# Safe Learning for Control

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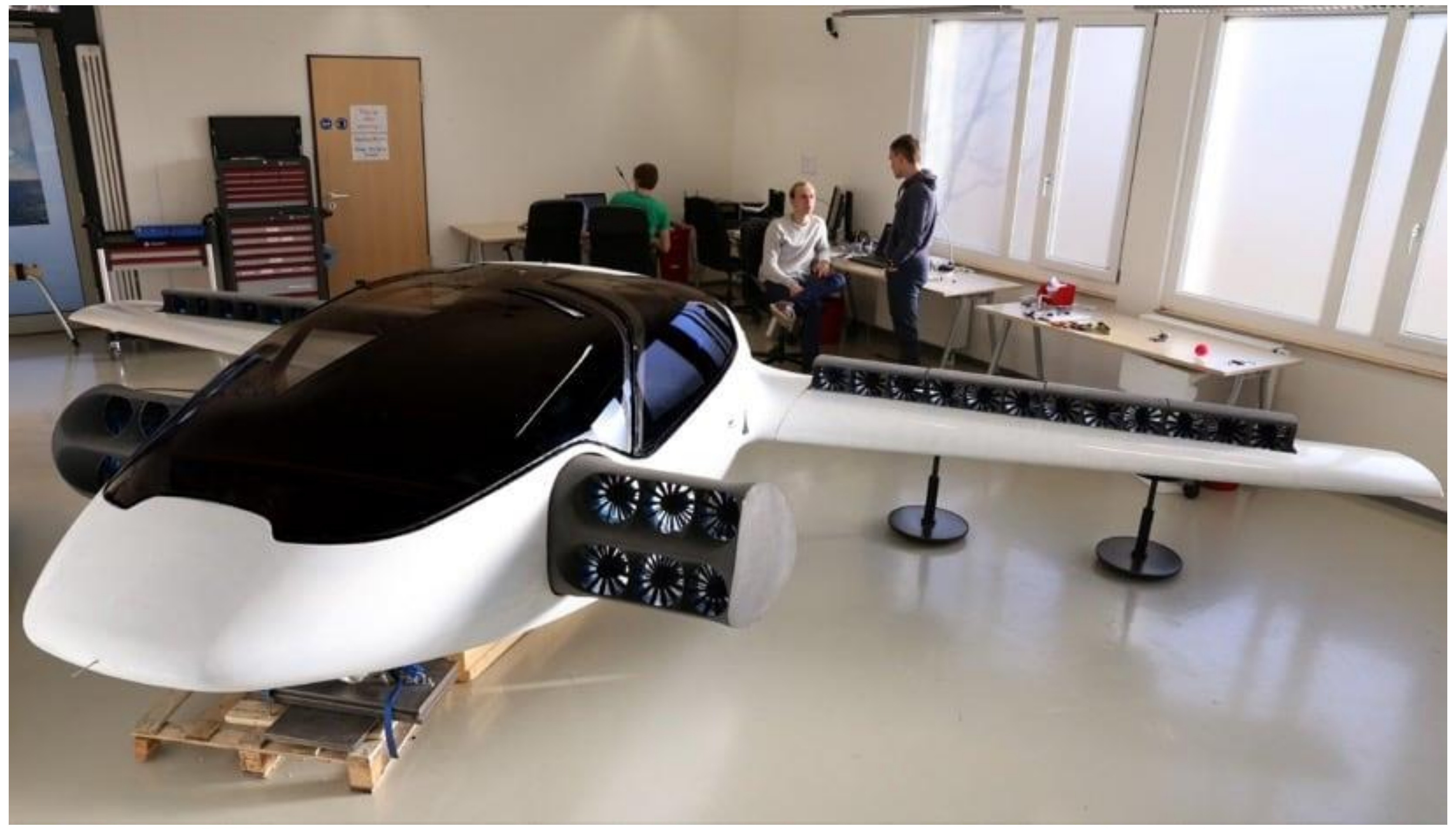
BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

Hybrid Systems Lab

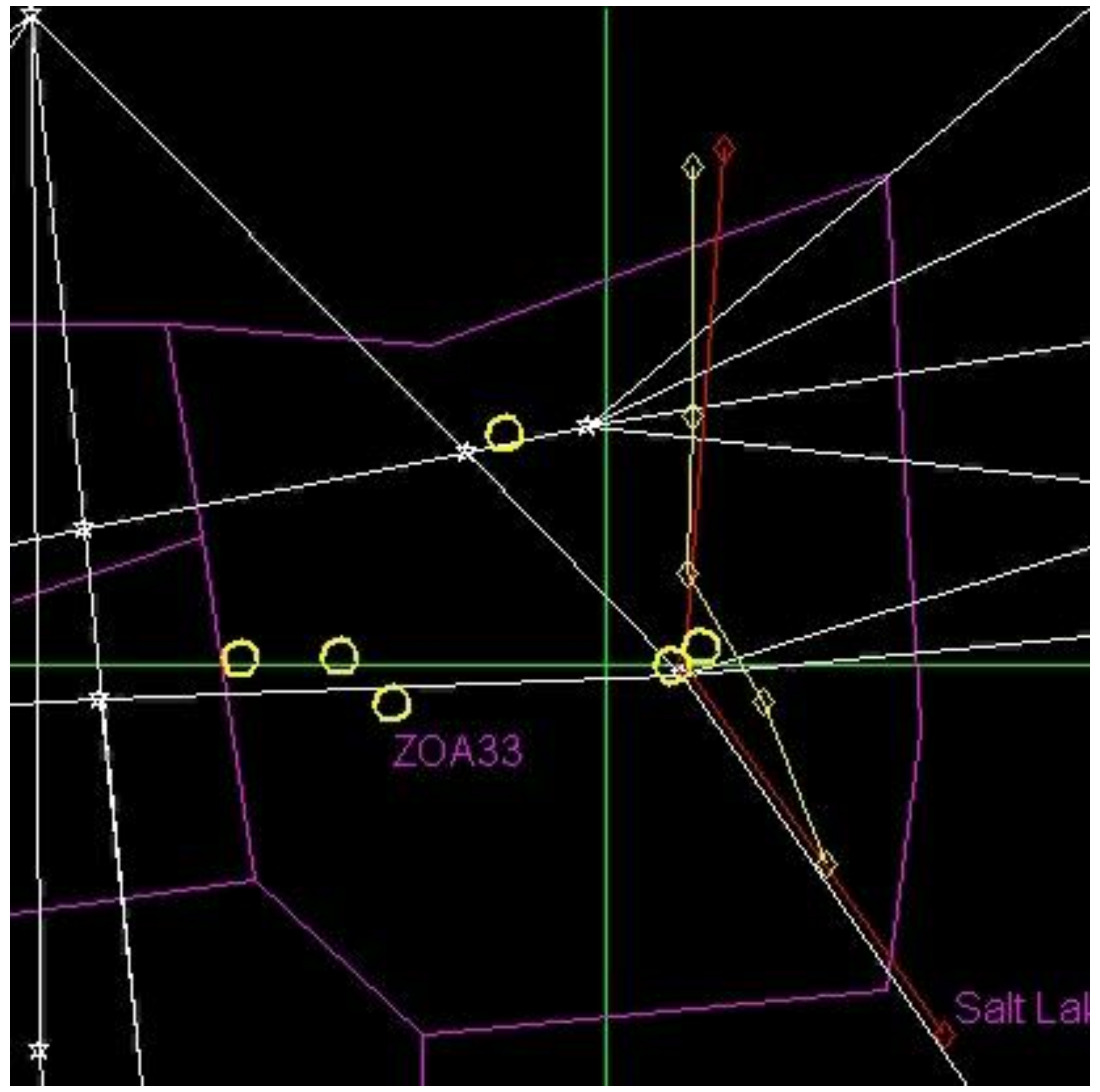
# Growing numbers of new applications


[Amazon]


[Zipline]



[Lilium]




1. Safety
2. Simplicity
3. Ability to adapt to new information

[NASA]

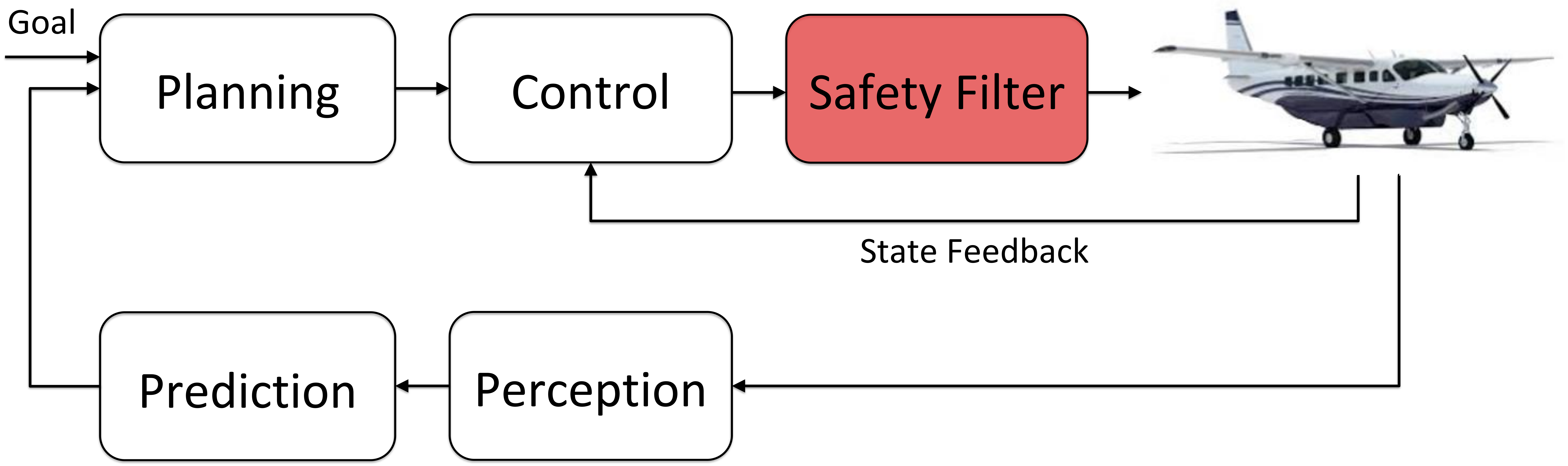
- Collision avoidance system
- Forced landing system
- Air taxi control

