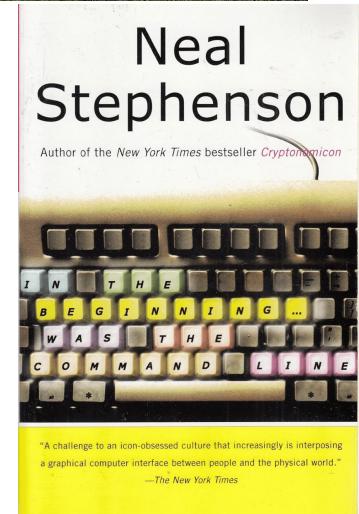


# A bit about me



Teaching is only half of my job...

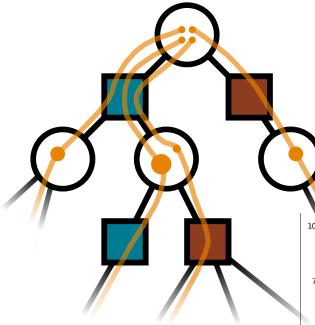


# Autonomous Decision and Control Laboratory

[cu-adcl.org](http://cu-adcl.org)

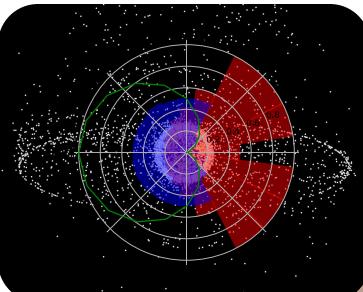
- **Algorithmic Contributions**

- Scalable algorithms for partially observable Markov decision processes (POMDPs)
- Motion planning with safety guarantees
- Game theoretic algorithms



- **Theoretical Contributions**

- Particle POMDP approximation bounds



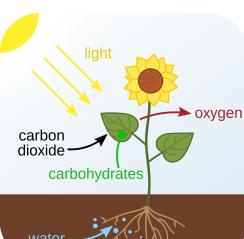
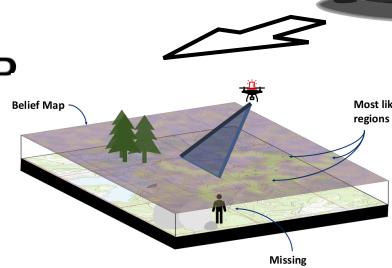
- **Applications**

- Space Domain Awareness
- Autonomous Driving
- Autonomous Aerial Scientific Missions
- Search and Rescue
- Space Exploration
- Ecology



- **Open Source Software**

- POMDPs.jl Julia ecosystem

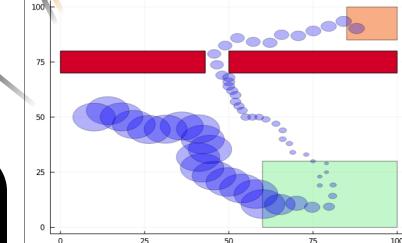


University of Colorado Boulder



**PI: Prof. Zachary Sunberg**

**Postdoc**



**PhD Students**





# Example 1: Autonomous Driving

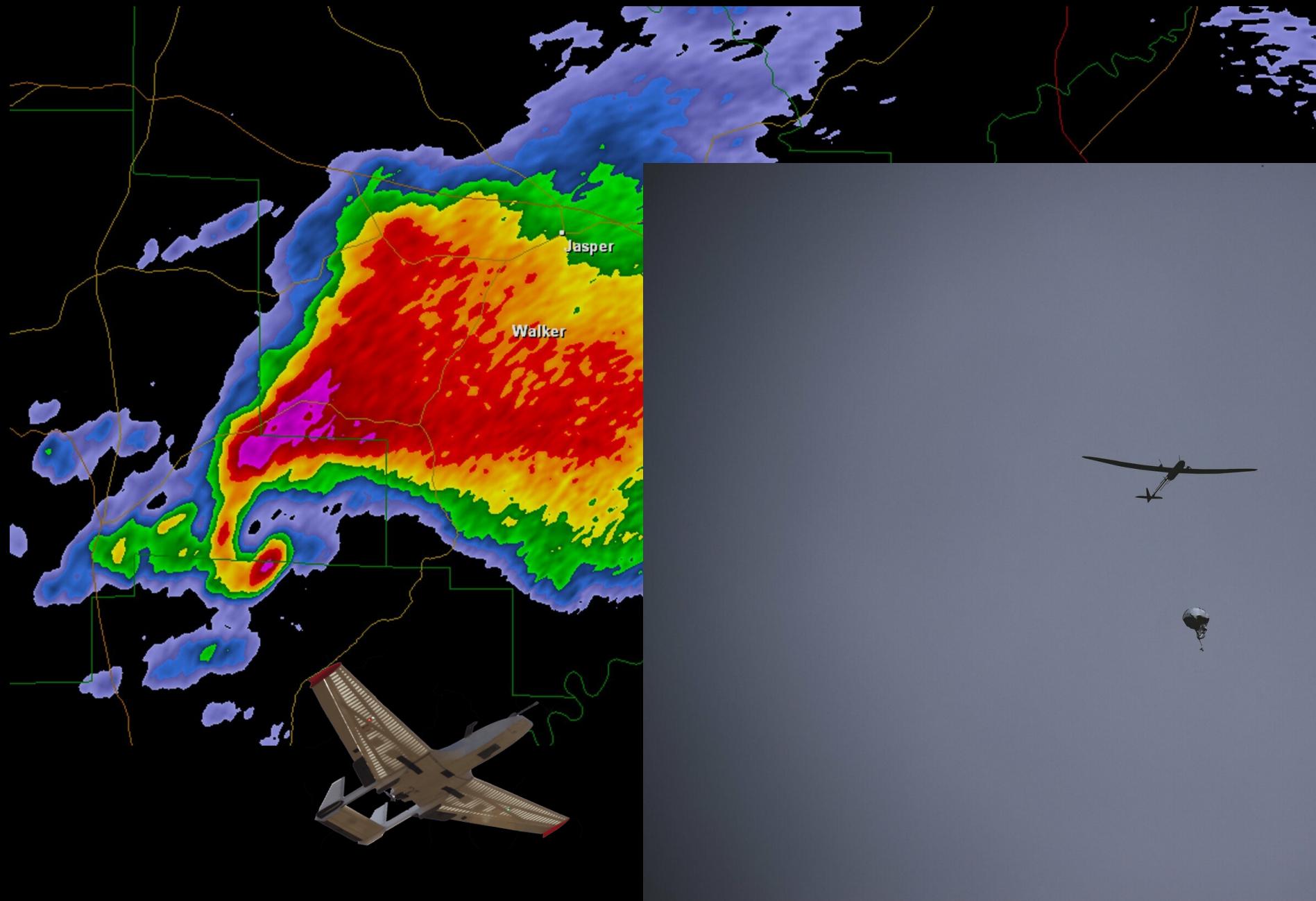


Tweet by Nitin Gupta  
29 April 2018  
<https://twitter.com/nitguptaa/status/990683818825736192>

