Safe Human-Interactive Control via Shielding

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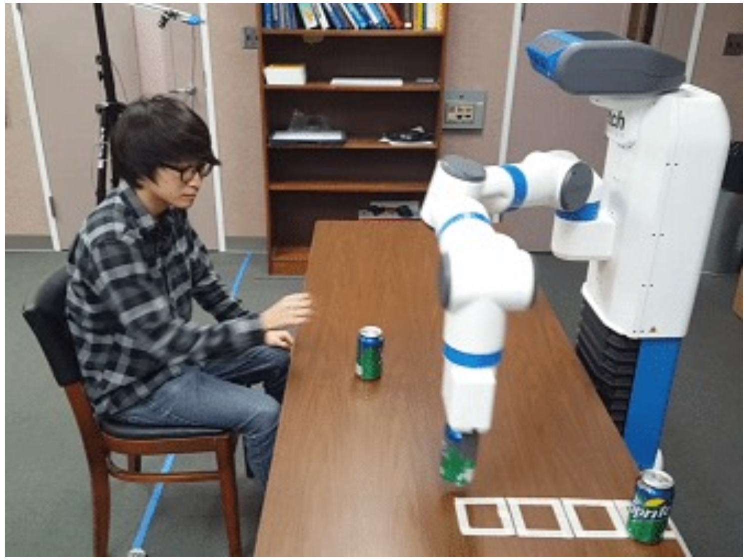
Human-Robot Interaction

- Robots are increasingly being deployed in settings where they must interact with humans
  - Both **cooperative** and **non-cooperative** (not necessarily zero-sum!)

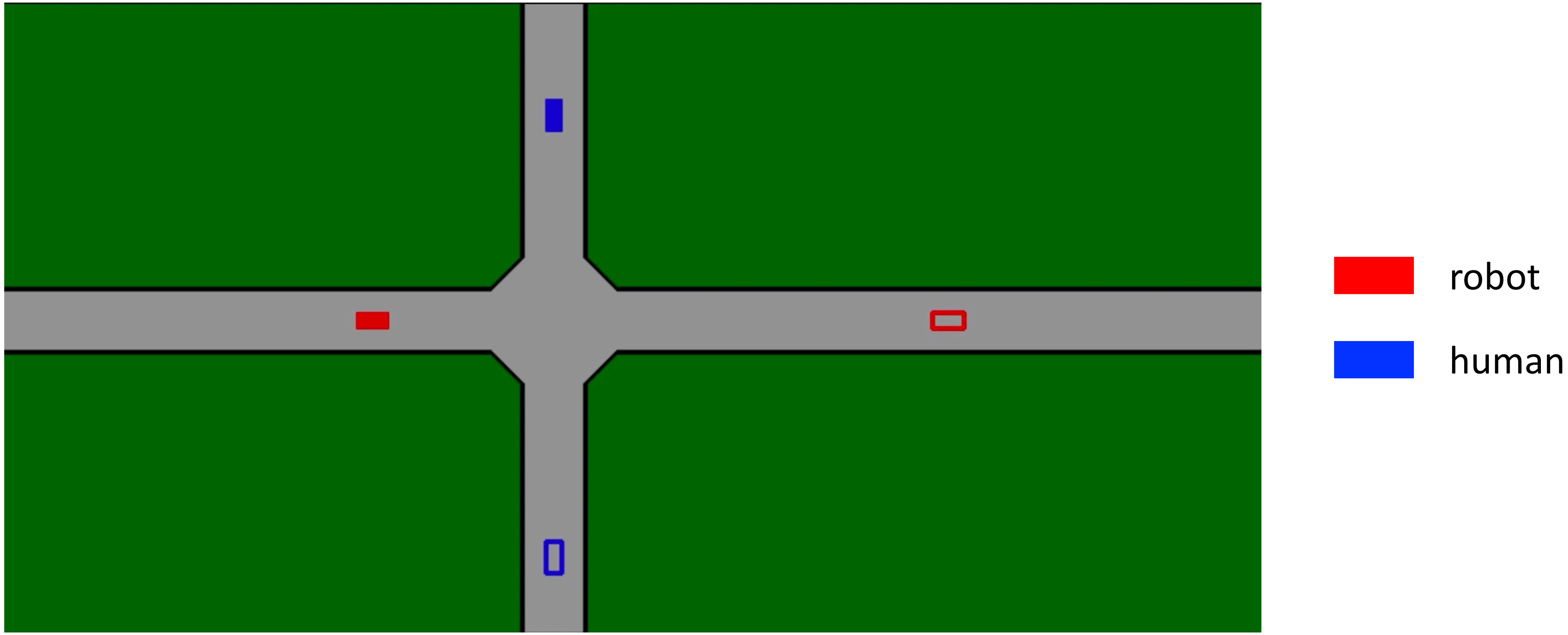


Park et al. Intention-Aware Motion Planning Using Learning Based Human Motion Prediction. RSS 2017

Human-Robot Interaction

- **Key question:** How to model the human?
- **General solution:** Two-player dynamic game

Human-Robot Interaction



(Actual) human and robot negotiate who passes first at an intersection

Roadmap

- Problem formulation
- Background on human interactive control
- Background on shielding
- Our algorithm
- Theoretical guarantees
- Experiments

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Game Theoretical Formulation

- **Two-player dynamic game**
  - Dynamics $x_{t+1} = f(x_t, u_{R,t}, u_{H,t})$
  - Agent $\delta \in \{R, H\}$ has utility

$$J_\delta(x; \vec{u}_R, \vec{u}_H) = \sum_{t=1}^{T} r_\delta(x_t, u_{\delta,t})$$

- **Human strategy**
  - Nash equilibrium action sequence

Control Problem

- **Robot control**
  - Construct a robot controller $u_{R,t} = \pi_R(x_t)$
- **Goal reaching**
  - Goal region $\mathcal{X}_{\text{goal}}$
  - Reach $x_t \in \mathcal{X}_{\text{goal}}$ for some t
- **Safety**
  - Safe region $\mathcal{X}_{\text{safe}}$
  - Ensure $x_t \in \mathcal{X}_{\text{safe}}$ for all $t \in \{1, \dots, T\}$

Challenges

- **Challenge 1:** Computational complexity
  - Hard to compute Nash equilibrium strategies

- **Challenge 2:** Unknown human reward function
  - Human reward function r_H is unknown

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Prior Work (Sadigh et al. 2016)

- **Challenge 1:** Computational complexity
  - Re-formulate as Stackelberg game
- **Challenge 2:** Unknown human reward function
  - Use inverse reinforcement learning to infer human reward function

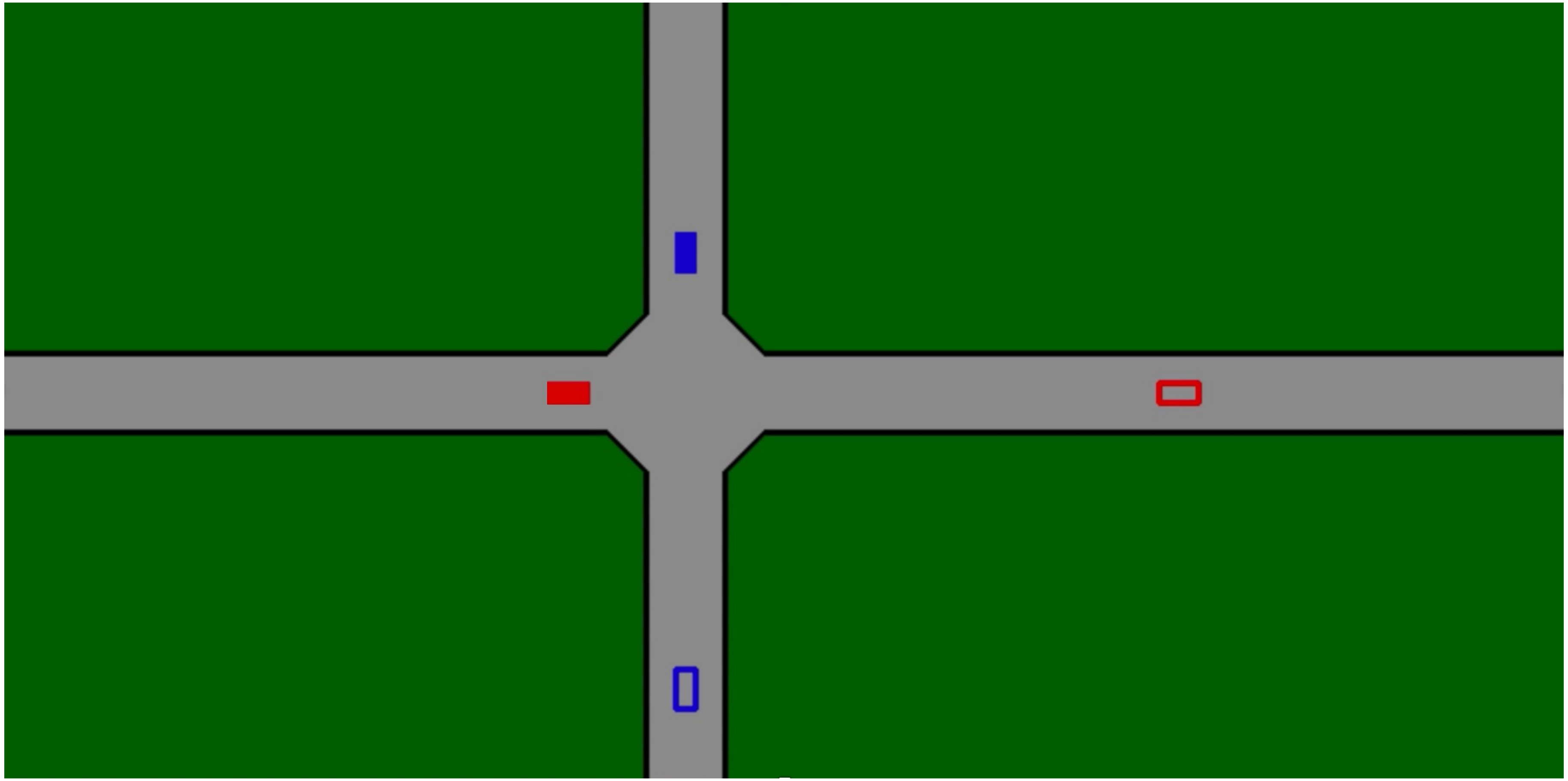
Sadigh, Sastry, Seshia, Dragan, Planning for Autonomous Cars that Leverage Effects on Human Actions. RSS, 2016.

Computational Complexity

- **Stackelberg Game**
  - Agents play sequentially (not simultaneously)
  - Dynamics $x_{t+1} = f_H(f_R(x_t, u_{R,t}), u_{H,t})$

Sadigh, Sastry, Seshia, Dragan, Planning for Autonomous Cars that Leverage Effects on Human Actions. RSS, 2016.