[ONR]

- Interdiction system

[US Coast Guard]

# Safety Filter



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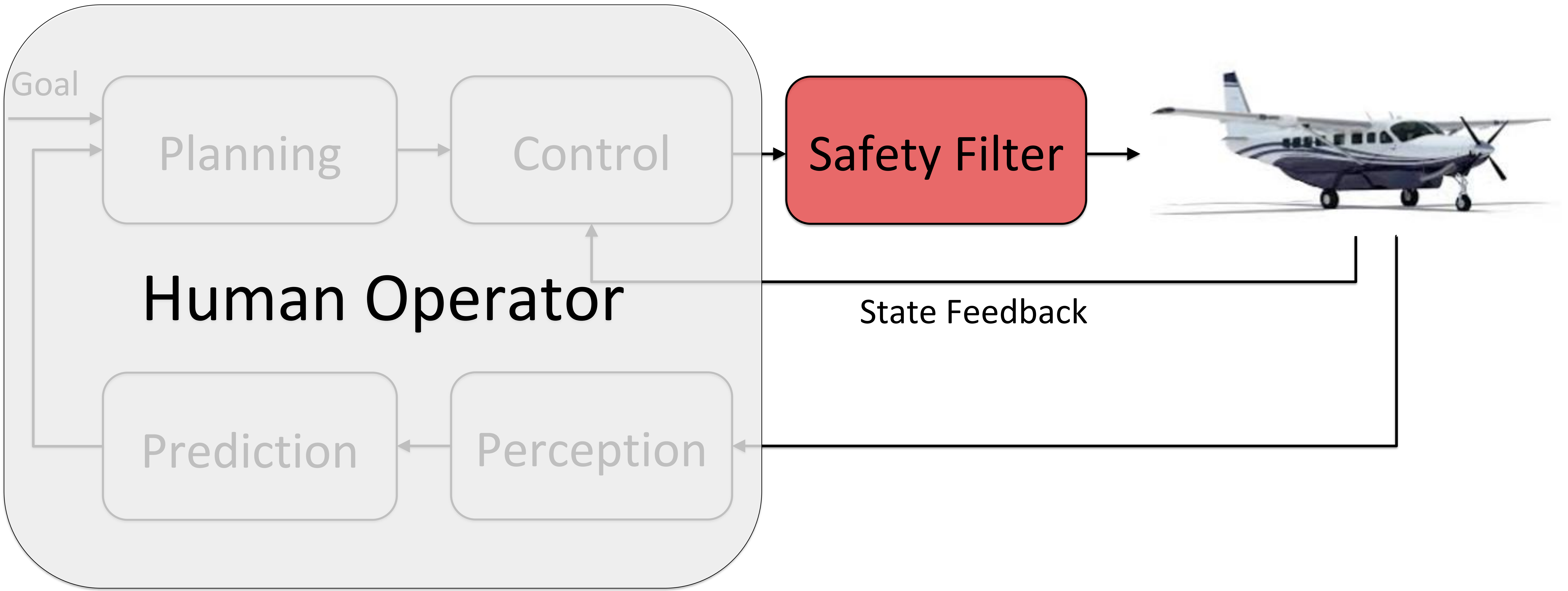


# Safety Analysis: Hamilton-Jacobi Reachability

$$\dot{z} = f(z, u, d)$$

State

Control

Disturbance

Compute all states for which, for all possible disturbances, there is a control which can drive the system state into a target set over a time horizon

Reachability as game: disturbance attempts to force system into unsafe region, control attempts to stay safe

[Bansal et al, CDC 2017 Tutorial]

# Safety Analysis: Hamilton-Jacobi Reachability

1. Cost Function

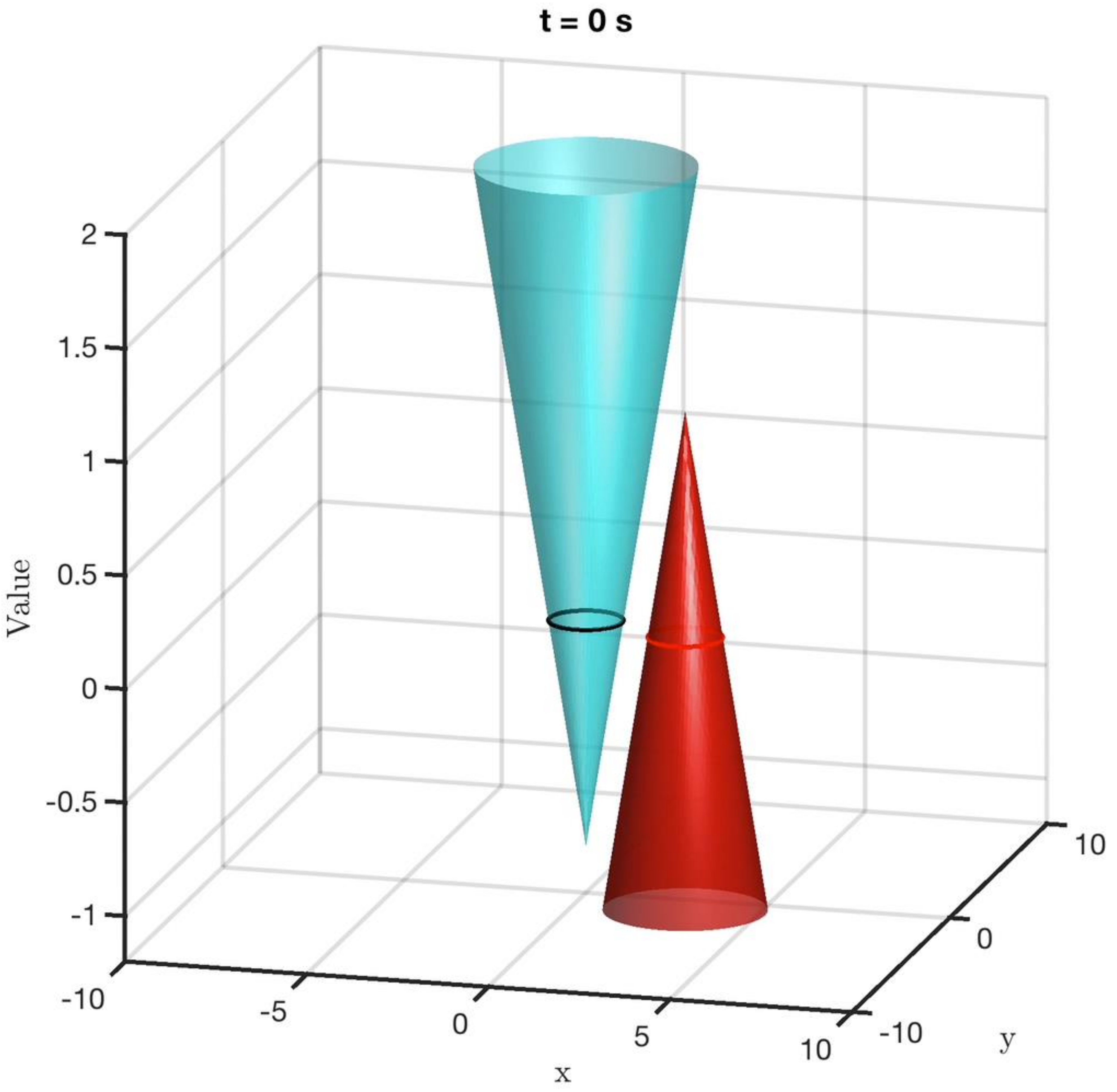
$$z \in \mathcal{L} \leftrightarrow l(z) \leq 0$$
$$z \in \mathcal{G} \leftrightarrow g(z) \leq 0$$

2. Value function:

$$V(z,T) = \inf_{u(\cdot)} \sup_{d(\cdot)} \min_{t \in [0,T]} \max\left\{ l(\xi_{z,T}^{u,d}(t)), \max_{s \in [t,T]} g(\xi_{z,T}^{u,d}(s)) \right\}$$

3. Update equation (Hamilton-Jacobi-Isaacs PDE)

$$\max\left\{\min\left\{\frac{\partial V}{\partial t} + H(z, \nabla V), l(z) - V(z,t), g(z) - V(z,t)\right\}\right\} = 0$$




[Sylvia Herbert]