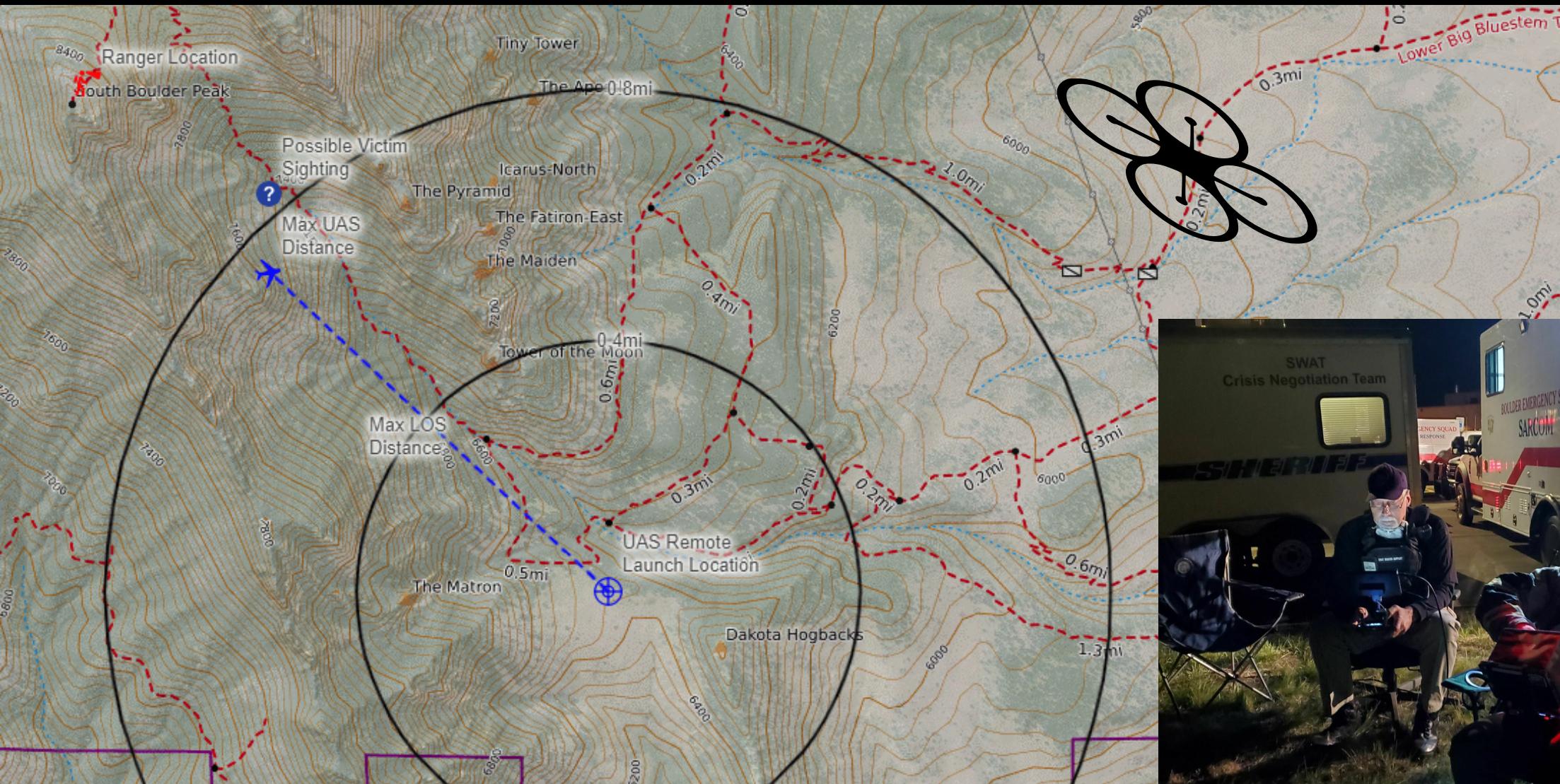


Video: Eric Frew

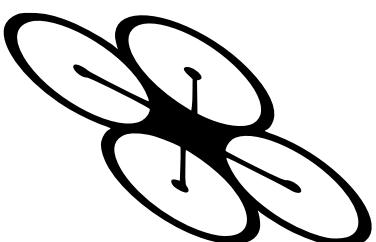
# Example 2: Tornados



# Example 3: Search and Rescue



# What do they have in common?



All are sequential decision-making problems with uncertainty!

Driving: what are the other road users going to do?

Tornado Forecasting: what is going on in the storm?

Search and Rescue: where is the lost person?

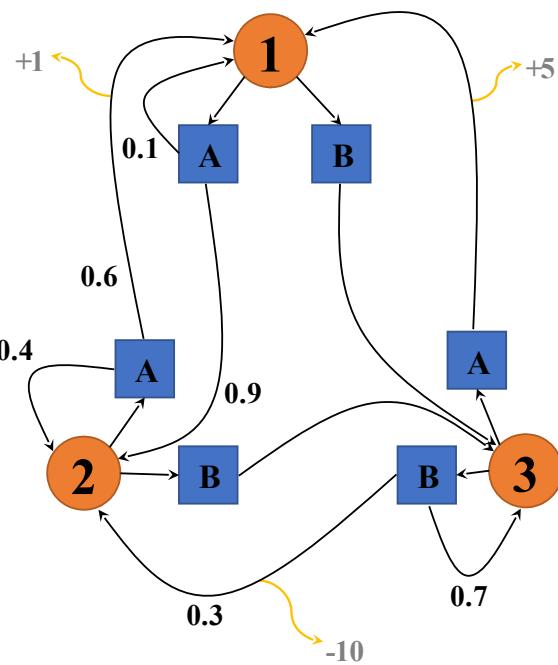
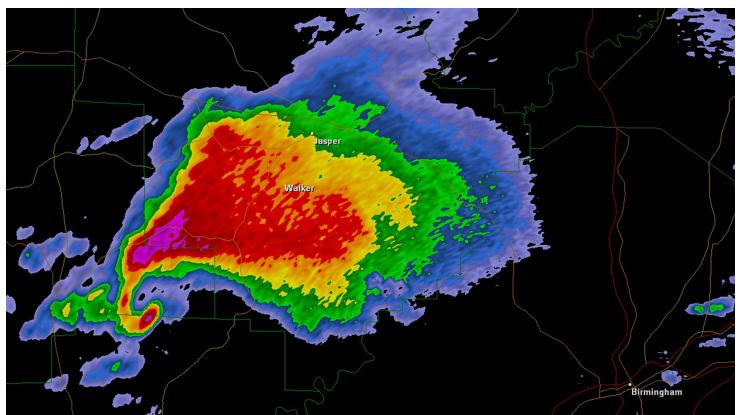
All can be modeled as a **POMDP** (with a very large state and observation spaces).

# Markov Decision Process (MDP)



$[x, y, z, \phi, \theta, \psi, u, v, w, p, q, r]$

$$\mathcal{S} = \mathbb{R}^{12} \times \mathbb{R}^\infty$$



- $\mathcal{S}$  - State space
- $T : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}$  - Transition probability distribution
- $\mathcal{A}$  - Action space
- $R : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$  - Reward

$$\underset{\pi: \mathcal{S} \rightarrow \mathcal{A}}{\text{maximize}} \quad \mathbb{E} \left[ \sum_{t=0}^{\infty} R(s_t, a_t) \right]$$

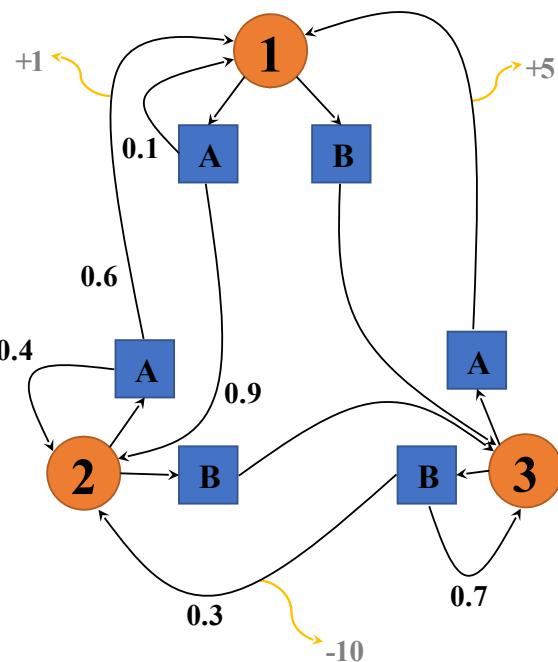
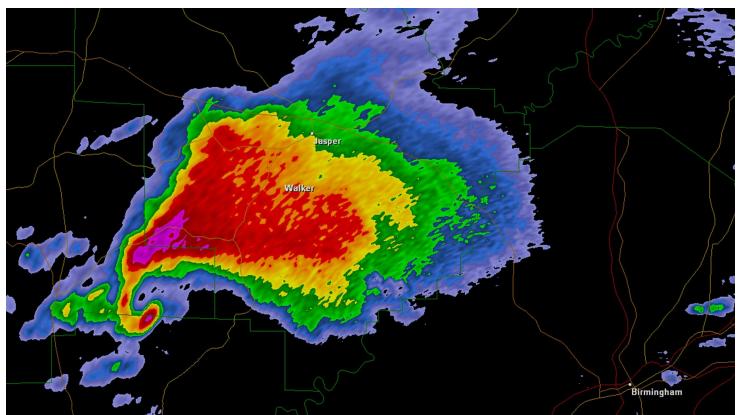
Aleatory

