

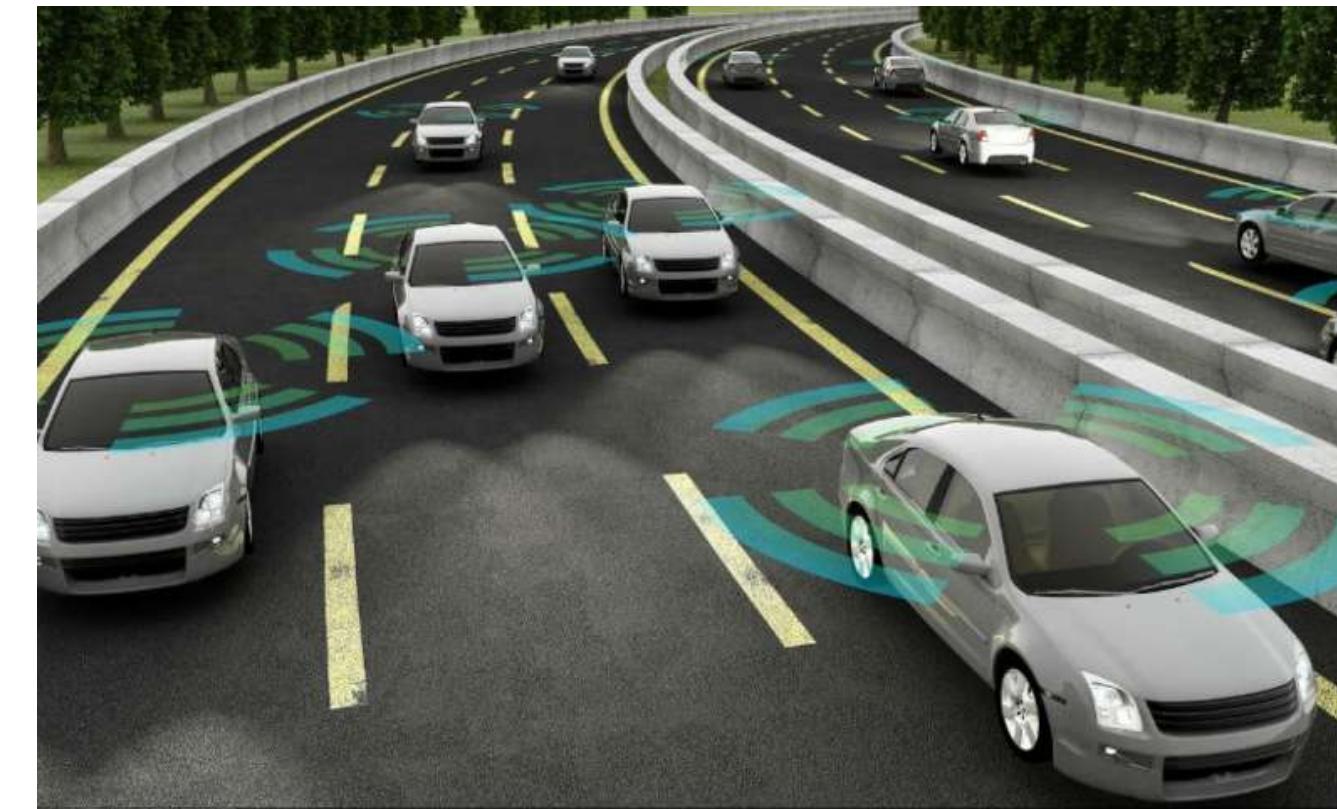
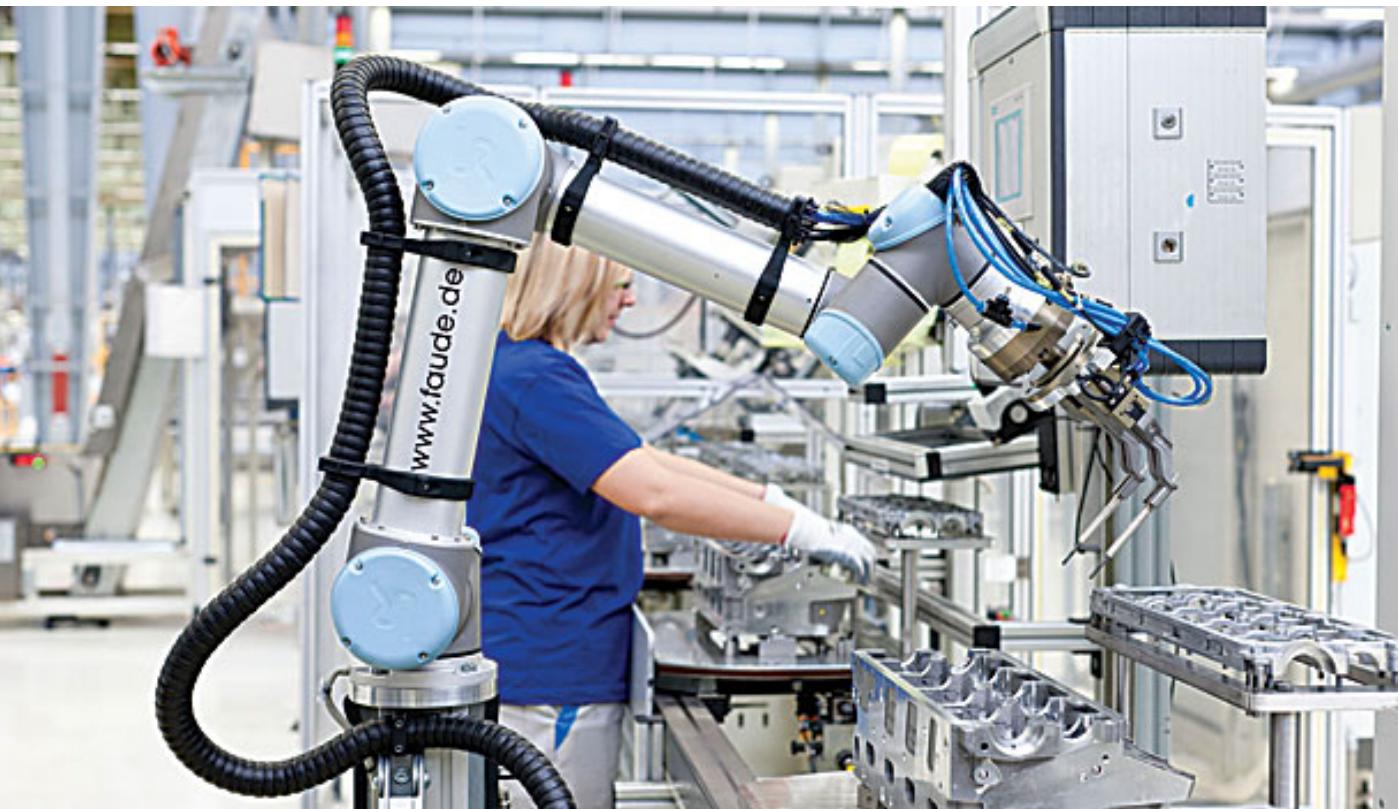
# Navigation in Safety-Critical Environments

