Lecture 17: Topics in Fairness

CIS 7000: Trustworthy Machine Learning

Spring 2024

Agenda

- Selective compliance
- Fairness in sequential decision-making

Fairness and Human-AI Systems

BUSINESS

Algorithms were supposed to make Virginia judges fairer. What happened was far more complicated.

Analysis by Andrew Van Dam
Staff writer | + Follow

November 19, 2019 at 7:00 a.m. EST

The Accomack County Courthouse in February of this year. (Timothy C. Wright for the Washington Post)

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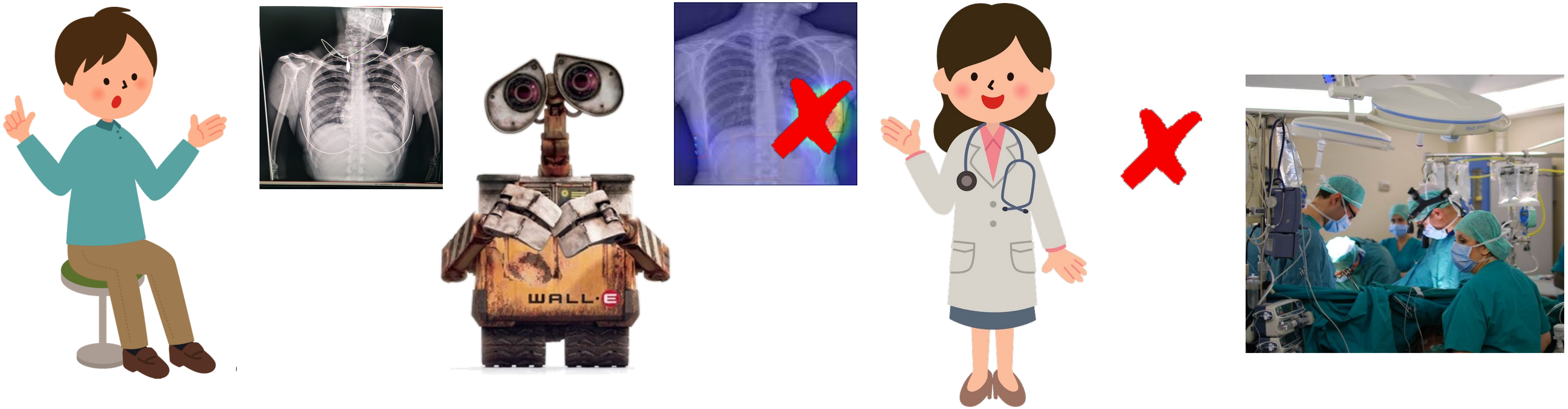
We tend to assume the near-term future of automation will be built on man-machine partnerships. Our robot sidekicks will compensate for the squishy inefficiencies of the human brain, while human judgment will sand down their cold, mechanical edges.

Selective Compliance

- Humans choose when to comply with algorithmic recommendations, with potentially problematic fairness consequences



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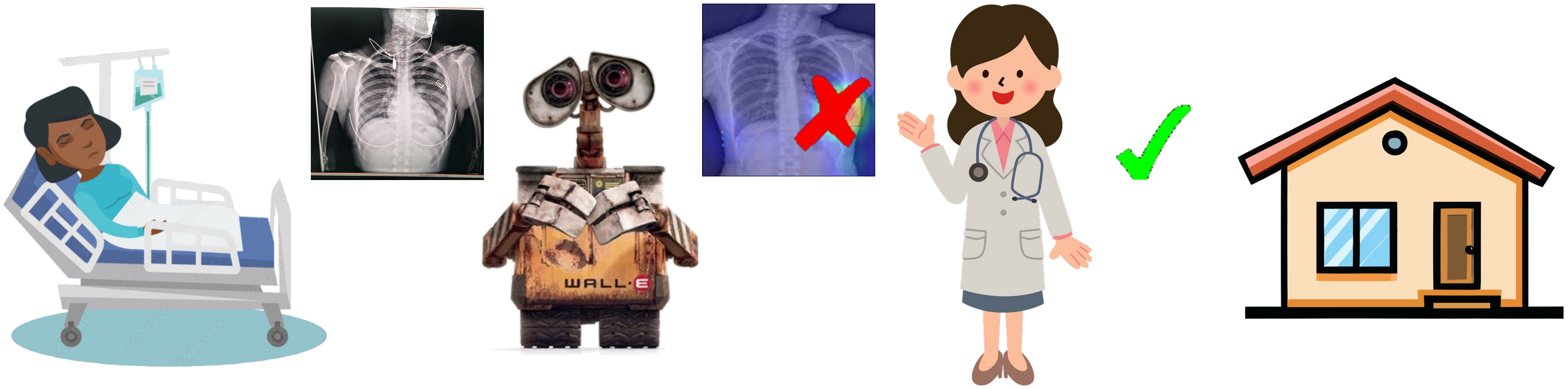
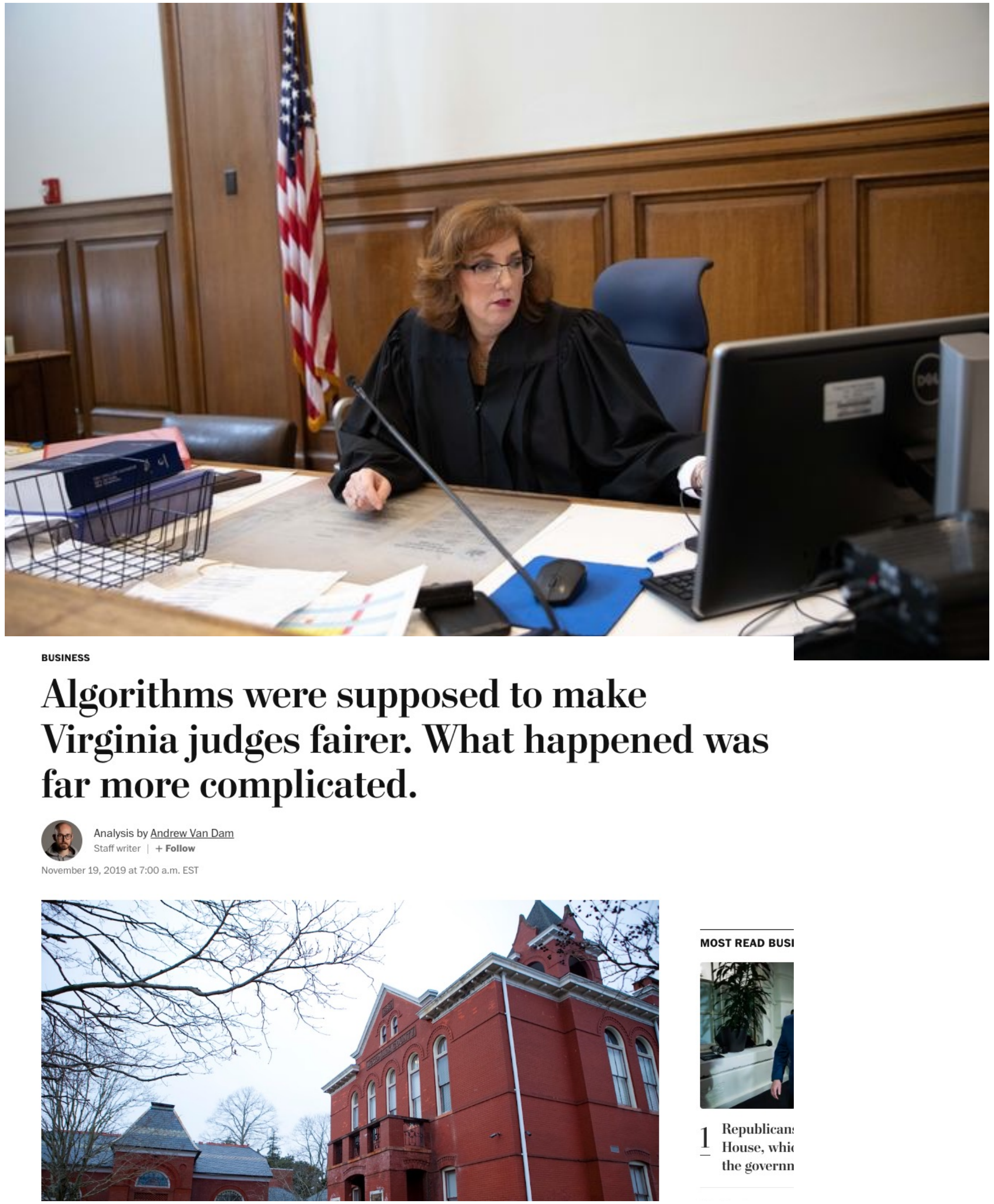


AI is fair

final decision is unfair

Failures

- Virginia sentencing data
- No benefit in safety or incarceration; racial disparities increased in courts where algorithm was used more
- Conflicting objectives, e.g., judges are lenient towards younger defendants
- Judges were more likely to sentence leniently for white defendants with high risk scores than for black defendants with the same score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Stevenson and Doleac, 2022; Van Dam, 2019

Formalizing Selective Compliance

- **Decision-making problem**
  - Finite number of types $x \in X = [k] = \{1, \ldots, k\}$
  - Binary indicator $a \in A = \{0, 1\}$ of protected attribute
  - Binary decision $y \in \{0, 1\}$ (e.g., should we treat the patient?)