# Reinforcement Learning



$[x, y, z, \phi, \theta, \psi, u, v, w, p, q, r]$

$$\mathcal{S} = \mathbb{R}^{12} \times \mathbb{R}^\infty$$



- $\mathcal{S}$  - State space
- $T : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}$  - Transition probability distribution
- $\mathcal{A}$  - Action space
- $R : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$  - Reward

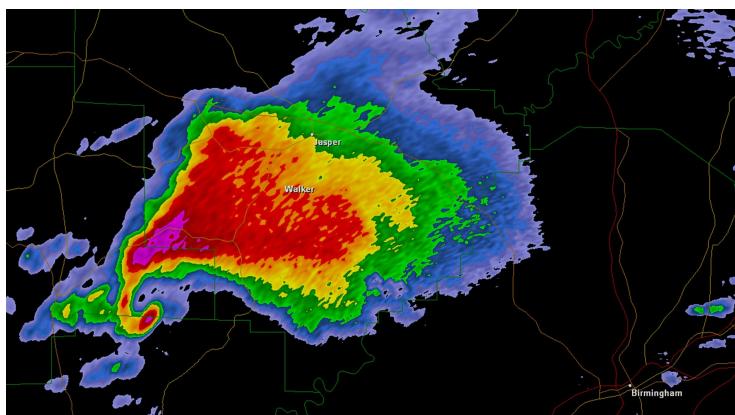
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Epistemic (Static)

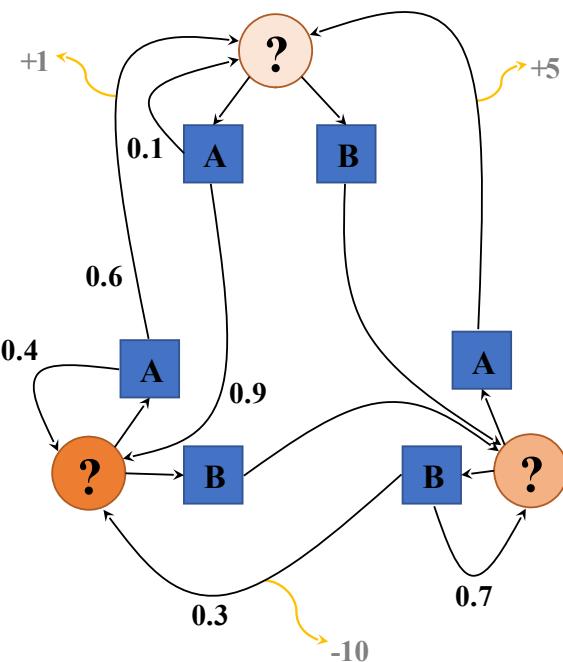


$[x, y, z, \phi, \theta, \psi, u, v, w, p, q, r]$

$$\mathcal{S} = \mathbb{R}^{12} \times \mathbb{R}^\infty$$



# Partially Observable Markov Decision Process (POMDP)



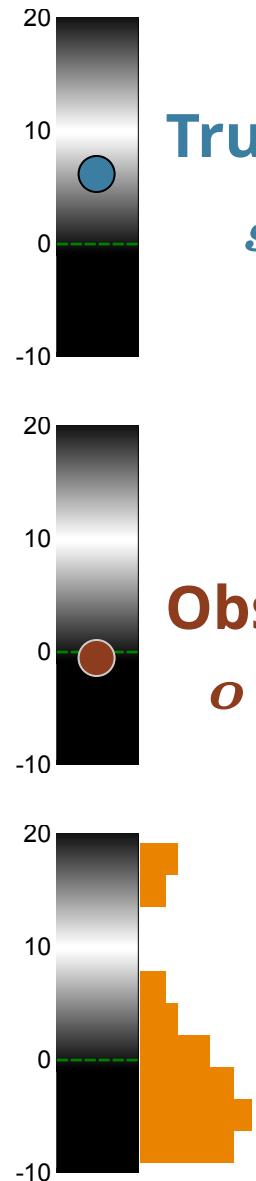
- $\mathcal{S}$  - State space
- $T : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}$  - Transition probability distribution
- $\mathcal{A}$  - Action space
- $R : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$  - Reward
- $\mathcal{O}$  - Observation space
- $Z : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \times \mathcal{O} \rightarrow \mathbb{R}$  - Observation probability distribution

Aleatory

Epistemic (Static)

Epistemic (Dynamic)

# Solving a POMDP



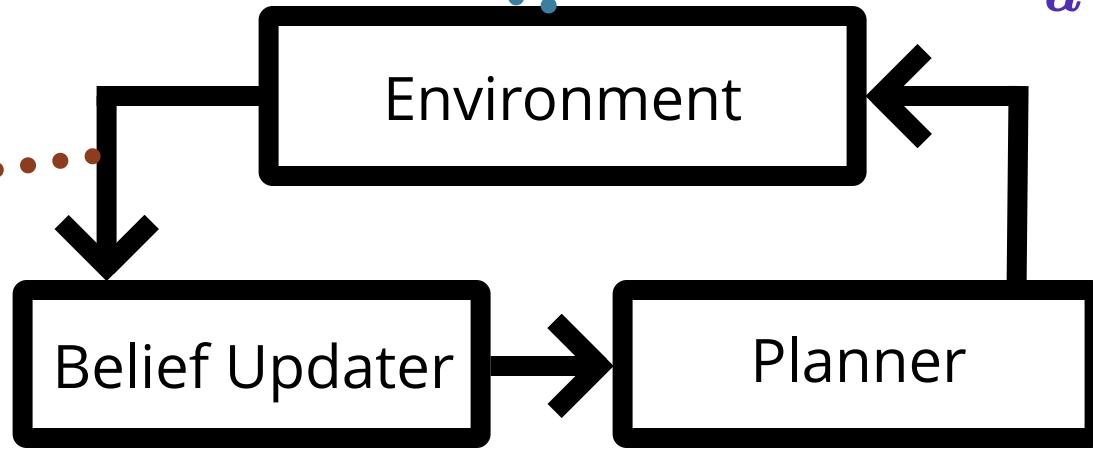
True State

$$s = 7$$

Observation

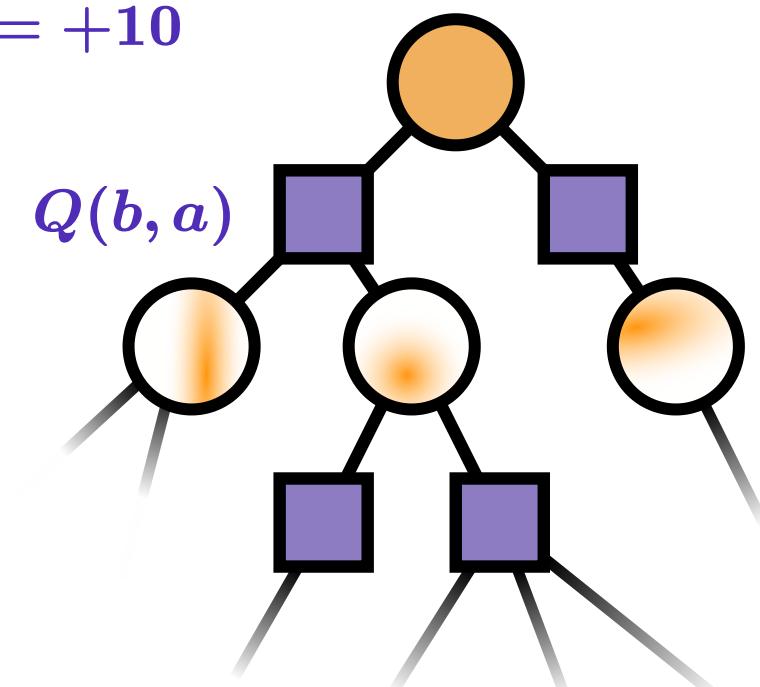
$$o = -0.21$$

$$\begin{aligned} b_t(s) &= P(s_t = s \mid b_0, a_0, o_1 \dots a_{t-1}, o_t) \\ &= P(s_t = s \mid b_{t-1}, a_{t-1}, o_t) \end{aligned}$$