Stackelberg Game



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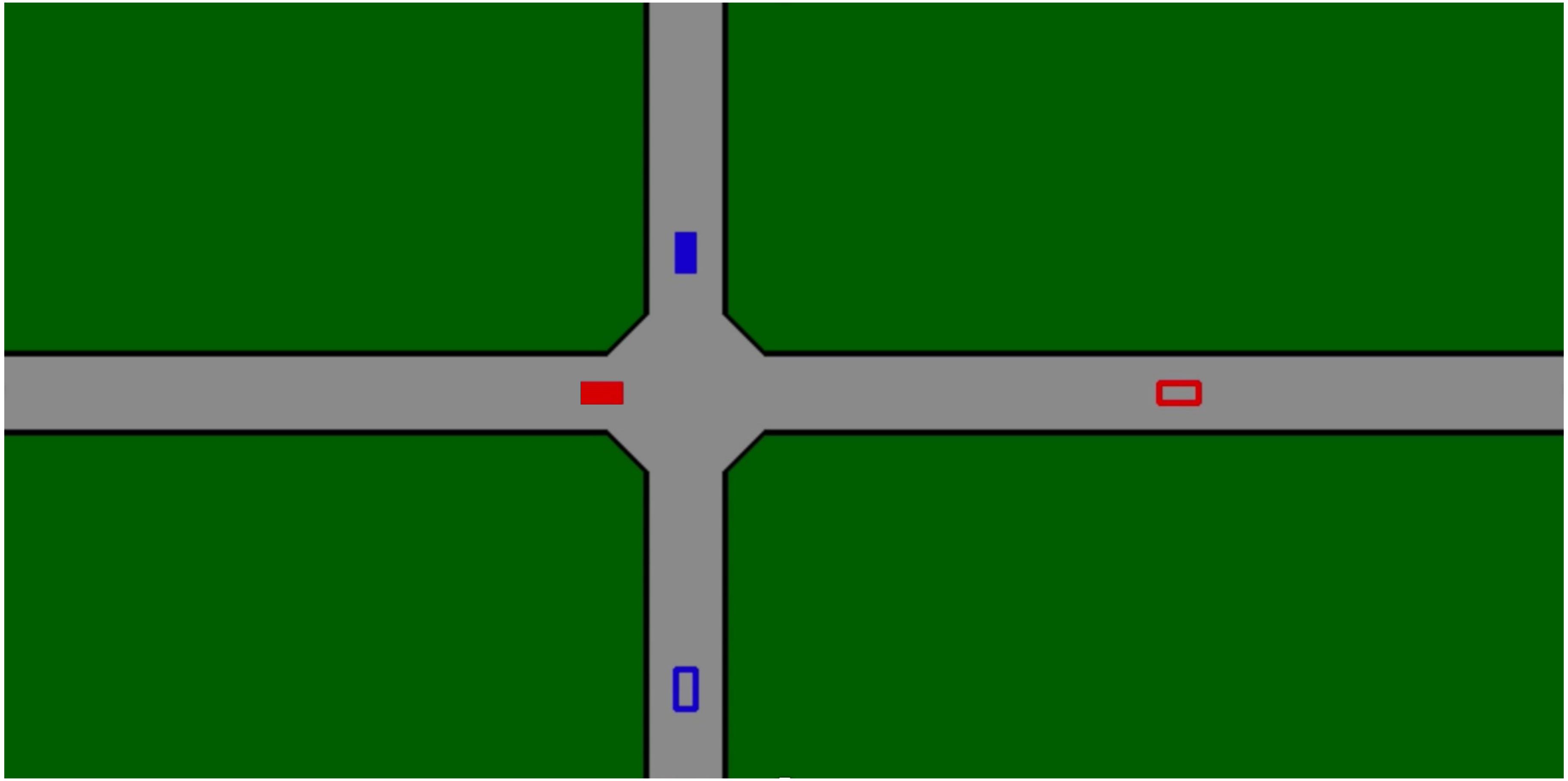

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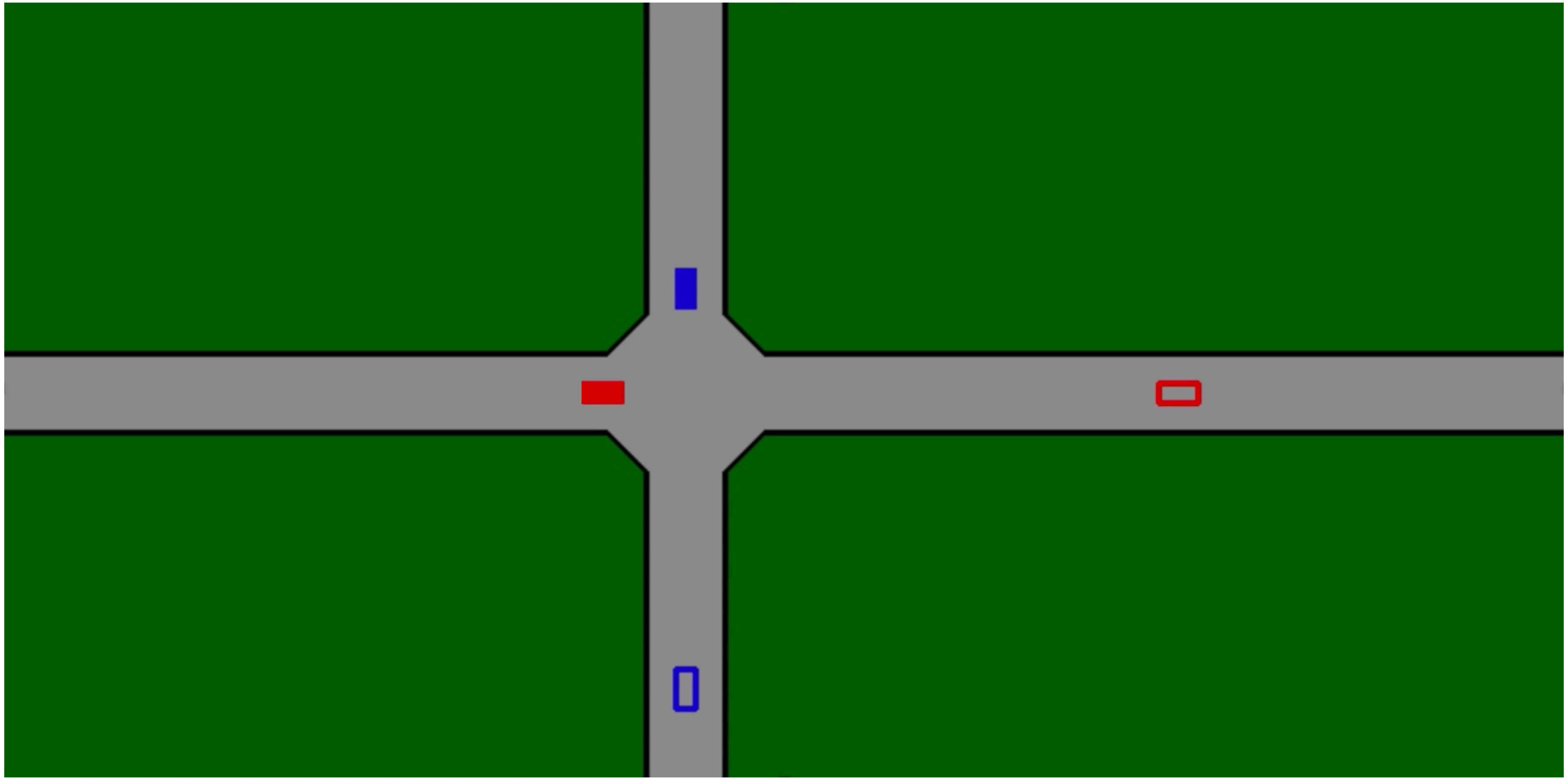

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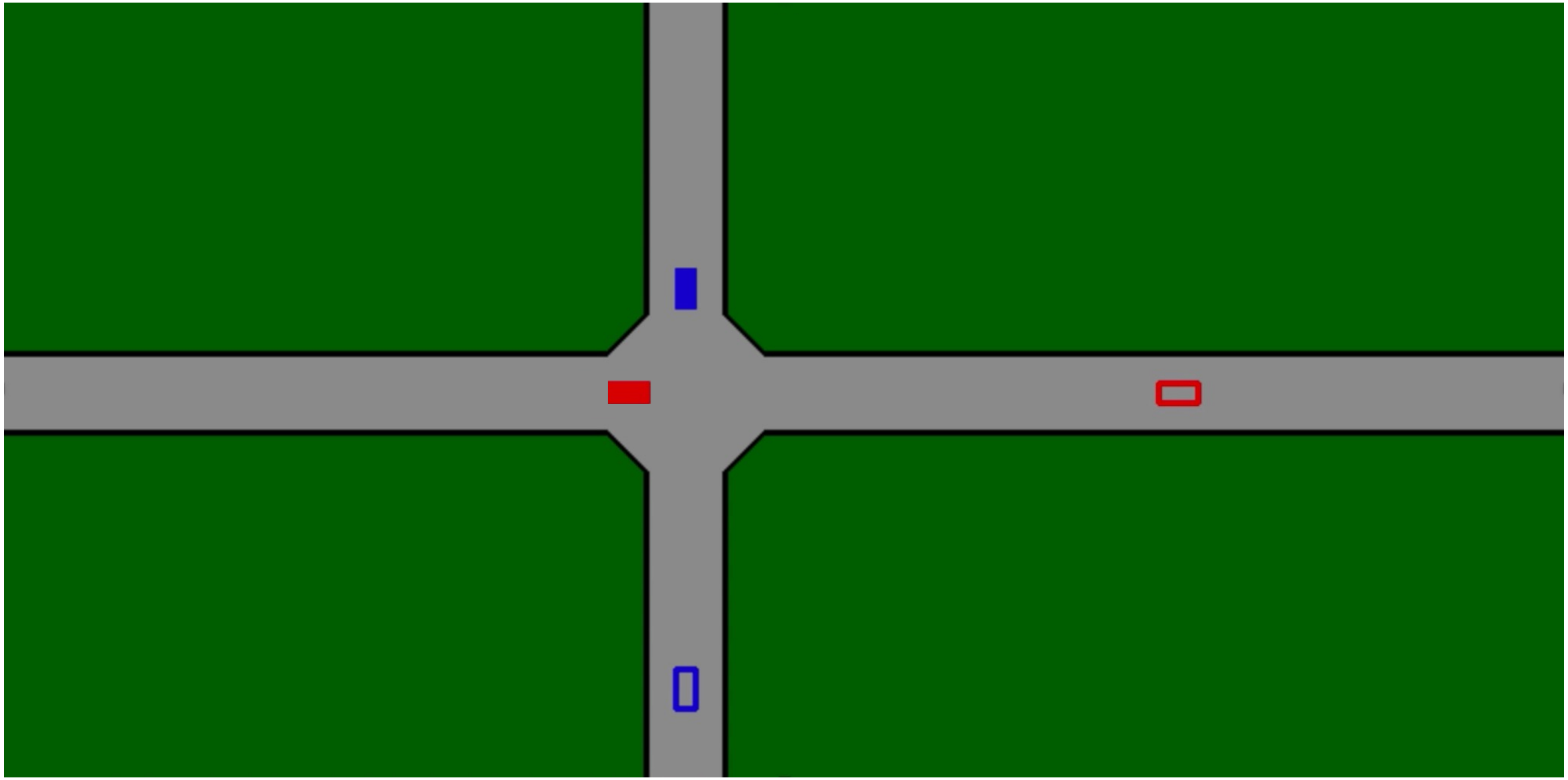

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Stackelberg Game

- **Solution strategy**
  - Finite state, finite horizon
  - Then, we can use backward induction:

$$u_{R,t}^*(x) = \arg\max_{u_R} \left\{ r_R(x) + J_{R,t+1}^*\left(f_H\left(f_R(x, u_R), u_{H,t}^*\big(f_R(x, u_R)\big) \right) \right) \right\}$$

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  - Here, $u_{R,t}^*(x)$ is the optimal policy and $J_{R,t}^*(x)$ is the value function
  - Computes a subgame-perfect Nash equilibrium

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Stackelberg Game

- **Solution strategy**
  - Continuous state, finite horizon (MPC)
  - Optimize $u_{R,t}^*$ using gradient descent
  - Compute derivative of arg-max using implicit differentiation

Sadigh, Sastry, Seshia, Dragan, Planning for Autonomous Cars that Leverage Effects on Human Actions. RSS, 2016.

Human Reward Function

- **Inverse Reinforcement Learning**
  - Given demonstrations of the human's behavior, choose the reward function that best "describes" the human behavior:

$$\hat{r}_H = \arg\max_r L(\pi(r); D)$$

  - Here, $\pi(r)$ is the optimal policy if the reward function is r, D is the observed dataset of human state-action pairs, and L is a loss function

- **Human Reward Function Inference**
  - Gather demonstrations of human behavior
  - Use off-the-shelf inverse reinforcement learning algorithms to estimate r_H

Sadigh, Sastry, Seshia, Dragan, Planning for Autonomous Cars that Leverage Effects on Human Actions. RSS, 2016.

Shortcomings

- **Challenge 1:** Computational complexity
  - Formulate as Stackelberg game
  - Susceptible to local minima, so not guaranteed to be a Nash equilibrium
- **Challenge 2:** Unknown human reward function
  - Use inverse reinforcement learning to infer human reward function
  - No guarantee that inferred reward function is correct

Sadigh, Sastry, Seshia, Dragan, Planning for Autonomous Cars that Leverage Effects on Human Actions. RSS, 2016.