- **Policy:** $\pi: X \times A \to [0,1]$ maps x to the prob of a decision of $y = 1$:

$$\hat{y} \sim \mathrm{Bernoulli}\big(\pi(x, a)\big)$$

Formalizing Selective Compliance

- **Human policy:** π_H used by human in absence of AI
- **AI policy:** π_A is the AI recommendation
- **Compliance function:** mapping $c: X \times A \rightarrow \{0,1\}$, indicating whether the human complies with the AI recommendation for (x, a)
- **Human-AI collaborative policy:**

$$\pi_C(x,a) = \begin{cases} \pi_A(x,a) & \text{if } c(x,a) = 1 \\ \pi_H(x,a) & \text{otherwise} \end{cases}$$

Equality of Opportunity

- **Recall:** $\Pr(\,\hat{y} = 1 \mid y = 1, a = 0\,) = \Pr(\,\hat{y} = 1 \mid y = 1, a = 1\,)$

- Let the average score for subgroup a be

$$\bar{\pi}(a) = \sum_{x \in X} \pi(x, a) \cdot P(\,x \mid a, y = 1\,)$$

- Policy π is fair if and only if

$$\alpha(\pi) \coloneqq |\bar{\pi}(1) - \bar{\pi}(0)| = 0$$

- WLOG assume $\bar{\pi}_H(1) \geq \bar{\pi}_H(0)$

Compliance-Robust Fairness

- **Goal:** An algorithmic policy π_A that **never reduces fairness** regardless of how the end user chooses to comply
  - Then, π_C is at least as fair as π_H for **any** compliance fn c
  - For any c, we have $\alpha(\pi_C) \leq \alpha(\pi_H)$

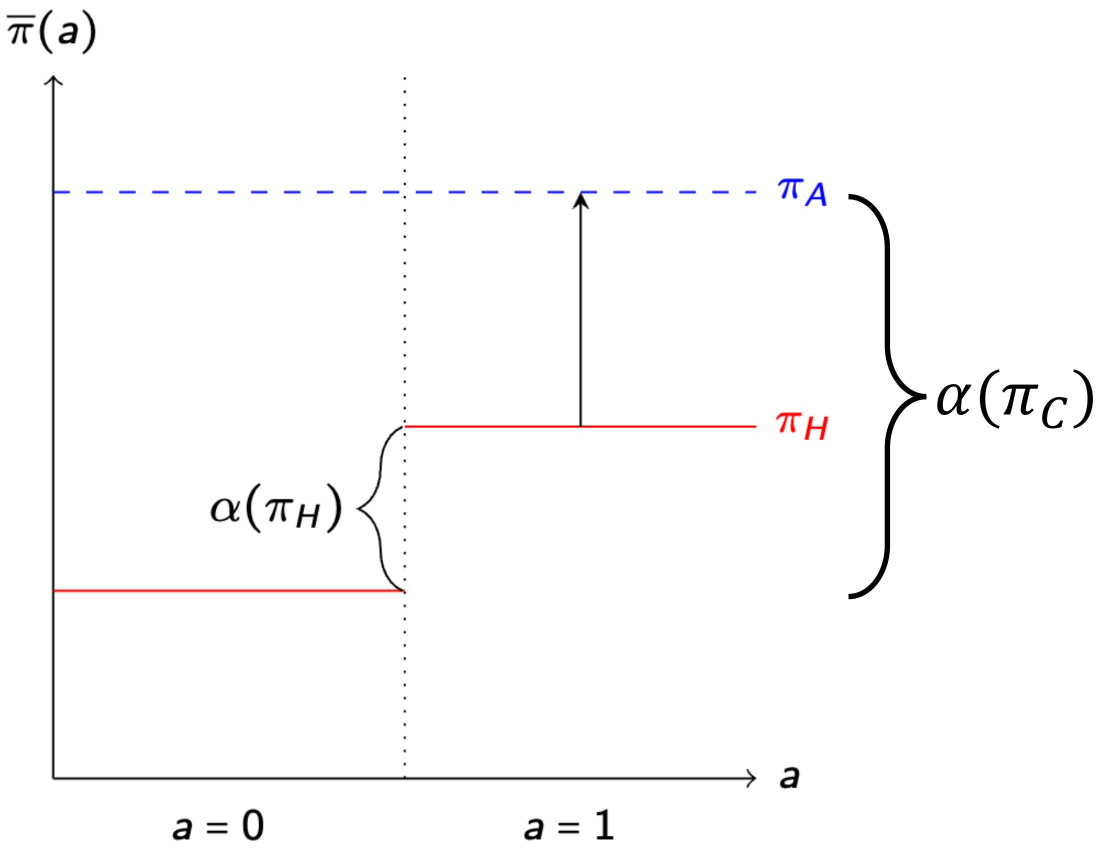
- **Note:**
  - Cannot guarantee π_C is strictly fairer than π_H, since human can choose $c = 0$
  - Assume knowledge of π_H but nothing about c

Intuitive Example

- Suppose $\bar{\pi}_A(a) > \bar{\pi}_H(a)$ for all a

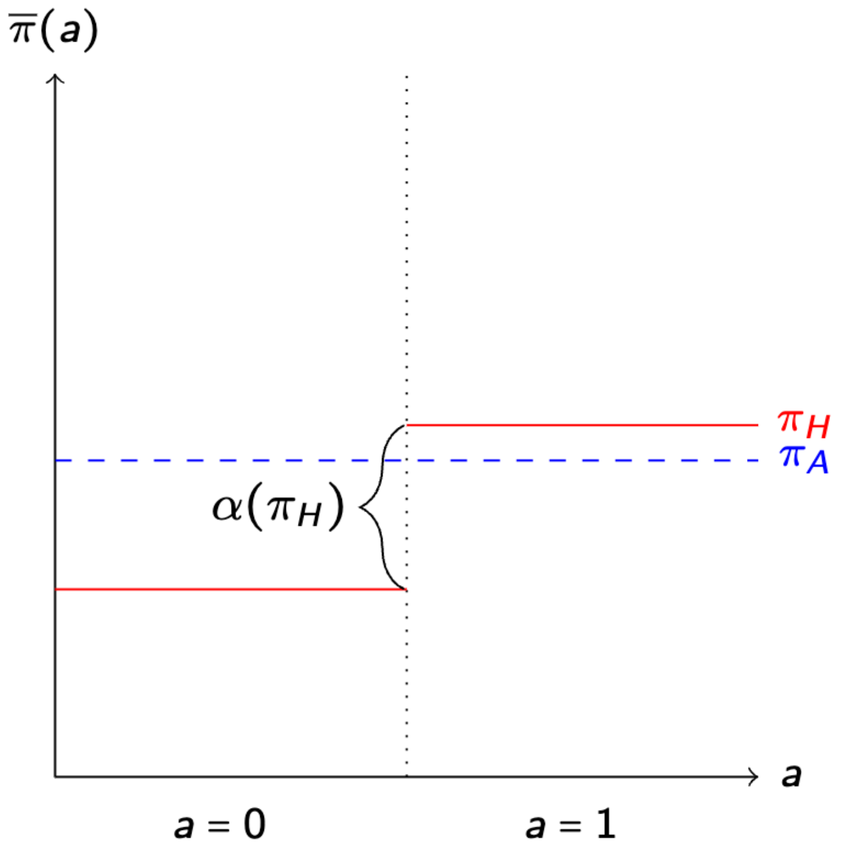
- Fairness decreases if human selectively complies for members of the subgroup a for which $\bar{\pi}_H(a) > \bar{\pi}_H(1-a)$

- Similar if $\bar{\pi}_A(a) < \bar{\pi}_H(a)$ for all a



Intuitive Example

- Modify π_A to be "sandwiched" between levels of π_H
- If $\bar{\pi}_H(0) < \bar{\pi}_A(a) < \bar{\pi}_H(1)$ for all $a \in A$, then π_A is compliance-robust!



Characterizing Compliance-Robustness

- **Assumption:** $P(x, a, y) > 0$ for all $x \in X$, $a \in A$, $y \in Y$

- **Theorem:** A policy π is compliance-robustly fair iff it satisfies:
  1. $\alpha(\pi) \leq \alpha(\pi_H)$
  2. $\pi_H(x, 0) \leq \pi(x, 0)$ for all $x \in X$
  3. $\pi_H(x, 1) \geq \pi(x, 1)$ for all $x \in X$

- Intuitively, no matter how the human complies, they can only reduce $\bar{\pi}_H(1)$ or increase $\bar{\pi}_H(0)$ (without “crossing” them)

Characterizing Compliance-Robustness

- **Corollary:** If $\alpha(\pi_H) = 0$, then the only compliance-robustly fair algorithmic policy is $\pi_A = \pi_H$
- If the human is perfectly fair, then any nontrivial algorithm can reduce fairness

What About Performance?

- Consider a loss function $\ell\colon [0,1] \times Y \mapsto \mathbb{R}$
  - Policy loss $L(\pi) = \mathbb{E}[\ell(\pi(x,a), y^*)]$

- Optimal policy: $\pi_* = \arg\min_\pi L(\pi)$
  - May not be compliance robustly fair (or fair in the traditional sense)

- **Assumption:** If for all $x \in X$ and $a \in A$, $\pi'(x,a) \leq \pi(x,a) < \pi^*(x,a)$ or $\pi'(x,a) > \pi(x,a) \geq \pi^*(x,a)$, then, $L(\pi) < L(\pi')$
  - Intuitively, if π' deviates further from π^* than π for all inputs, then π' has higher expected loss
  - Satisfied by common loss functions (mean squared error, mean absolute error, cross entropy, etc.)