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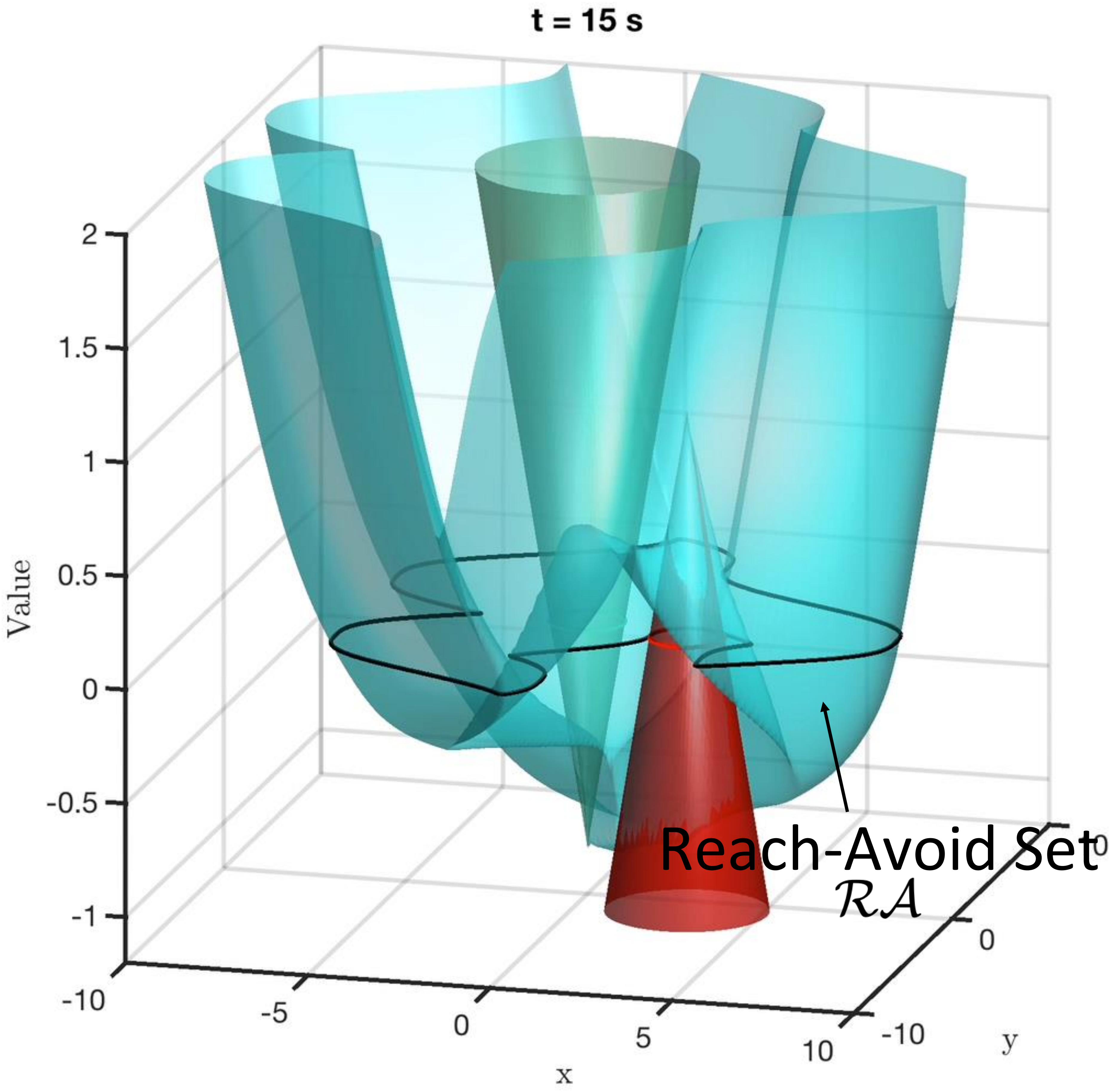
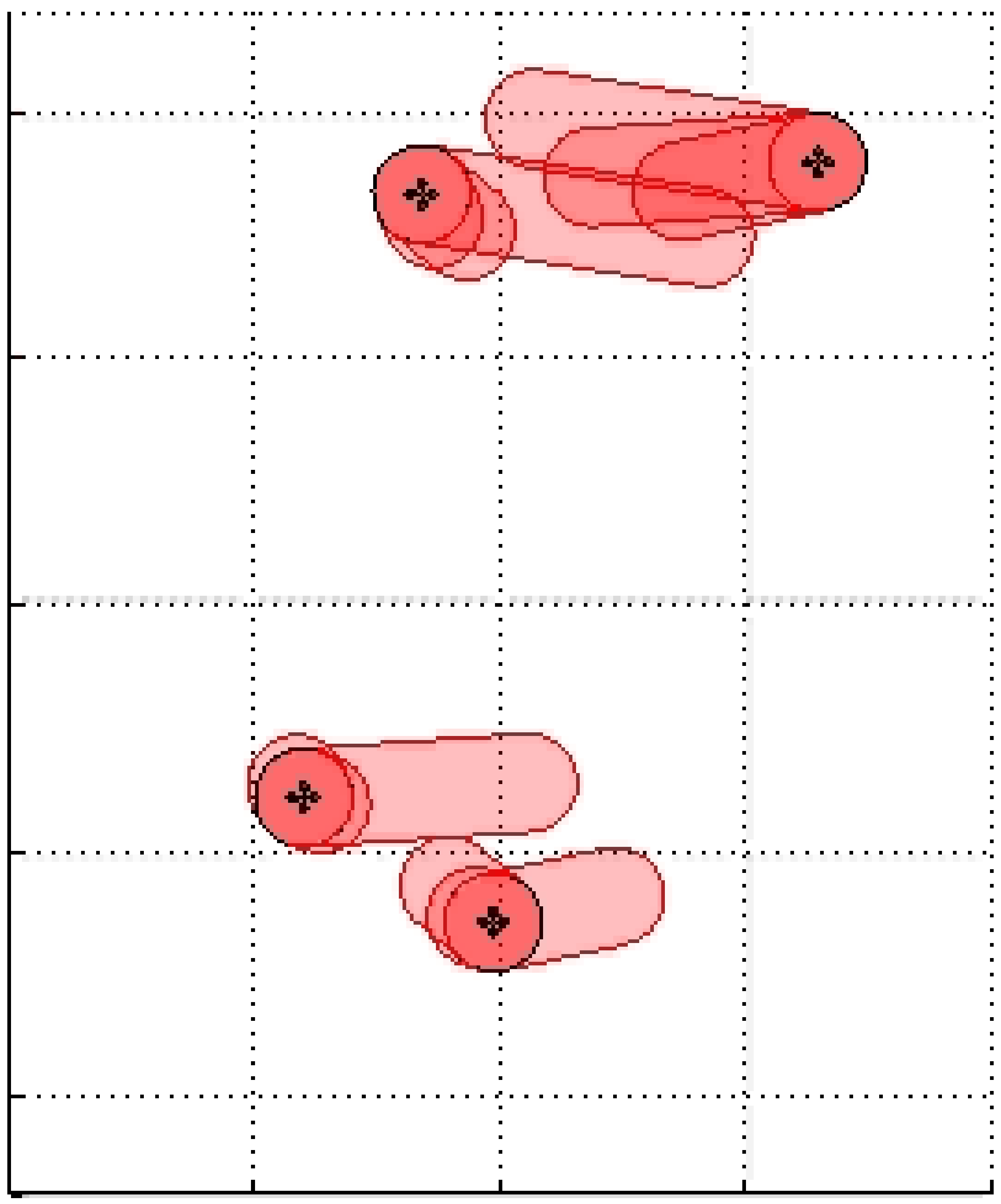


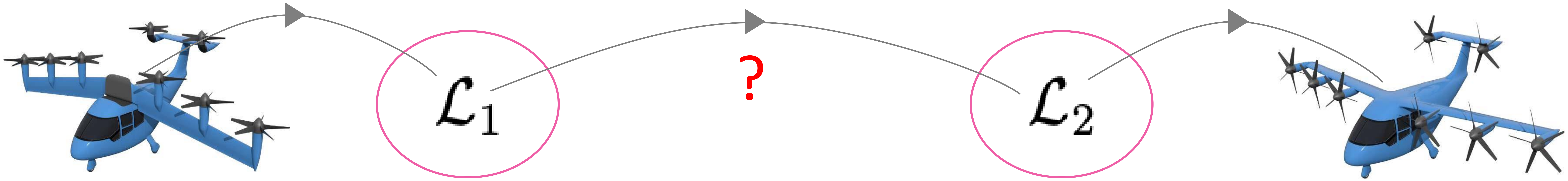

[Sylvia Herbert]

# Pilots attempting to collide vehicles



# Reachable sets for Safety Assurances

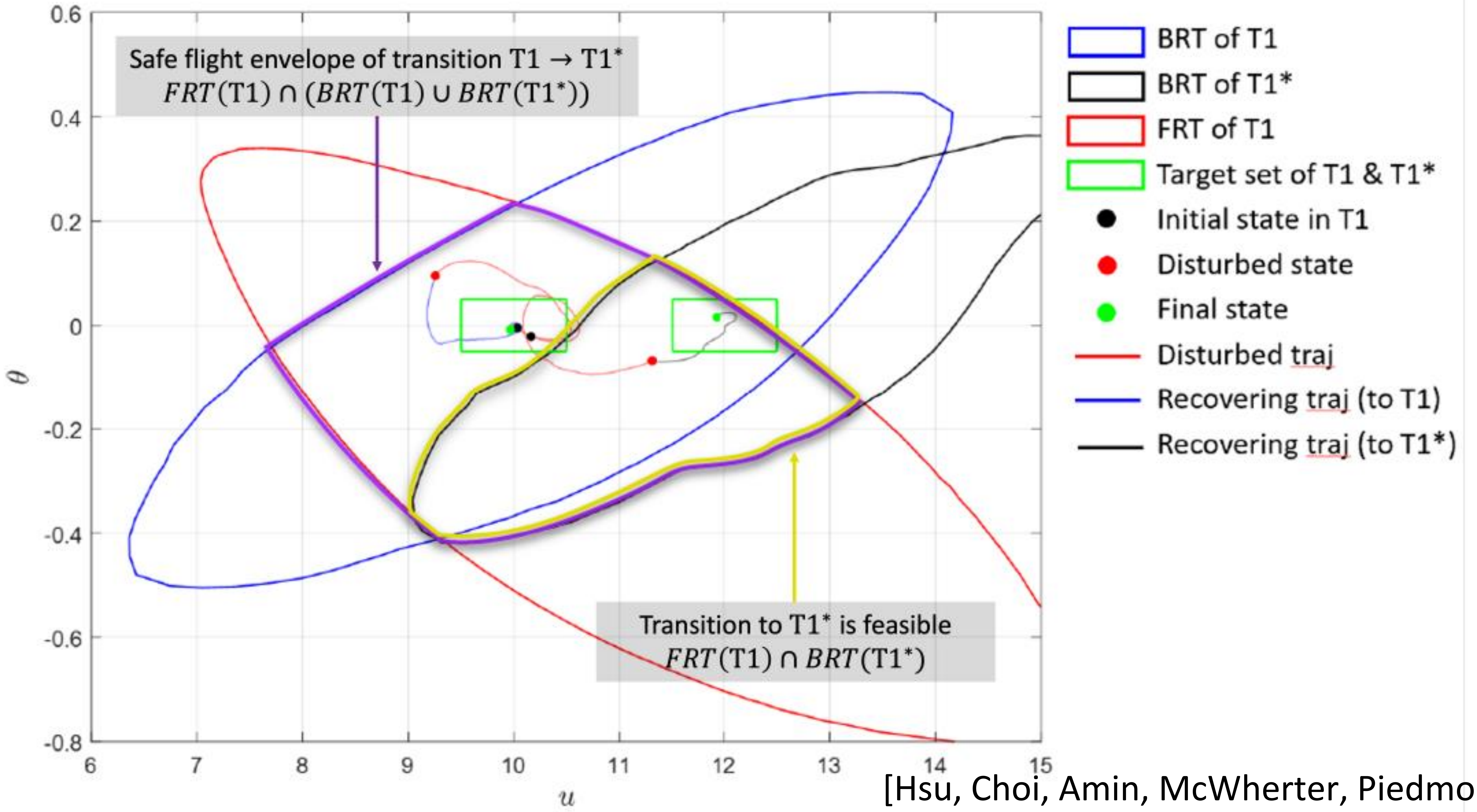
[Joby Aviation]




How to ensure <u>safe transition between the trim states</u> during the flight mode transition?

