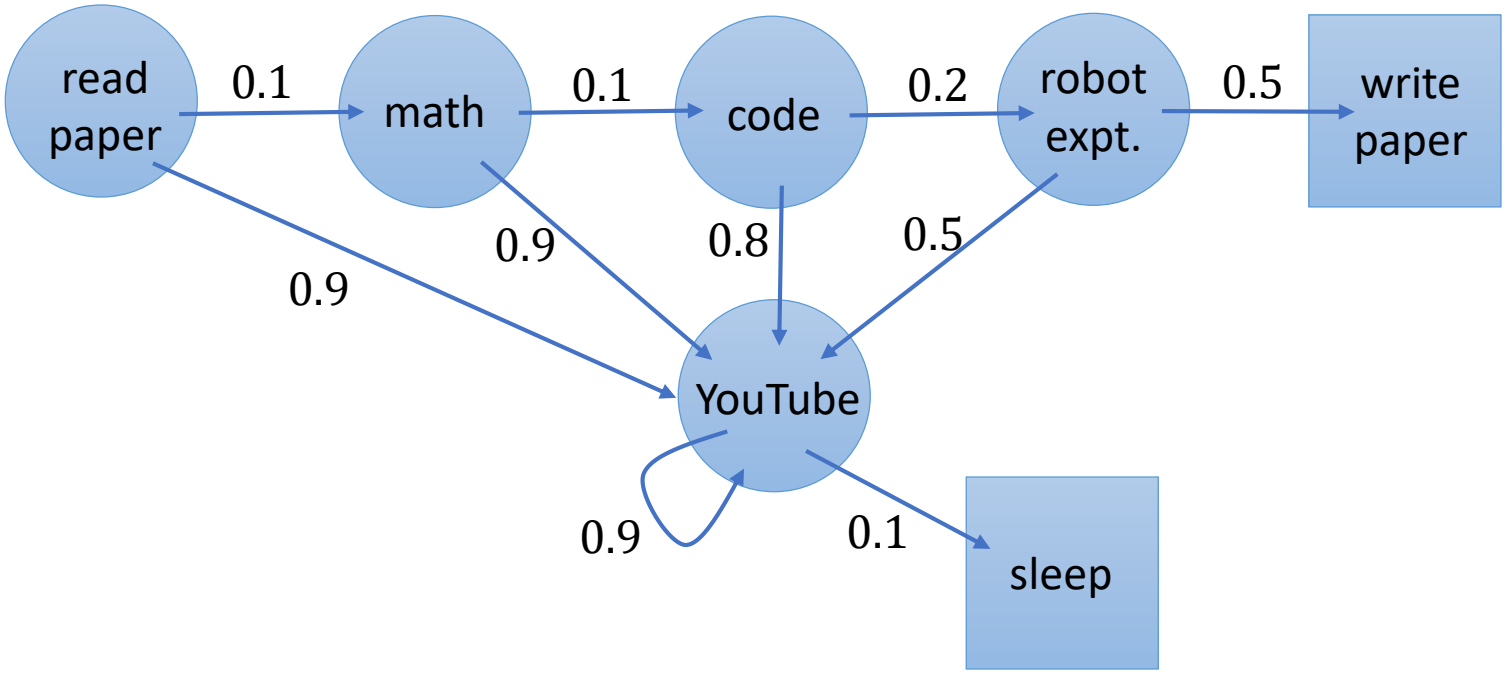
Mar. 15

Outline

- Markov Decision Process
- Imitation Learning

Markov Decision Process

- An MDP with a particular policy results in a Markov chain: $p(s_{t+1}|s_t, a_t), a_t \sim \pi_\theta(a_t|s_t)$