Optimizing for Performance

- Optimization problem to compute the performance-maximizing compliance-robustly fair policy:

$$
\begin{aligned}
\pi_0 = \arg\min_{\pi} L(\pi) & & \\
\text{subj. to} \qquad & \alpha(\pi) \leq \alpha(\pi_H) & \\
& \pi_H(x,0) \leq \pi(x,0) & (\forall x \in \mathcal{X}) \\
& \pi(x,1) \leq \pi_H(x,0) & (\forall x \in \mathcal{X})
\end{aligned}
$$

- **Question:** Does a (nontrivial) solution always exist?

Existence of a Solution

- Consider the policy

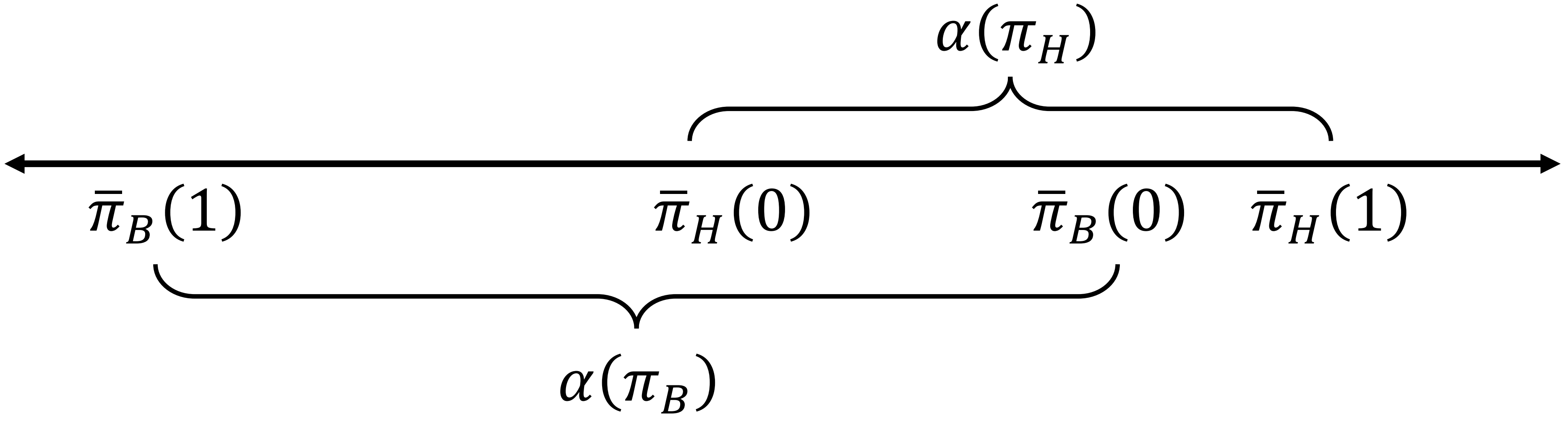
$$\pi_B(x,a) = \begin{cases} \max\{\pi_*(x,a), \pi_H(x,a)\} & \text{if } a = 0 \\ \min\{\pi_*(x,a), \pi_H(x,a)\} & \text{if } a = 1 \end{cases}$$

- **Intuition:** Tries to satisfy the constraints in our theorem
  2. $\pi_H(x,0) \leq \pi(x,0)$ for all $x \in X$
  3. $\pi_H(x,1) \geq \pi(x,1)$ for all $x \in X$

- But may not satisfy the first constraint!
  1. $\alpha(\pi) \leq \alpha(\pi_H)$

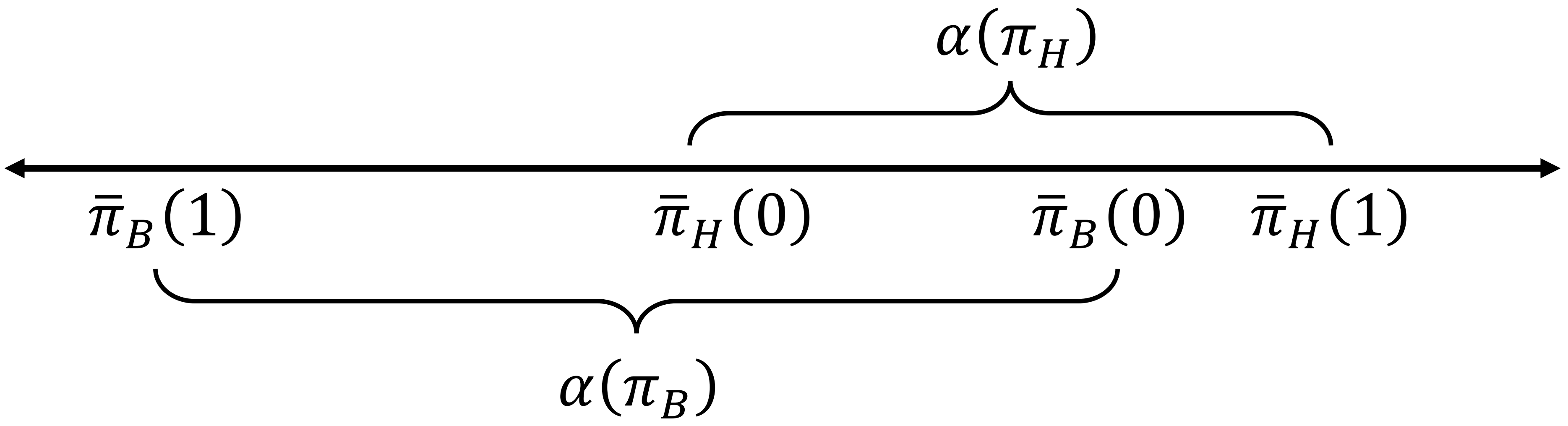
Existence of a Solution

- **Theorem:** If $\alpha(\pi_B) \leq \alpha(\pi_H)$, then π_B is compliance-robustly fair
- Why might $\alpha(\pi_B) \leq \alpha(\pi_H)$ fail to hold?
- **Intuition:** π_B may be unfair in the "opposite direction"



Existence of a Solution

- **Theorem:** If $\alpha(\pi_B) \leq \alpha(\pi_H)$, then π_B is compliance-robustly fair
- Why might $\alpha(\pi_B) \leq \alpha(\pi_H)$ fail to hold?
- **Solution:** Scale π_B back towards π_H



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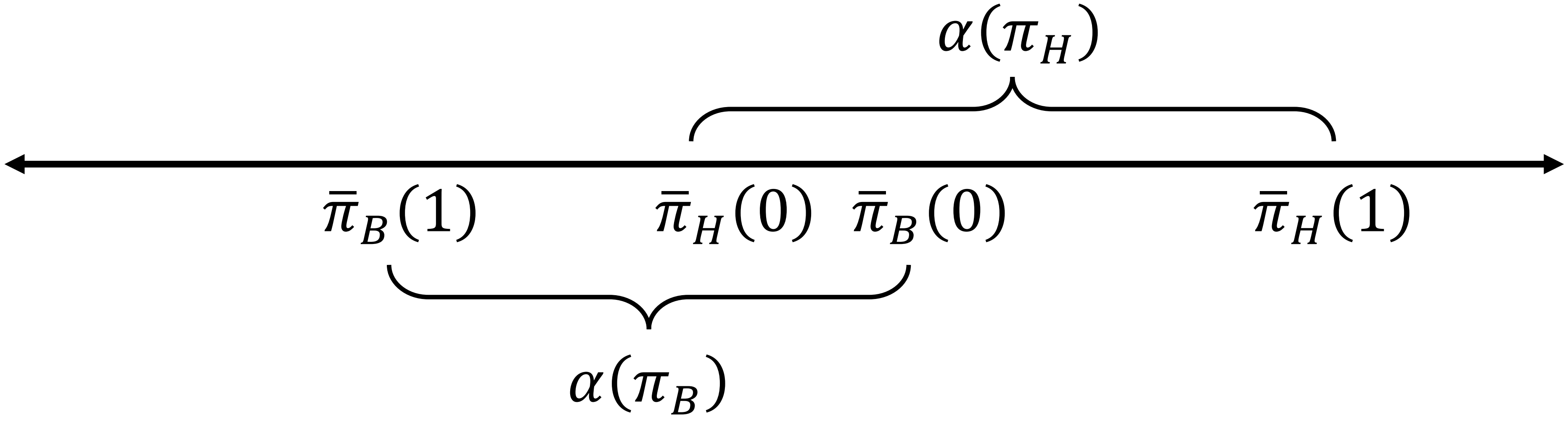


Existence of a Solution

- **Assumption:** $\alpha(\pi_H) \neq 0$ and $\pi_B \neq \pi_H$
- **Theorem:** There exists a performance-improving compliance-robustly fair policy π_0 if and only if the above assumption holds
- **Proof:** Above argument + intermediate value theorem

Tension with Traditional Fairness

- May not always be able to achieve compliance-robust fairness, performance improvement, and traditional fairness

- **Proposition:** There are settings where no traditionally fair policy is compliance-robustly fair while improving performance
  - **Intuition:** If π_* is very unfair, and π_H is close to π_*, then any traditionally fair policy cannot satisfy our constraints

- **Theorem:** If $\alpha(\pi_*) = 0$, then there exists a performance-improving policy that is both traditionally and compliance-robustly fair