[Hsu, Choi, Amin, McWherter, Piedmonte]

# Reachable sets for Safety Assurances




[Hsu, Choi, Amin, McWherter, Piedmonte]

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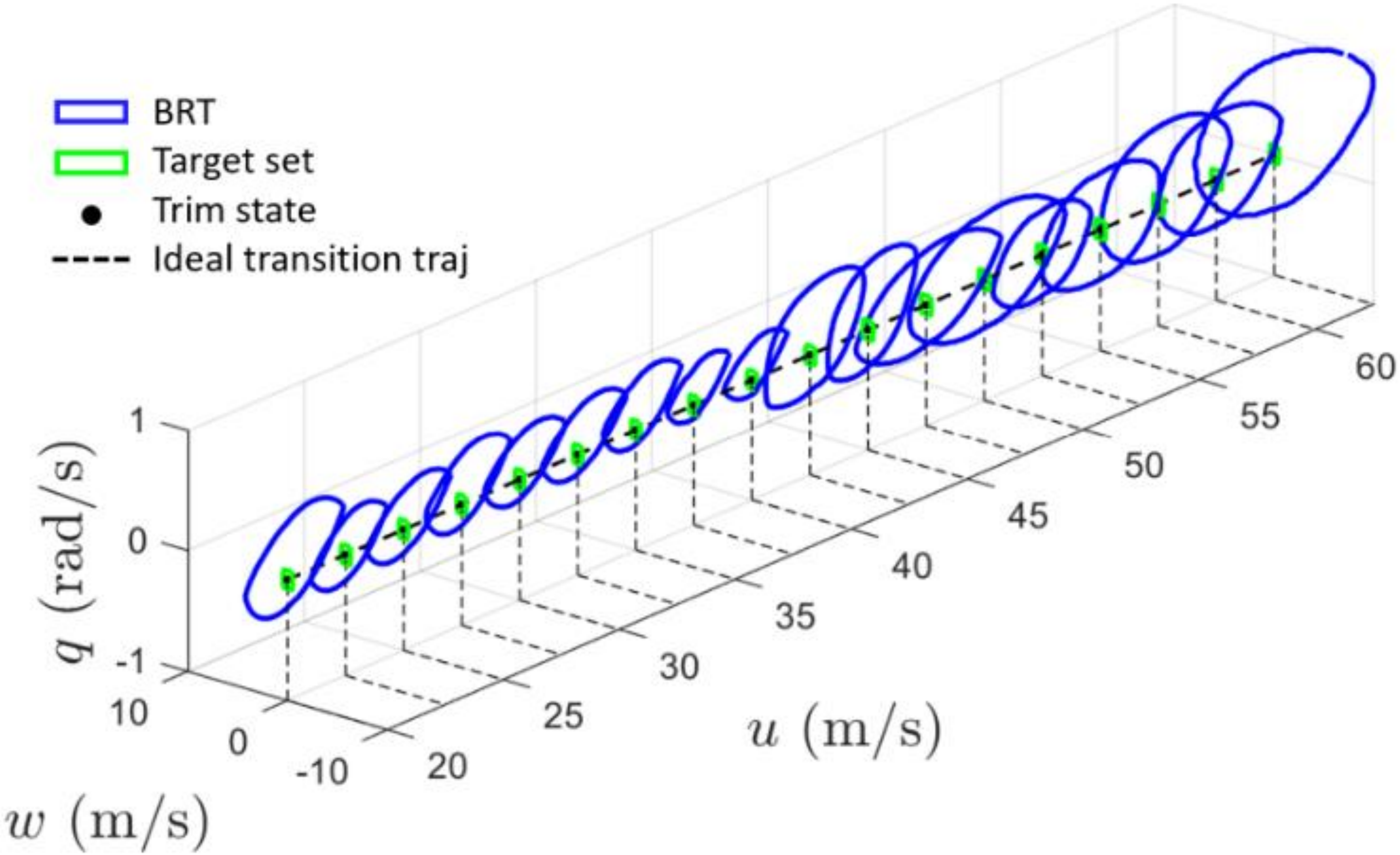
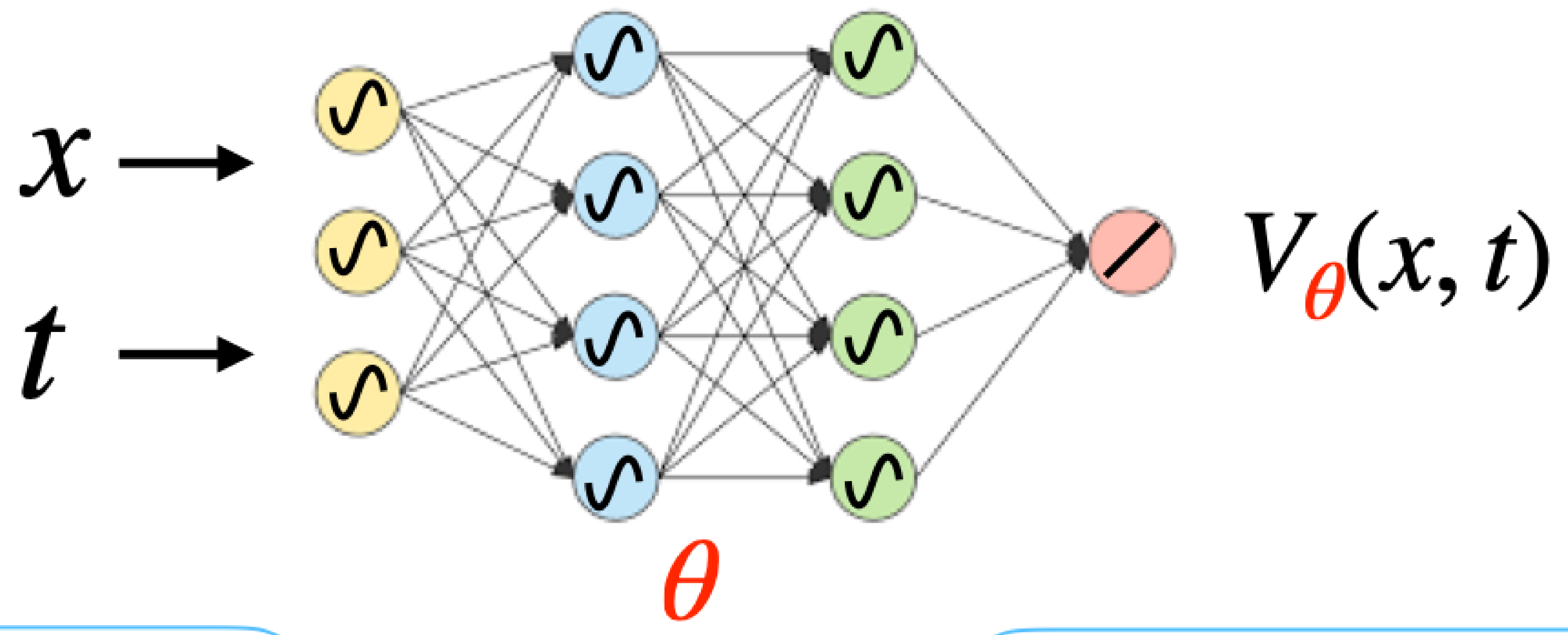



[Hsu, Choi, Amin, McWherter, Piedmonte]

# DeepReach




Randomly Sample State and Time

$$\{(x_i, t_i)\}$$

Compute the Loss Function

$$h(\theta) = \sum_i \| \frac{\partial V_\theta(x_i, t_i)}{\partial t} + H(x_i, \nabla V_\theta(x_i, t_i)) \| + \lambda \| V_\theta(x_i, T)) - l(x_i) \|$$

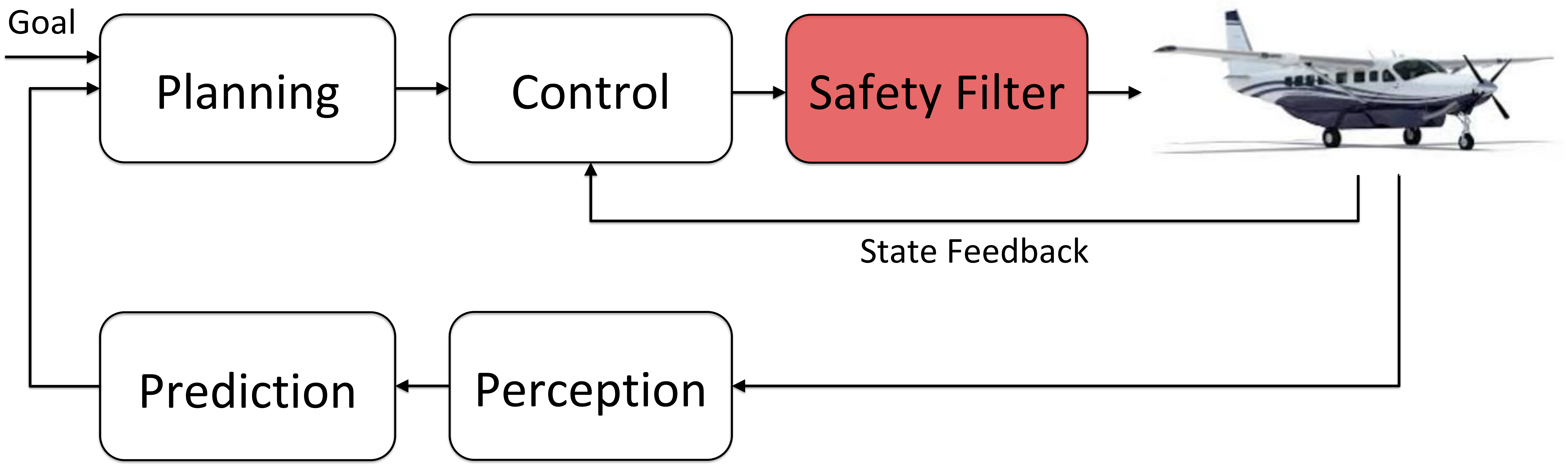
Fit the Value Function

$$\theta \leftarrow \theta - \alpha \nabla h(\theta)$$

**Repeat**

[Somil Bansal]