Our Goal

- **Design a robot controller that**
  - Guarantees safety
  - Best attempt to reach goal (but no guarantees)

- **Assumptions**
  - Necessary to make some assumptions about human reward function
  - Goal is to minimize the required assumptions

Roadmap

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- **Background on shielding**
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Shielding

- **Untrustworthy Policy $\hat{\boldsymbol{\pi}}$**
  - Achieves good performance
  - May be unsafe
- **Backup Policy $\boldsymbol{\pi}_{\mathbf{backup}}$**
  - May perform poorly
  - Can safely bring the system to a stop from $x \in \mathcal{X}_{\text{rec}} \subseteq \mathcal{X}_{\text{safe}}$
  - Say x is **recoverable**
- **Strategy**
  - **Safety:** Override $\hat{\pi}$ using π_{backup} to guarantee safety
  - **Goal-reaching:** Minimally override $\hat{\pi}$ to ensure performance (no guarantees)

Recoverability

We have $x \in \mathcal{X}_{\text{rec}}$ if π_{backup} safely brings the robot to a stop ($v = 0$)

Shielding Algorithm

- **Algorithm**
  - Use $\hat{\pi}$ if $\hat{x}_{t+1} = f\left(x_t, \hat{\pi}(x_t)\right) \in \mathcal{X}_{\text{rec}}$
  - Use π_{backup} otherwise
- **Theorem:** This algorithm maintains the invariant

$$x_t \in \mathcal{X}_{\text{rec}} \Rightarrow x_{t+1} \in \mathcal{X}_{\text{rec}}$$

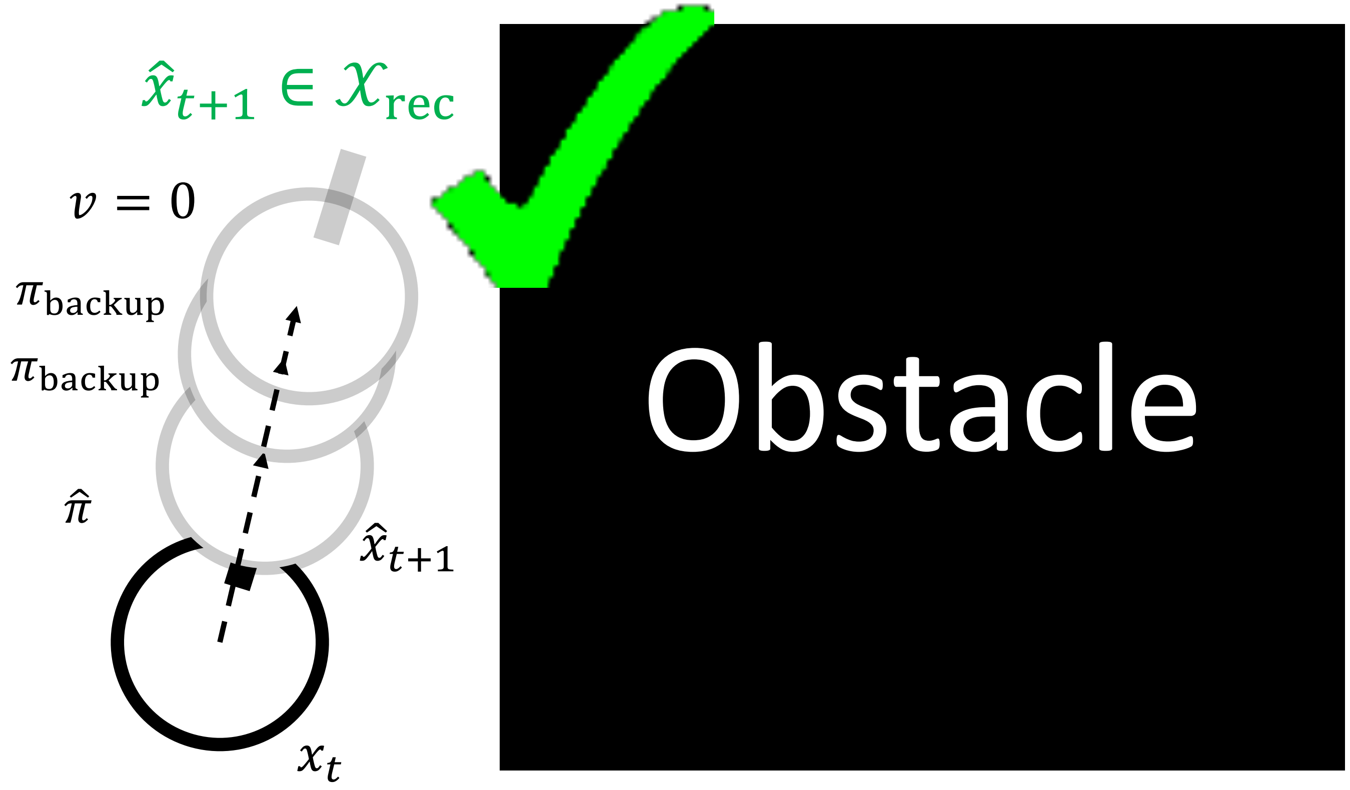
- **Proof**
  - **Case 1:** It uses $\hat{\pi}$; then, the result follows by the condition
  - **Case 2:** It uses π_{backup}; then, it follows since $x_t \in \mathcal{X}_{\text{rec}}$ implies that using π_{backup} is safe, so $x_{t+1} = f\left(x_t, \pi_{\text{backup}}(x_t)\right)$ must also be recoverable

Model Predictive Shielding

- **Challenge:** $\mathcal{X}_{\mathrm{rec}}$ is often hard to compute in closed form
- **Key idea:** We can check $x \in \mathcal{X}_{\mathrm{rec}}$ using model-based simulation

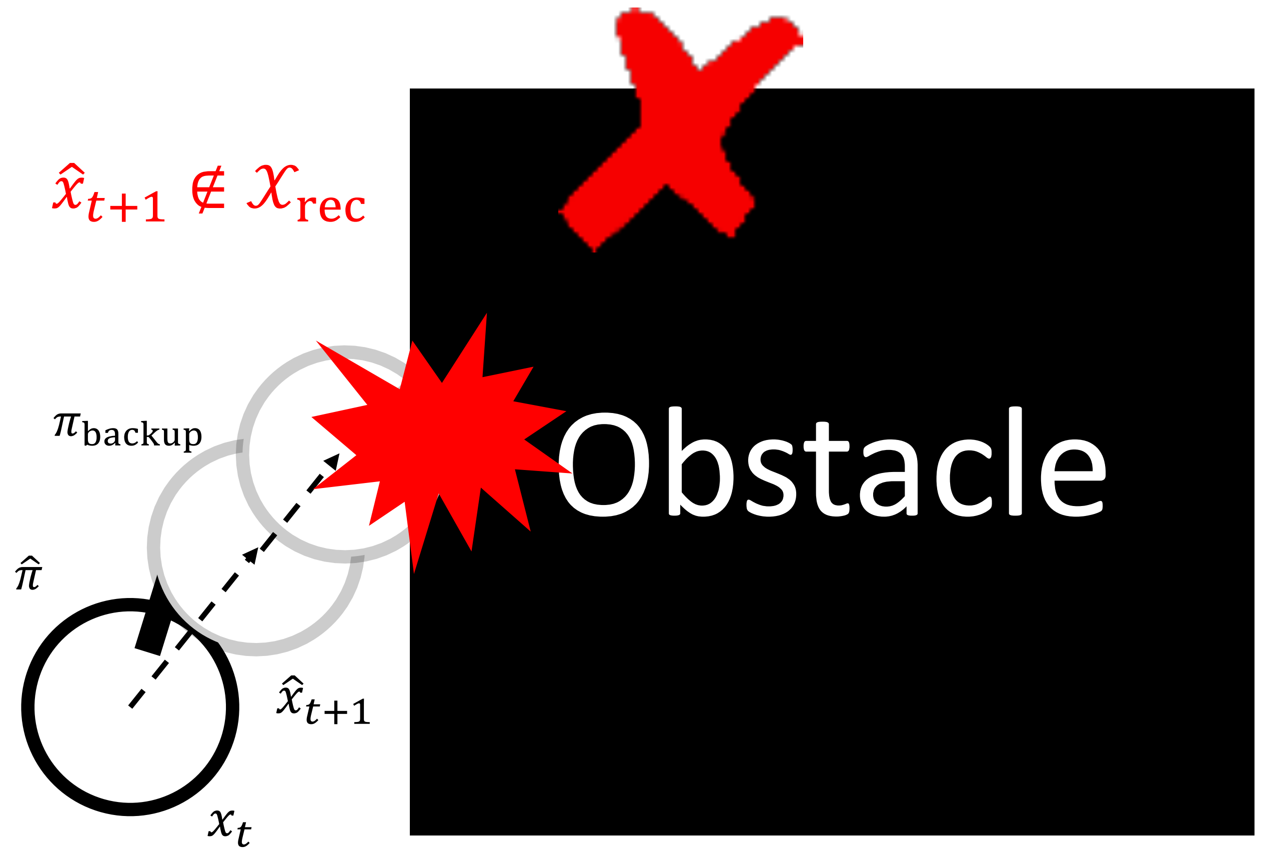
Li & Bastani 2020, Bastani 2021

Checking Recoverability



Simulation to see if $\hat{x}_{t+1} \in \mathcal{X}_{\text{rec}}$

Checking Recoverability



Simulation to see if $\hat{x}_{t+1} \in \mathcal{X}_{\text{rec}}$

Model Predictive Shielding

if $\hat{x}_{t+1} \in \mathcal{X}_{\mathrm{rec}}$ ✓ **then use** $\hat{\pi}$

if $\hat{x}_{t+1} \notin \mathcal{X}_{\mathrm{rec}}$ ✗ **then use** π_{backup}

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Our Approach

- **High-level strategy**
  - Do **not** try to compute a Nash Equilibrium solution
  - Instead, act conservatively with respect to rational human

- **Key idea**
  - Assume human prioritizes safety
  - We only need to prove that the human **can** maintain safety
  - Then, rationality implies that the human **does** maintain safety

Simplified Human Model

- **Simplified Stackelberg Game**
  - Assume that human plays conservatively with respect to possible future robot actions $\vec{u}_R \subseteq \hat{\mathcal{U}}_R$:

$$\vec{u}_R^* = \arg\max_{\vec{u}_R} J_R\left(x; \vec{u}_R, \vec{u}_H^*(\vec{u}_{R,1})\right)$$

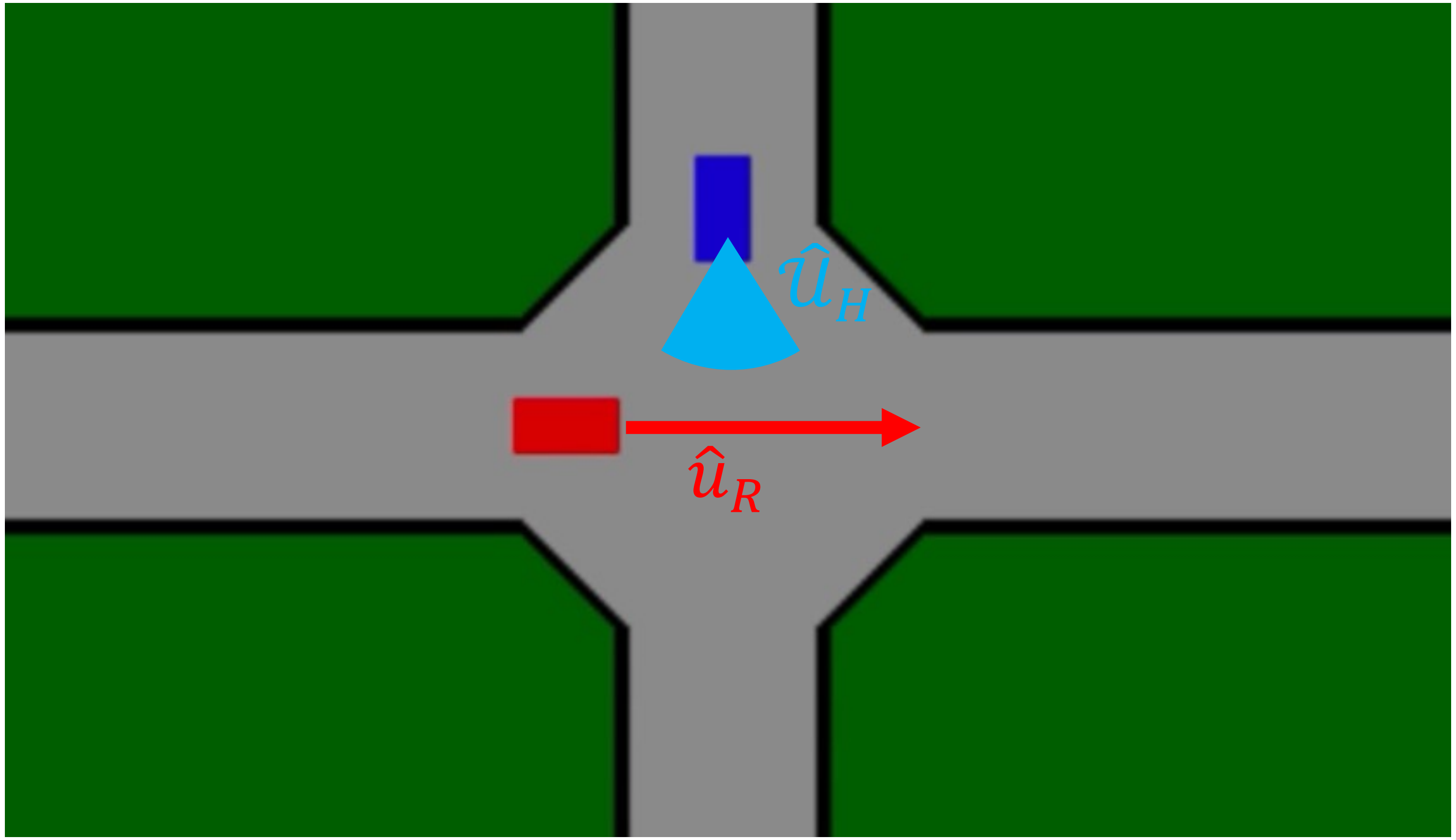
$$\vec{u}_H^*(u_{R,1}) = \arg\max_{\vec{u}_H} \min_{\vec{u}_{R,2:T}} J_H(x; u_{R,1} \circ \vec{u}_{R,2:T}, \vec{u}_H)$$