Cherie Ho

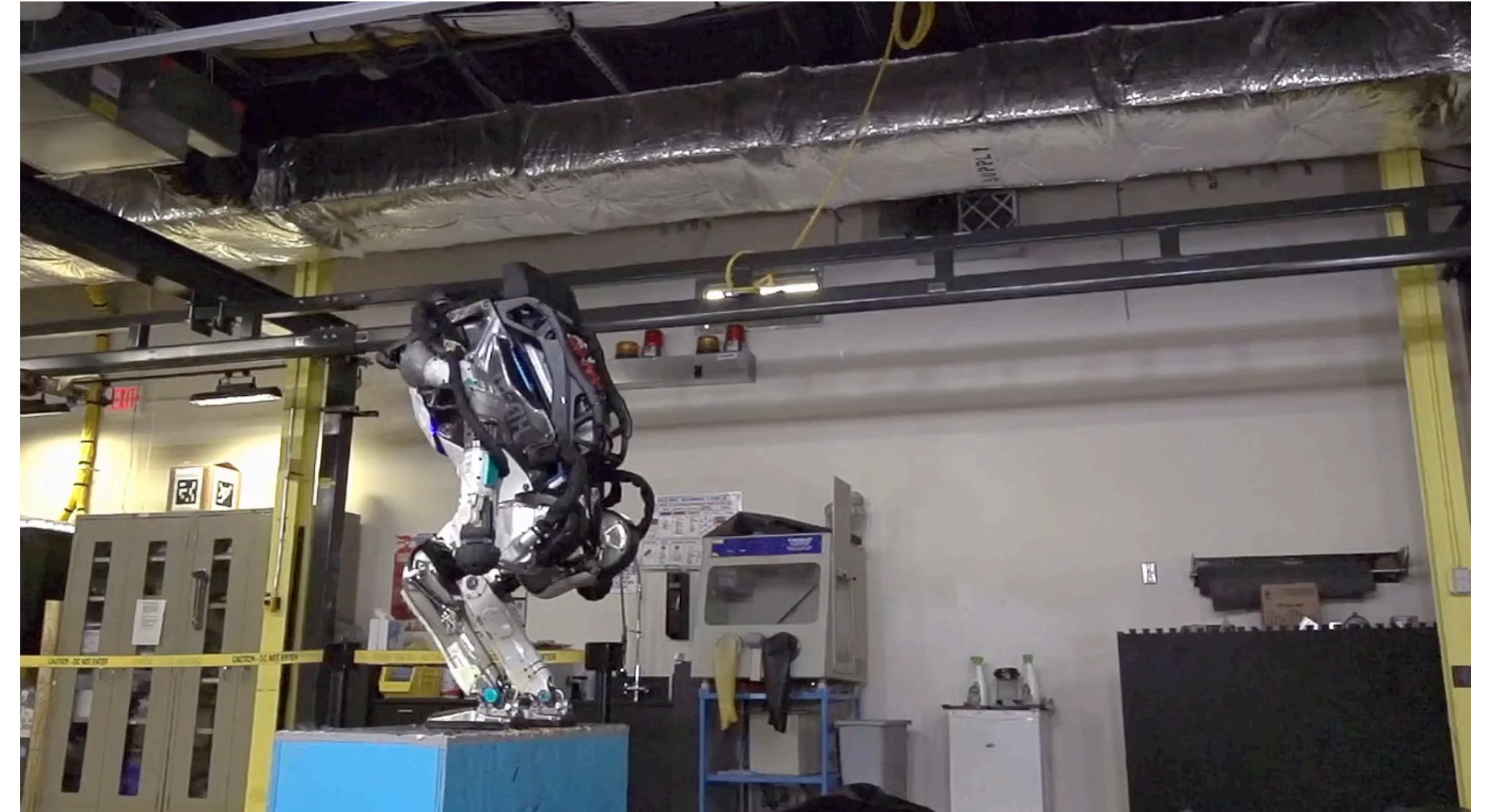
8/19/2019



# We're increasingly deploying robots to **safety-critical** environments.



# Requirement: Safety in a Predictable Manner



Experts say video of Uber's self-driving car killing a p

Los Angeles Times - 4 hours ago

On Monday, the San Francisco Chronicle quoted Tempe Police saying: "It's very clear it would have been difficult to avoid this mode [autonomous or human-driven] based on how she came right into the roadway.... I suspect preliminarily it appears ..."

Police release footage from Uber's fatal self-driving car crash

The INQUIRER - 13 hours ago

Uber Video Shows the Kind of Crash Self-Driving Cars Are Made to ...

Featured - WIRED - Mar 21, 2018

A pedestrian has been killed by a self-driving car

Opinion - The Economist - 9 hours ago

Uber Operator of Self-Driving Car in Fatal Crash Had Criminal Record

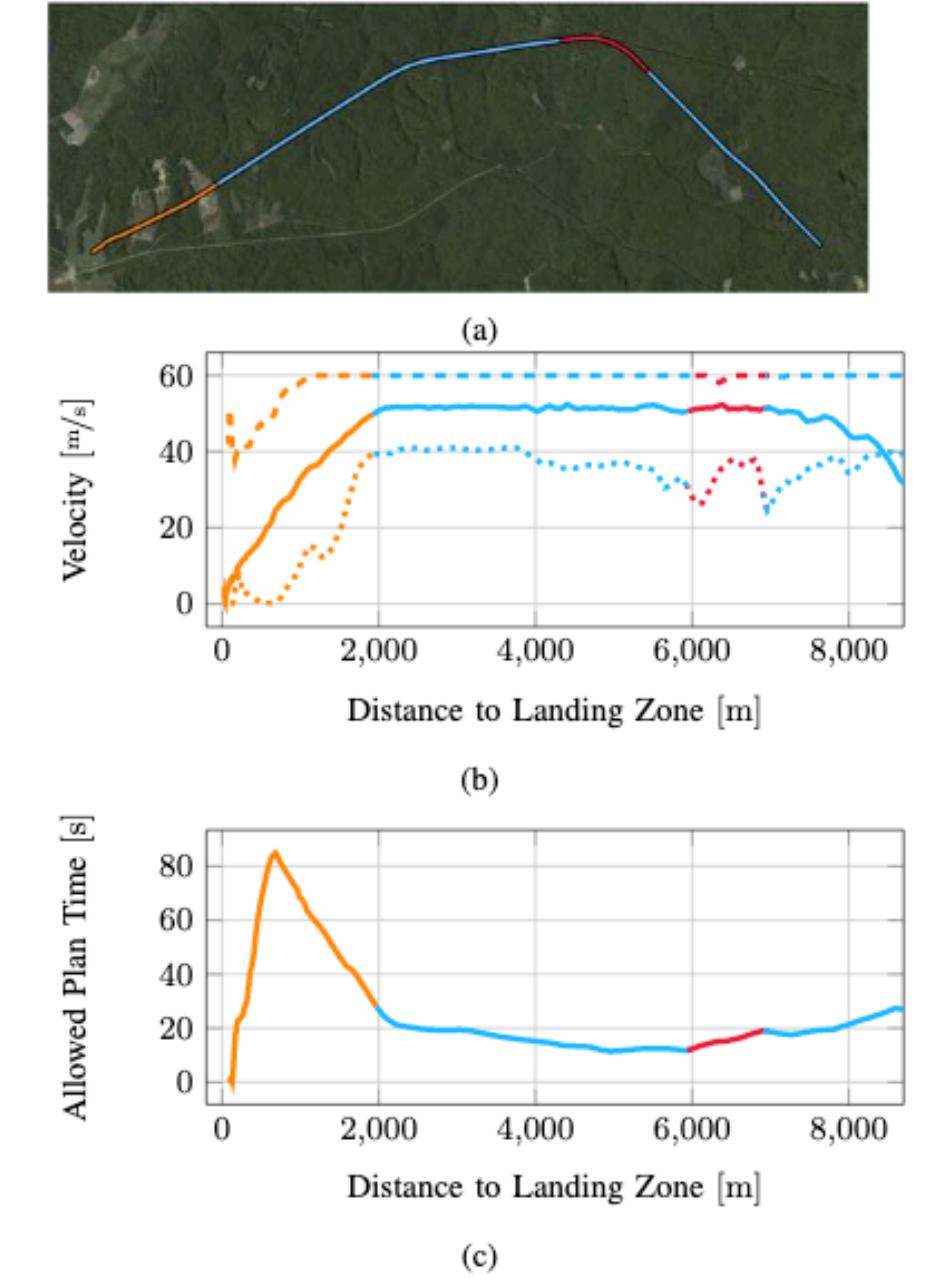
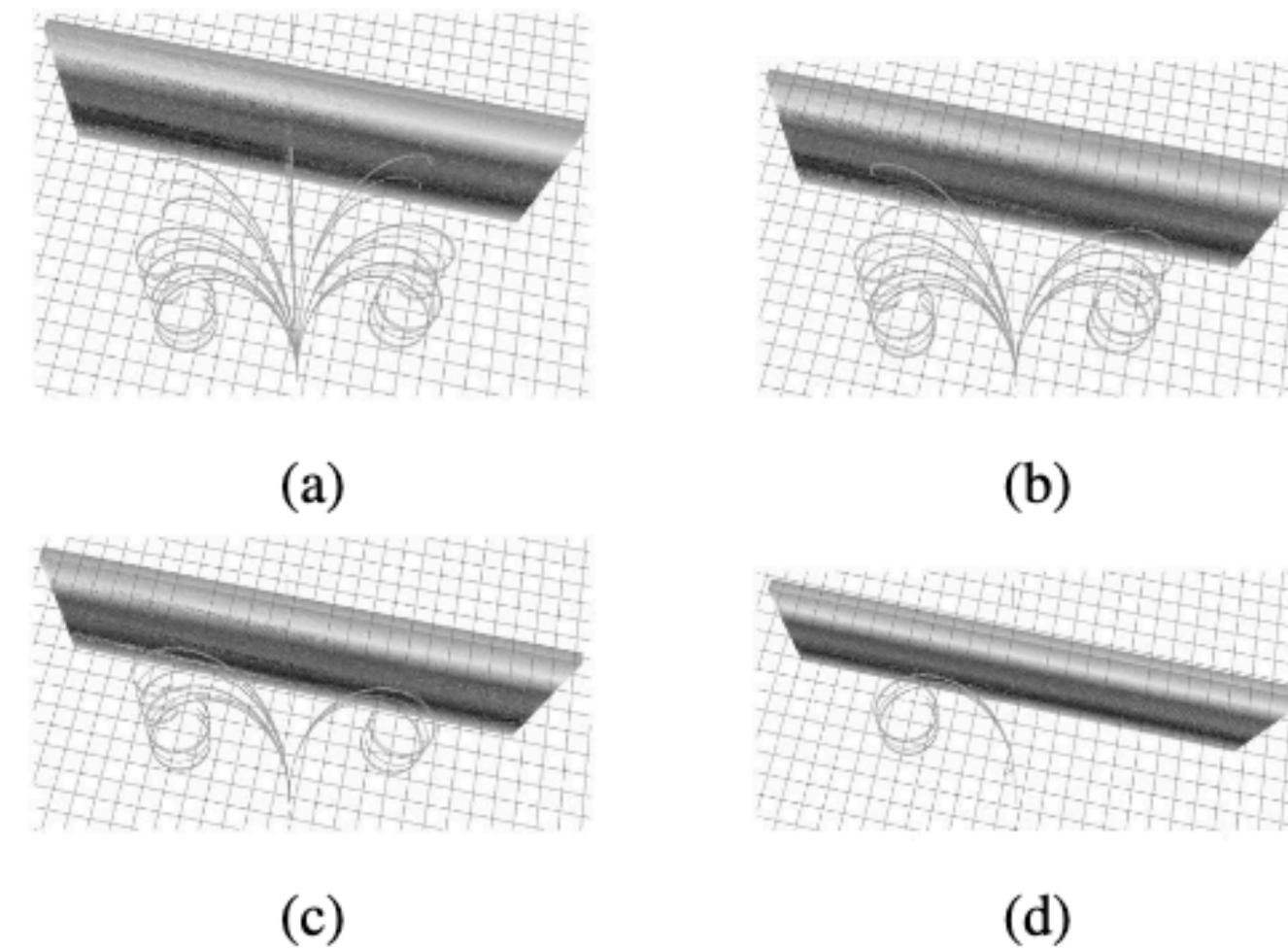
In-Depth - Wall Street Journal - 7 hours ago