State space includes

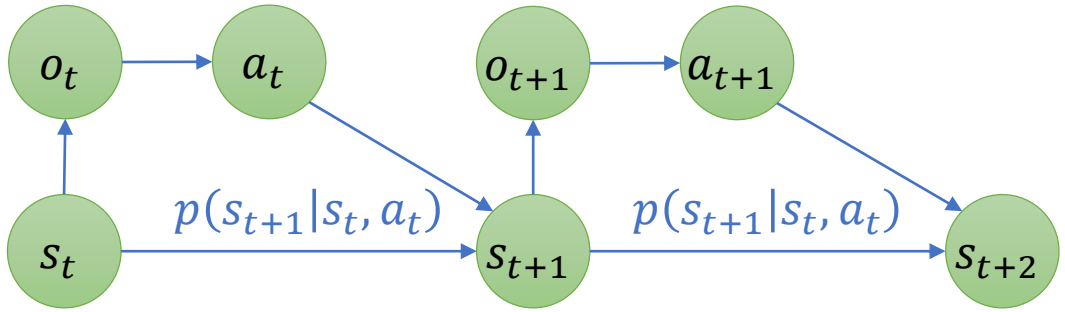
- Reading paper
- Doing math
- Coding
- Doing robotic experiments
- Watching YouTube
- Writing paper
- Sleeping

Transition probabilities

$$\mathcal{T} = \begin{bmatrix} 0.1 & & & 0.9 & & \\ & 0.1 & & 0.9 & & \\ & & 0.2 & 0.8 & & \\ & & & 0.5 & 0.5 & \\ & & & 0.9 & & 0.1 \\ & & & & 1 & \\ & & & & & 1 \end{bmatrix}$$

Extensions of Problem Setup

- Partially observability
  - Partially Observable Markov Decision Process (POMDP)
  - State not fully known; instead, act based on observations



  - Policy: $\pi_\theta(a|o)$
- In this class, state s will be synonymous with observation o.

Reinforcement Learning Objective

- Given: an MDP with state space $\mathcal{S}$, action space $\mathcal{A}$, transition probabilities $\mathcal{T}$, and reward function $r(s, a)$

- Objective: Maximize discounted sum of rewards ("return")

$$\underset{\pi_\theta}{\text{maximize}}\ \mathbb{E} \sum_t \gamma^k r(s_t, a_t)$$

  - $\gamma \in (0,1]$: discount factor – larger roughly means "far-sighted"
    - Prioritizes immediate rewards
    - $\gamma < 1$ avoids infinite rewards; $\gamma = 1$ is possible if all sequences are finite

- Constraints: often implicit
  - Subject to transition matrix $\mathcal{T}$ (system dynamics)