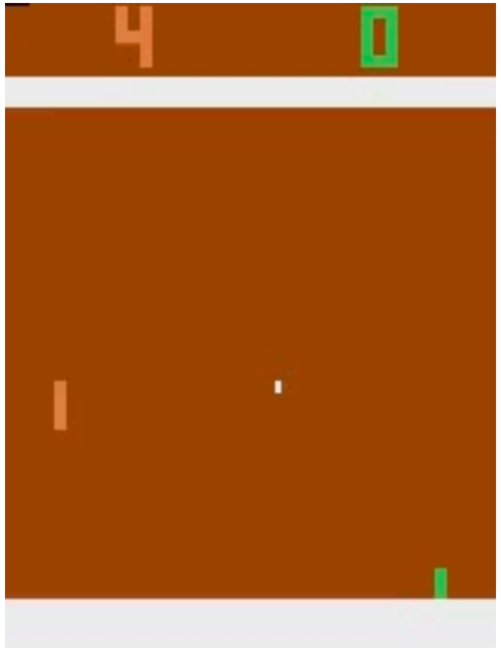
Summary

- Fairness for human-AI collaboration looks very different from traditional fairness
  - May need to forgo traditional fairness to improve end-to-end outcomes!
- New algorithms are needed to ensure fairness of final decisions