- **Intuition:** Reduces problem to 1-step Stackelberg game
- **Justification:** Human cannot anticipate exactly what the robot is going to do, so they must act conservatively

Assumptions on Human Objective

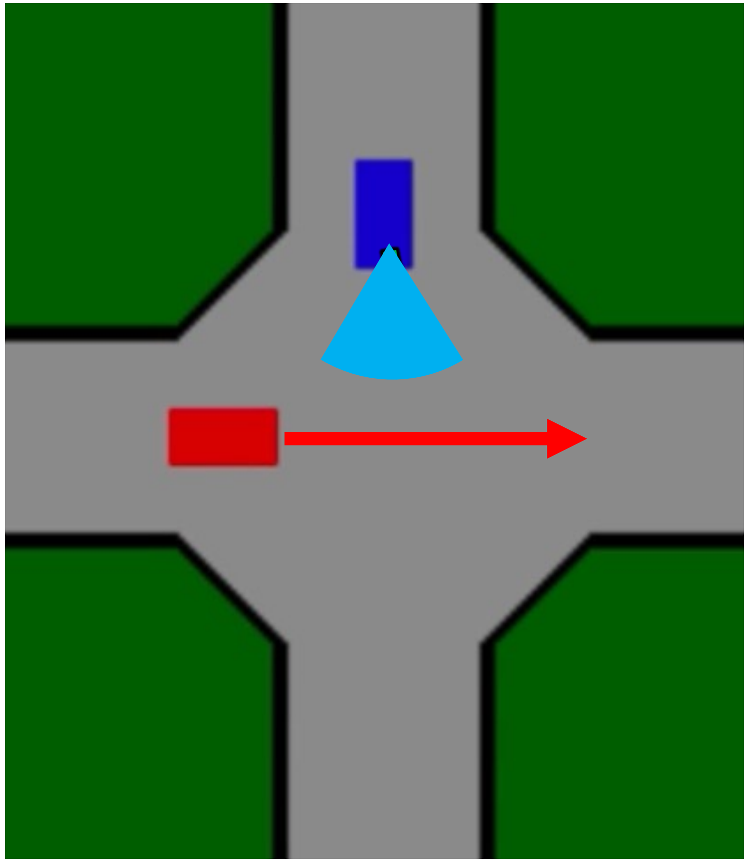
- **Human policy:** $\vec{u}_H^*(u_{R,1}) = \arg\max_{\vec{u}_H} \min_{\vec{u}_{R,2:T}} J_H(x; u_{R,1} \circ \vec{u}_{R,2:T}, \vec{u}_H)$
- **Assumption 1:** Human rewards for unsafety
  - We have $r_H(x_t, u_{H,t}) = -\infty$ if $x_t \notin \mathcal{X}_{\text{safe}}$
- **Assumption 2:** Human predicted robot backup action
  - We are given a **robot backup action** $\hat{u}_R$ that the robot can use to come to a stop
  - The human acts conservatively with respect to this action
- **Assumption 3:** Human backup actions
  - We are given **human backup actions** $\hat{\mathcal{U}}_H$ that the human can use to come to a stop
  - If the human's objective value is $-\infty$, then they use some action $u_H \in \hat{\mathcal{U}}_H$

Assumptions on Human Objective



Algorithm Overview

- **Human model**
  - $\vec{u}_H^* = \arg\max_{\vec{u}_H} \min_{\vec{u}_{R,2:T}} J_H(x; u_{R,1} \circ \vec{u}_{R,2:T}, \vec{u}_H)$
- **Recoverability**
  - Say x is **recoverable** if using $\hat{u}_R$ from x safely brings the system to a stop
  - Depends on the **unknown human policy**
- **Algorithm**
  - Say x is **recoverable** if the system safely comes to a stop for $\vec{u}_{R,2:T} = \vec{\hat{u}}_R$ and for all $\vec{u}_H \subseteq \hat{U}_H$



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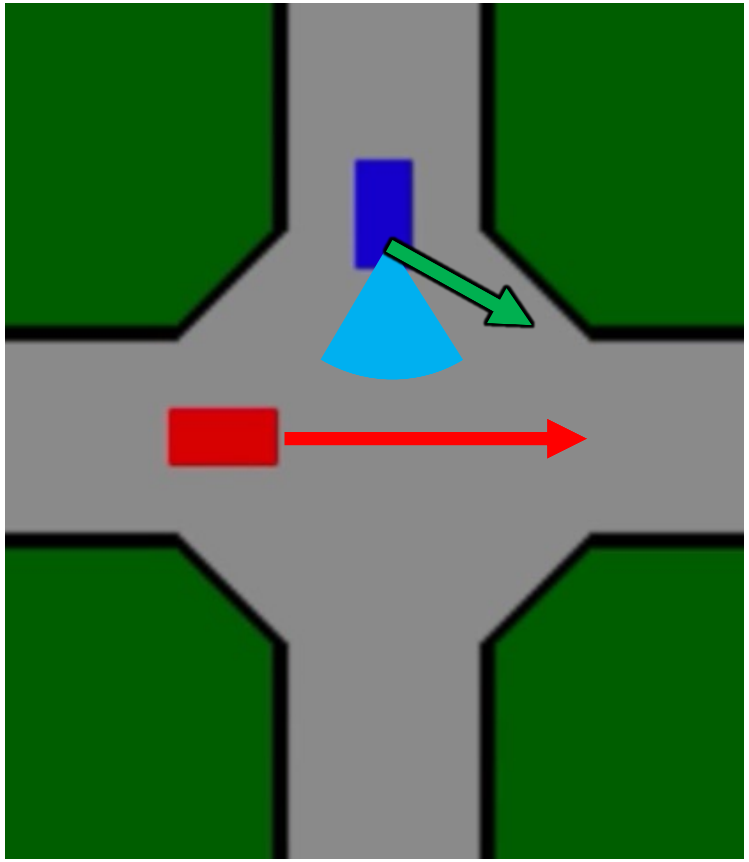
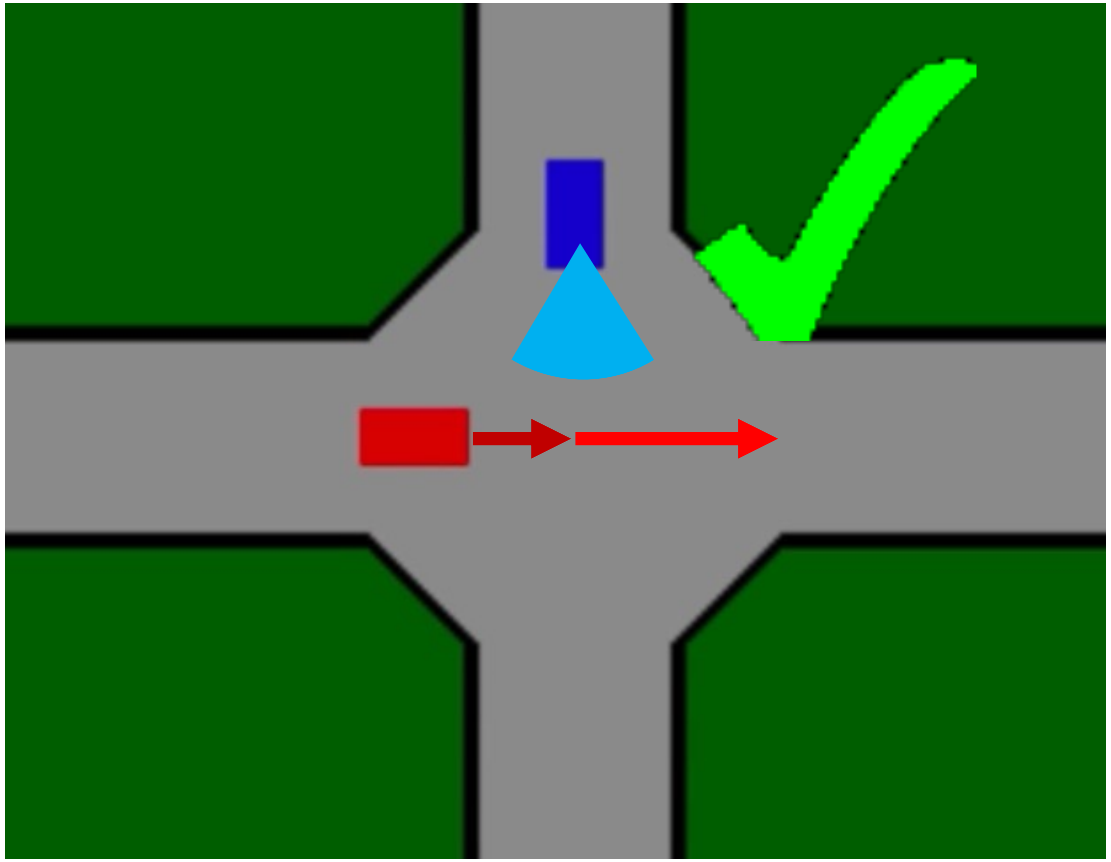
  - The human may not take such a $\vec{u}_H$, but then they take an action $\vec{u}_H'$ that is **better** than $\vec{u}_H$



Algorithm

- **Step 1:** Compute the **human backup region** that the human can reach using $u_H \in \hat{\mathcal{U}}_H$
  - It is **not a reachable set**; the human may drive outside of it
- **Step 2:** Compute the **robot backup trajectory** that the robot takes using $\hat{\pi}$ for one step followed by $\hat{u}_R$
- **Step 3:** Use $\hat{\pi}$ if these do not overlap, and $\hat{u}_R$ otherwise



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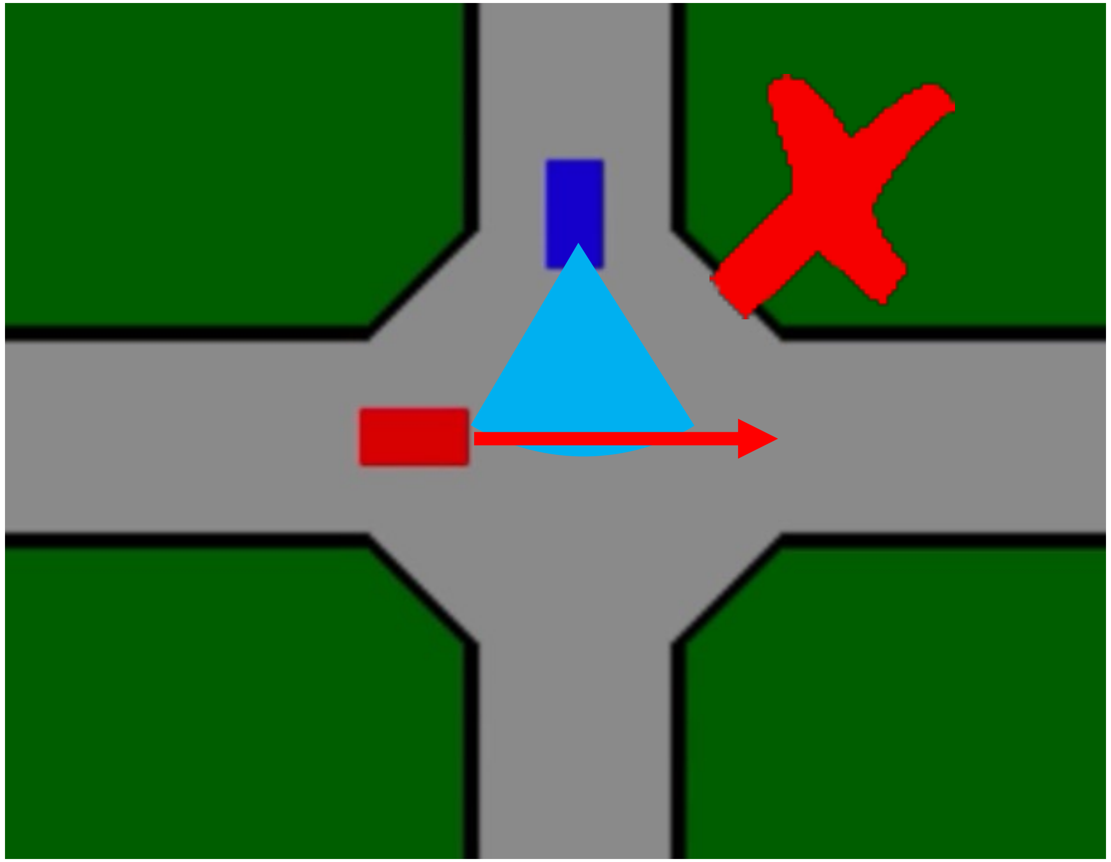