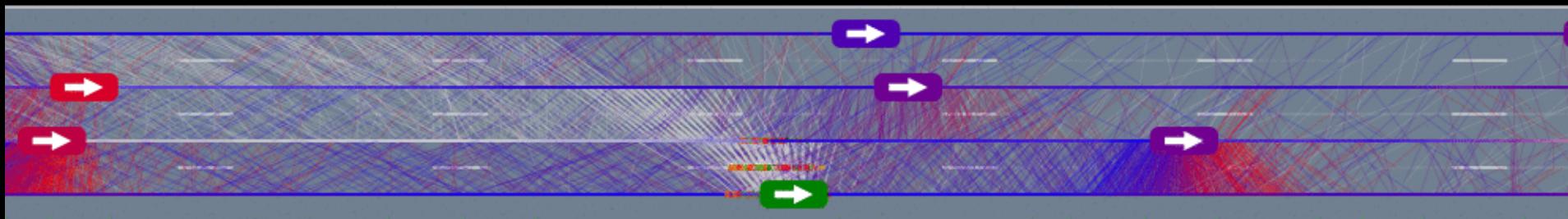


$$a = +10$$

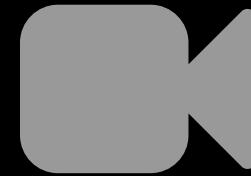
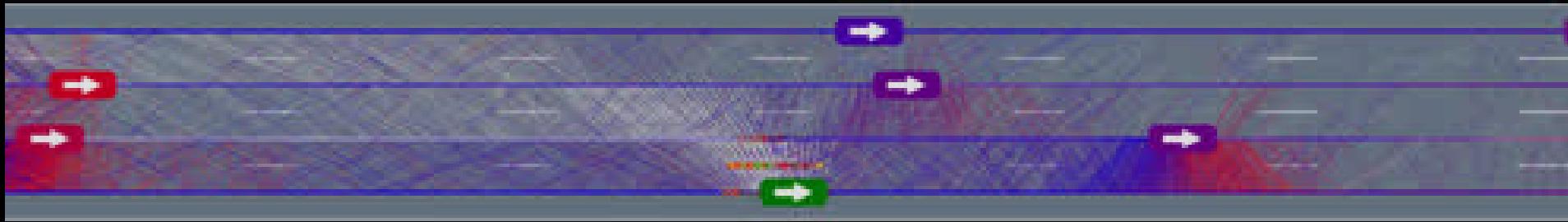
$$O(|\mathcal{S}|^2)$$



t: 0.15  
x: 4.87  
vel: 32.89  
r: 0.00



t: 0.00  
x: 0.00  
vel: 33.19  
r: 0.00



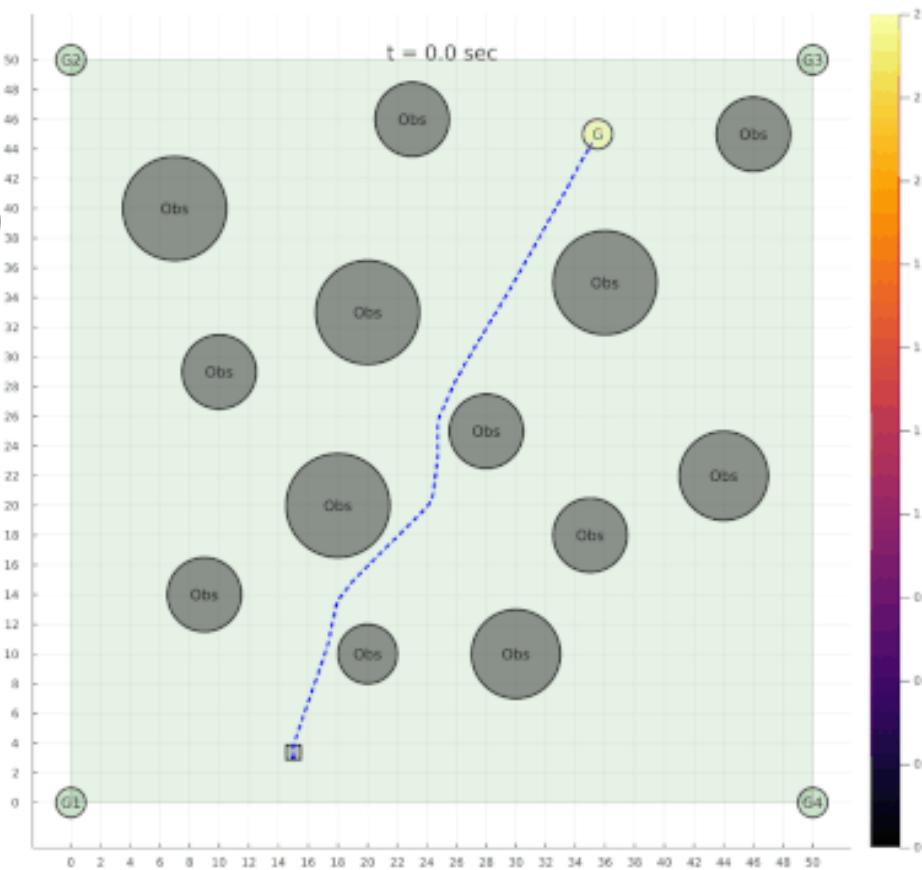
# Navigation among Pedestrians



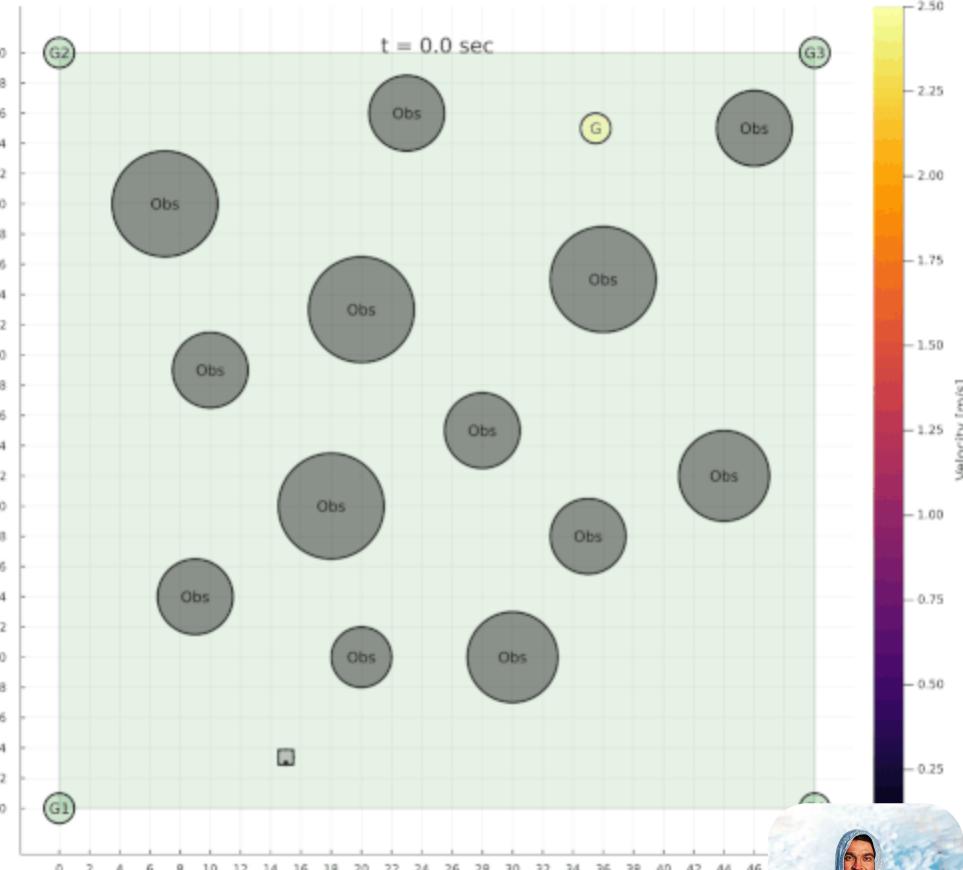
State:

- Vehicle physical state
- Human physical state
- Human intention

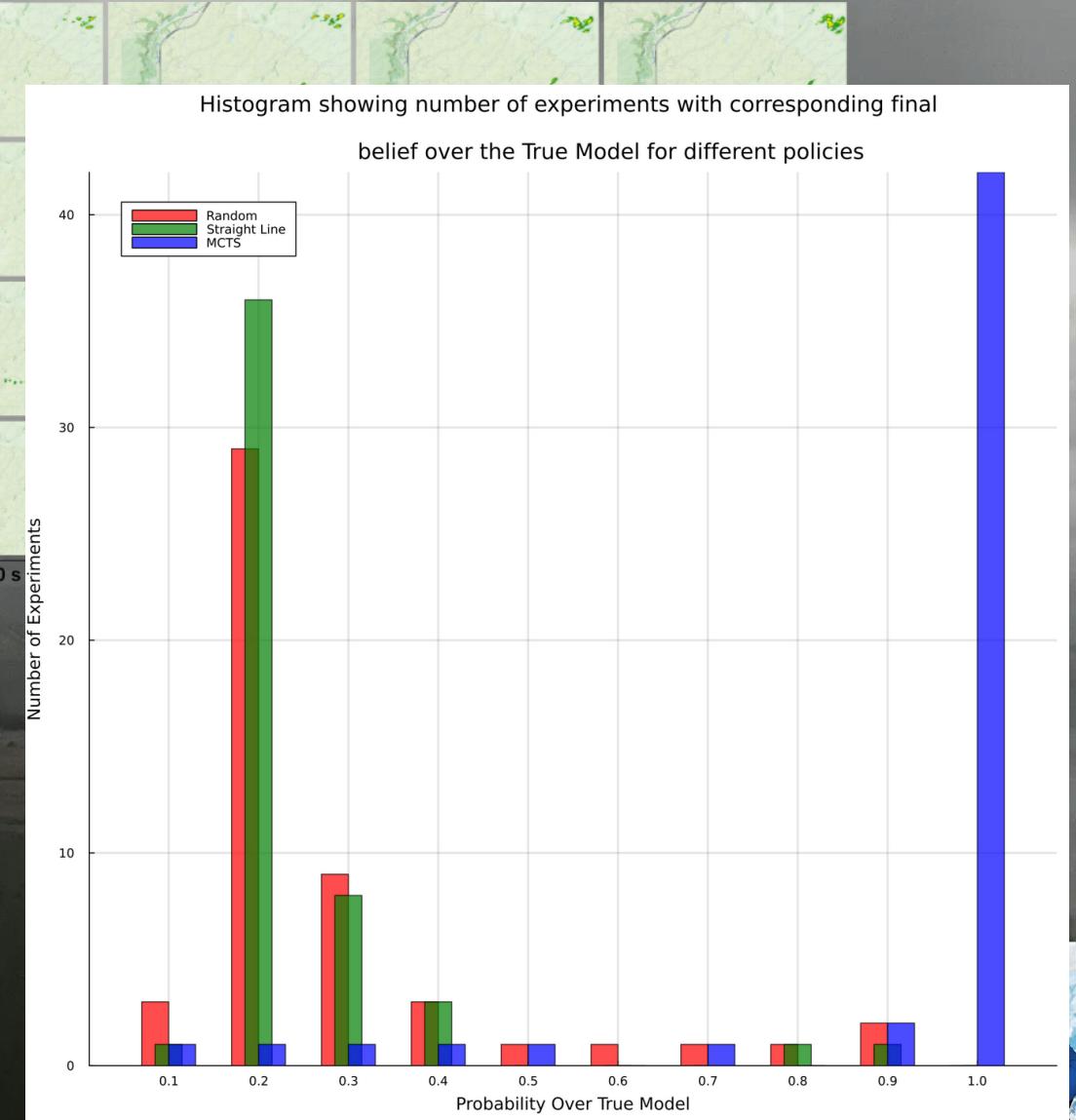
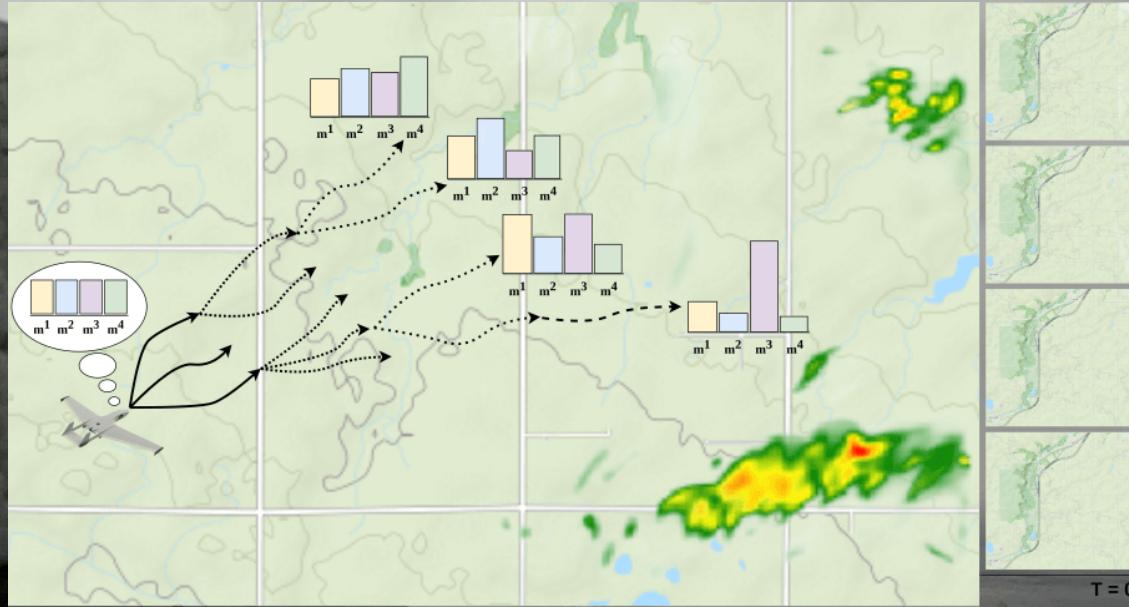
Previous solution: 1-D POMDP (92s avg)



Our solution (65s avg)

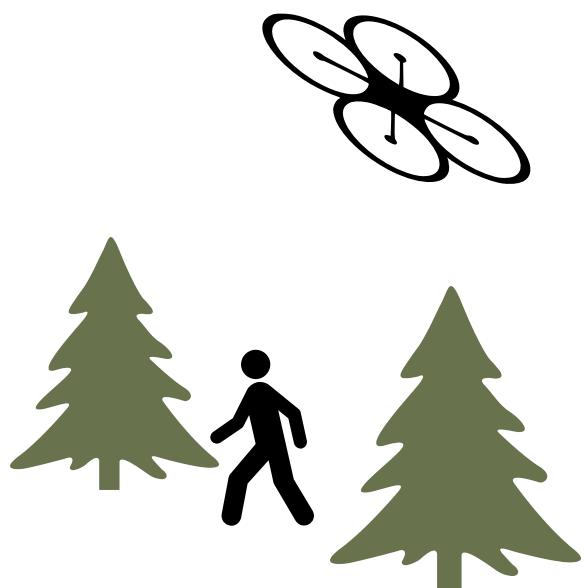


# Meteorology

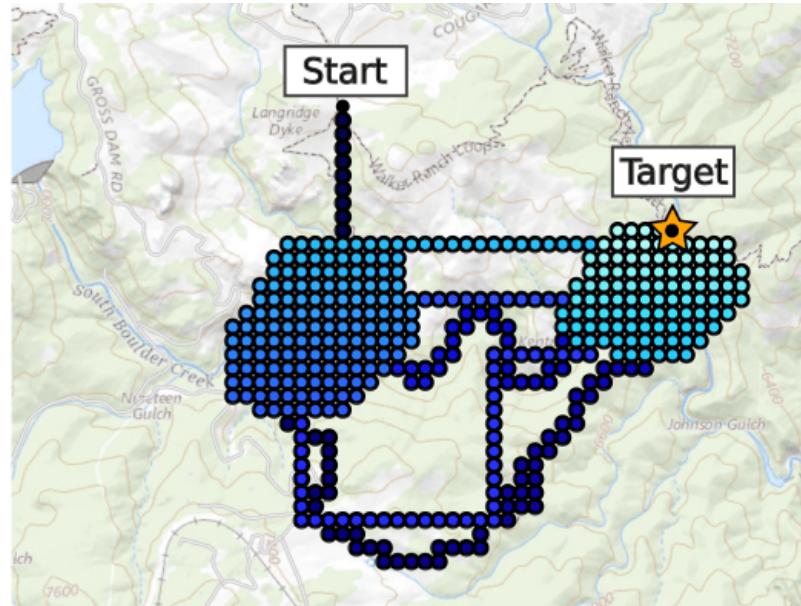


- State: (physical state of aircraft, which forecast is the truth)
- Action: (flight direction, drifter deploy)
- Reward: Terminal reward for correct weather prediction