Markov Decision Process

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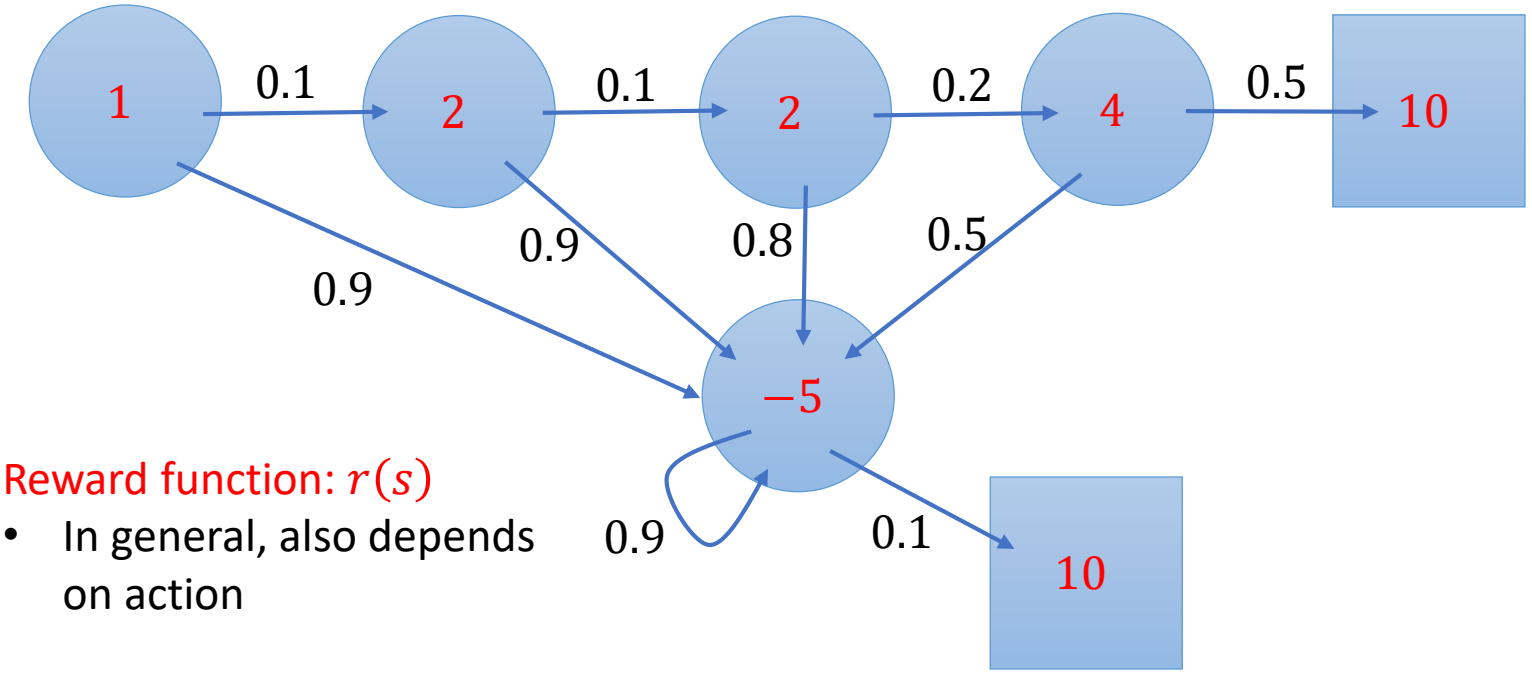

Reward function: $r(s)$

- In general, also depends on action

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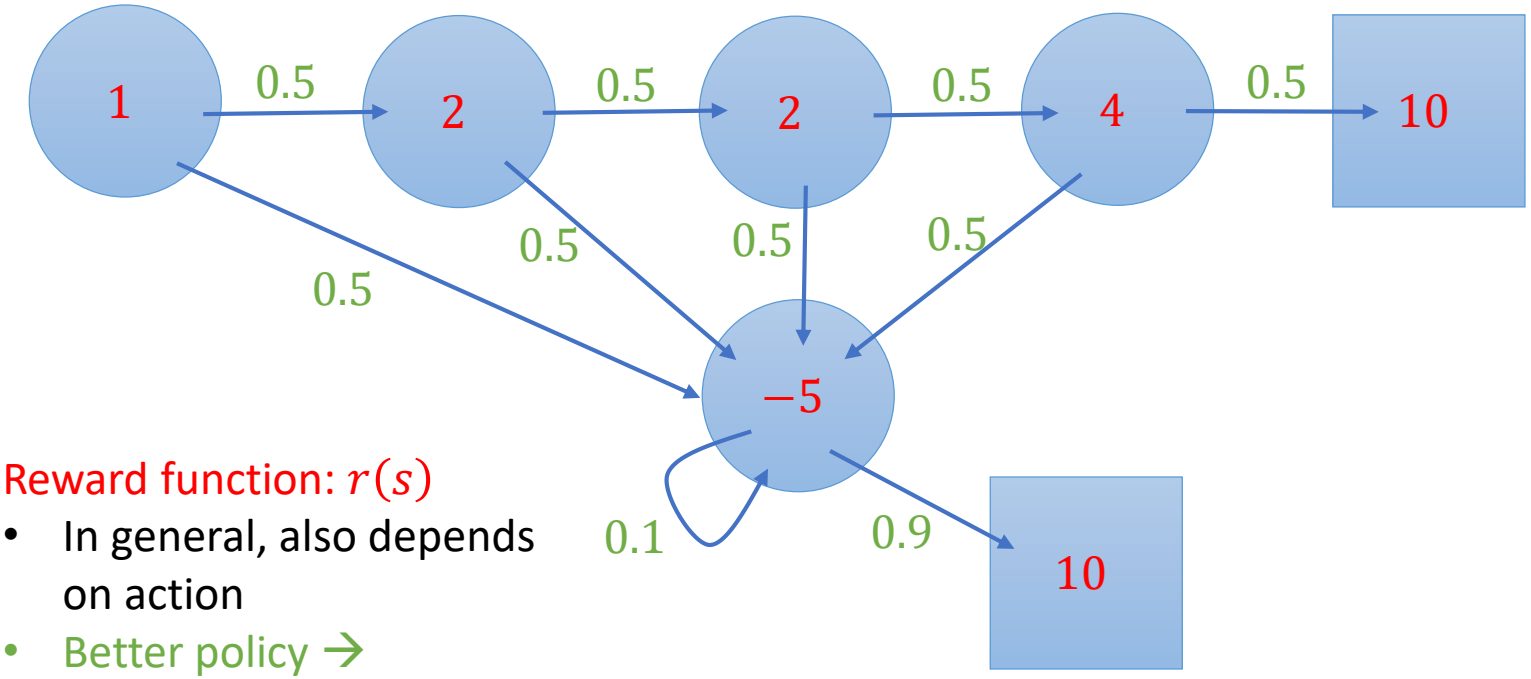