Uber's Fatal Crash Is About More Than Just a Car and a Pedestrian

Featured - Popular Mechanics - Mar 21, 2018



# Case Study: AACUS Helicopter



Trajectory Executive: guaranteed safe Emergency Maneuver Library

**high performance whilst remaining safe**

**From how much can we get away with  
to safety-first design**

# Ensuring safety is hard

- Unknown actions by other agents (humans)
- Unmodeled disturbances (wind)

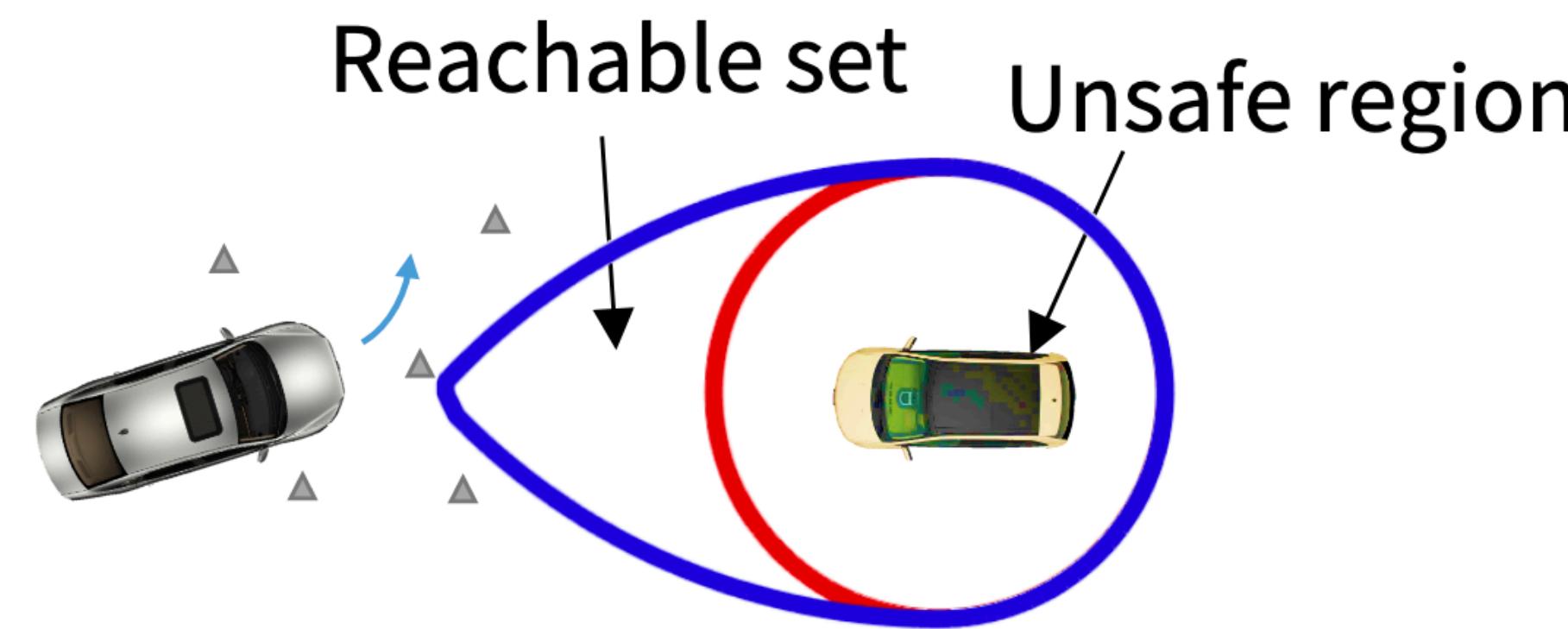
# Ensuring safety in the field is even harder

- Real-time
- Sensor and actuator noise
- Rapidly-changing partially known surroundings
- Unknown obstacle locations

# Safe Control Techniques

- **Hamilton-Jacobi (HJI) Reachability**
  - **Control Barrier Function**
  - **Safety Envelopes**
- Key Tools:**
- **Reachability**
  - **Lyapunov functions**

# Reachability analysis: avoidance



Assumptions:

- Model of robot
- Unsafe region: e.g., obstacle

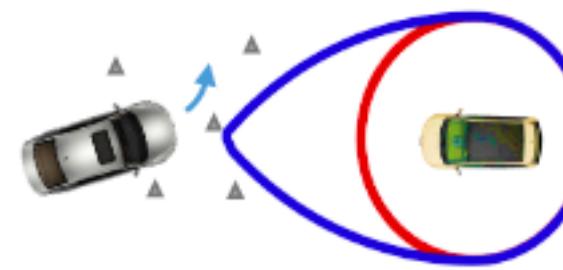
Control policy

Backward reachable set  
(States leading to danger)

Adapted from Stanford AA203 Optimal and Learning-based Control [https://stanfordasl.github.io/aa203/pdfs/lecture/lecture\\_6.pdf](https://stanfordasl.github.io/aa203/pdfs/lecture/lecture_6.pdf)  
& Somil Bansal's Introduction to Reachability [https://people.eecs.berkeley.edu/~somil/Papers/Introduction\\_to\\_Reachability\\_to\\_Share.pdf](https://people.eecs.berkeley.edu/~somil/Papers/Introduction_to_Reachability_to_Share.pdf)

# A optimal control problem cursed by dimensionality.

- Avoiding danger



- BRS definition

$$\mathcal{A}(t) = \{\bar{\mathbf{x}}: \exists \Gamma[\mathbf{u}](\cdot), \forall \mathbf{u}(\cdot), \dot{\mathbf{x}} = f(\mathbf{x}, \mathbf{u}, \mathbf{d}), \mathbf{x}(t) = \bar{\mathbf{x}}, \mathbf{x}(0) \in \mathcal{T}\}$$