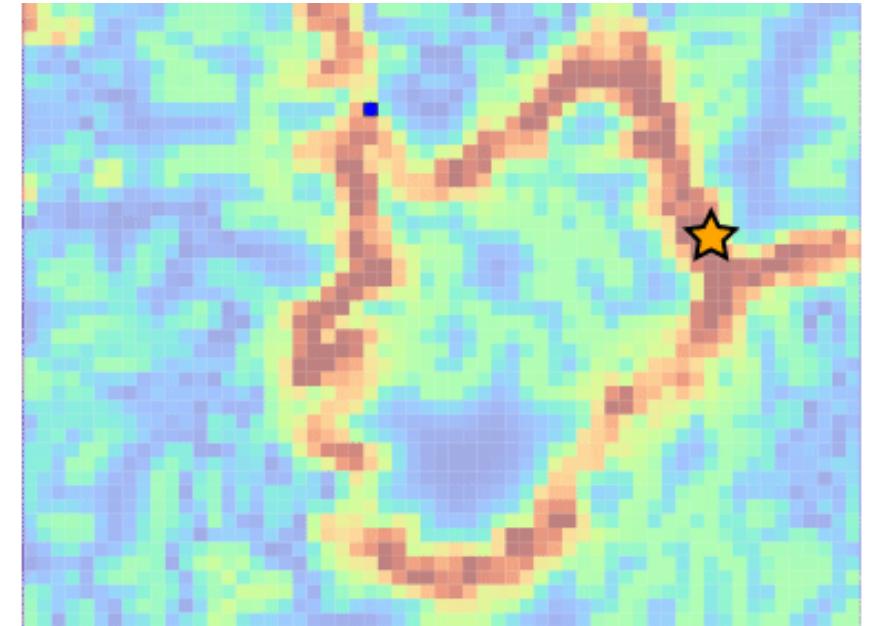
# Drone Search and Rescue



Baseline



Our POMDP Planner

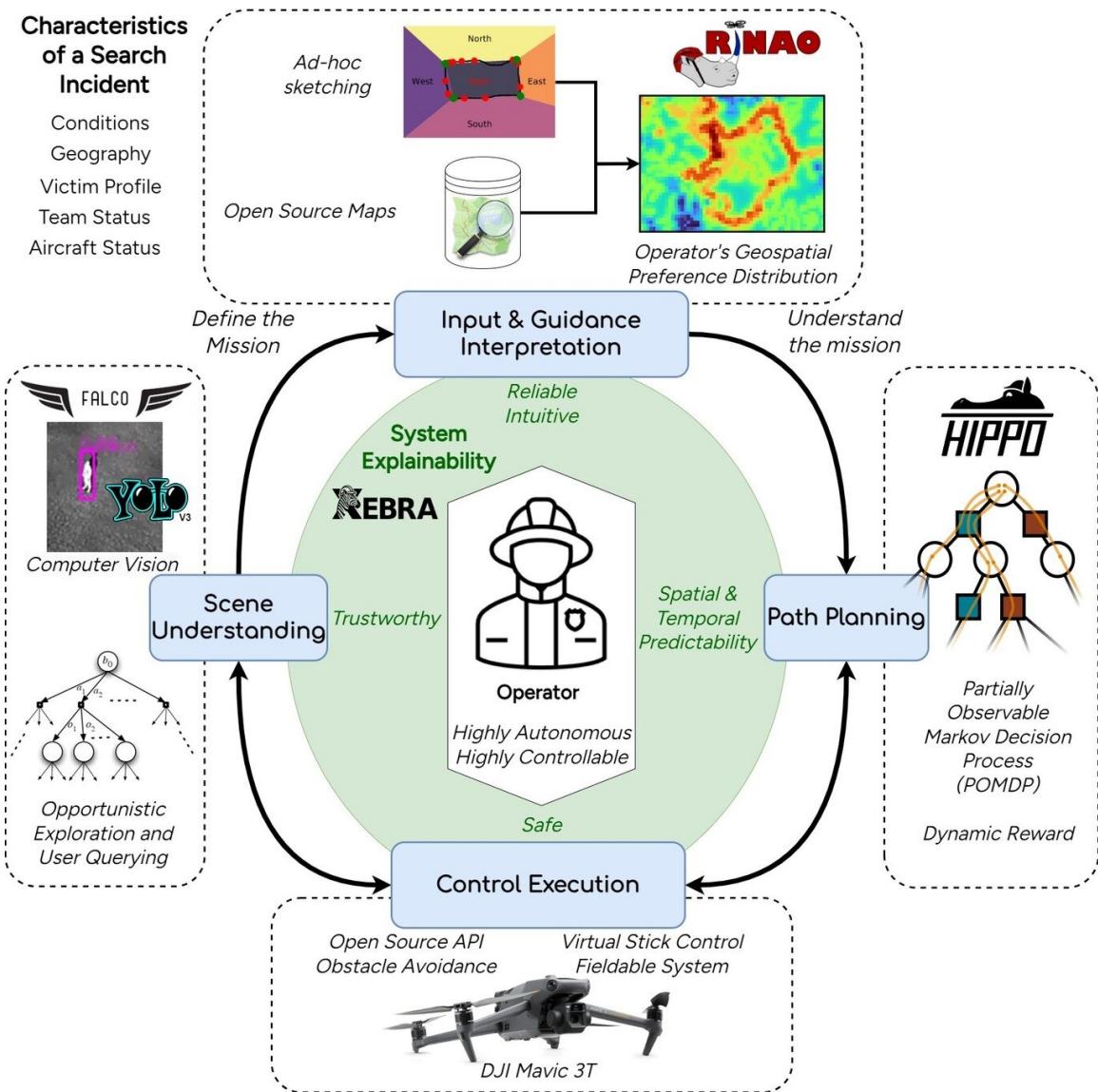


State:

- Location of Drone
- Location of Human



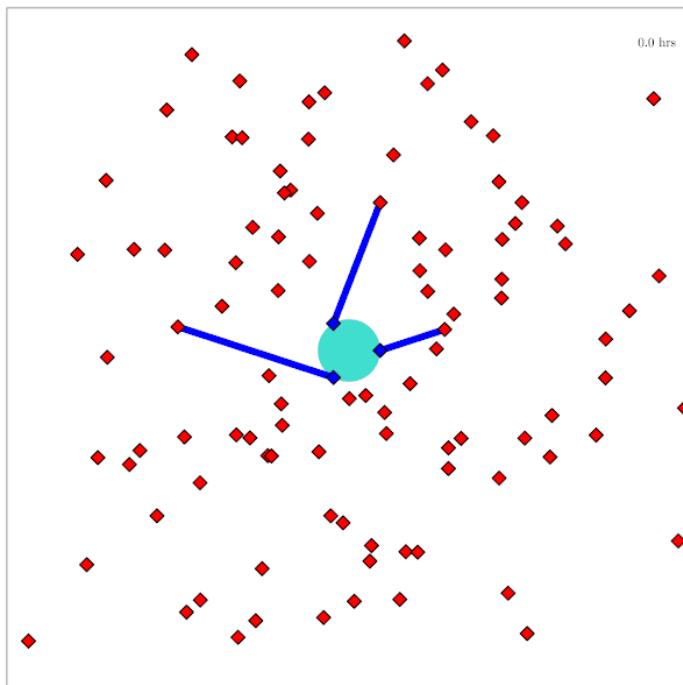
# Drone Search and Rescue



[Ray, Laouar, Sunberg, & Ahmed, ICRA 2023]