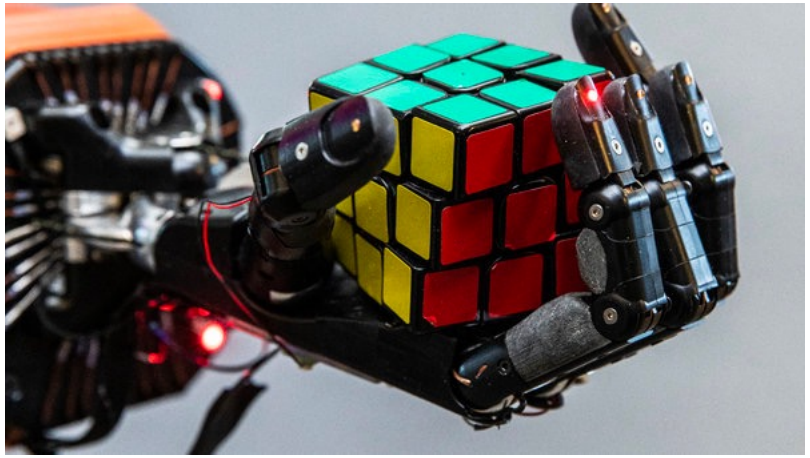
Agenda

- Selective compliance
- Fairness in sequential decision-making

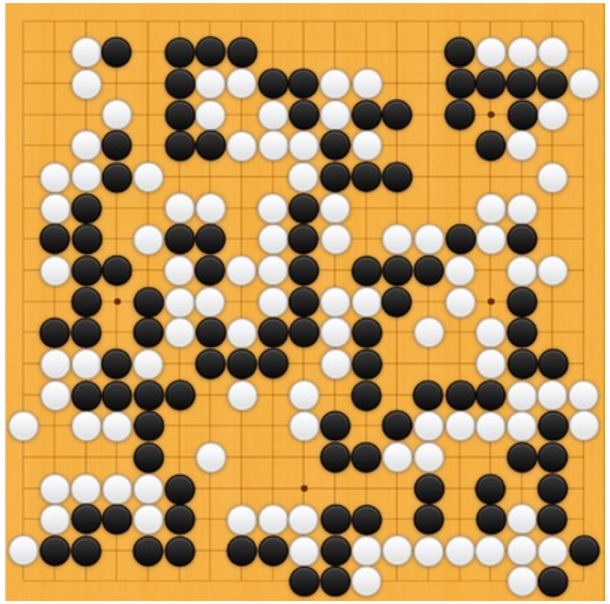
Reinforcement Learning



Atari

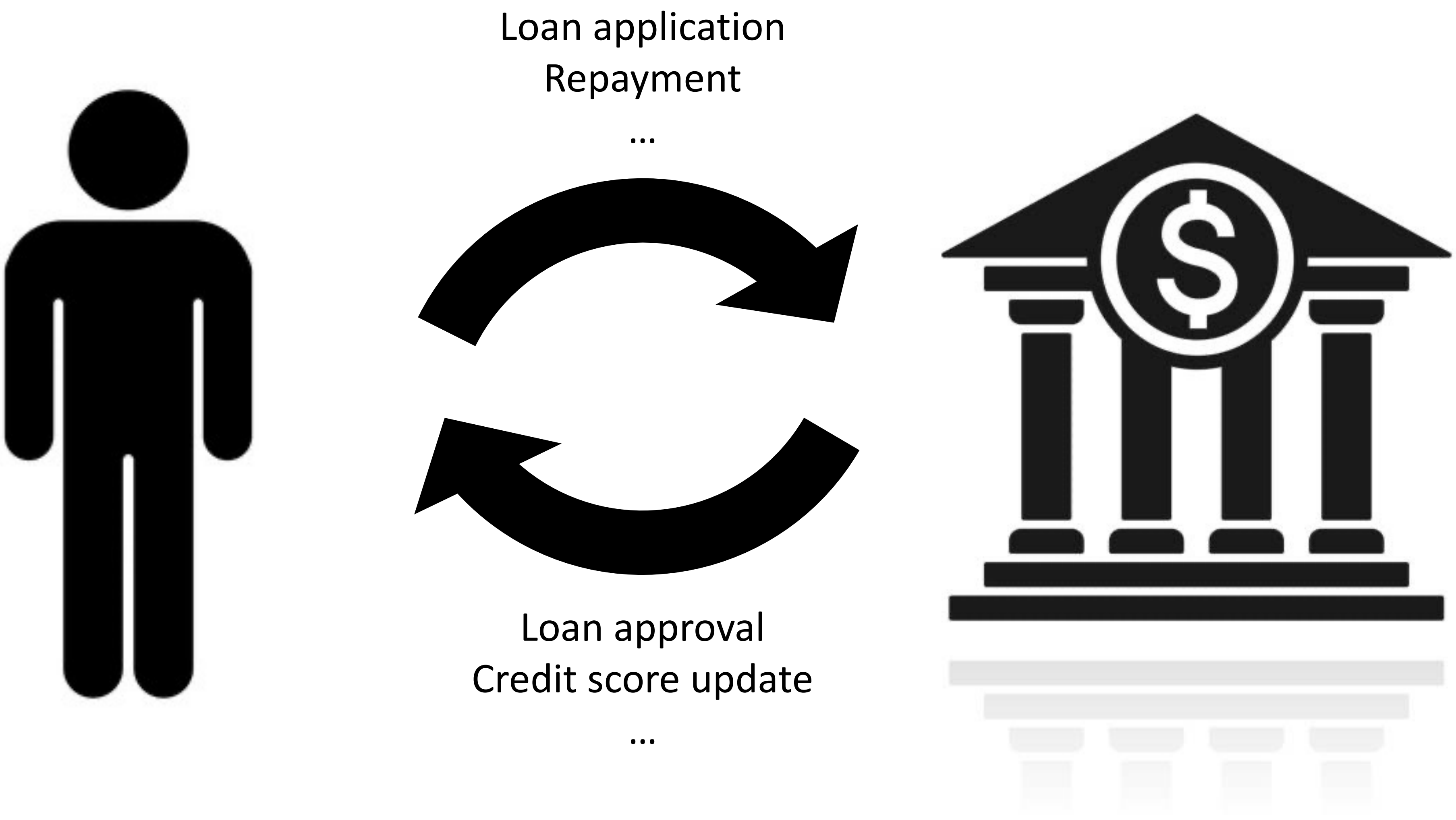


Robotics



AlphaGo

Real World Reinforcement Learning



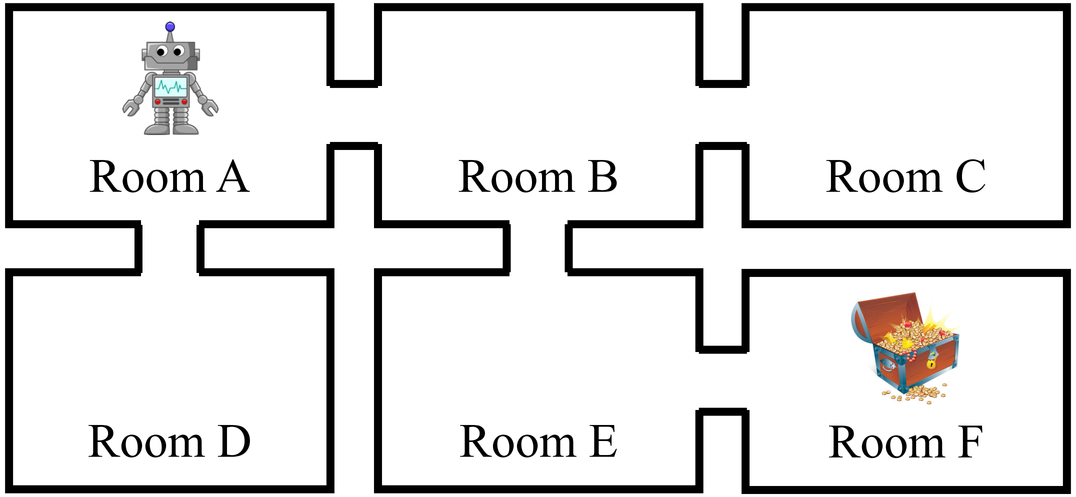
Real World Reinforcement Learning

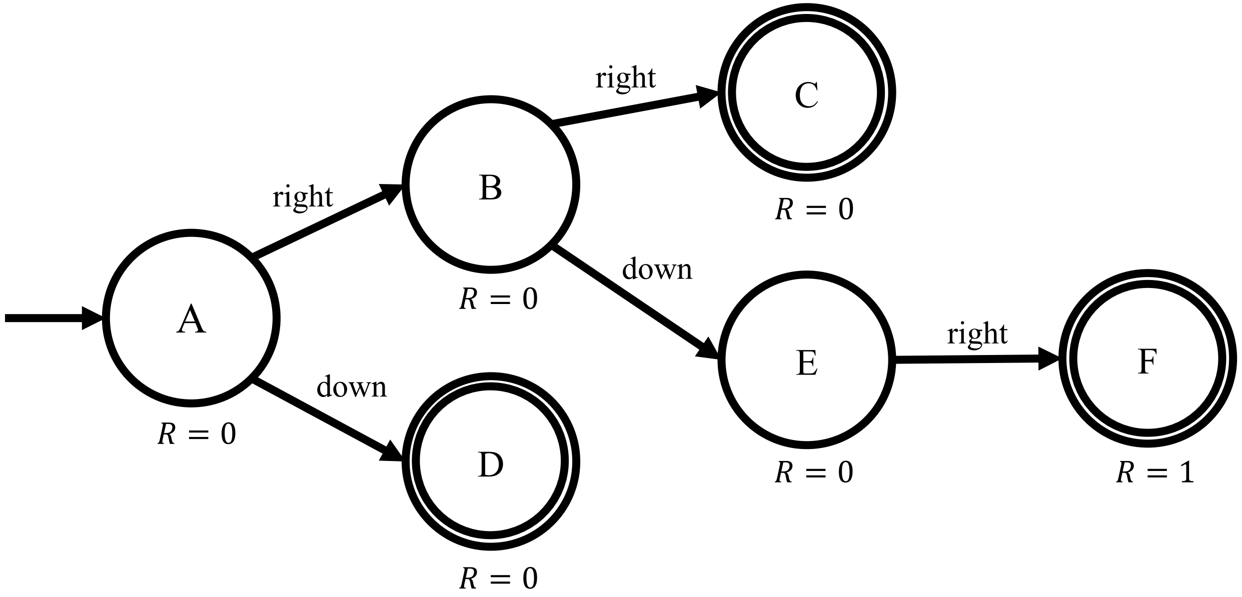
- Lots of systems involve sequential decisions
  - Banking/financial decision-making
  - Judicial decision-making
  - Medical decision-making
  - Education

- These systems should satisfy fairness for long-term outcomes

Markov Decision Processes (MDPs)

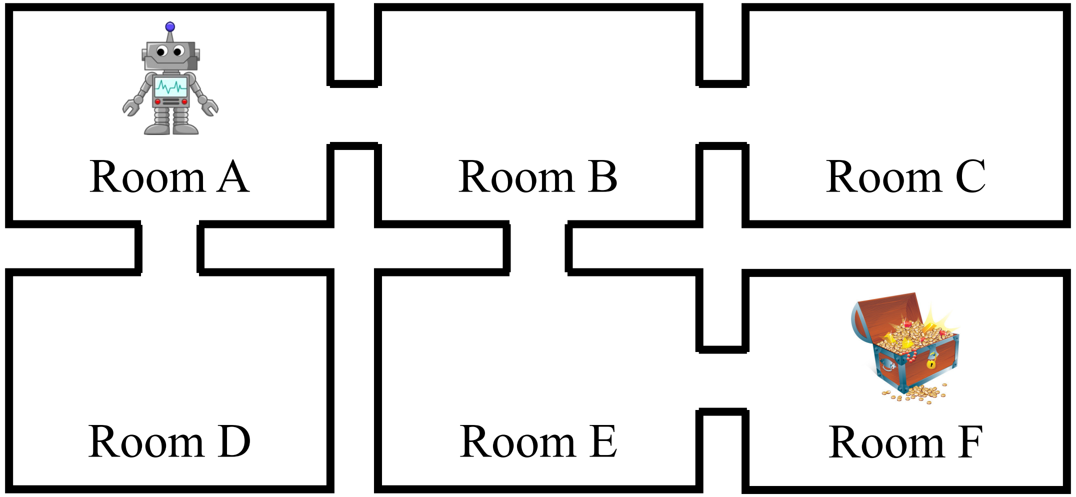
- **States** S
  - Set of rooms
- **Initial state** s_0
  - Room A
- **Actions** A
  - Direction to go
- **Transitions** $P: S \times A \to S$
  - Room that the robot ends up in
- **Rewards** $R: S \times A \to \mathbb{R}$
  - 1 for room F, 0 otherwise
- **Time horizon** T
  - How many steps the robot can take

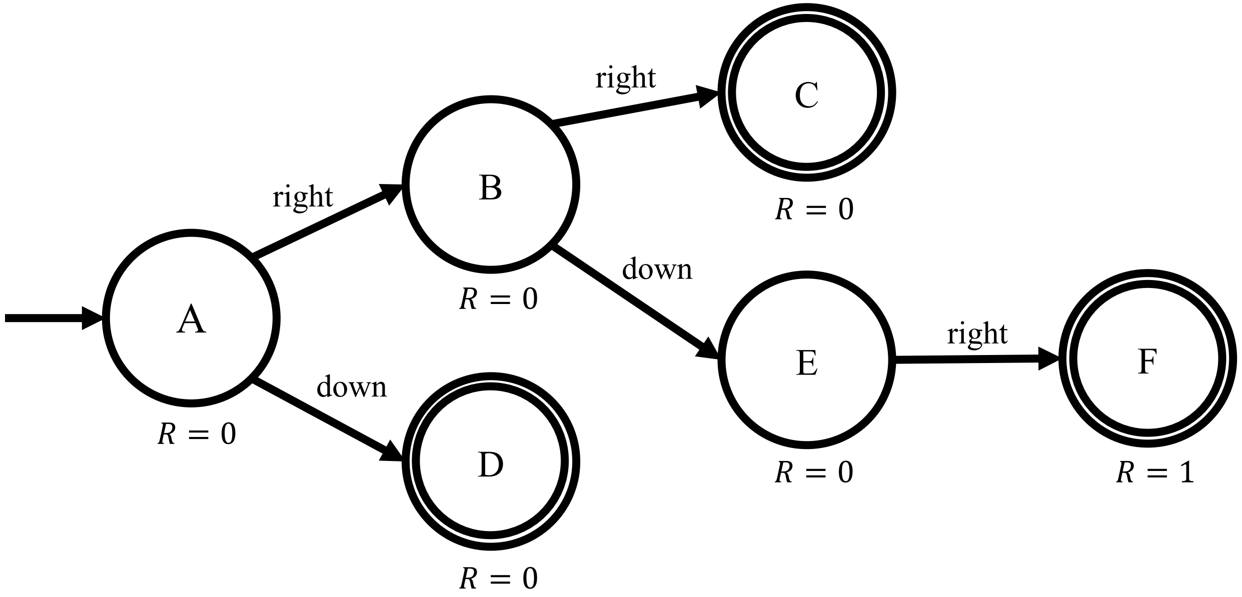




Markov Decision Processes (MDPs)

- **Policy** $\pi: S \rightarrow A$
  - Maps room to direction to take





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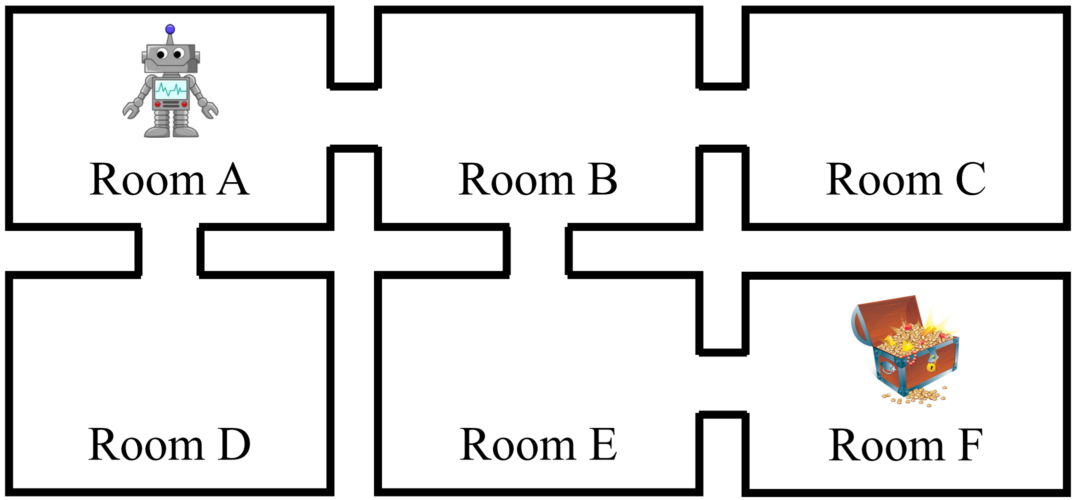