Step 1 & 2: Robot/Human Backup Regions

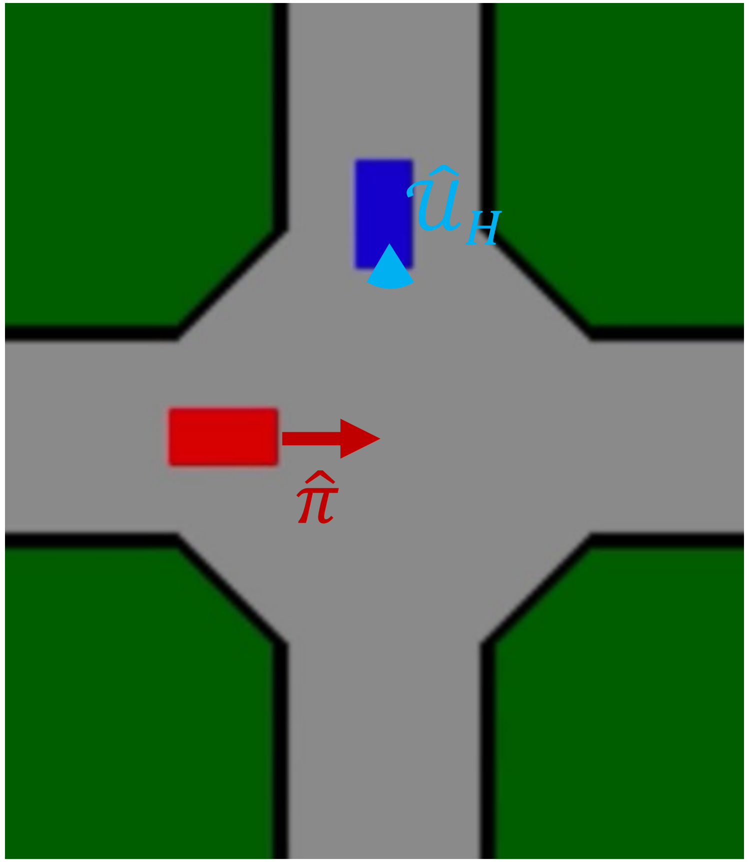
- **Goal**
  - Compute reachable set under robot backup action $\hat{u}_R$ and human backup actions $\hat{\mathcal{U}}_H$

- **Algorithm**
  - Given $F_\delta: 2^{\mathcal{X}} \times 2^{\mathcal{U}_\delta} \to 2^{\mathcal{X}}$ for $\delta \in \{R, H\}$ s.t.

$$\{ f_\delta(x, u) \mid x \in X, u \in U \} \subseteq F_\delta(X, U)$$

  - Compute

$$X_2 = F_H\big(F_R(\{x\}, \{\hat{\pi}(x)\}), \hat{\mathcal{U}}_H\big)$$
$$X_{t+1} = F_H\big(F_R(X_t, \{\hat{u}_R\}), \hat{\mathcal{U}}_H\big)$$



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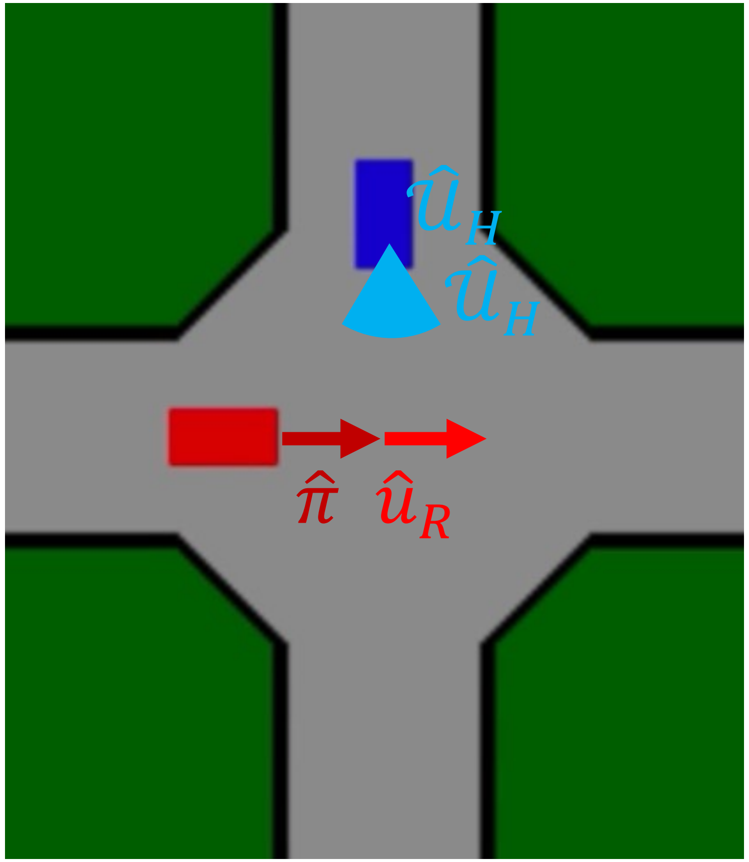

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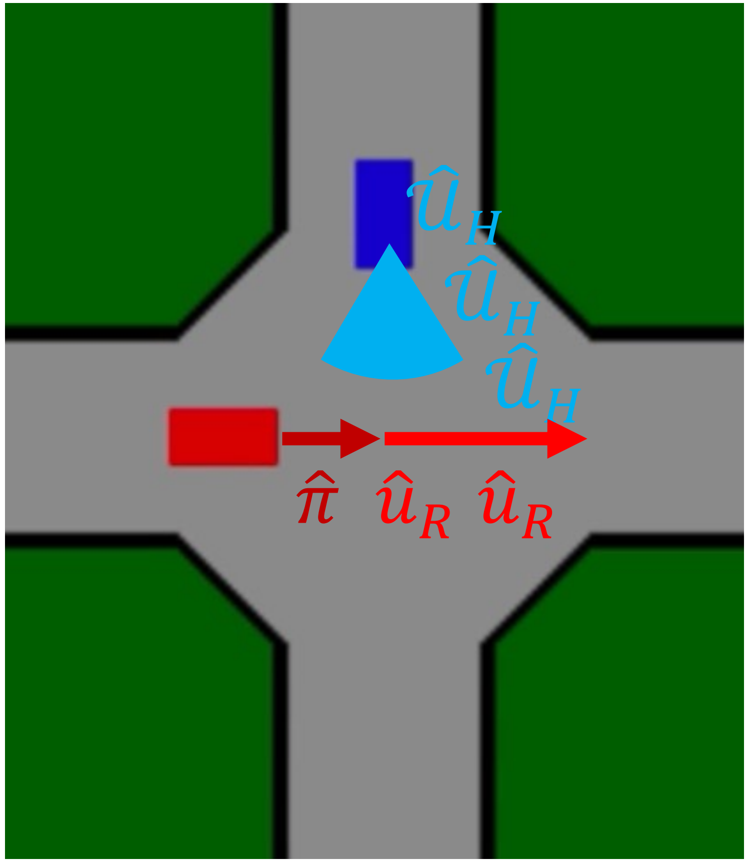
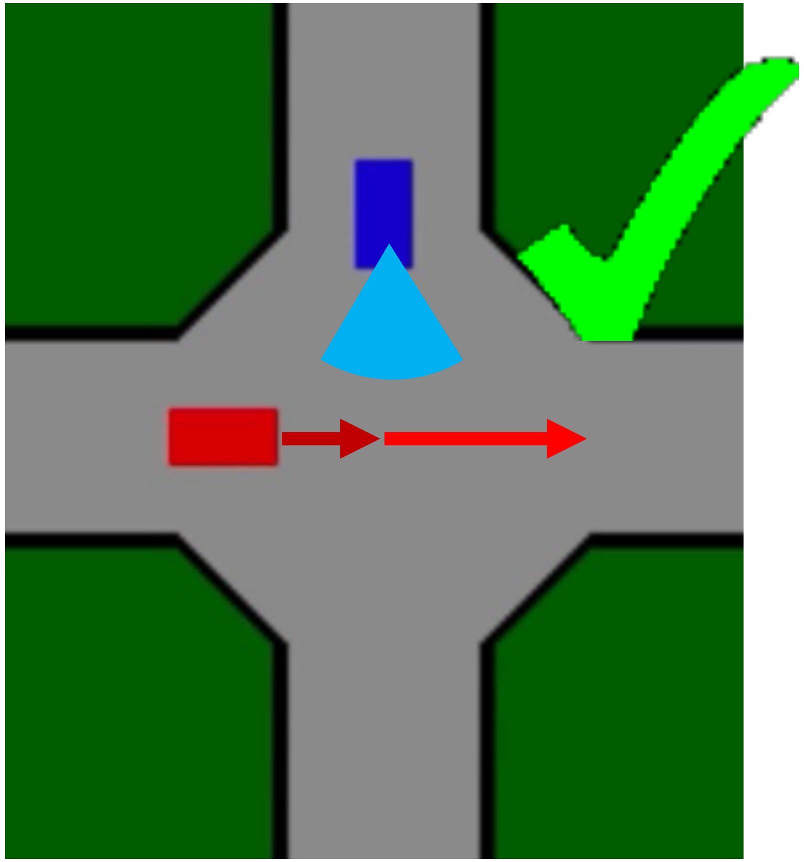


Step 3: Robot/Human Backup Regions

- **Goal**
  - Check safety
  - Check if the system comes to a stop

- **Algorithm**
  - Check $X_t \subseteq \mathcal{X}_{\text{safe}}$ (for all t)
  - Check $X_T \subseteq \mathcal{X}_{\text{eq}}$



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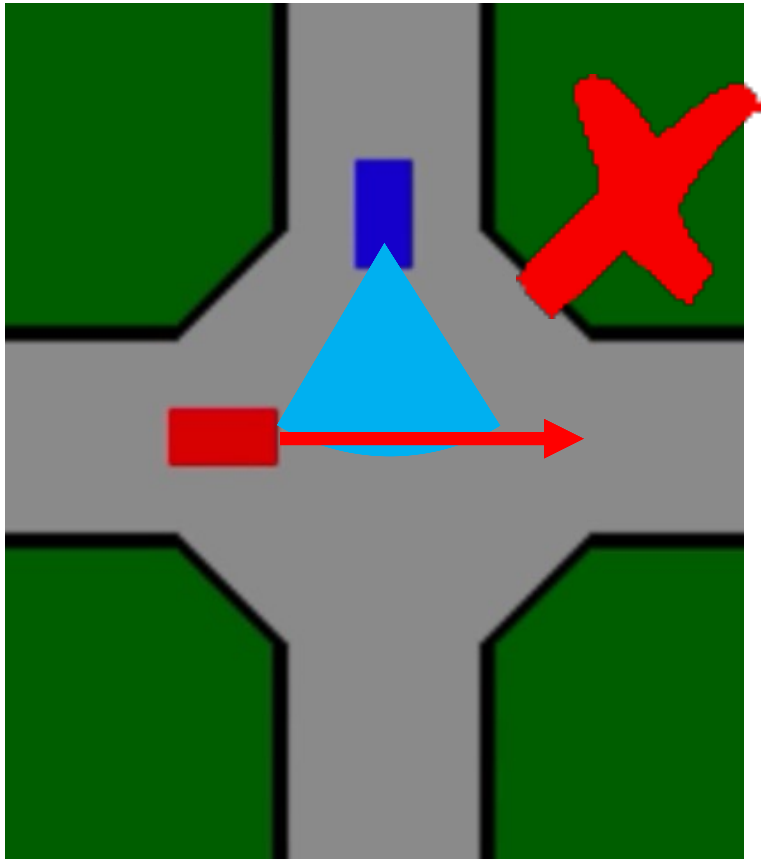