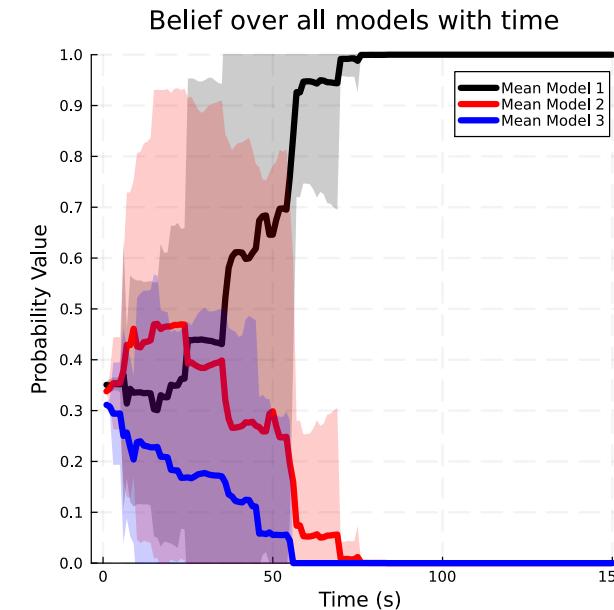
# Space Domain Awareness

Catalog Maintenance Plan



State:

- Position, velocity of object-of-interest
- Anomalies: navigation failure, suspicious maneuver, thruster failure, etc.

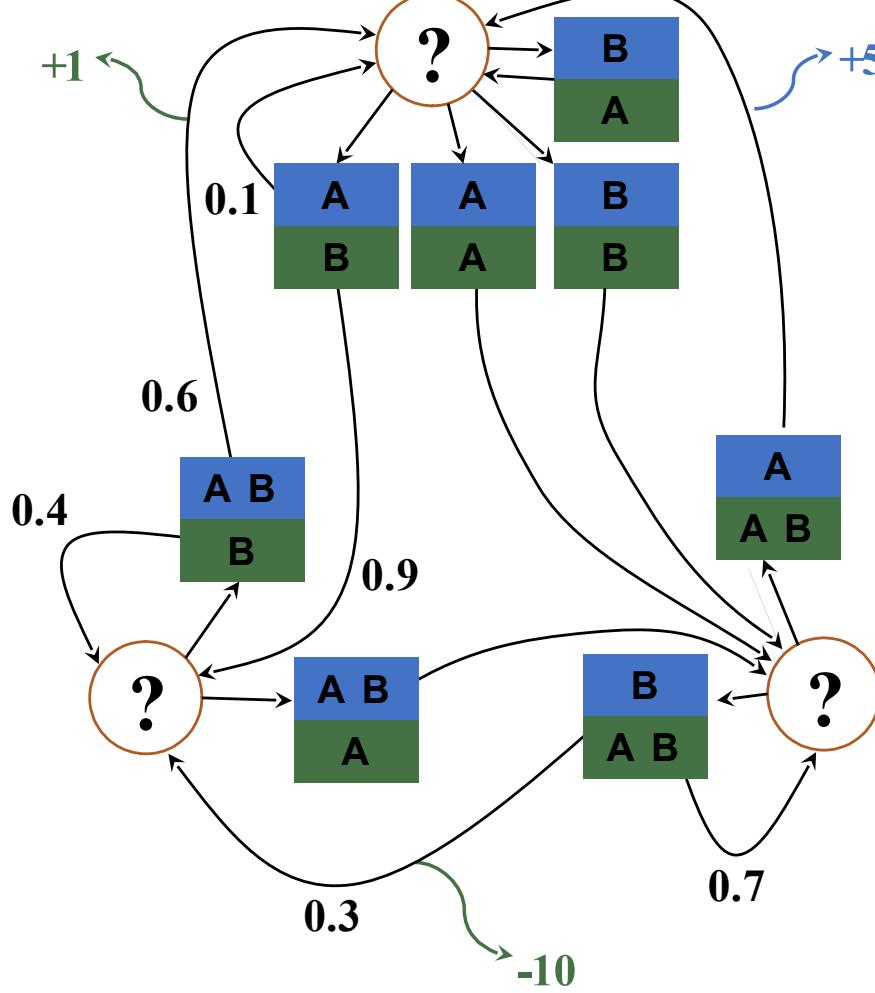


(Result for simplified dynamical system)

Innovation: Large language models allow analysts to quickly specify anomaly hypotheses



# Partially Observable Stochastic Game (POSG)



$s$ -State space

- $T(s' | s, a)$  - Transition probability distribution
- $\mathcal{A}^i, i \in 1..k$  - Action spaces
- $R^i(s, a)$  - Reward function (cooperative, opposing, or somewhere in between)
- $\mathcal{O}^i, i \in 1..k$  - Observation spaces
- $Z(o^i | a, s')$  - Observation probability distributions

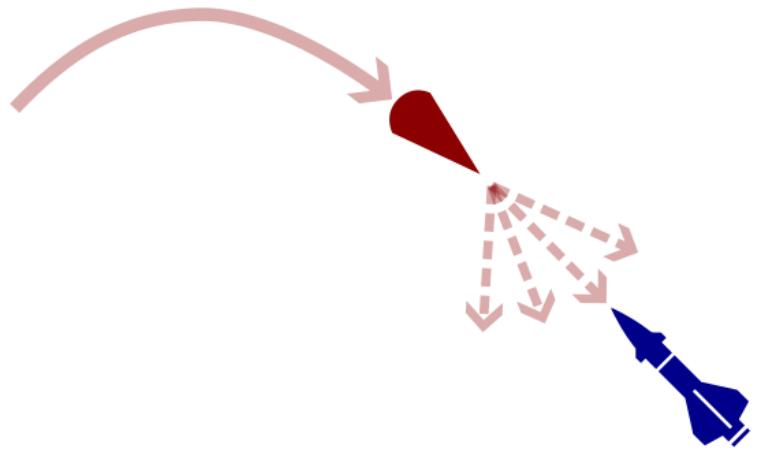
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Epistemic (Static)

Epistemic (Dynamic)

Interaction

# POSG Example: Missile Defense



## POMDP Solution:

1. Assume a distribution for the missile's actions
2. Update belief according to this distribution
3. Use a POMDP planner to find the best defensive action