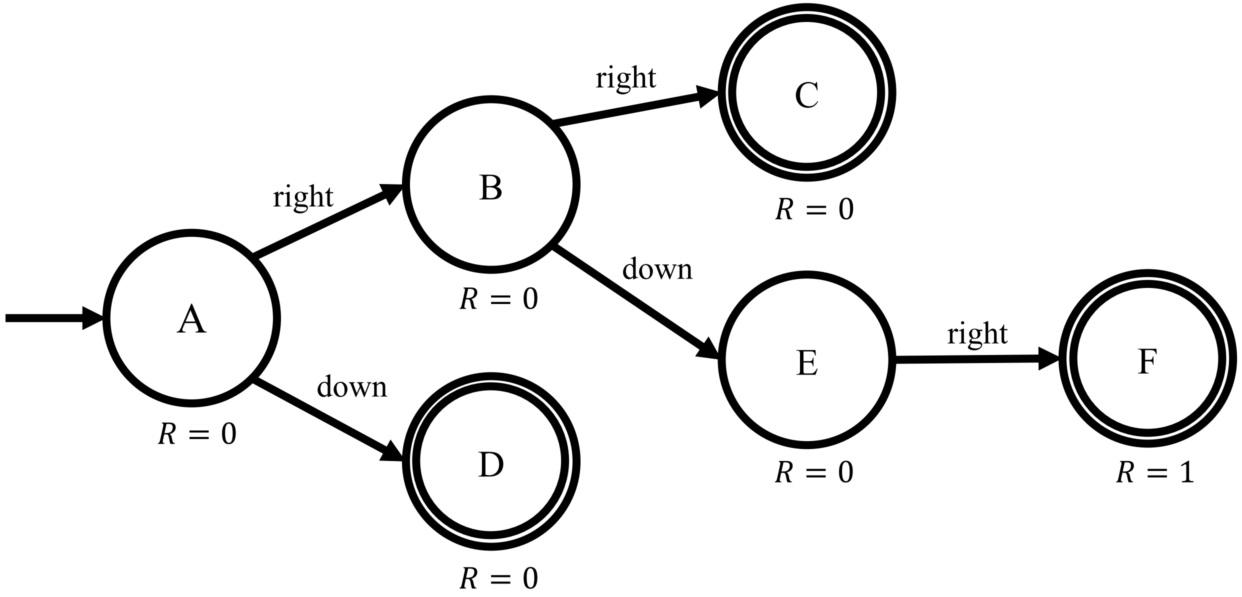

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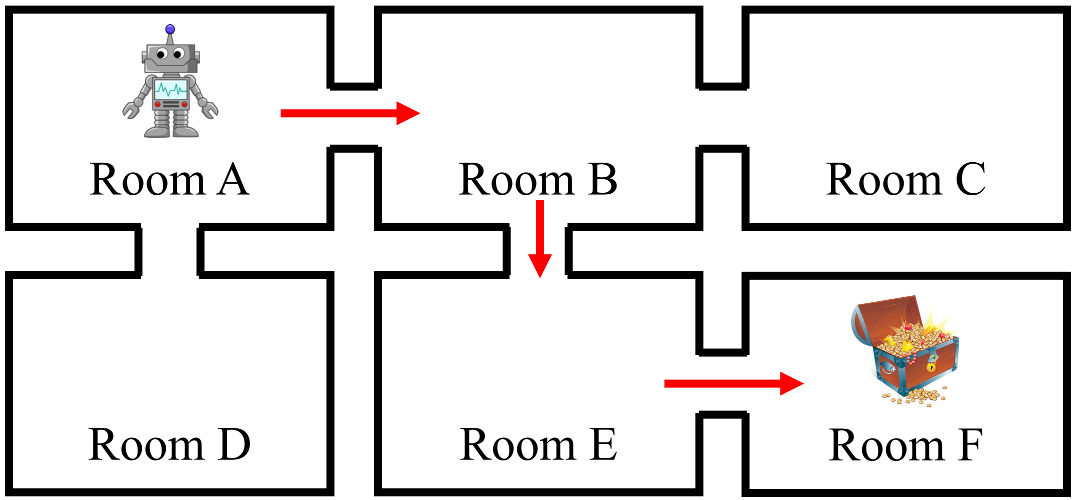

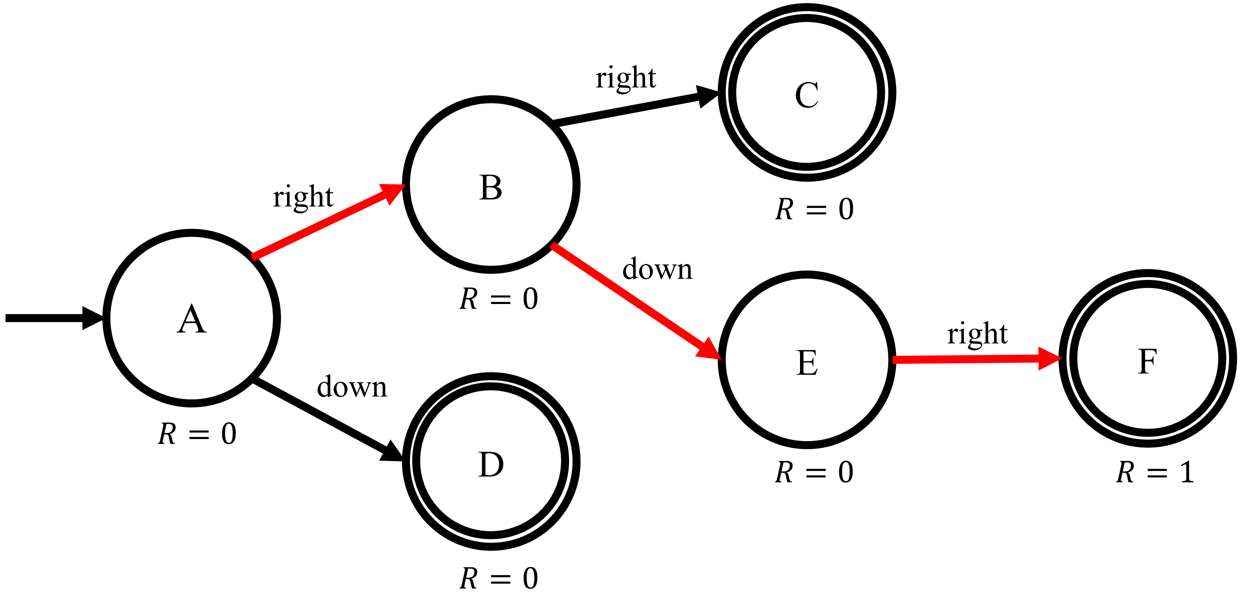

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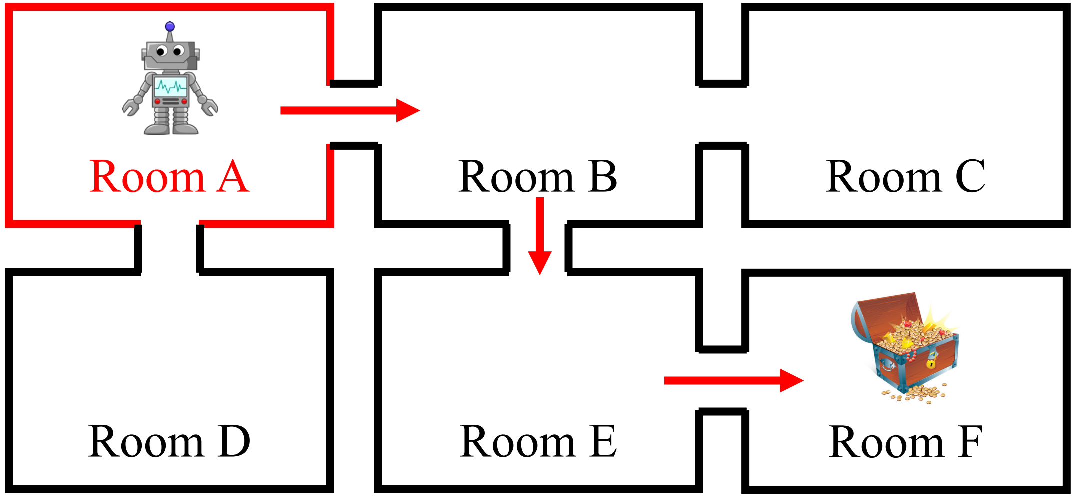