# Safety Filter



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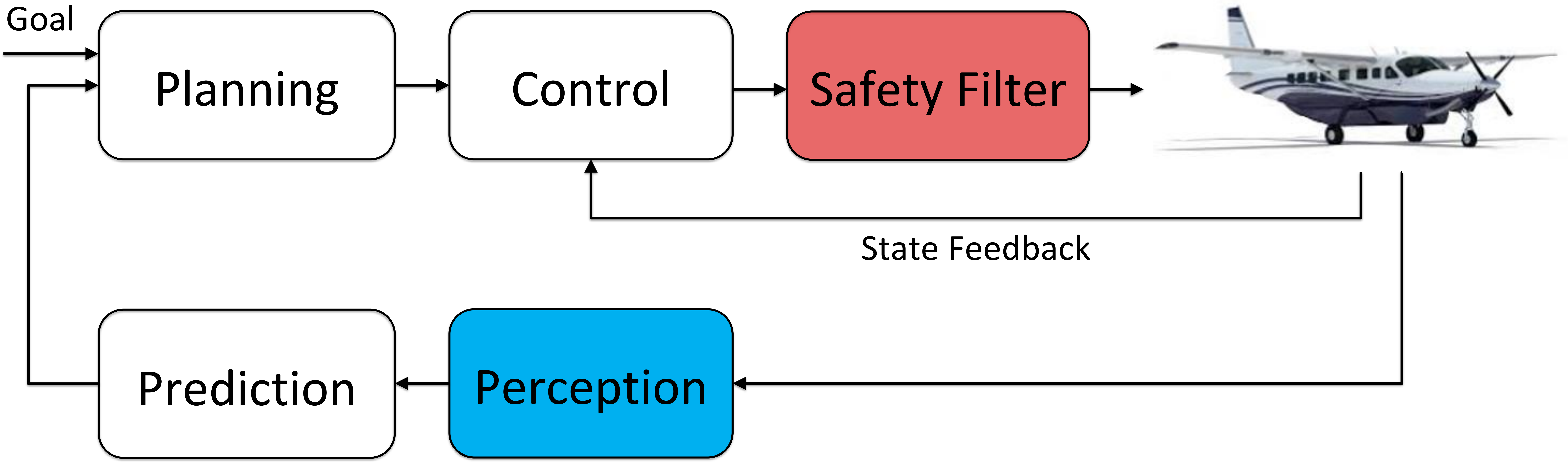


# Capturing (and Tracking) Perception Uncertainty

**Without Incorporating Uncertainty**

**Incorporating Uncertainty**

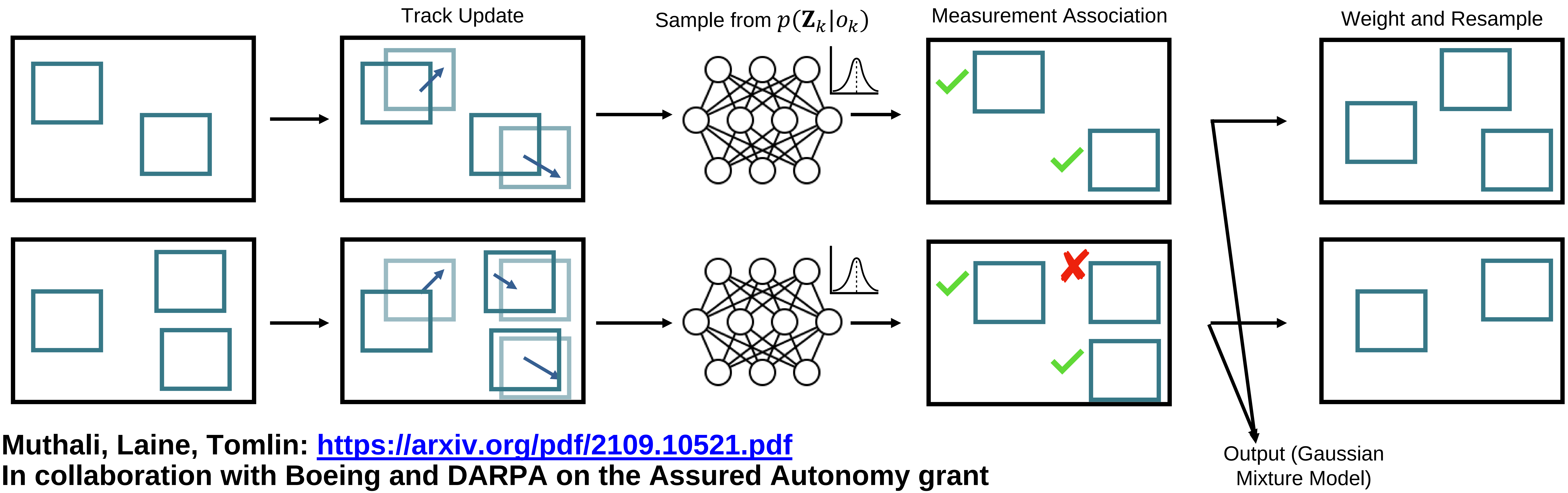

Images from Waymo Open Dataset 2D Tracking Challenge

# Our Approach

$\mathbf{X}_k$ - state of tracks at stage k
$\mathbf{Z}_{1:k}$ - set of measurements from stages 1 to k
$o_{1:k}$ - set of observations from stages 1 to k

## With Neural Network Uncertainty

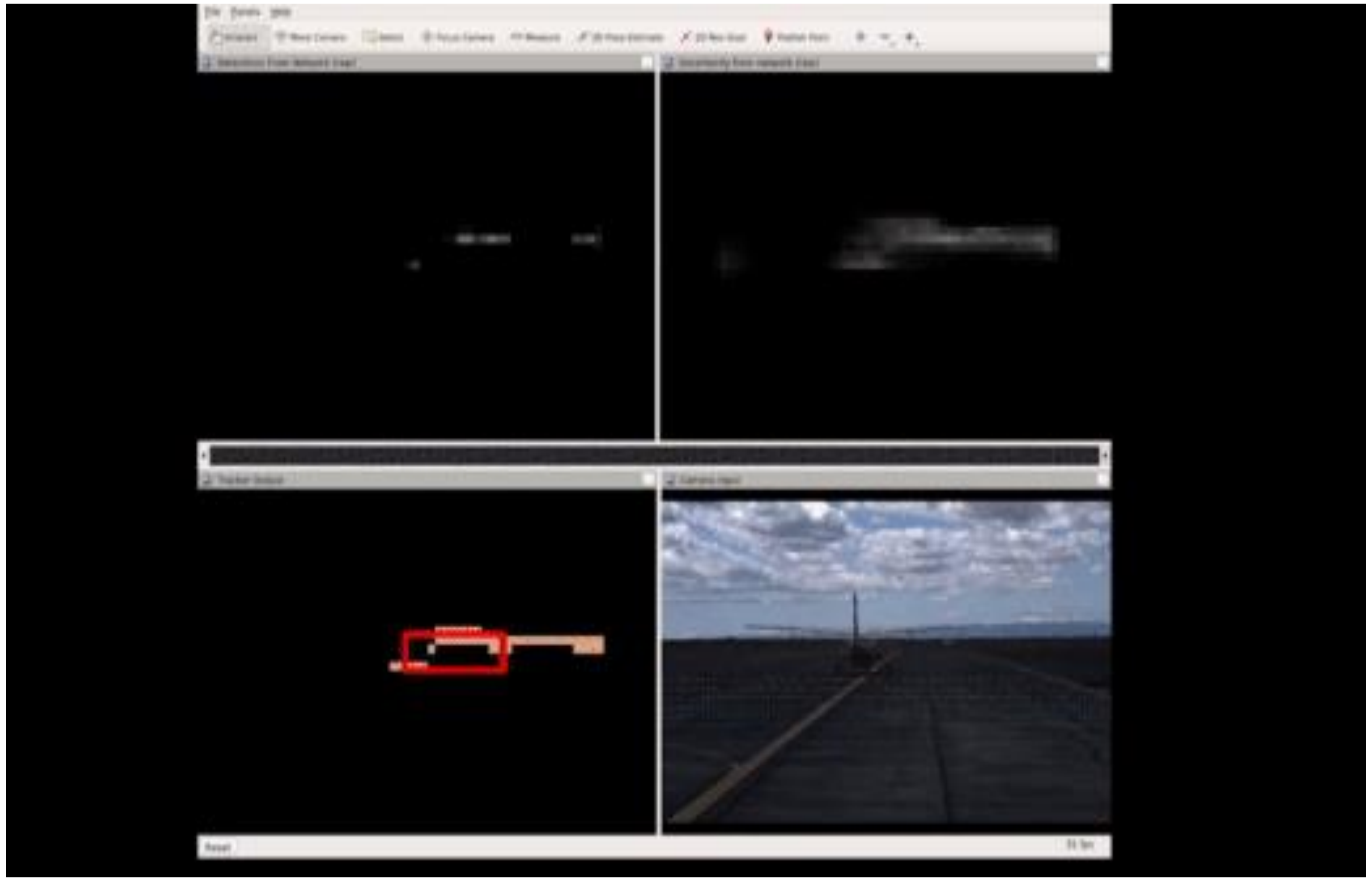
How do we incorporate randomness in $\mathbf{Z}_{1:k}$? It is possible to extend this to estimate $p(\mathbf{X}_k|o_{1:k})$!