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- Experiments

Theoretical Guarantee

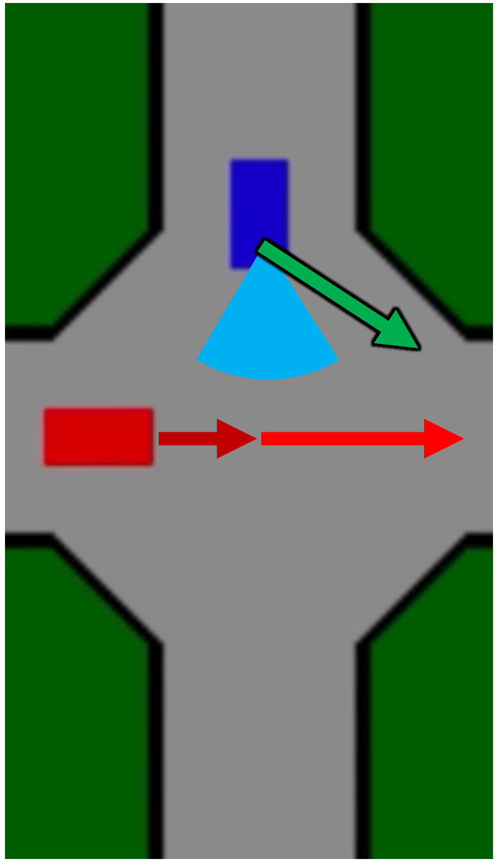
- **Assumptions**
  - Our model of human behavior holds
  - Assumptions 1, 2, & 3
  - The human and robot are at rest at x_1 (i.e., $x_1 \in \mathcal{X}_{\text{eq}}$)

- **Theorem**
  - Our algorithm ensures $x_t \in \mathcal{X}_{\text{safe}}$ for all t

- **Proof**
  - Prove by induction that $x_t \in \mathcal{X}_{\text{rec}} \subseteq \mathcal{X}_{\text{safe}}$
  - **Case 1:** Robot uses $\hat{\pi}$
  - **Case 2:** Robot uses $\pi_{\text{backup}}(x) = \hat{u}_R$

Case 1: Robot uses $\hat{\pi}$

- **Human model**
  - $\vec{u}_H^*(\vec{u}_{R,2:T}) = \arg\max_{\vec{u}_H} \tilde{J}_H(x; u_{R,1}, \vec{u}_H)$
  - $\tilde{J}_H(x; u_{R,1}, \vec{u}_H) = \min_{\vec{u}_{R,2:T}} J_H(x; u_{R,1} \circ \vec{u}_{R,2:T}, \vec{u}_H)$
- **Proof that $x_t \in \mathcal{X}_{\text{rec}} \Rightarrow x_{t+1} \in \mathcal{X}_{\text{rec}}$**
  - Since the robot uses $\hat{\pi}$, the **human backup region** and the **robot backup trajectory** do not overlap
  - If $\tilde{J}_H(x; u_{R,1}, \vec{u}_H) > -\infty$, then the human action is safe for $\vec{u}_{R,2:T}$ (Assumption 1), which includes $\vec{\hat{u}}_R$ (Assumption 2)



Case 1: Robot uses $\hat{\pi}$

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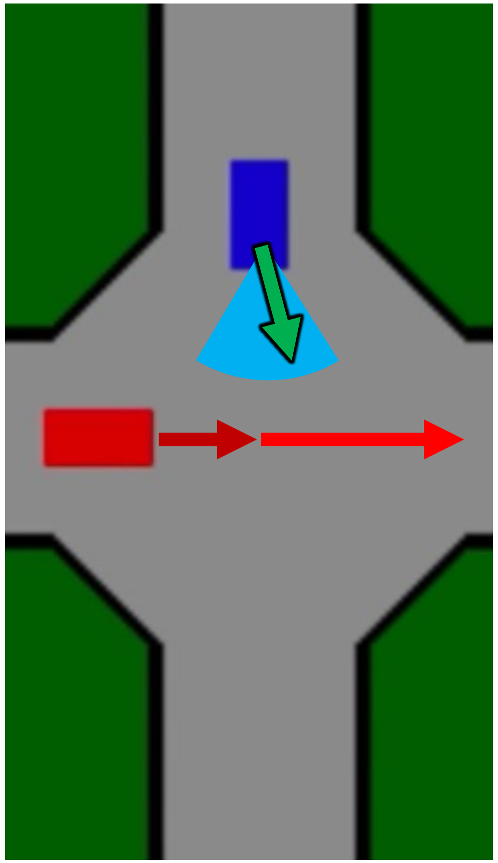
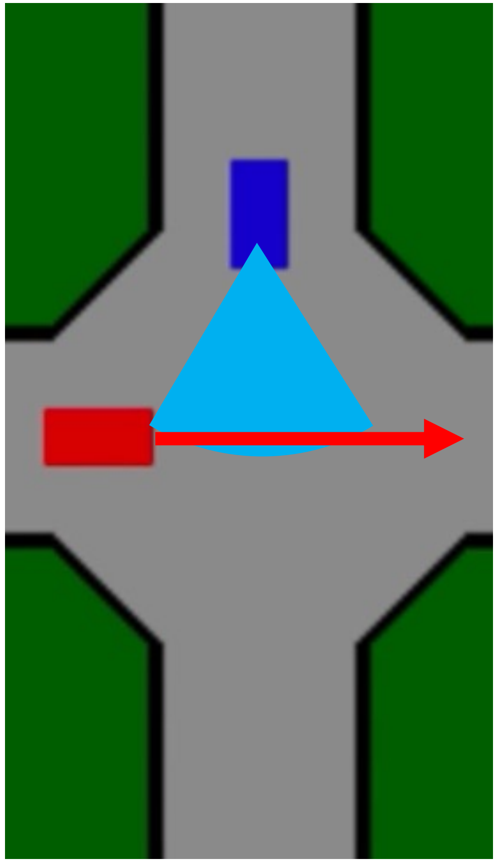
  - If $\tilde{J}_H(x; u_{R,1}, \vec{u}_H) = -\infty$, then the human takes an action $u_{H,1} \in \hat{\mathcal{U}}_H$ (Assumption 3), which is safe



Case 2: Robot uses π_{backup}

- **Proof that** $x_t \in \mathcal{X}_{\text{rec}} \Rightarrow x_{t+1} \in \mathcal{X}_{\text{rec}}$
  - The **human backup region** and the **robot backup trajectory** may overlap
  - However, by definition of $x_t \in \mathcal{X}_{\text{rec}}$, using π_{backup} from x_t safely brings the system to a stop
  - Since we used π_{backup}, the same must be true of x_{t+1}



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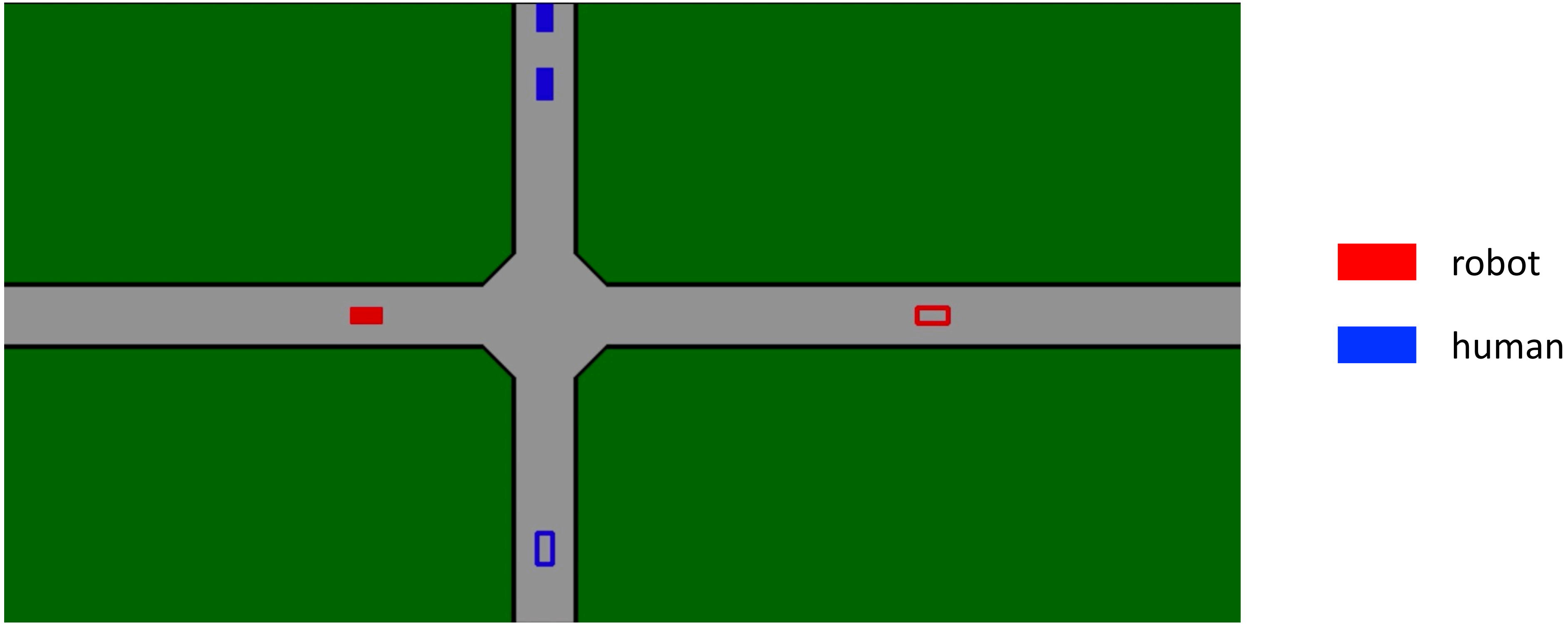
Experimental Setup

- **Environment**
  - Cars with bicycle dynamics
  - Control input is acceleration and steering angle
  - Several different driving tasks
- **Robot**
  - Our approach (MPS) + Aggressive controller that drives straight to goal
  - Model predictive control (MPC) baseline
- **Humans**
  - Simulated humans (social forces model)
  - Real humans interacting with the simulation via keyboard

MPS Parameters

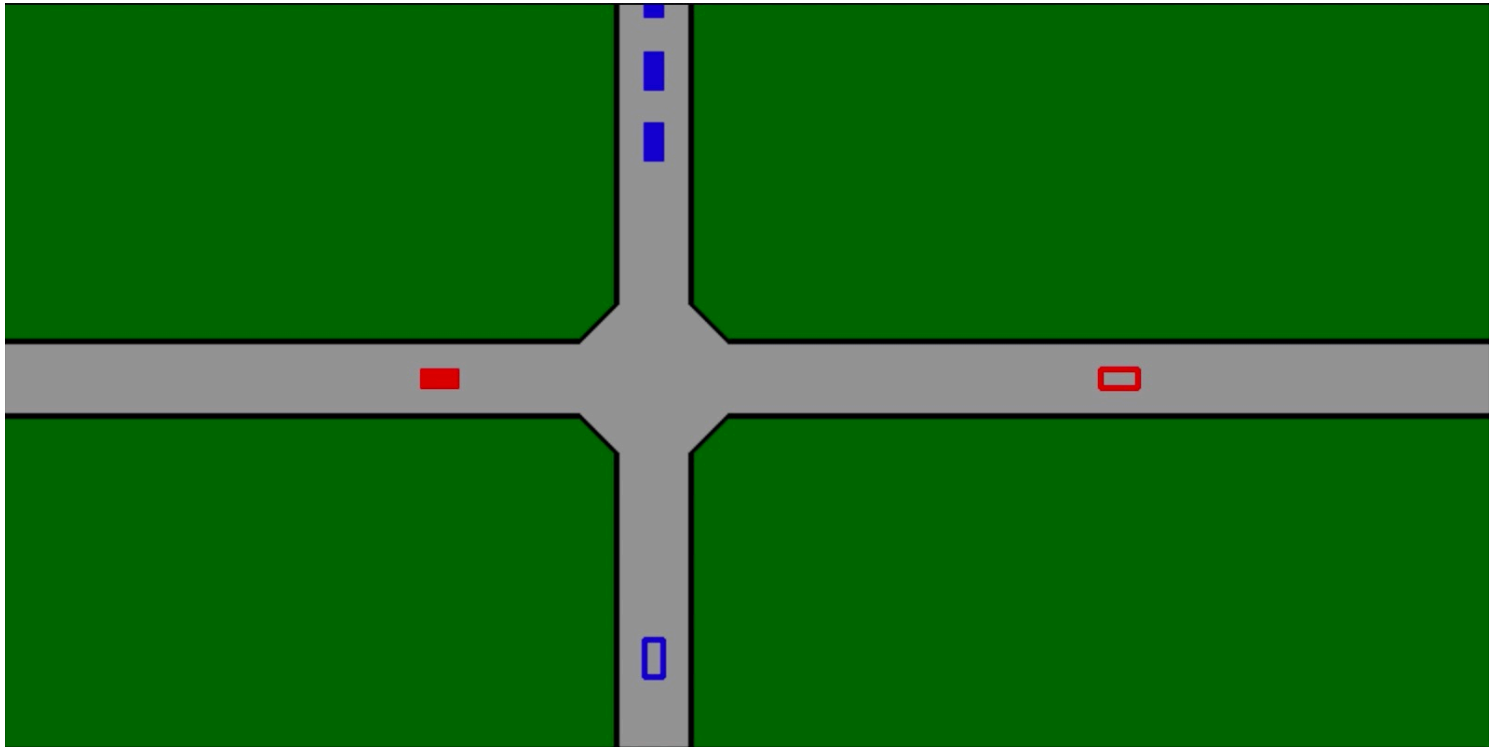
- **Robot backup action $\hat{\boldsymbol{u}}_{\boldsymbol{R}}$**
  - Brake at a given deceleration $a = -a_R$
  - Steering angle $\phi = 0$
- **Human backup actions $\widehat{\mathcal{U}}_{\boldsymbol{H}}$**
  - Brake at a deceleration $a \in [-a_H, -a_H']$
  - Steering angle $\phi \in [-\phi_H, \phi_H]$