Reward function: $r(s)$

- In general, also depends on action
- Better policy → different Markov chain → different reward

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Reinforcement Learning and Optimal Control

- Reinforcement Learning

$$\underset{\pi_\theta}{\text{maximize}}\ \mathbb{E}\sum_t \gamma^k r(s_t, a_t)$$

  - Dynamics constraint is implicit
    - And not necessary needed
  - Typically, no other explicit constraints
  - Problem set up captured entirely in the reward
  - Probabilistic

- Optimal control

$$\underset{u(\cdot)}{\text{minimize}}\ l\big(x(t_f), t_f\big) + \int_0^{t_f} c(x(t), u(t), t)dt$$

$$\text{subject to } \dot{x}(t) = f\big(x(t), u(t)\big)$$

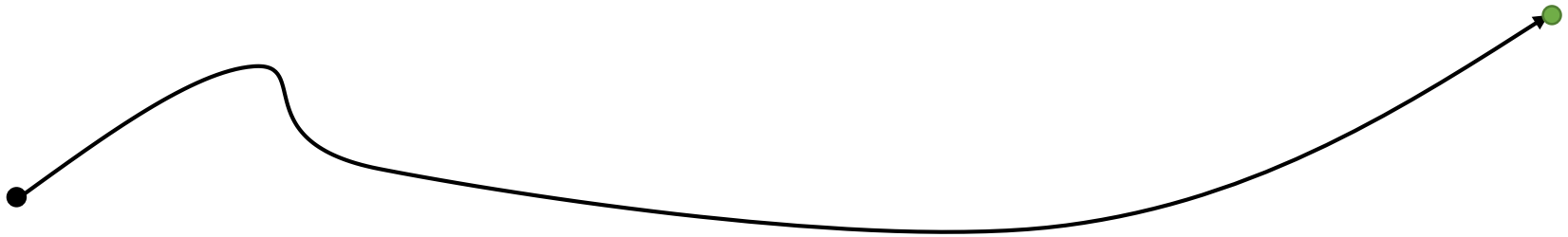
$$g\big(x(t), u(t)\big) \geq 0$$

$$x(t) \in \mathbb{R}^n, u(t) \in \mathbb{R}^m, x(0) = x_0$$

  - Explicit constraints
  - Can be continuous time
  - Not necessarily probabilistic