- Value function

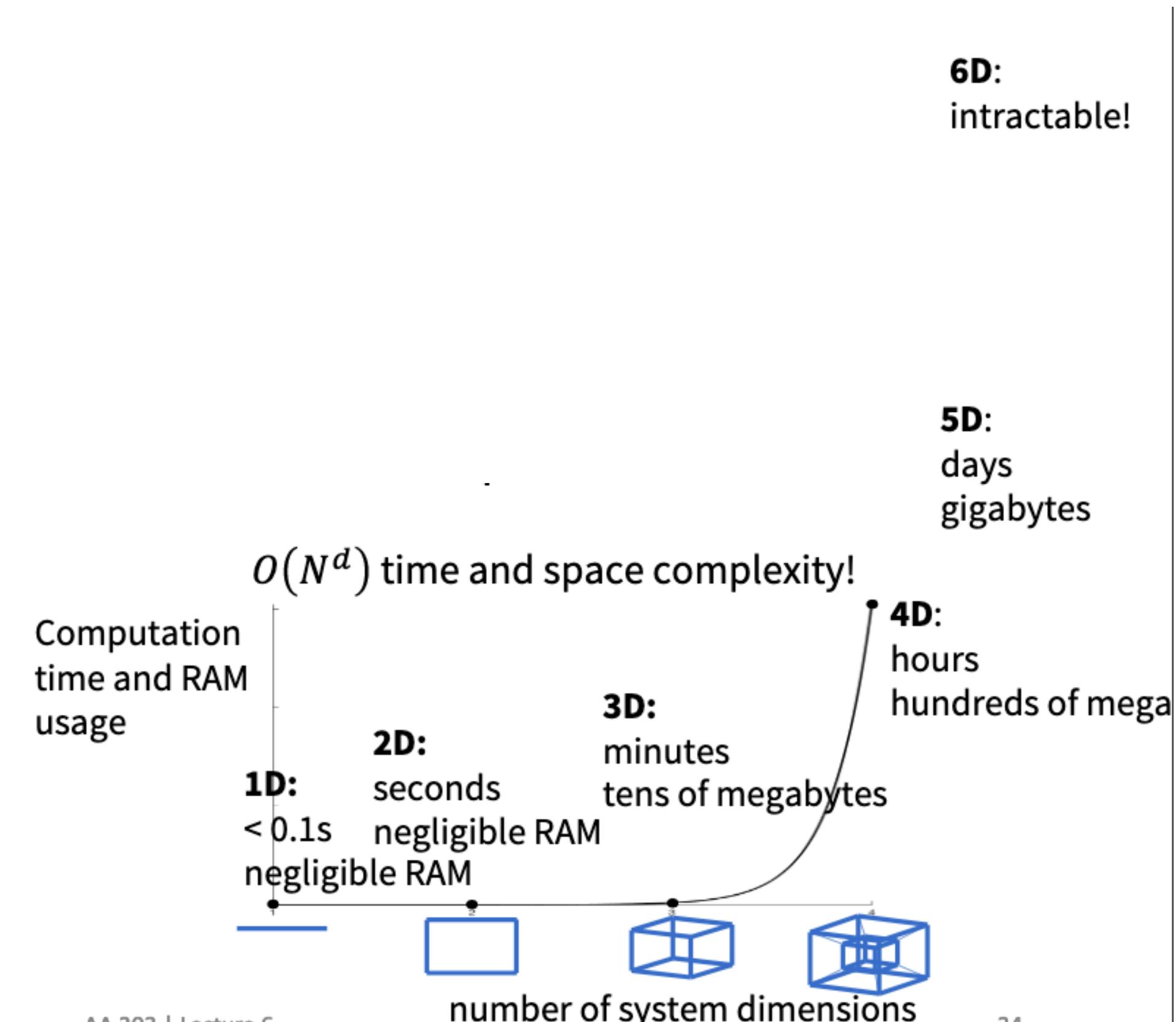
$$J(\mathbf{x}, t) = \min_{\Gamma[\mathbf{u}]} \max_{\mathbf{u}} h(\mathbf{x}(0))$$

- HJI

$$\frac{\partial J}{\partial t} + \max_{\mathbf{u}} \min_{\mathbf{d}} \left[ \left( \frac{\partial J}{\partial \mathbf{x}} \right)' f(\mathbf{x}, \mathbf{u}, \mathbf{d}) \right] = 0$$