Muthali, Laine, Tomlin: https://arxiv.org/pdf/2109.10521.pdf
In collaboration with Boeing and DARPA on the Assured Autonomy grant

# Deployment on an Autonomous Aircraft

A sampling-free, segmentation based method to speed up the inference stage of the tracking pipeline:  measurement association model leverages sparsity of scenes



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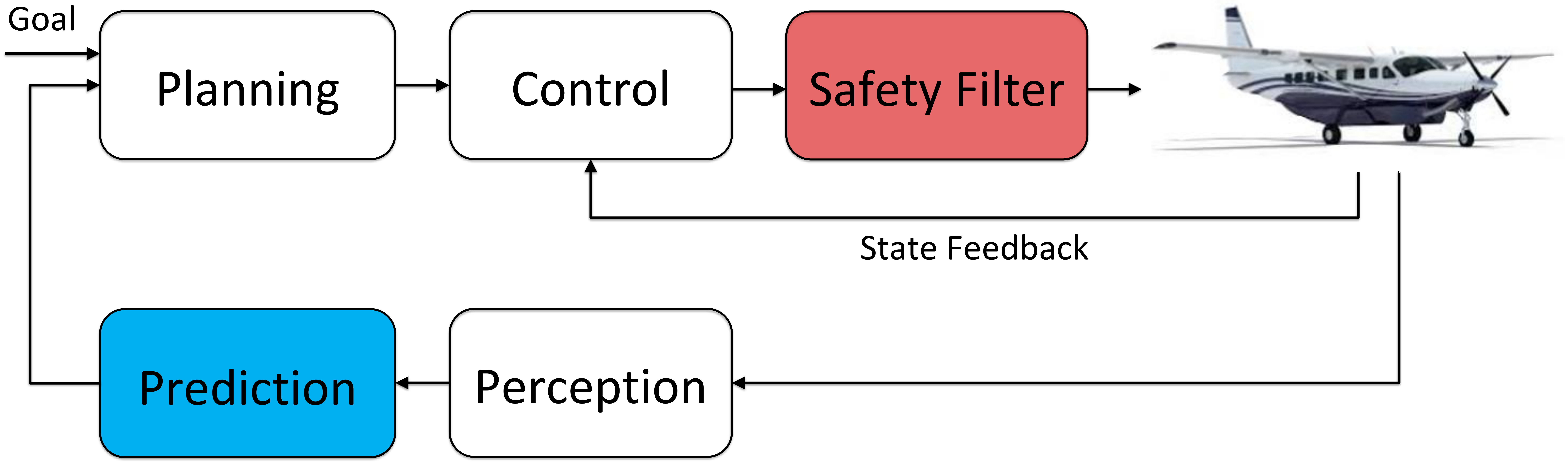
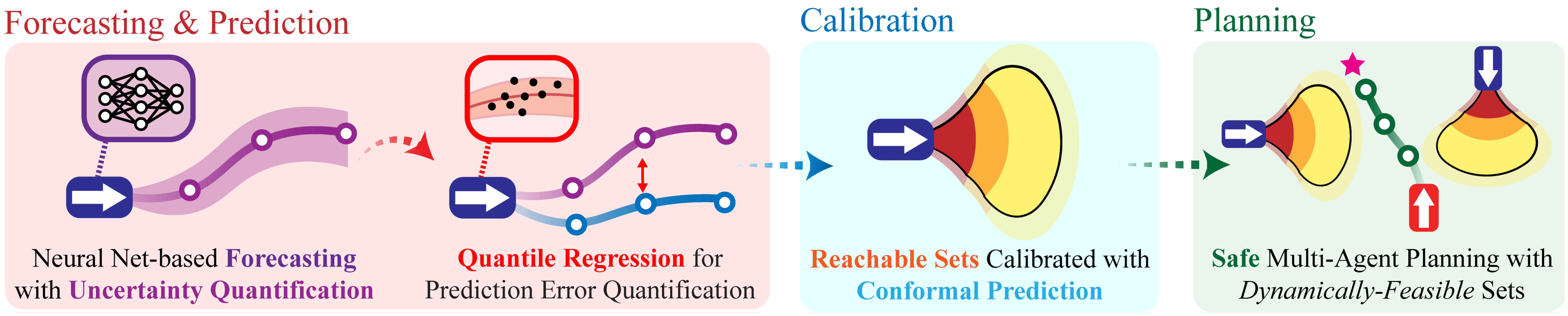


# Predicting the behavior of other agents

(Photo: Transportation Safety Board of Canada)

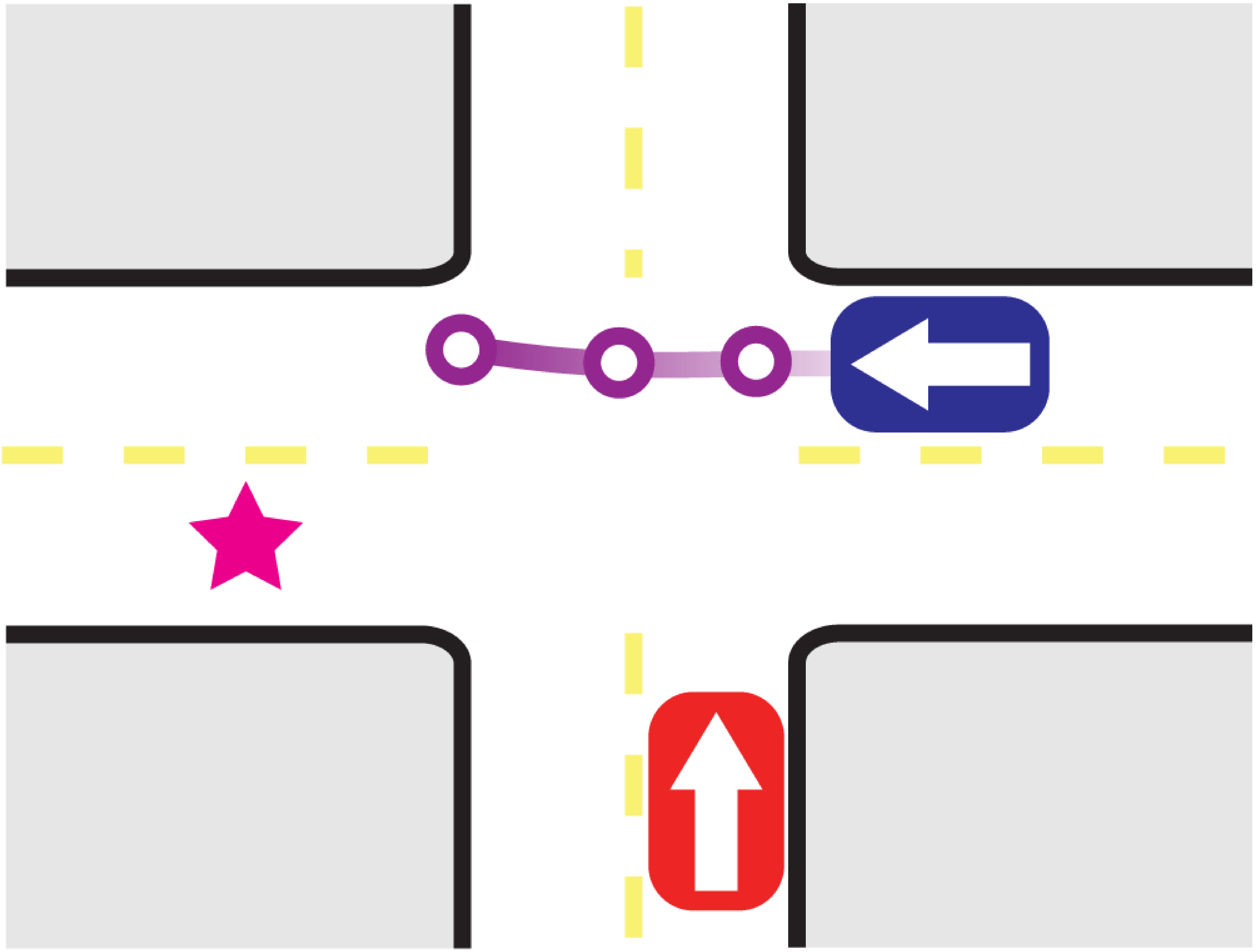
Based on the observed behavior of ground vehicles on or around the runway, predict with calibrated certainty if the runway will be clear for the aircraft to land

# Approach Outline



# Forecasting and Uncertainty

- Forecast agents' actions using a trajectory prediction model
  - Trajectron++
- Obtain a measure of uncertainty
  - Conditional on each prediction



Salzmann et al. (2020), Trajectron++: Dynamically-Feasible Trajectory Forecasting With Heterogeneous Data

# Quantile Regression

- Use uncertainty to predict model error
- Obtain an *approximate* $1 - \alpha$ prediction interval on model error
- Quantile regression uses a linear model
  - Easier to “understand” uncertainty by looking at regression coefficients
  - Update regression coefficients online using gradient descent

$$\mathbf{u}_{t:t+h} \in \left[\widehat{\mathbf{u}}_{t:t+h} + \widehat{\mathbf{e}}_{\frac{\alpha}{2}}, \widehat{\mathbf{u}}_{t:t+h} + \widehat{\mathbf{e}}_{1-\frac{\alpha}{2}}\right]$$

# Conformal Prediction

- Make the *approximate* confidence intervals *exact*
  - Stretch intervals by $\varphi(\theta)$ which is “learned” online
- Note: “stretching” is <u>not</u> conditional on the neural network’s prediction uncertainty
  - Quantile regression is still important!