Imitation Learning

- Collect data through expert demonstration – sequence of states and actions, $\{s_0, a_0, s_1, a_1, \dots, s_{N-1}, a_{N-1}, s_N\}$
  - Note: Expert may not be solving $\underset{\pi}{\text{maximize}}\ \mathbb{E}[\sum_t \gamma^k r(s_t, a_t)]$



- Learn $\pi_\theta(a_t|s_t)$ from data via regression
  - Minimize $\mathbb{E}[\sum \|a_t - \pi_\theta(a_t|s_t)\|]$

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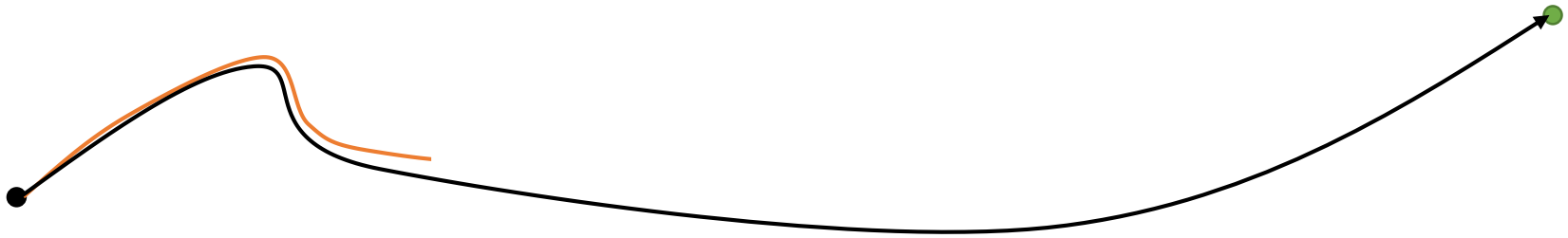