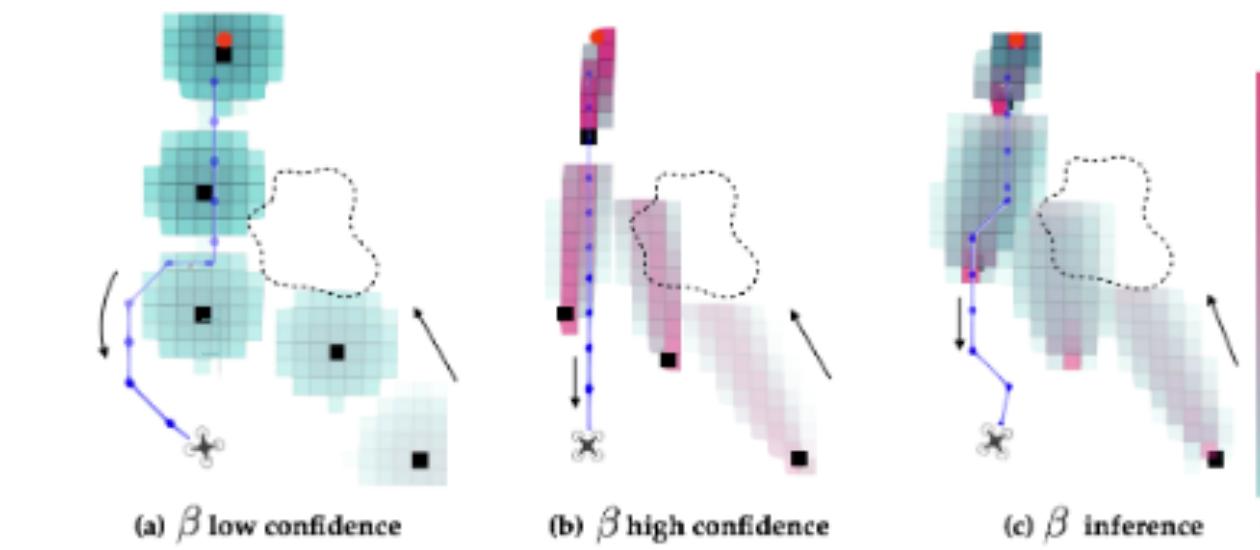
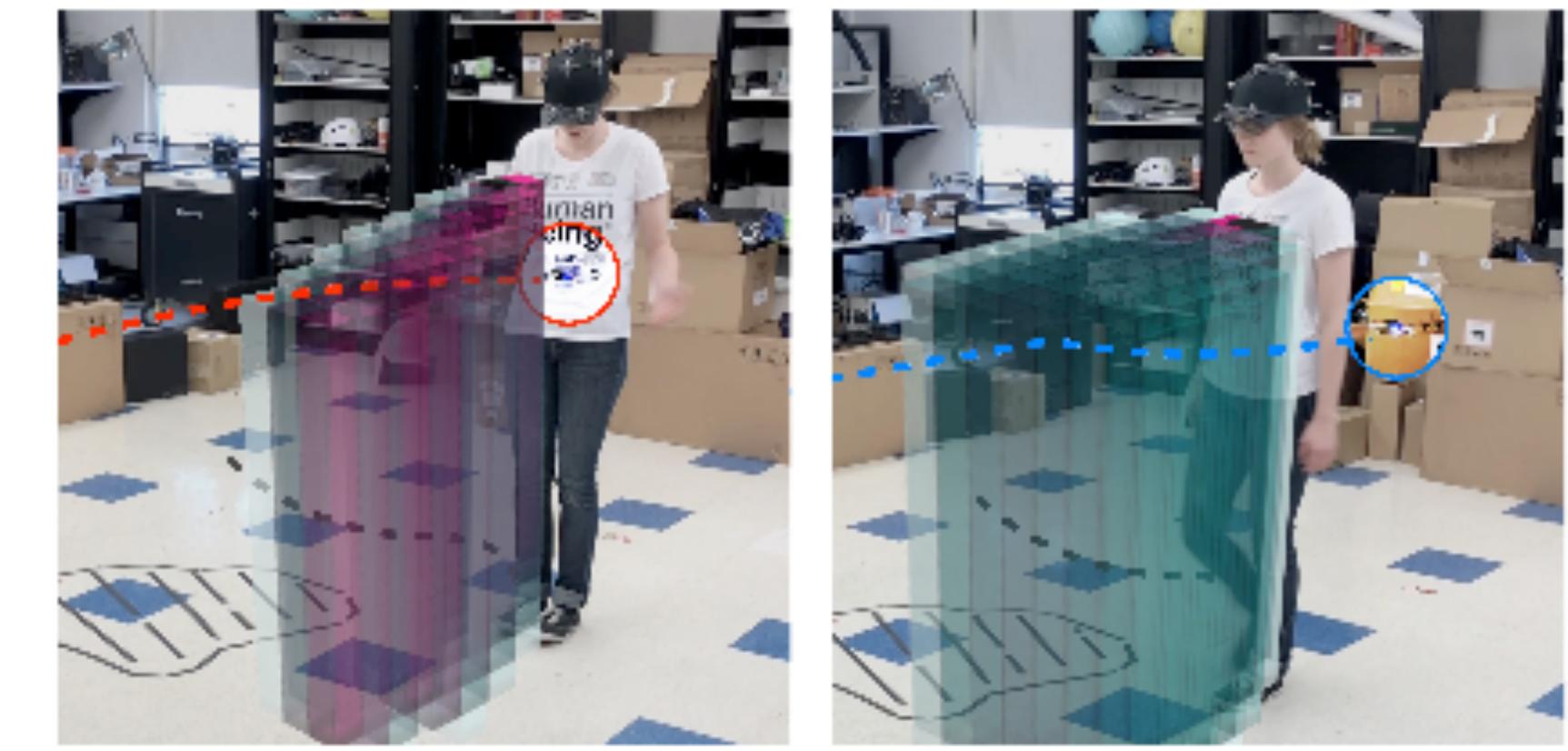
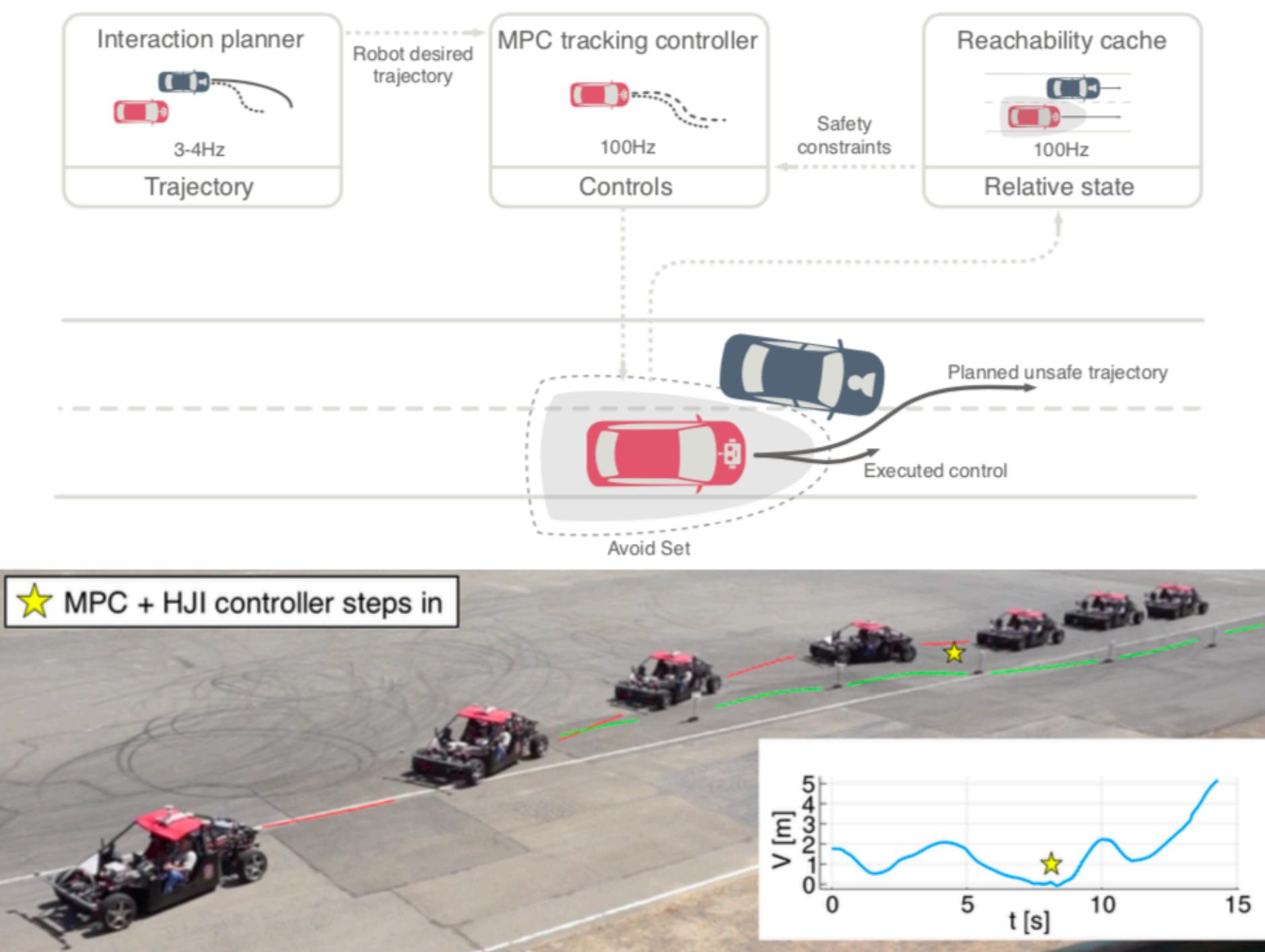
- Optimal control

$$\mathbf{u}^* = \arg \max_{\mathbf{u}} \min_{\mathbf{d}} \left( \frac{\partial J}{\partial \mathbf{x}} \right)' f(\mathbf{x}, \mathbf{u}, \mathbf{d})$$



Adapted from Stanford AA203 Optimal and Learning-based Control [https://stanfordasl.github.io/aa203/pdfs/lecture/lecture\\_6.pdf](https://stanfordasl.github.io/aa203/pdfs/lecture/lecture_6.pdf)  
& Somil Bansal's Introduction to Reachability [https://people.eecs.berkeley.edu/~somil/Papers/Introduction\\_to\\_Reachability\\_to\\_Share.pdf](https://people.eecs.berkeley.edu/~somil/Papers/Introduction_to_Reachability_to_Share.pdf)