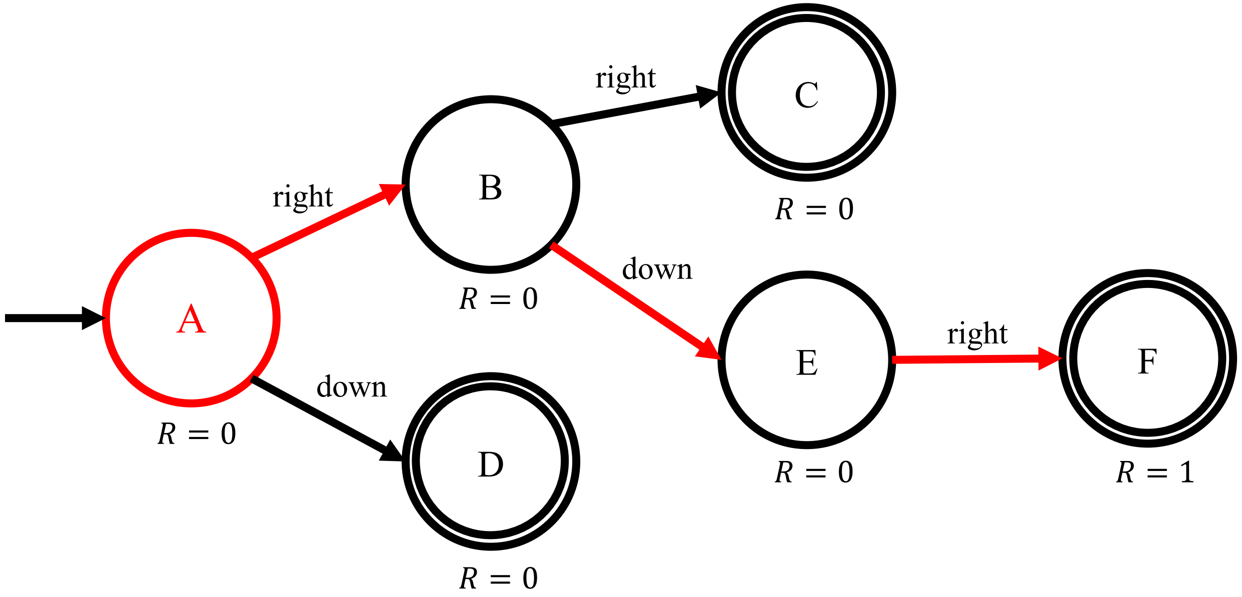

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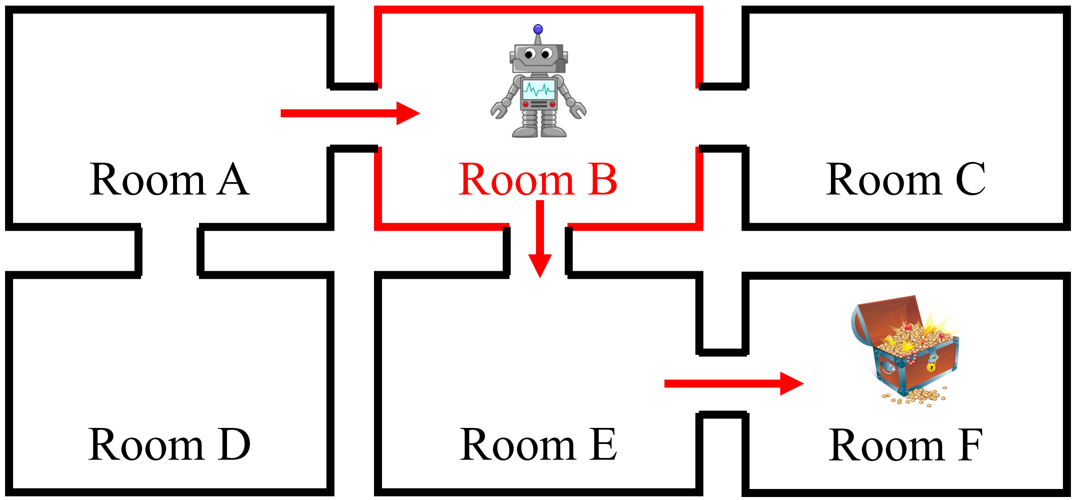

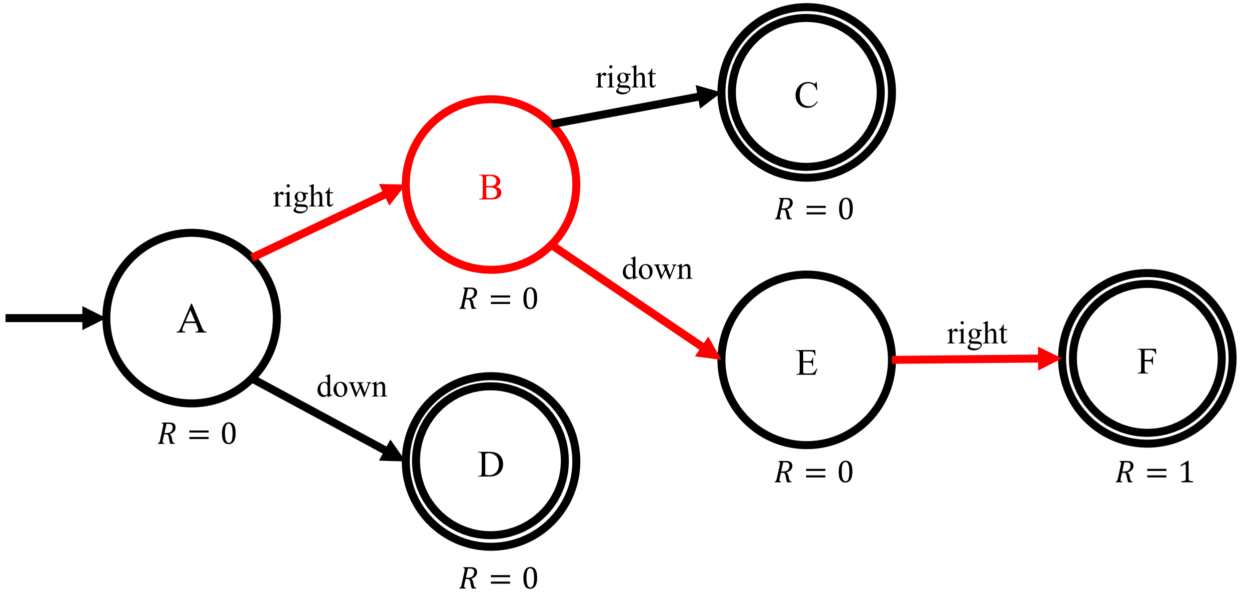

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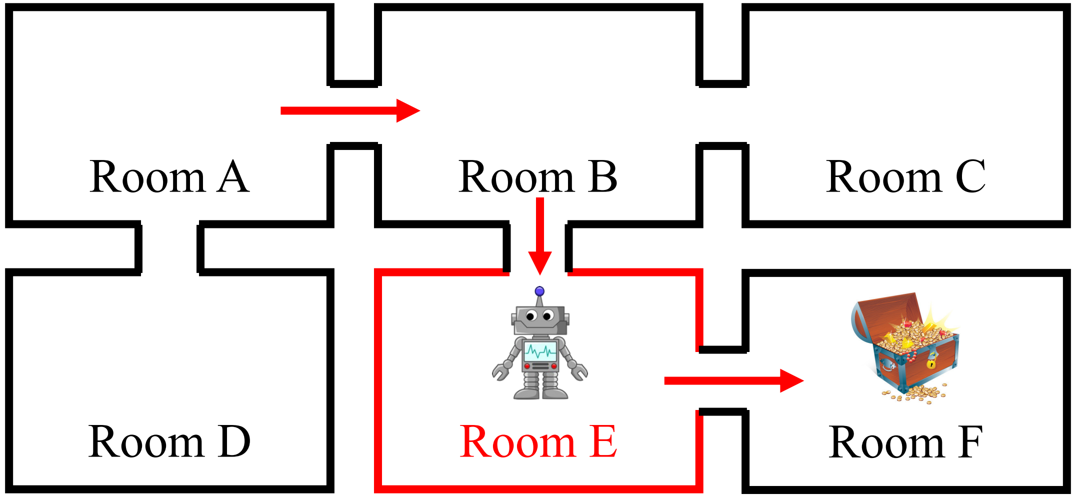