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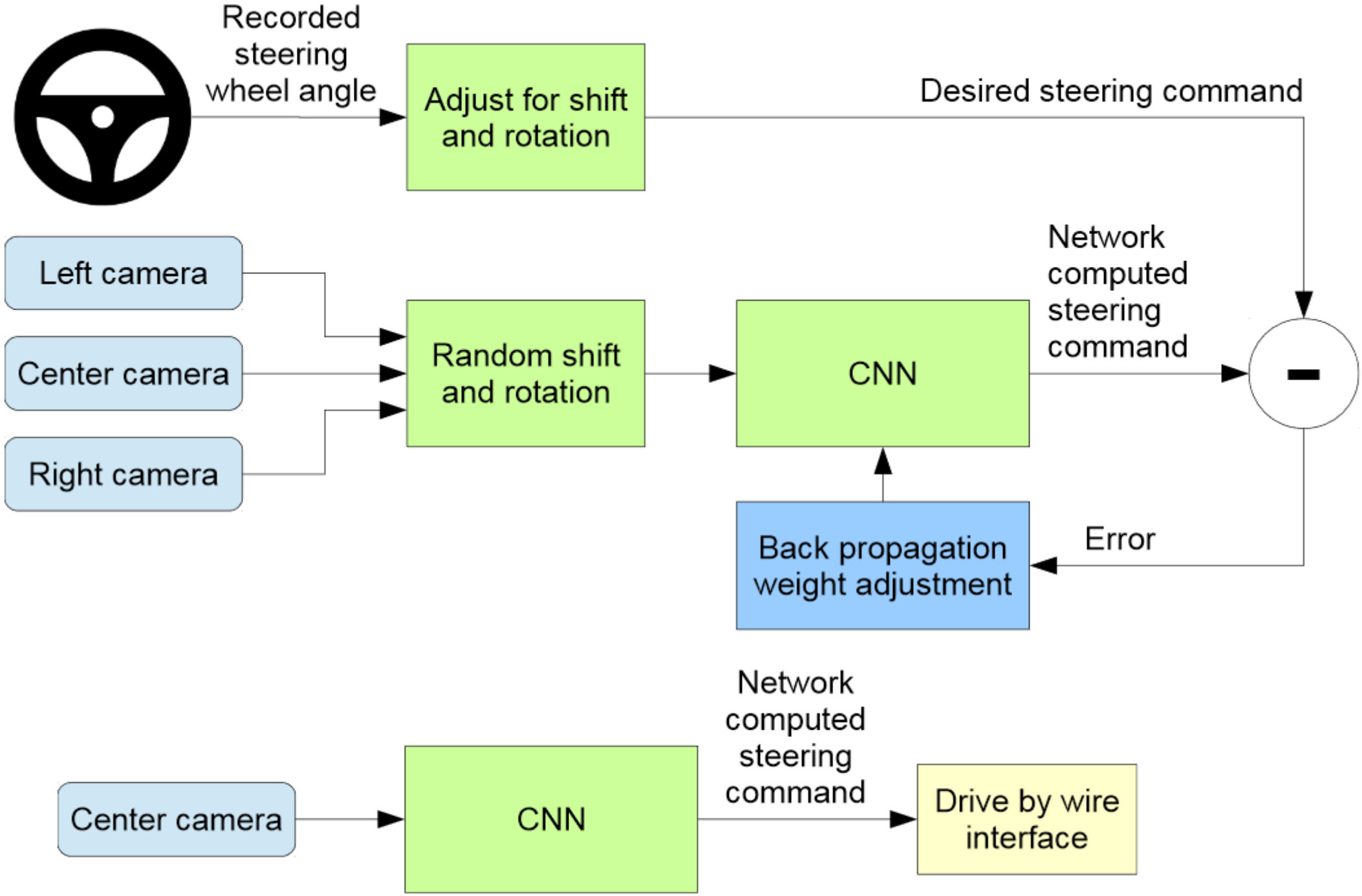
- Learn $\pi_\theta(a_t|s_t)$ from data via regression
  - Minimize $\mathbb{E}(\sum \|a_t - \pi_\theta(a_t|s_t)\|)$

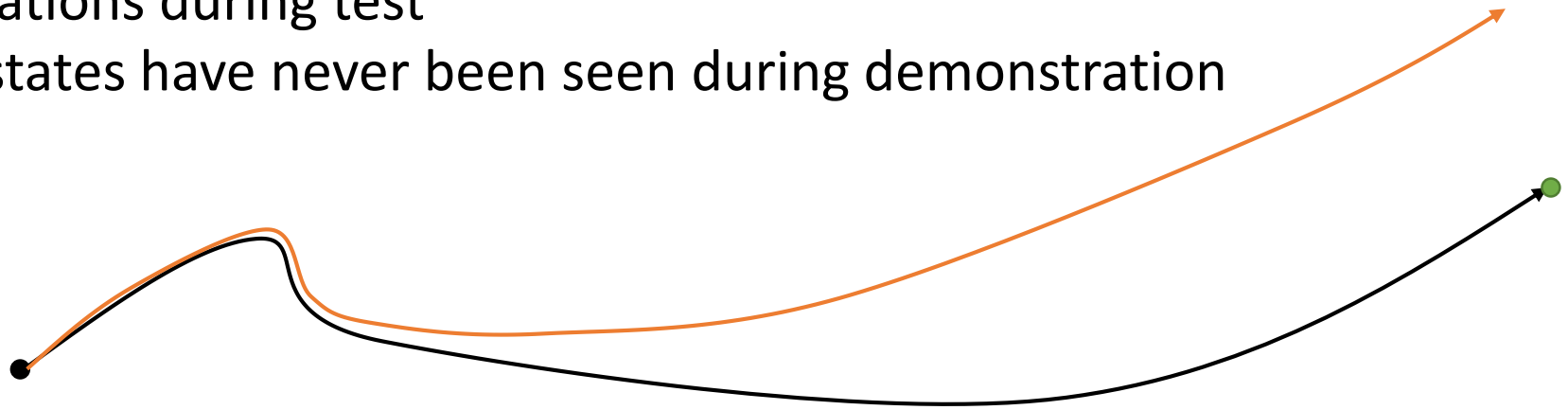
- Usually doesn't work due to "drift": small mistakes add up, and takes the system far from trained states
  - Sometimes, there can be "tricks" to make imitation learning work!