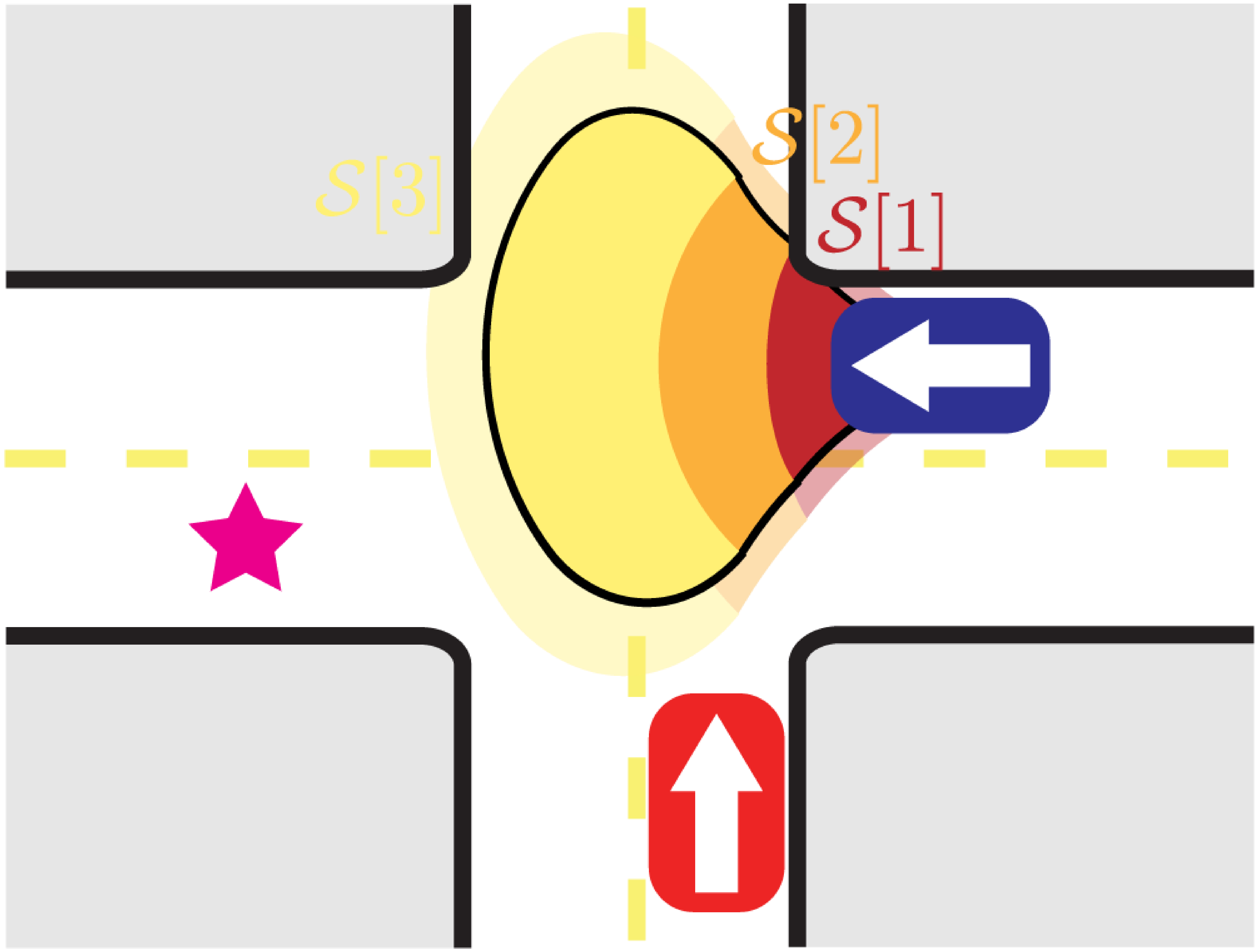
$$\mathbf{u}_{t:t+h} \in \left[\widehat{\mathbf{u}}_{t:t+h} + \widehat{\mathbf{e}}_{\frac{\alpha}{2}} - \varphi(\boldsymbol{\theta}), \widehat{\mathbf{u}}_{t:t+h} + \widehat{\mathbf{e}}_{1-\frac{\alpha}{2}} + \varphi(\boldsymbol{\theta})\right]$$

- Coverage rate guarantee: $1 - \alpha + \mathcal{O}(1/t)$

Feldman et al. (2022), Achieving Risk Control in Online Learning Settings

# Hamilton-Jacobi Reachability

- Transform intervals in control space to sets in state space
- Incorporate dynamical constraints
- Easier to leverage for downstream planning tasks
- HJ sets are time indexed
  - $\Delta t, 2\Delta t, \ldots, h$ second forward reachable tubes
  - Indexed by prediction timestep



# Multi-Agent Setting

- Require that *total* miscoverage rate does not exceed a given $\gamma$

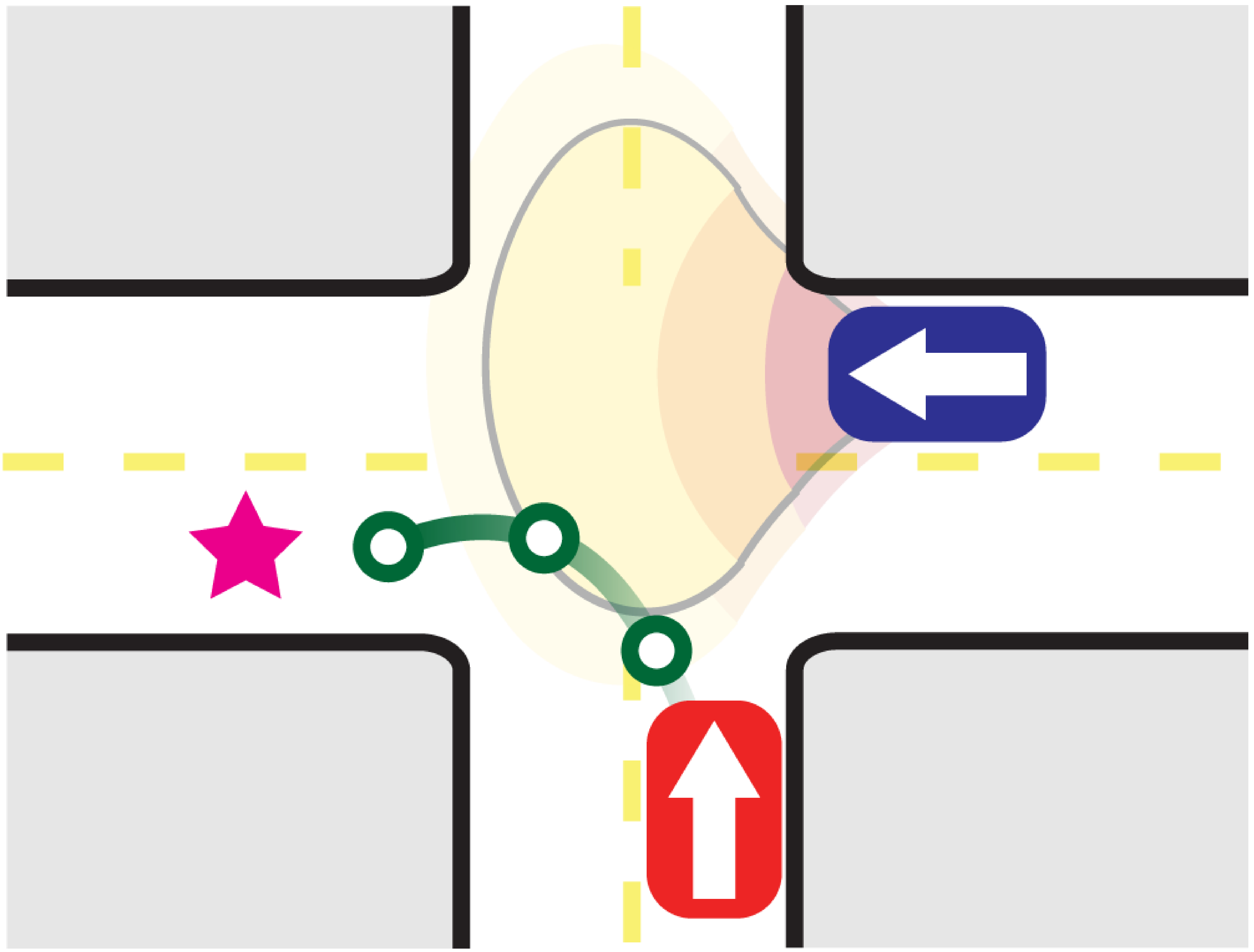
$$\mathbb{P}_t\left(\bigcup_{i=1}^{N}\left\{\mathbf{x}_t^{(i)} \notin \mathcal{S}[t]^{(i)}\right\}\right) \leq \gamma$$

- Thus, set the desired miscoverage rate for each agent to

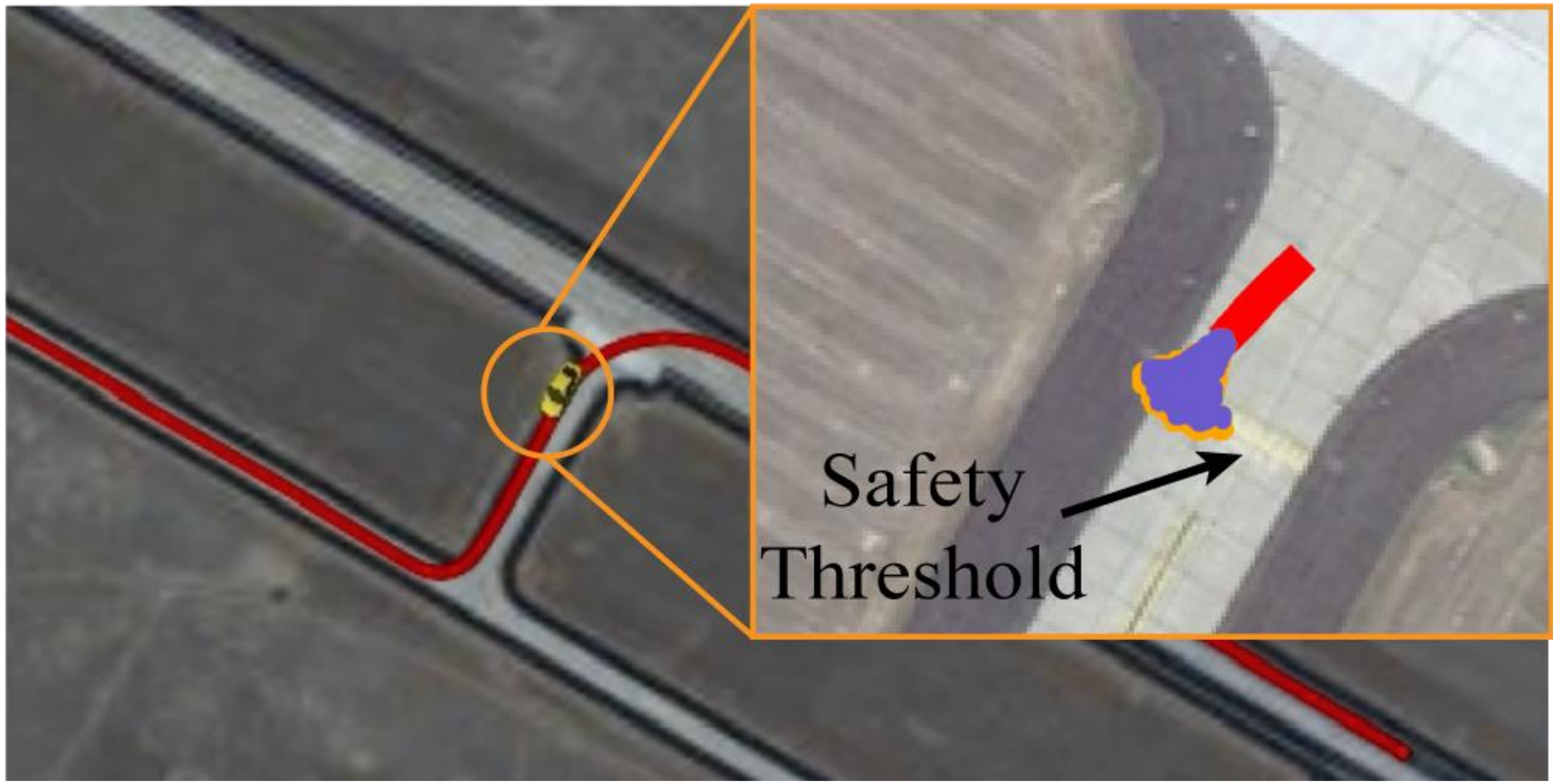
$$\alpha = 1 - (1-\gamma)^{\frac{1}{N}}$$