# Reachability - Applications

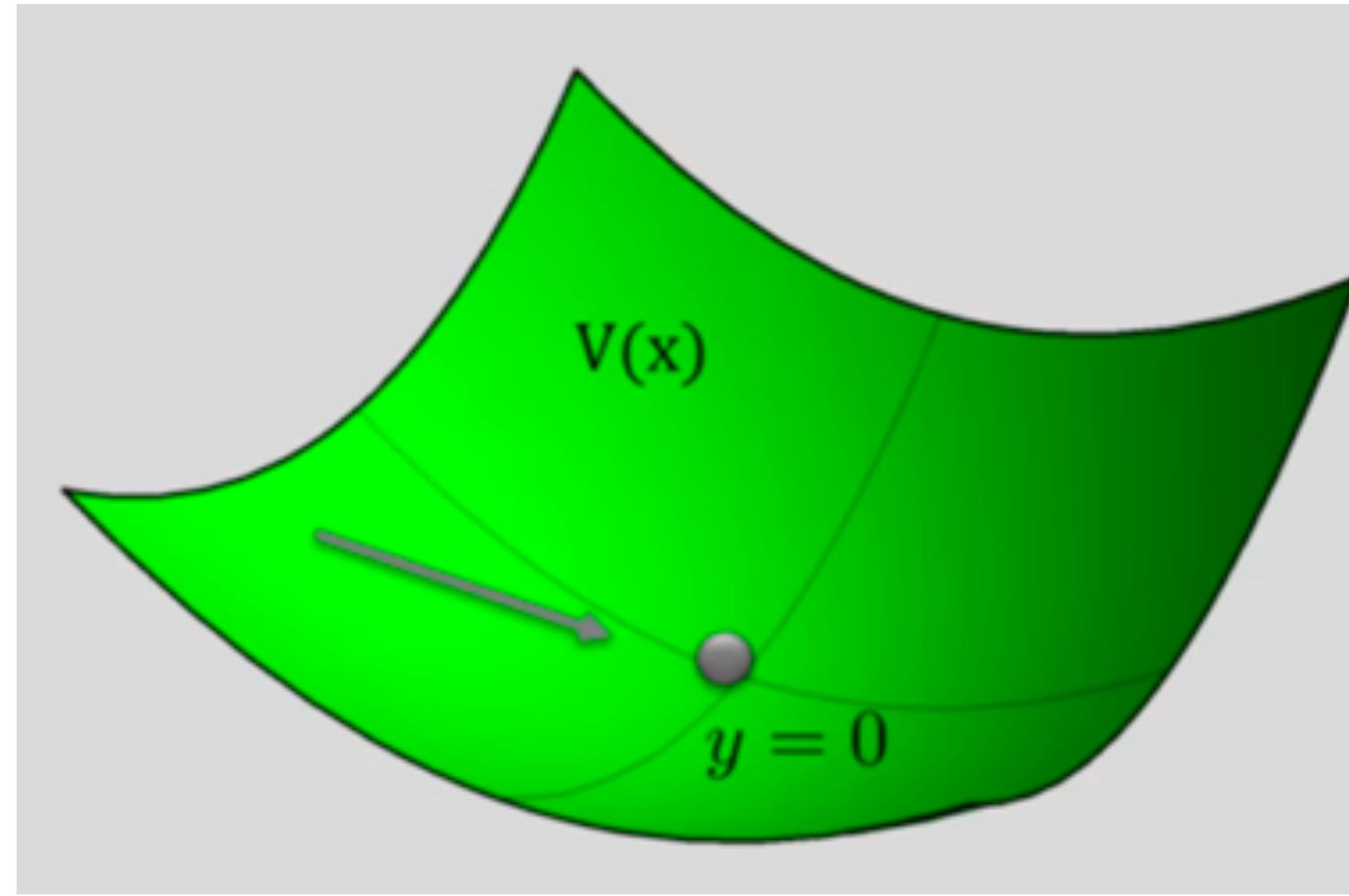


Fisac et al. Probabilistically Safe Robot Planning with Confidence-Based Human Predictions. 2018.  
<https://arxiv.org/pdf/1806.00109.pdf>

- How to guarantee safety with other sentient agent?
- HJI Reachability in MPC as constraint
- **Only tested one maneuver in real life**
- **No sensor, actuator noise. Simulated human agent.**
- Uses saved reachability analysis of pairwise interaction
- Not sure how this can realistically translate (many interactions modeled beforehand)

- **Vicon for state estimation**
- Estimate human model confidence to adjust planning risk

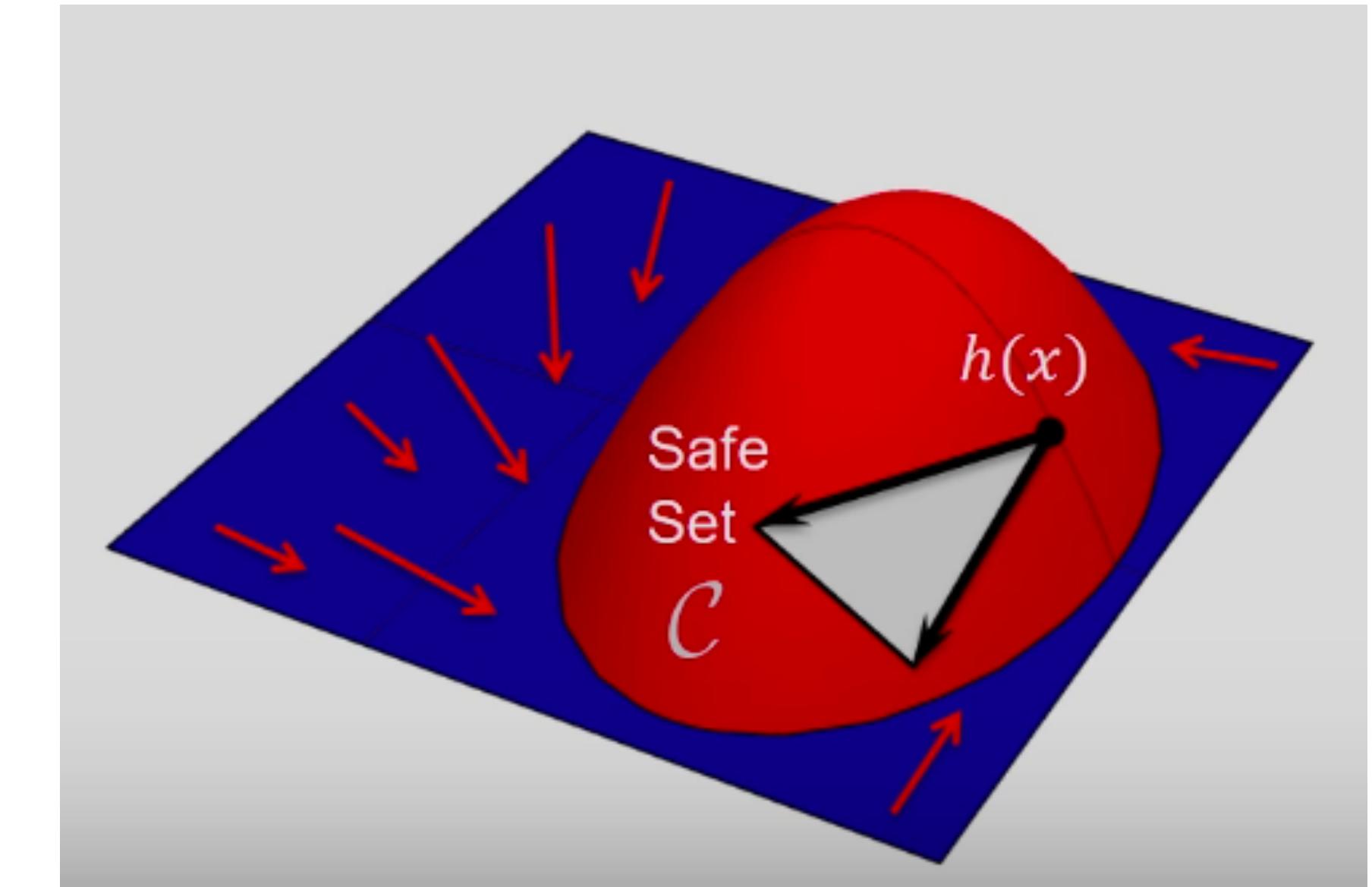
## Control Lyapunov to certify stability,