Autonomous Driving Through Imitation


Recorded steering wheel angle
Adjust for shift and rotation
Desired steering command
Left camera
Center camera
Right camera
Random shift and rotation
CNN
Network computed steering command
Back propagation weight adjustment
Error
Center camera
CNN
Network computed steering command
Drive by wire interface

Dataset Aggregation

- Imitation learning drawback:
  - Distribution of observations in training is different from distribution of observations during test
  - Some states have never been seen during demonstration



- How to make the distributions equal?
  - Train perfect policy
  - Change data set → DAgger (Dataset Aggregation)

Dataset Aggregation (DAgger) Algorithm

1. Train policy from some initial data, $\mathcal{D}_i = \{s_0, a_0, s_1, a_1, \dots, s_{N-1}, a_{N-1}, s_N\}$
2. Run policy to obtain new observations $\{s_{N+1}, s_{N+2}, \dots, s_{N+M}\}$
   - Note: time indices and states here may not continue from initial data
3. Use humans to label data by providing actions for new observations, $\{a_{N+1}, \dots, a_{N+M-1}\}$
   - This creates another data set, $\overline{\mathcal{D}}_i = \{s_{N+1}, a_{N+1}, s_{N+2}, a_{N+2} \dots, a_{N+M-1}, s_{N+M}\}$
4. Combine two datasets, $\mathcal{D}_i \leftarrow \mathcal{D}_i \cup \overline{\mathcal{D}}_i$
   - Go back to first step

Challenges

- Non-Markovian behaviour
  - Perhaps augment state/observation space to include some history
  - Use neural networks that implicitly capture time series data: RNNs/LSTMs
- Unnatural data collection
  - Humans are probably not very good at collecting correction data in this manner
- Inconsistencies in human action

Addressing Drift

- Main goal: Teach system to correct errors
- Explicitly demonstrate corrections (DAgger, Dataset Aggregation)
- During demonstration, add noise to “force” mistakes, and see how humans correct them
- Ask humans to intentionally make mistakes
- Prior knowledge and heurisitics
  - Example: Learn from stabilizing controller

Imitation Learning Tricks

- Common neural network architectures
  - LSTM – since we have time-series data
  - CNN – usually in combination with LSTM, if the observations are images
- Simplify action space:
  - Driving example: action space simplified to {left, centre, right}
- Clever data collection
  - Driving example: side cameras
- Inverse reinforcement learning
  - Learn goal, instead of policy, from data

Imitation Learning Drawbacks

- Very small amount of data – challenging for training deep neural networks
- Humans are not very good at providing some kinds of actions
  - Quadrotor motor speed
  - Non-humanoid machines
- Hard to perform better at tasks humans are not very good at

Reinforcement Learning

- Humans can learn without imitation
  - Given goal/task
  - Try an initial strategy
  - See how well the task is performed
  - Adjust strategy next time

- Reinforcement learning agent
  - Start with initial policy $\pi_\theta(a|s)$
  - Execute policy
  - Obtain reward, $\sum_t r(s_t, a_t)$
  - Improve policy by updating θ, based on rewards

RL vs. Other ML Paradigms

- No supervisor
- Sequential data in time
- Reward feedback is obtained after a long time
  - Many actions combined together will receive reward
  - Actions are dependent on each other
- In robotics: lack of data