# Ego Agent Planning

- Treat time-indexed sets as dynamic obstacles
- Compute forward reach-avoid tube using dynamic obstacles
- Derive optimal control to a desired goal inside reach-avoid tube
  - Hamiltonian-maximizing control



# Case Study: Runway Clear



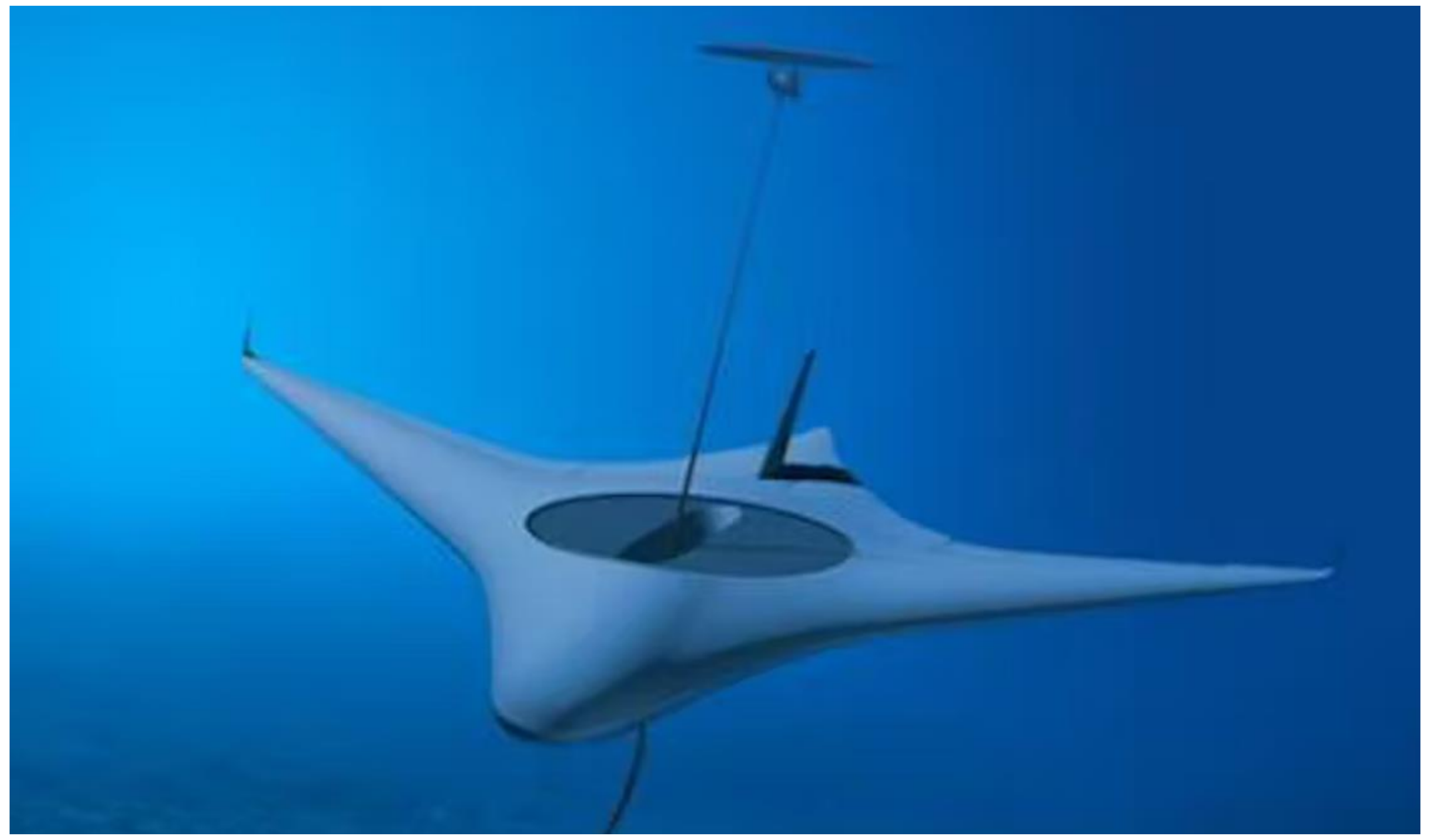
# Case Study: Runway Clear


Decision: No-go

**Muthali et al., arXiv 2304.00432**
**In collaboration with Boeing and DARPA on the Assured Autonomy grant**

# Today:  Automating platforms


[Amazon]



[Manta Ray UUV]

[Boeing]

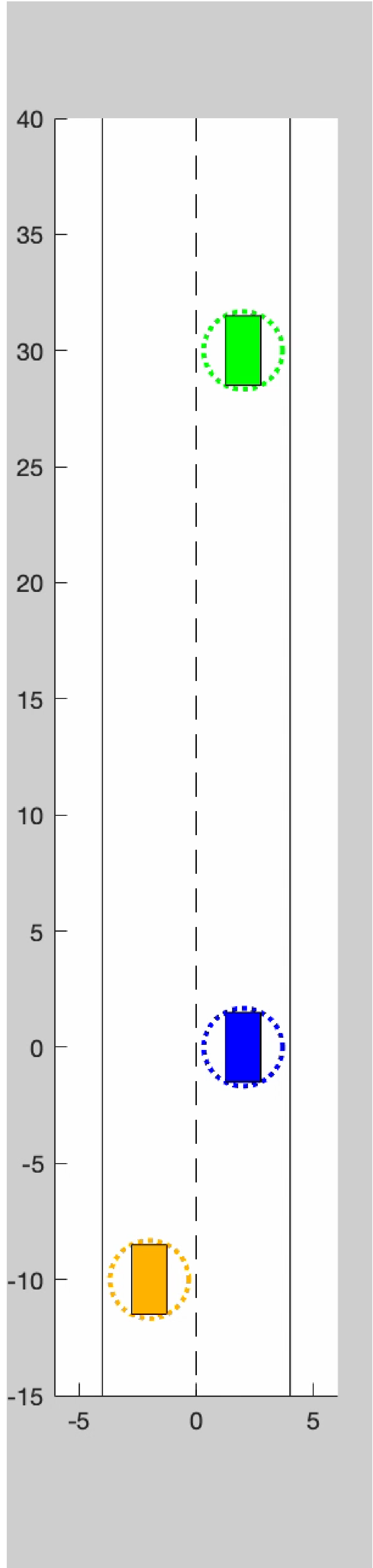

[Zipline]

Need to make guarantees about the behavior of these platforms even as they learn and evolve

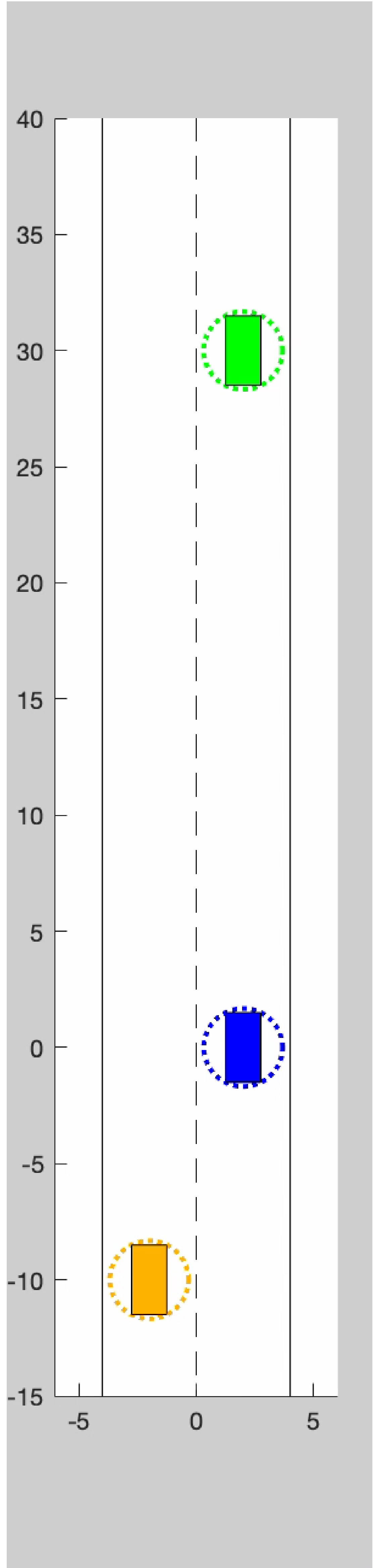
[Polaris MRZR]

# What’s needed: Automating Systems

FB Nash




OL Nash




[Laine and Tomlin, SIAM J Opt 2022]

- Predictions need to be closed loop!
- Enable predictable, safe, and high-confidence interactions between agents in multiple agent systems
- Even if specification is unknown
- Distribution of future data will not necessarily follow distribution of past
- Teams of humans and robots
- Focus on systems, not components

# Thanks

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