Our Approach + Simulated Humans



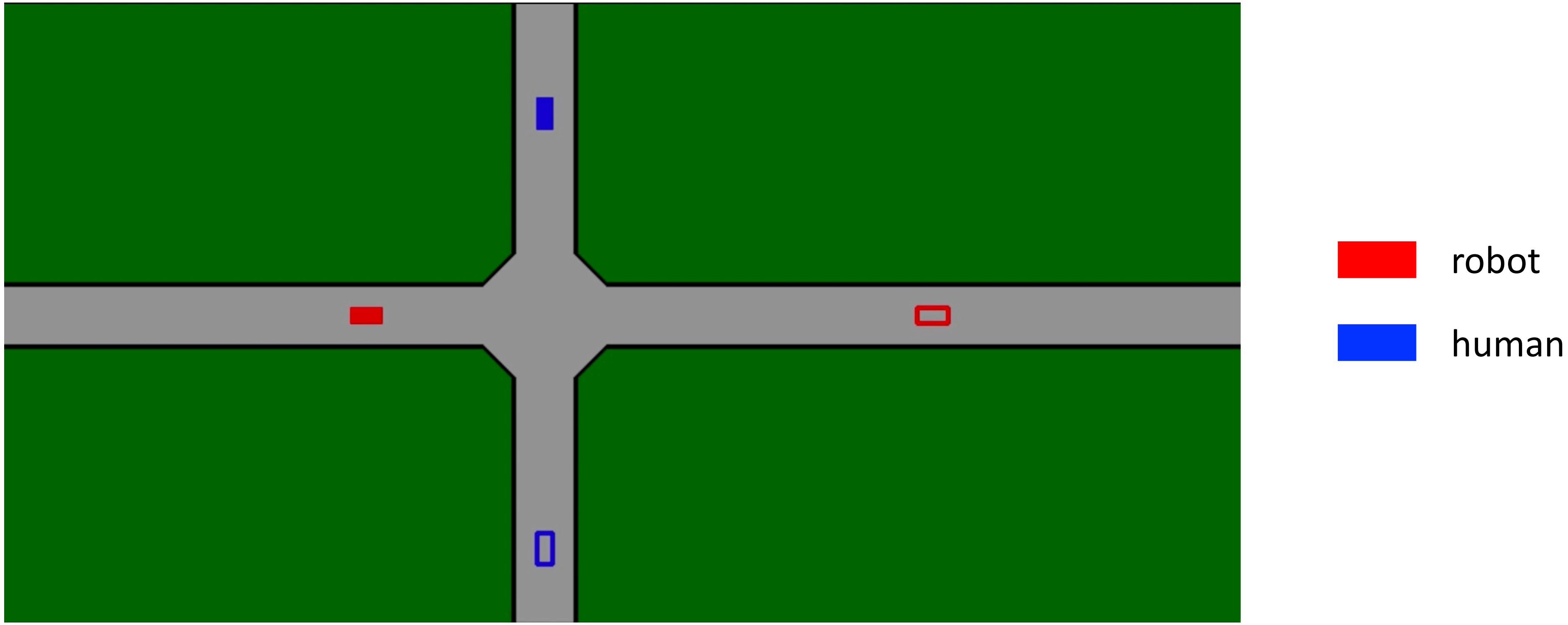
Shielded aggressive controller cuts in front of the human leveraging the fact that a responsible human driver will slightly brake

Our Approach + Simulated Humans



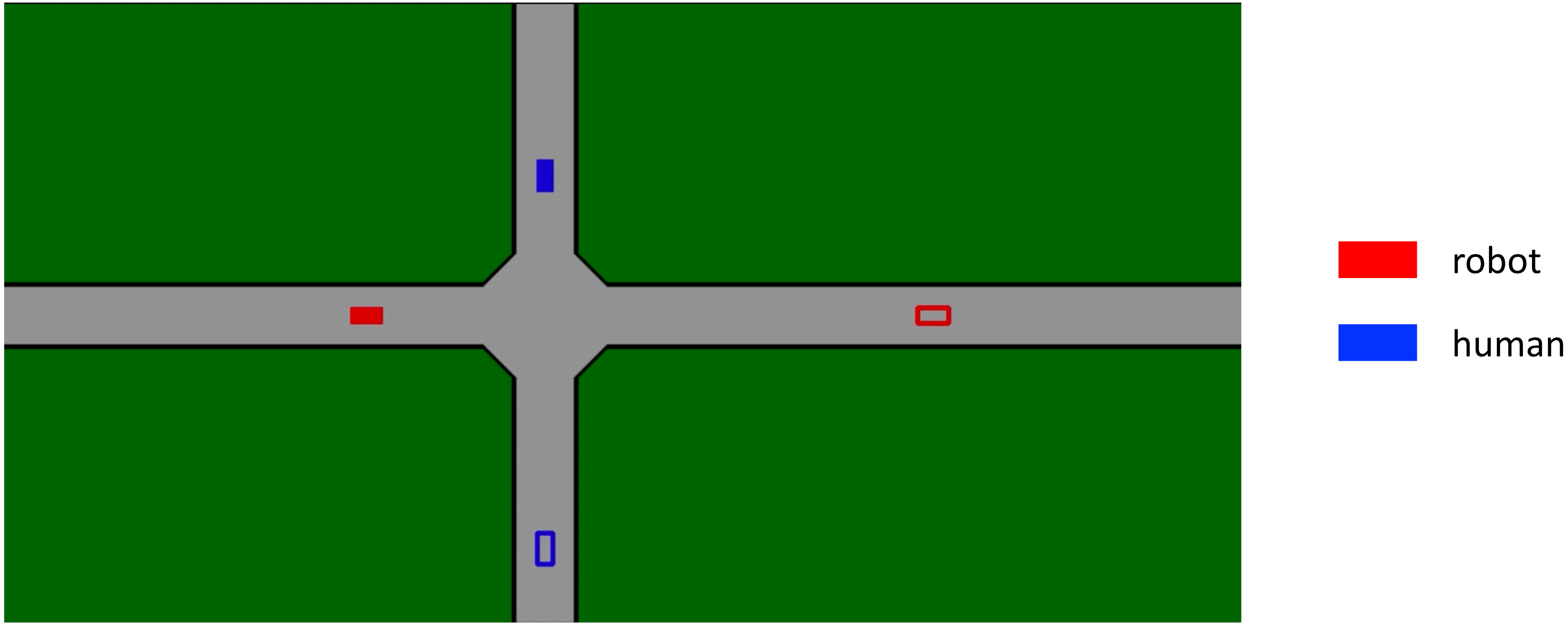
The robot triggers the shield to brake and allow the human to pass safely

Our Approach + Real Humans



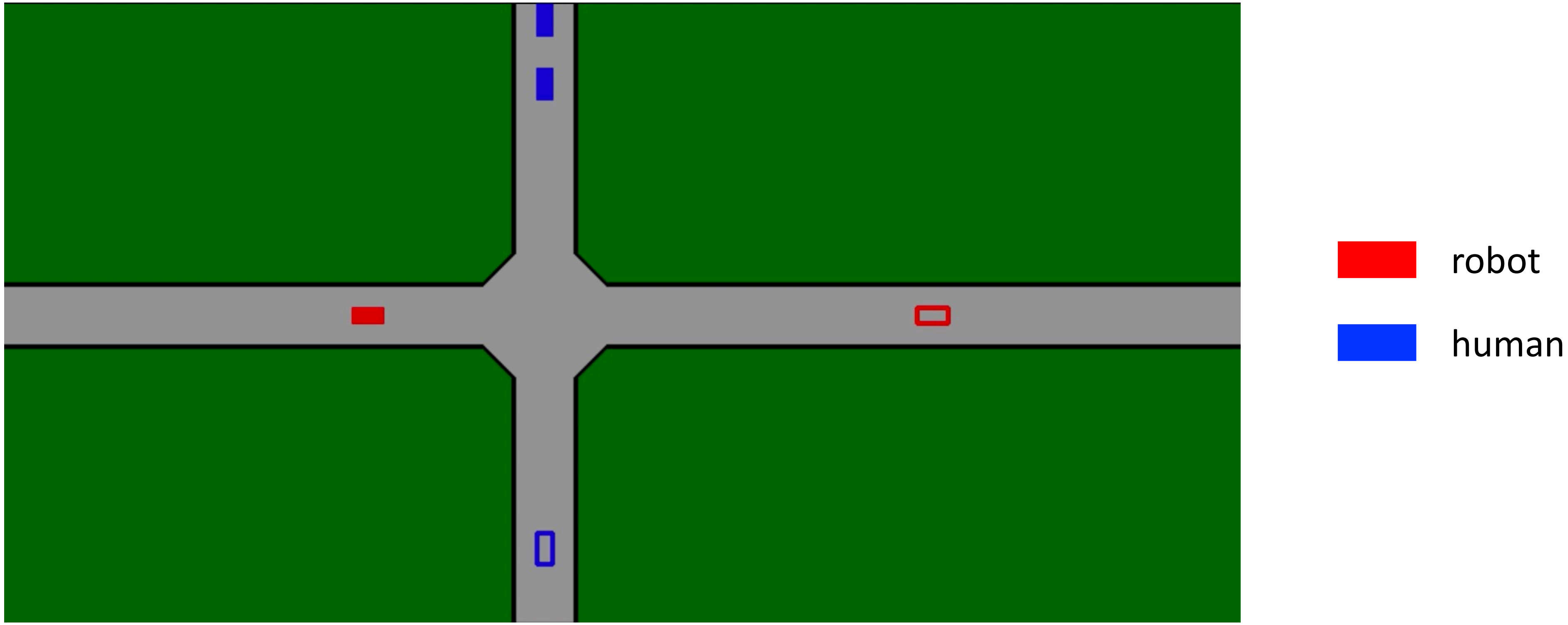
Shielded aggressive controller cuts in front of the human leveraging the fact that a responsible human driver will slightly brake