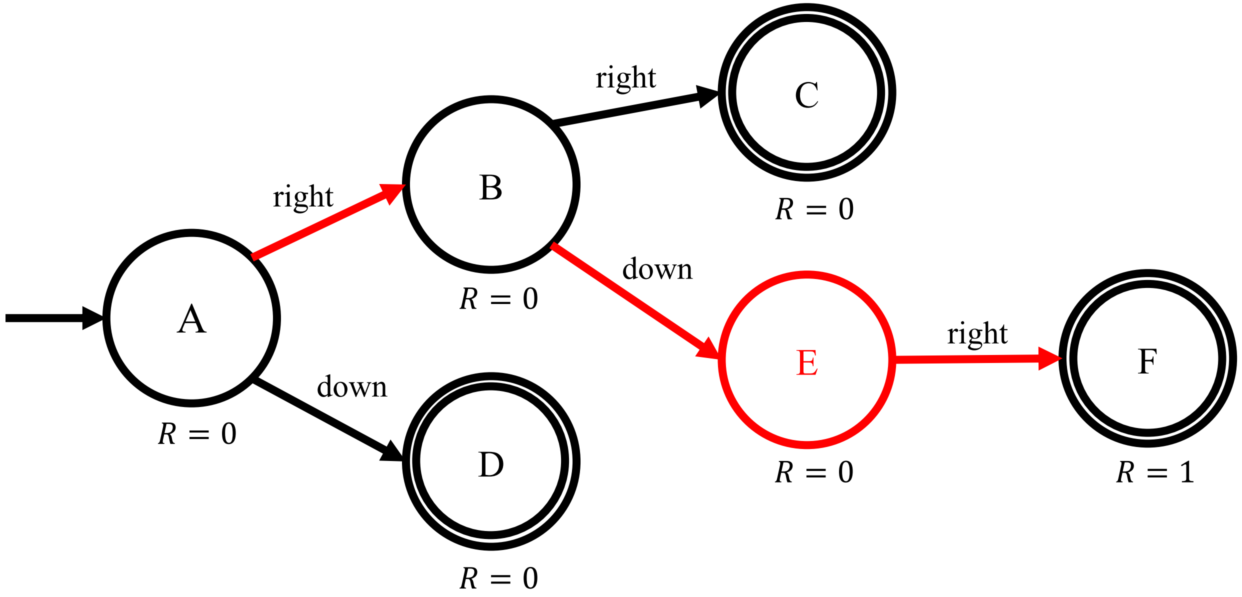

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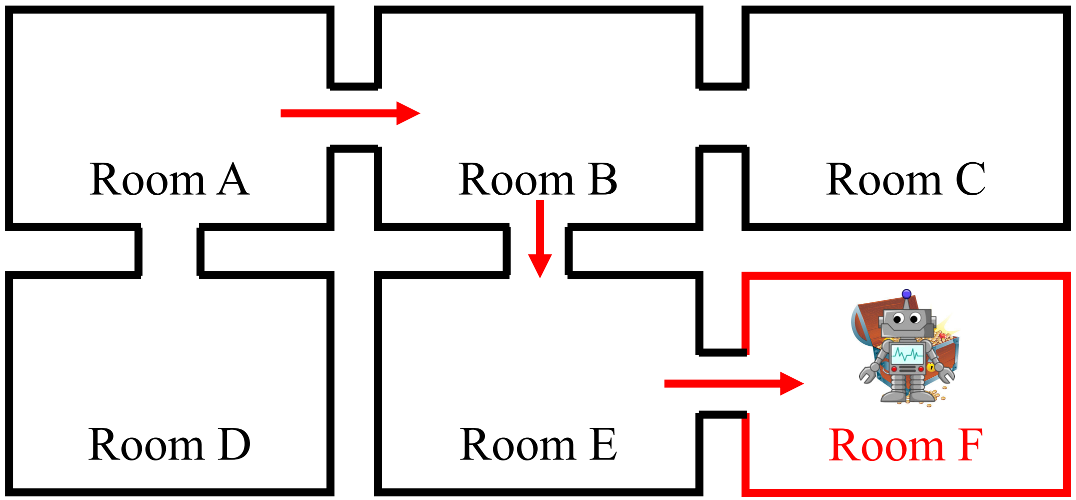

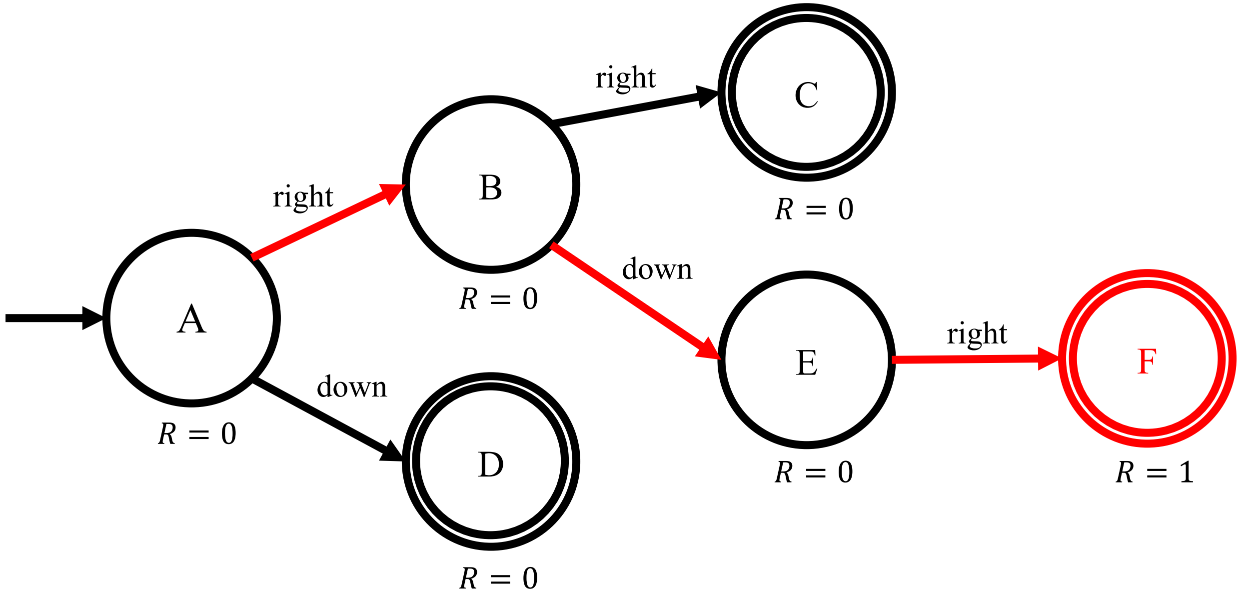

Reinforcement Learning

- **Goal:** Compute a policy π with high **cumulative reward**:

$$R^{(\pi)} = \sum_{t=1}^{T} R(s_t, a_t)$$

  - $s_1 = s_0$ is the initial state
  - $a_t = \pi(t, s_t)$ is the action taken
  - $s_{t+1} = P(s_t, a_t)$ is the state transition
  - T is the time horizon

- What about stochasticity?

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- What about stochasticity?

Fairness in Reinforcement Learning

- Note that $R^{(\pi)}$ is the reward for the decision maker (e.g., the bank), not for the individual

- We assume that there is additionally an **individual reward** $\rho(s, a)$, with corresponding **individual cumulative reward**

$$\rho^{(\pi)} = \mathbb{E}\left[\sum_{t=1}^{T} \rho(s_t, a_t)\right]$$

Fairness in Reinforcement Learning

- We assume each individual is associated with a subgroup $z \in \{0,1\}$
  - We assume z does not change over time
  - The reward for an individual in subgroup z is

$$\rho_z^{(\pi)} = \mathbb{E}\left[\sum_{t=1}^{T} \rho(s_t, a_t) \mid s_0 = (\tilde{s}_0, z)\right]$$

- π satisfies **demographic parity** if for all $z, z' \in \{0,1\}$, we have

$$\rho_z^{(\pi)} = \rho_{z'}^{(\pi)}$$

Imposing Fairness

- **Note:** Focus on planning, not learning
- Adding constraints to dynamic programming is hard!
- Typically, constrained MDPs are solved by formulating the cumulative reward objective as a **linear program**
- Then, we can impose fairness as a constraint in the linear programming

Linear Programming Formulation

- The **state-action** distribution of an MDP is

$$\lambda_{t,s,a}^{(\pi)} = \Pr[\text{ in state } s \wedge \text{take action } a \mid \text{on time step } t \ ]$$

- Defined recursively by

$$\lambda_{1,s,a}^{(\pi)} = P_0(s) \cdot \pi(\, a \mid 1, s\,)$$

$$\lambda_{t+1,s',a'}^{(\pi)} = \sum_{s \in S} \sum_{a \in A} \lambda_{t,s,a}^{(\pi)} \ \cdot P(\, s' \mid s, a\,) \cdot \pi(\, a' \mid t, s'\,)$$

Linear Programming Formulation

- **Idea:** Instead of computing π, compute the optimal $\lambda_{t,s,a}$
- Then, we have $\pi(\, a \mid t, s\,) = \frac{\lambda_{t,s,a}}{\sum_{a' \in A} \lambda_{t,s,a'}}$
- Given $\lambda_{t,s,a}$, the cumulative reward is

$$R = \sum_{t=1}^{T} \sum_{s \in S} \sum_{a \in A} \lambda_{t,s,a} \cdot R(s, a)$$

Linear Programming Formulation

- How to make sure λ represents an actual state-action distribution?

- For a given π, we have

$$\lambda_{1,s,a} = P_0(s) \cdot \pi(\, a \mid 1, s\,)$$

$$\lambda_{t+1,s',a'} = \sum_{s \in S} \sum_{a \in A} \lambda_{t,s,a} \cdot P(\, s' \mid s, a\,) \cdot \pi(\, a' \mid t, s'\,)$$

- Remember, π can be arbitrary here

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- Remember, π can be arbitrary here

Linear Programming Formulation

- How to make sure λ represents an actual state-action distribution?

- For a given π, we have

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- Implicitly, also constrain $\lambda_{t,s,a} \in [0,1]$

Linear Programming Formulation

- Solve the following linear program:

$$
\begin{aligned}
&\arg\max_{\lambda} \textstyle\sum_{t=1}^{T} \sum_{s \in S} \sum_{a \in A} \lambda_{t,s,a} \cdot R(s,a) \\
&\text{subj. to } \textstyle\sum_{a \in A} \lambda_{1,s,a} = P_0(s) \\
&\qquad\qquad \textstyle\sum_{a' \in A} \lambda_{t+1,s',a'} = \sum_{s \in S} \sum_{a \in A} \lambda_{t,s,a} \cdot P(s' \mid s,a)
\end{aligned}
$$

- **Note:** Dual of the more typical LP formulation

Imposing Fairness as a Constraint

- To impose fairness, add the constraint

$$p_z^{-1} \sum_{t=1}^{T} \sum_{(\tilde{s},z)\in S} \sum_{a\in A} \lambda_{t,s,a} \cdot \rho(s,a) = p_{z'}^{-1} \sum_{t=1}^{T} \sum_{(\tilde{s},z')\in S} \sum_{a\in A} \lambda_{t,s,a} \cdot \rho(s,a)$$

- Here, we have

$$p_z = \sum_{(\tilde{s},z)\in S} P_0\big((\tilde{s},z)\big)$$

Summary

- Algorithm for solving MDP by formulating it as a linear program
- Focus on computing the optimal state-action distribution
- Fairness is imposed as a constraint in the linear program

Agenda

- Selective compliance
- Fairness in sequential decision-making