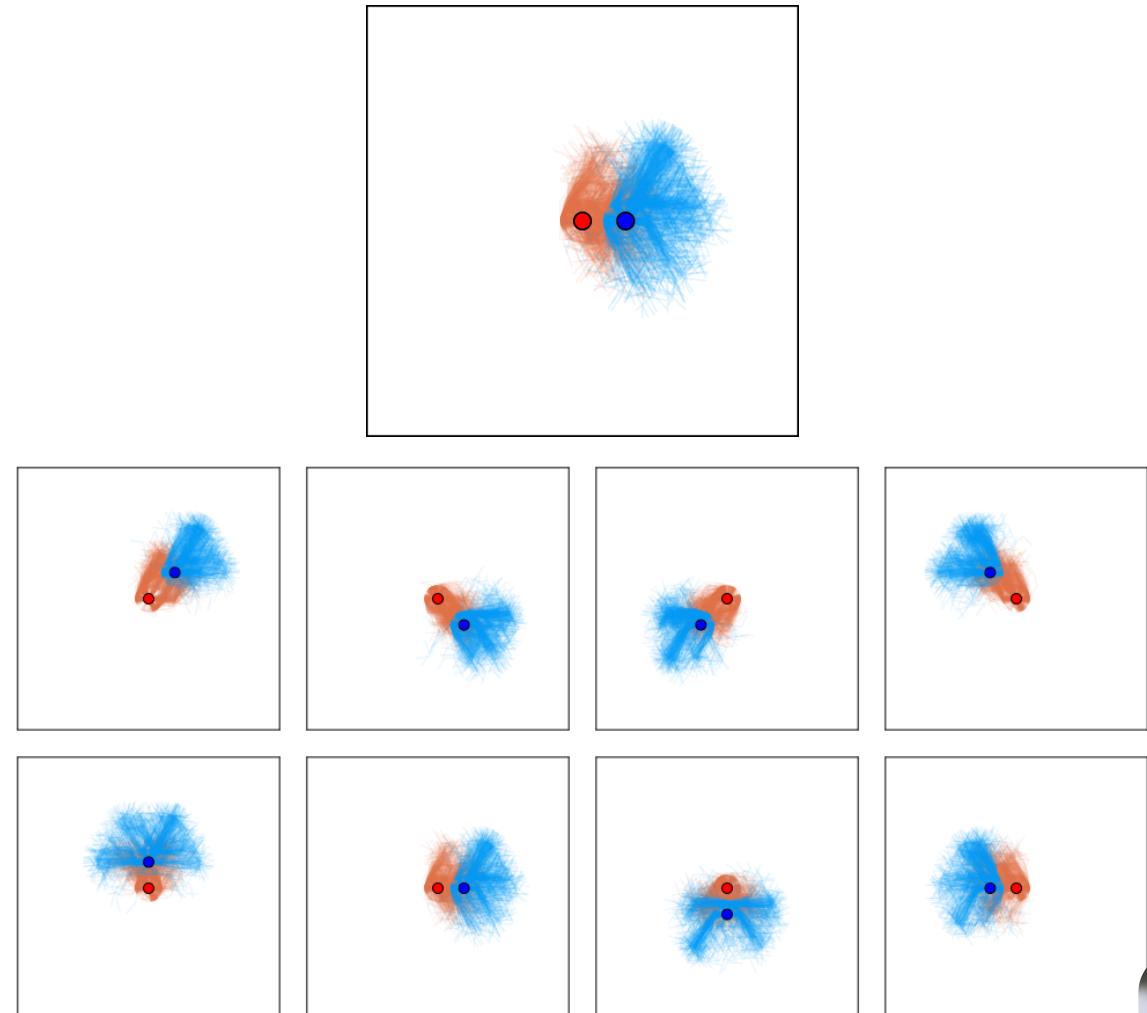
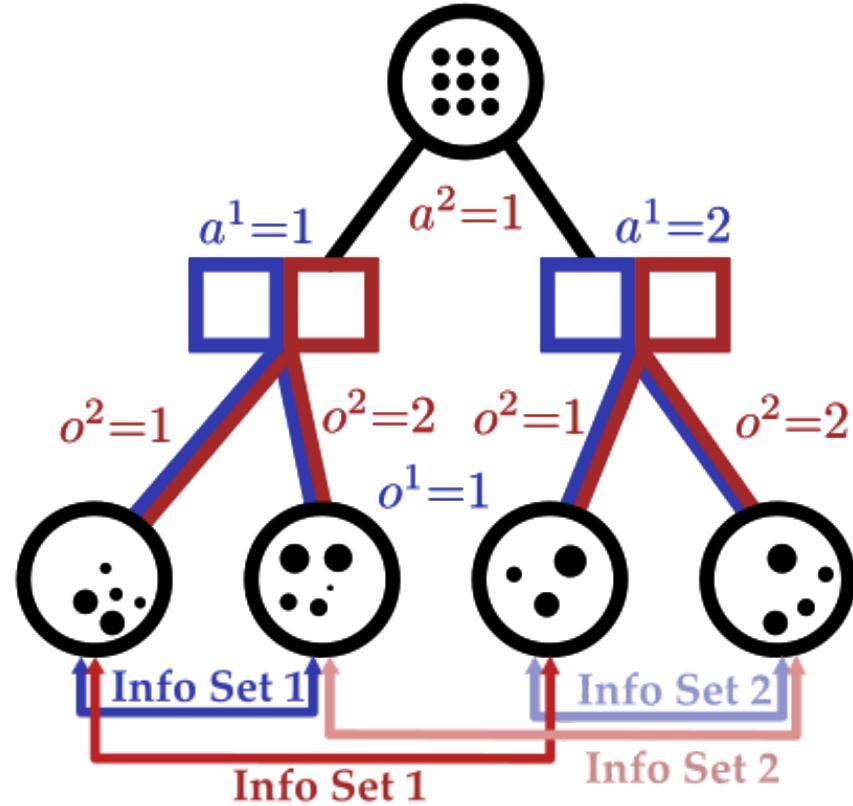
**A shrewd missile operator will use different actions, invalidating our belief**

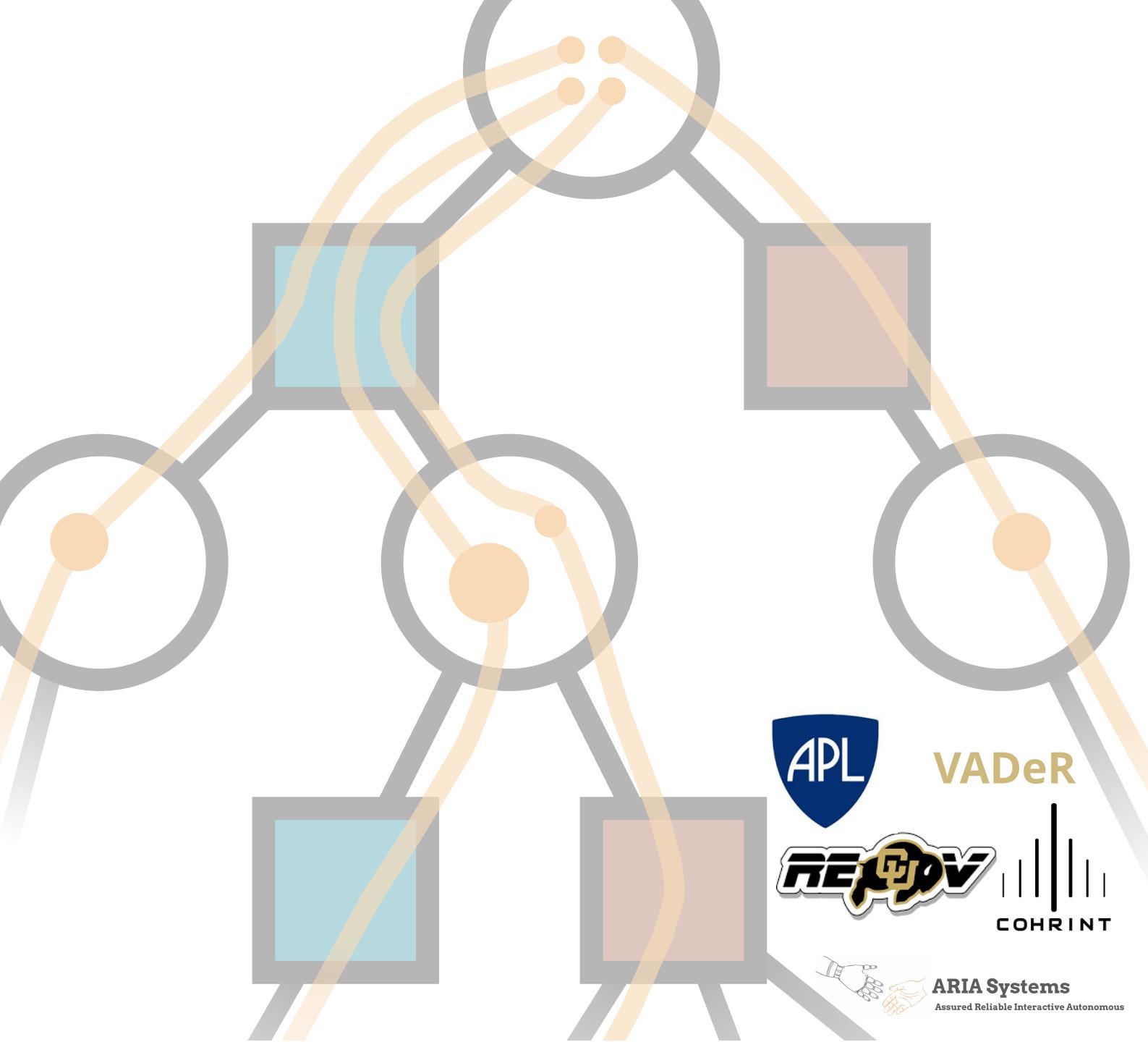
**Nash equilibrium:** All players play a best response to the other players

May include stochastic behavior (bluffing)

Fundamentally impossible for POMDP solvers to compute.

# Tree Search Algorithms for POSGs





# Thank You!

[www.cu-adcl.org](http://www.cu-adcl.org)

Funding orgs: (all opinions are my own)