For dynamical system ensure,

$$\dot{V}(x, u) \leq -\alpha V(x)$$

## Control Barrier Function to certify safety



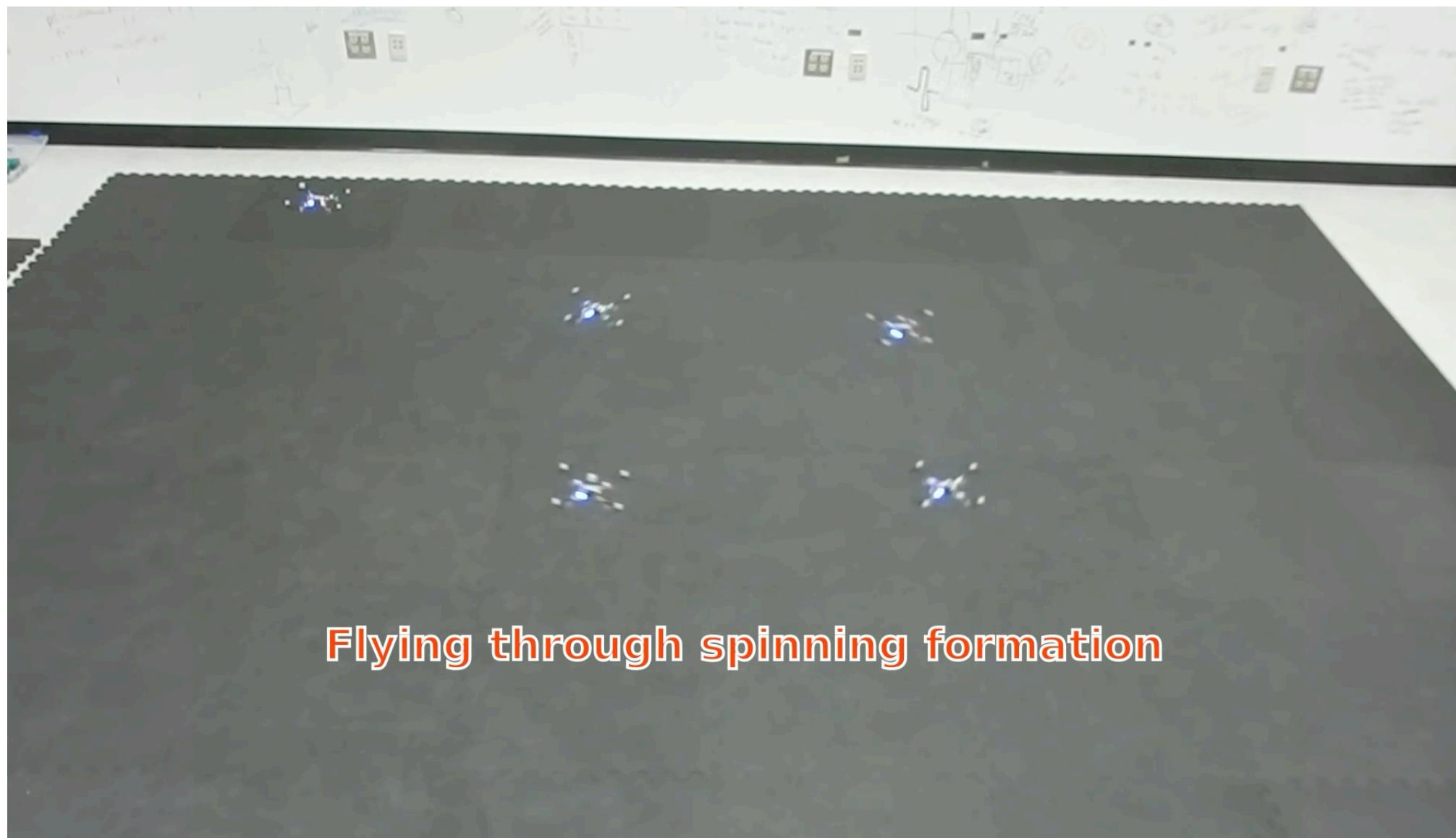
Given a control system and a safe set  $C$

$$\exists u \text{ s.t. } \dot{h}(x, u) \geq 0 \Rightarrow C \text{ is invariant}$$

Compute control action that  
guarantees vehicle never escape safe set

A cohesive QP framework to achieve  
control objective while guaranteeing safety

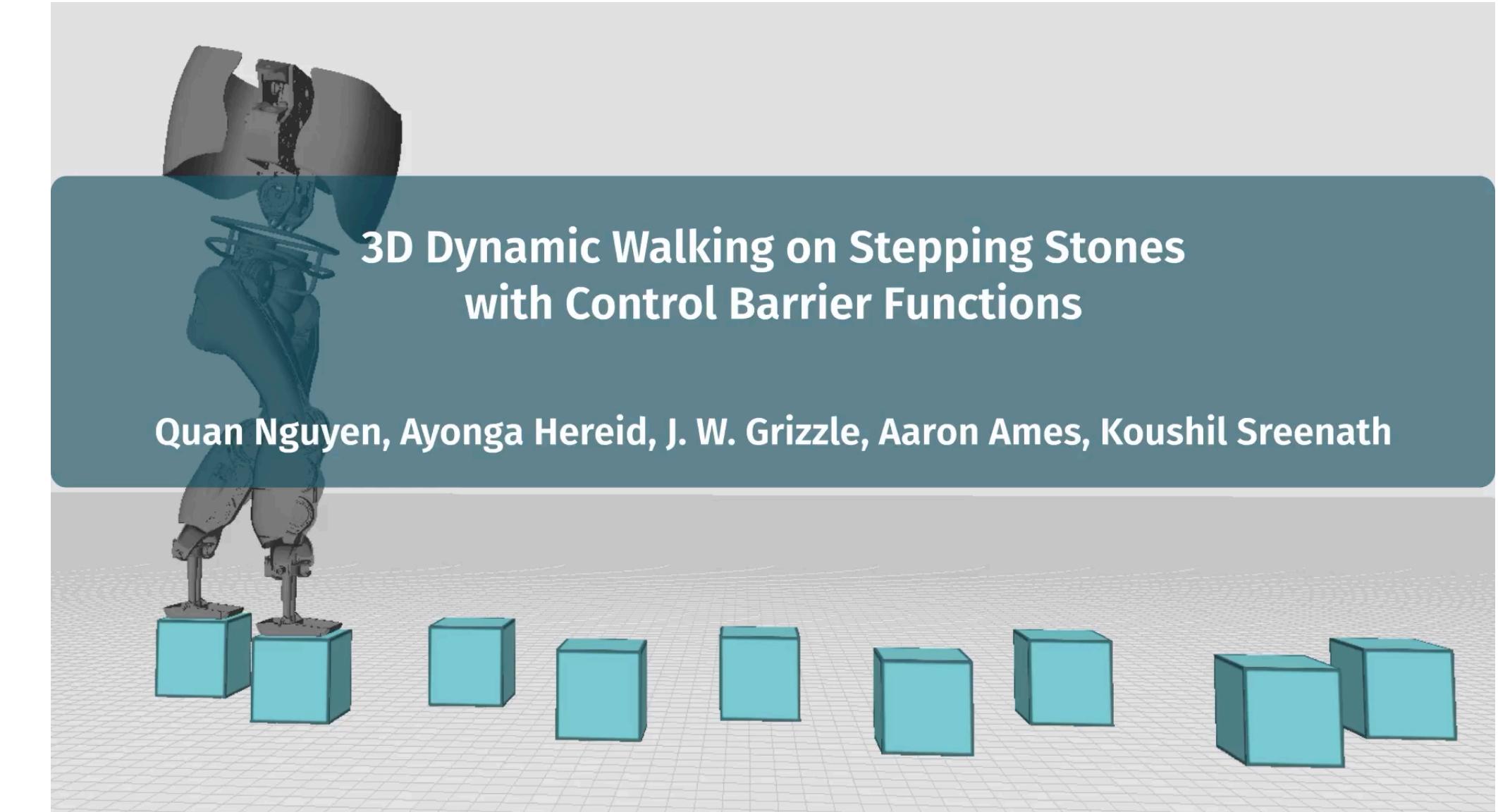
# Control Barrier Functions - Applications



<https://www.youtube.com/watch?v=rK9oyqccMJw>

Wang et al. Safe Certificate-Based Maneuvers for Teams of Quadrotors Using Differential Flatness. 2017.

- Modify nominal trajectories to avoid collisions
- Models safety region with super ellipsoids
- **During actual flights, quad rotors often crash due to strong wind**
- **Unclear on real time capability**

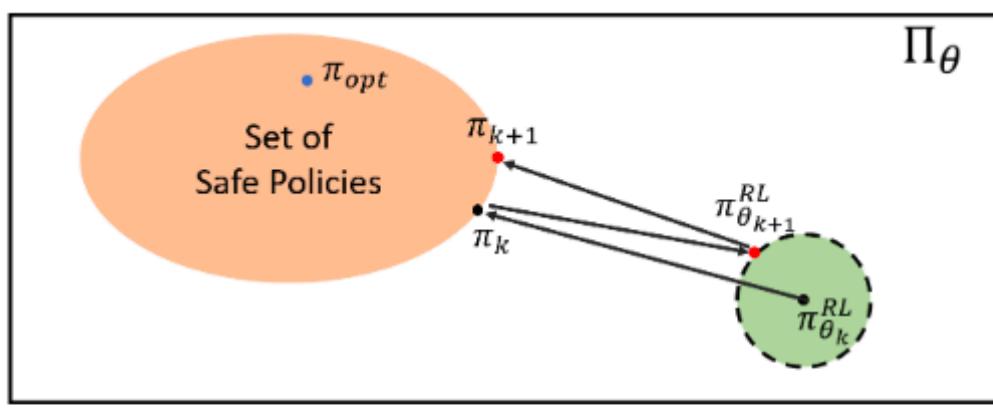


Nguyen et al. 3D Dynamic Walking on Stepping Stones with Control Barrier Functions.