Our Approach + Real Humans



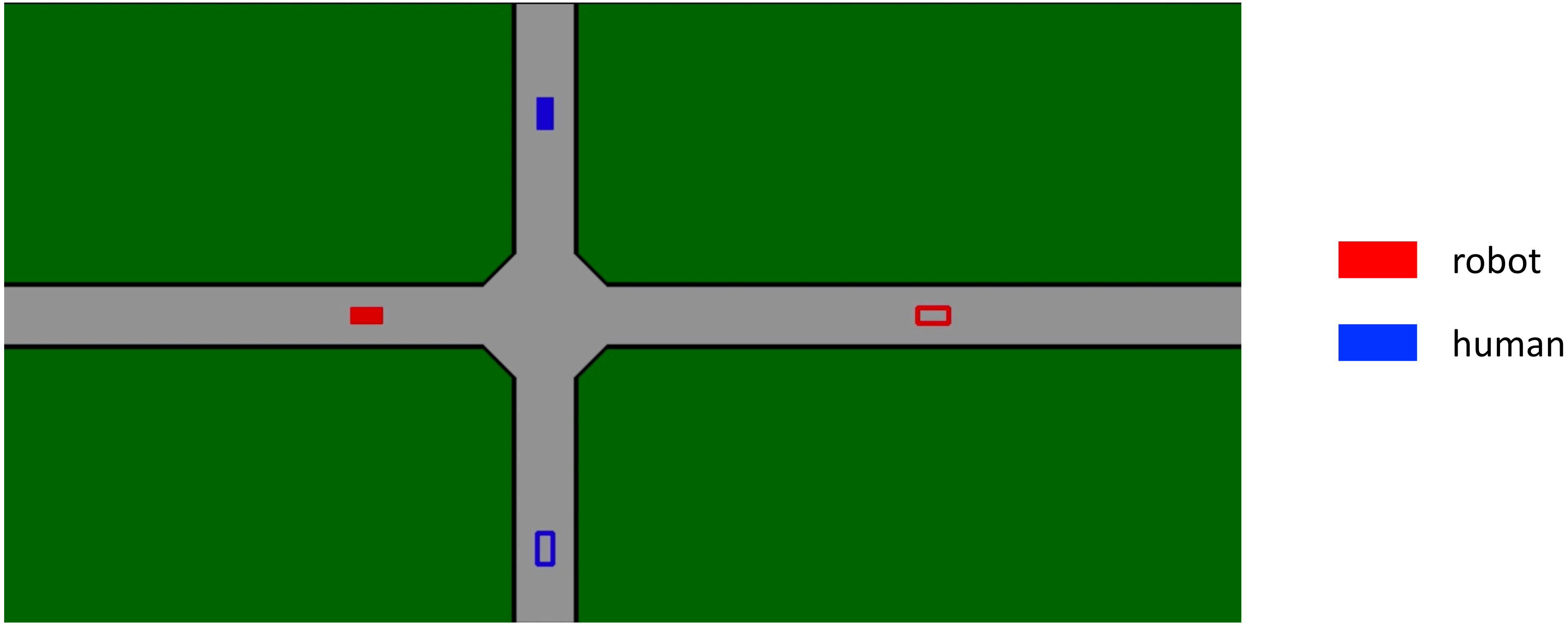
The robot triggers the shield to brake and allow the human to pass safely

MPC + Simulated Humans



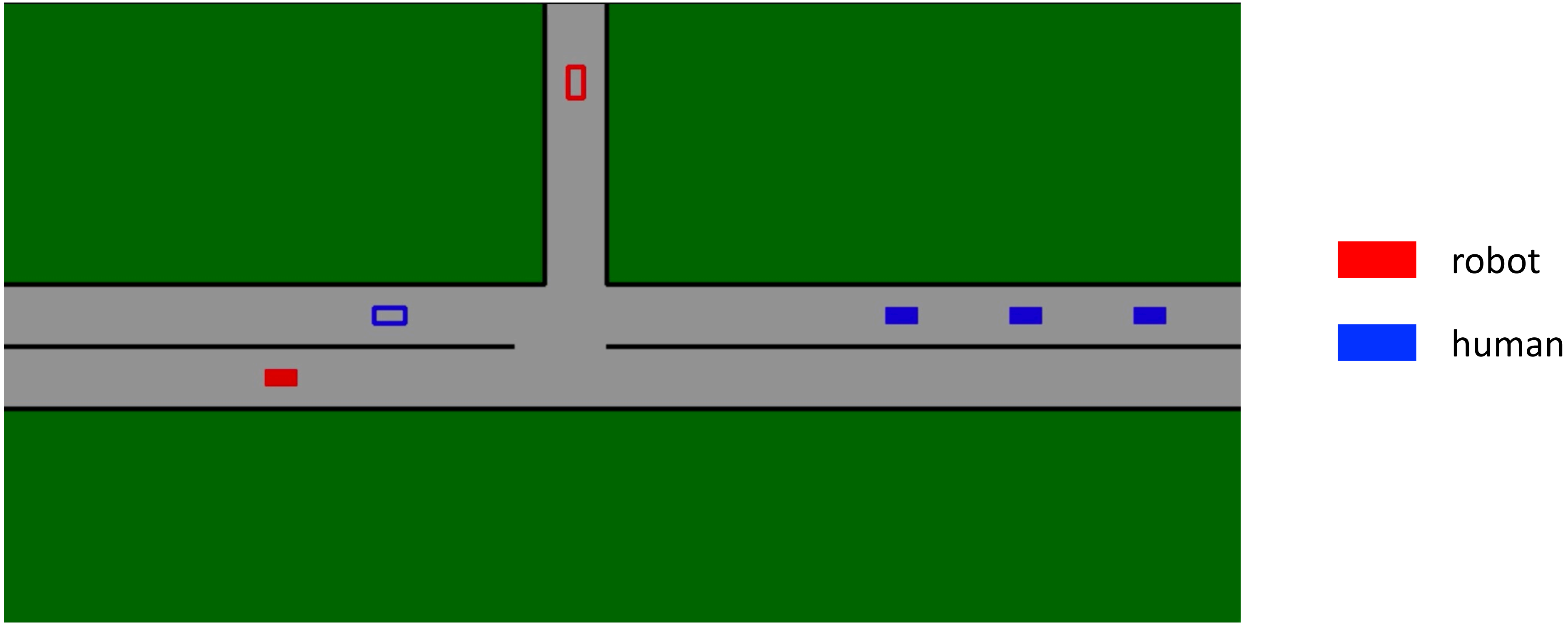
MPC control takes **longer** than the shielded aggressive control

Our Approach + Real Humans with an Accident



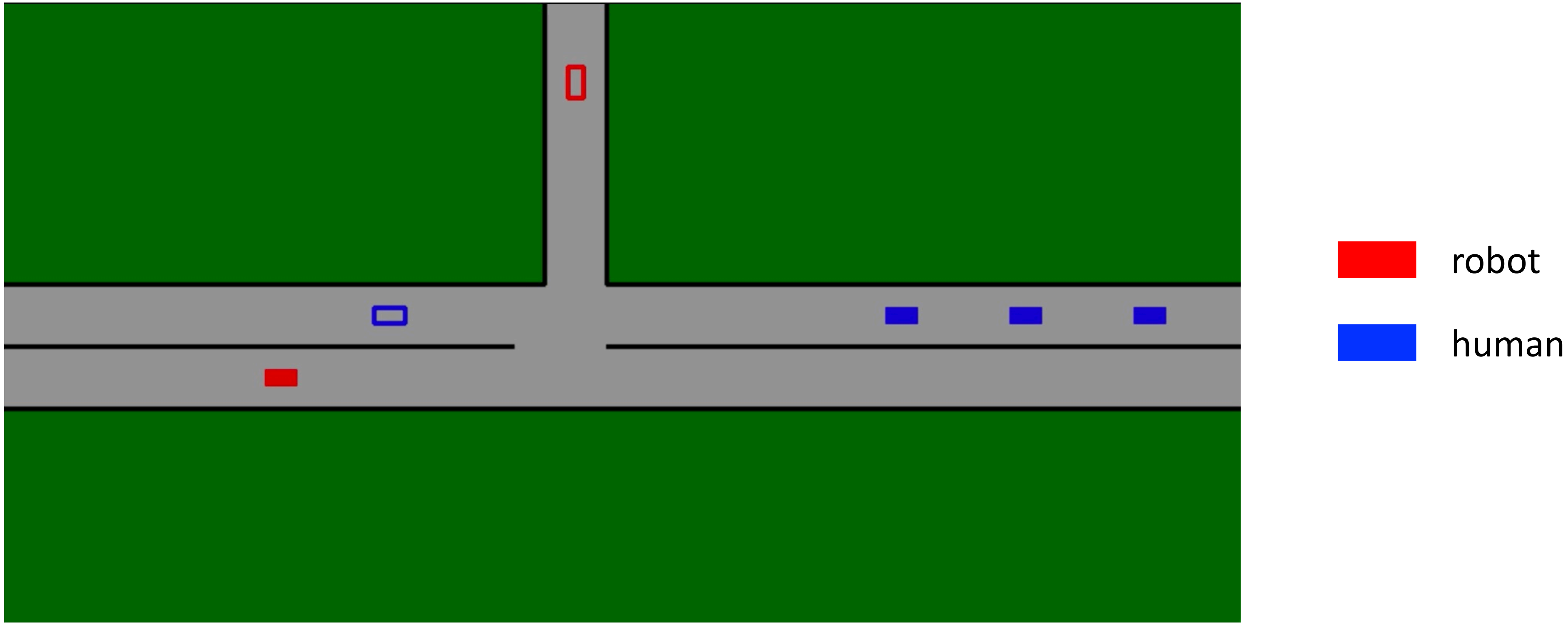
The human acted aggressively and collided with the stationary robot

No Stopping in Intersection



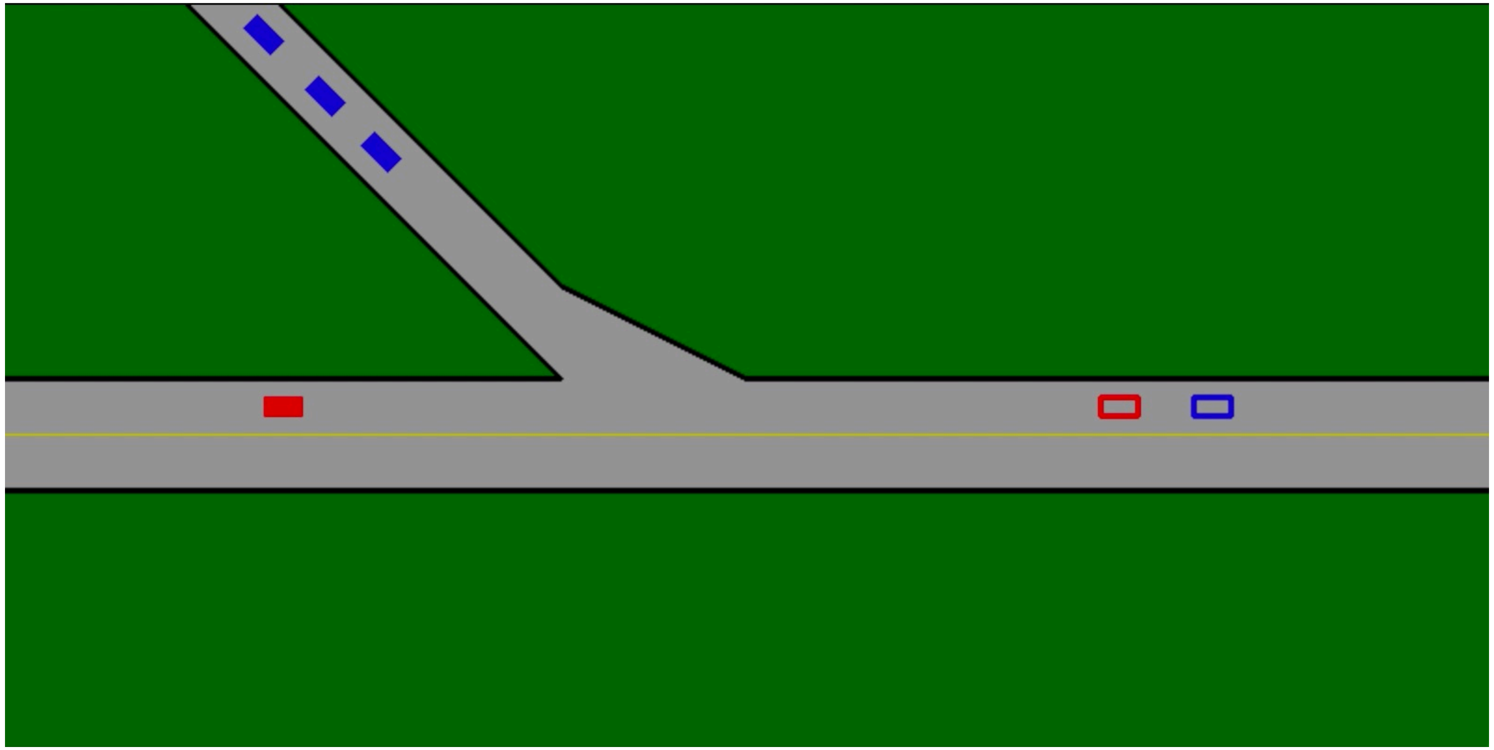
Old shielded controller **without** the no-stop-at-intersection constraint stops at the intersection, which leads to congestion

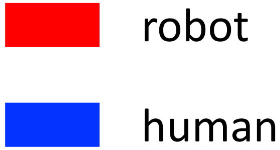
No Stopping in Intersection



New shielded controller **with** the no-stop-at-intersection constraint stops **before** the intersection

Pull-Over Backup Action





Instead of stopping in the middle of the highway, the robot pulls over to the next lane as a backup policy

Conclusion

- **Safe human-interactive control**
  - Game theoretic model of human behavior
  - Model predictive shielding + abstract interpretation to ensure safety