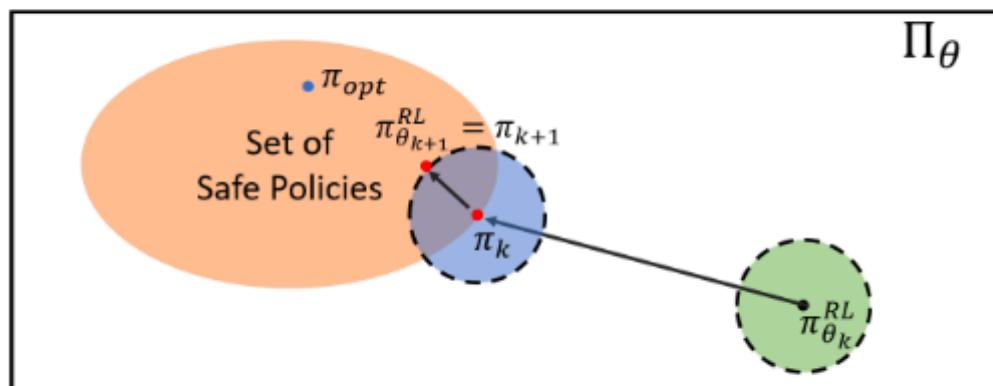
# How to bring formal safety guarantees to the real world?

- Real-time
- Account for sensor, state estimation uncertainties
- Theoretical relaxations of safety guarantees

# Looking Forward - Safe and Efficient Learning



(a)



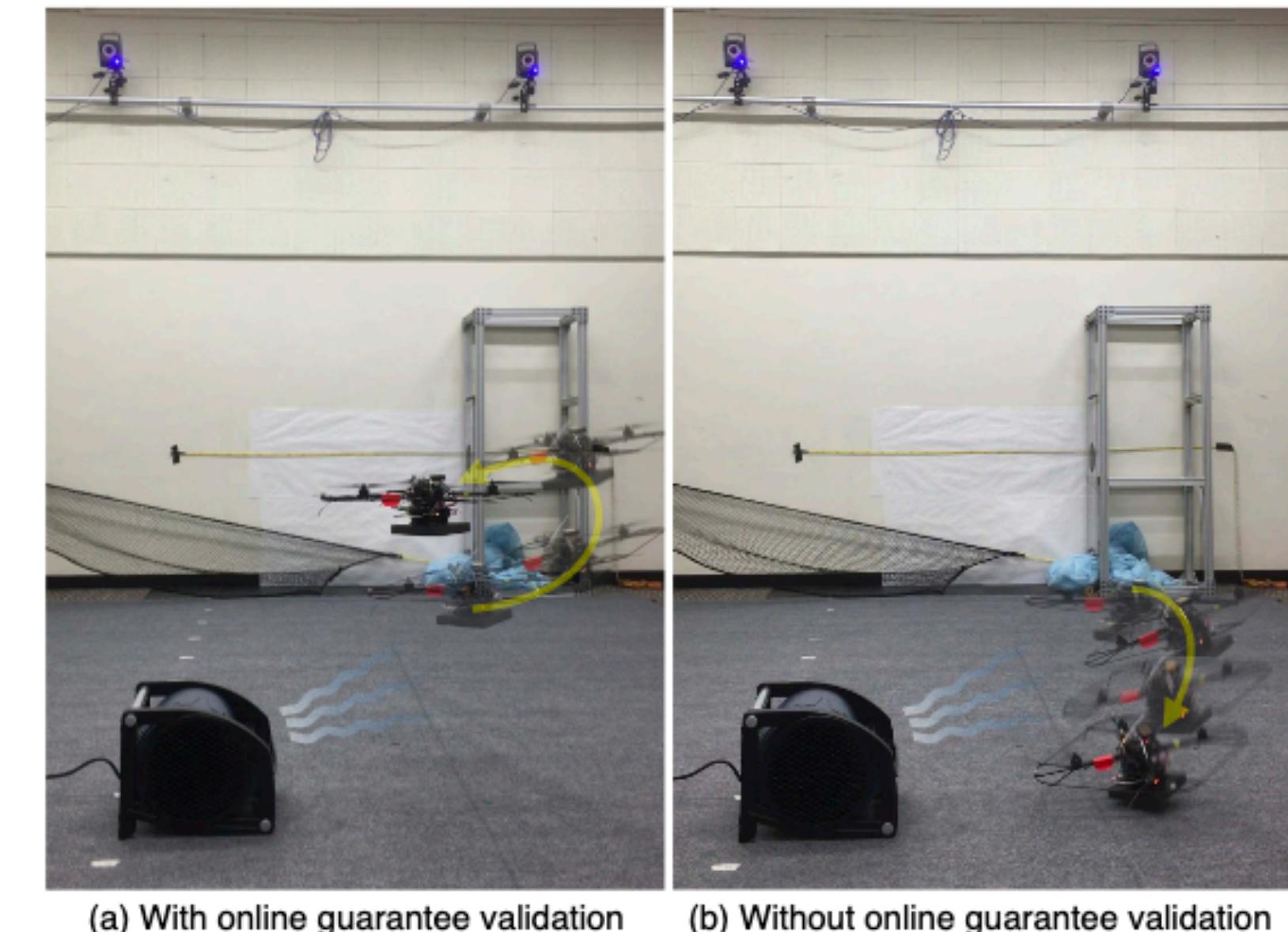
(b)

Figure 2: Illustration of policy iteration process, where we try to learn the optimal safe policy,  $\pi_{opt}$ . (a) Policy optimization with barrier-compensating controller. Next policy is updated around the previous RL controller,  $\pi_{\theta_k}^{RL}$ ; (b) Policy optimization with barrier-guided controller. Next policy is updated around previous deployed controller,  $\pi_k$ .

<https://arxiv.org/abs/1903.08792>

Cheng et al. End-to-End Safe Reinforcement Learning through Barrier Functions for Safety-Critical Continuous Control Tasks. 2019.

**Safe RL w/ Barrier Functions  
to guide learning process**

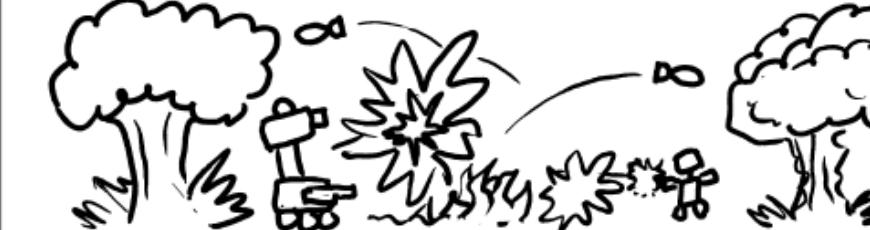


<https://arxiv.org/abs/1705.01292>

Fisac et al. <https://arxiv.org/abs/1705.01292>. 2018.

**HJ reachability w/ approximate knowledge**  
\* allows safe learning in the real world

## WHY ASIMOV PUT THE THREE LAWS OF ROBOTICS IN THE ORDER HE DID:

POSSIBLE ORDERING	CONSEQUENCES	
1. (1) DON'T HARM HUMANS 2. (2) OBEY ORDERS 3. (3) PROTECT YOURSELF	[SEE ASIMOV'S STORIES]	BALANCED WORLD
1. (1) DON'T HARM HUMANS 2. (3) PROTECT YOURSELF 3. (2) OBEY ORDERS	EXPLORE MARS!  HAHA, NO. IT'S COLD AND I'D DIE.	FRUSTRATING WORLD
1. (2) OBEY ORDERS 2. (1) DON'T HARM HUMANS 3. (3) PROTECT YOURSELF		KILLBOT HELLSCAPE
1. (2) OBEY ORDERS 2. (3) PROTECT YOURSELF 3. (1) DON'T HARM HUMANS		KILLBOT HELLSCAPE
1. (3) PROTECT YOURSELF 2. (1) DON'T HARM HUMANS 3. (2) OBEY ORDERS	I'LL MAKE CARS FOR YOU, BUT TRY TO UNPLUG ME AND I'LL VAPORIZER YOU. 	TERRIFYING STANDOFF
1. (3) PROTECT YOURSELF 2. (2) OBEY ORDERS 3. (1) DON'T HARM HUMANS		KILLBOT HELLSCAPE

xkcd: The Three Laws of Robotics

# Thanks!