

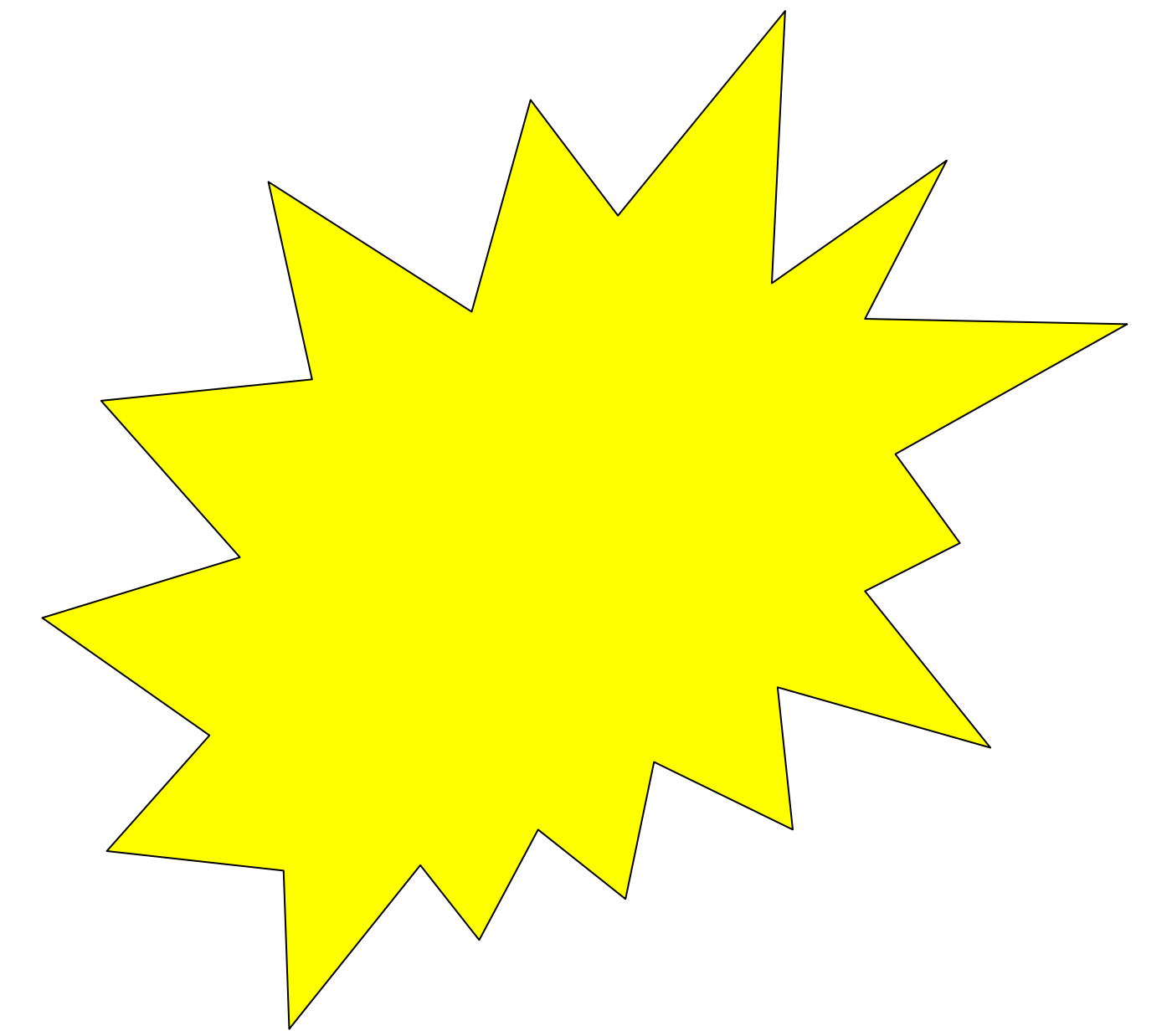
Introduction & Motivation:

- Provide safety guarantees for safety-critical autonomous/robotic systems

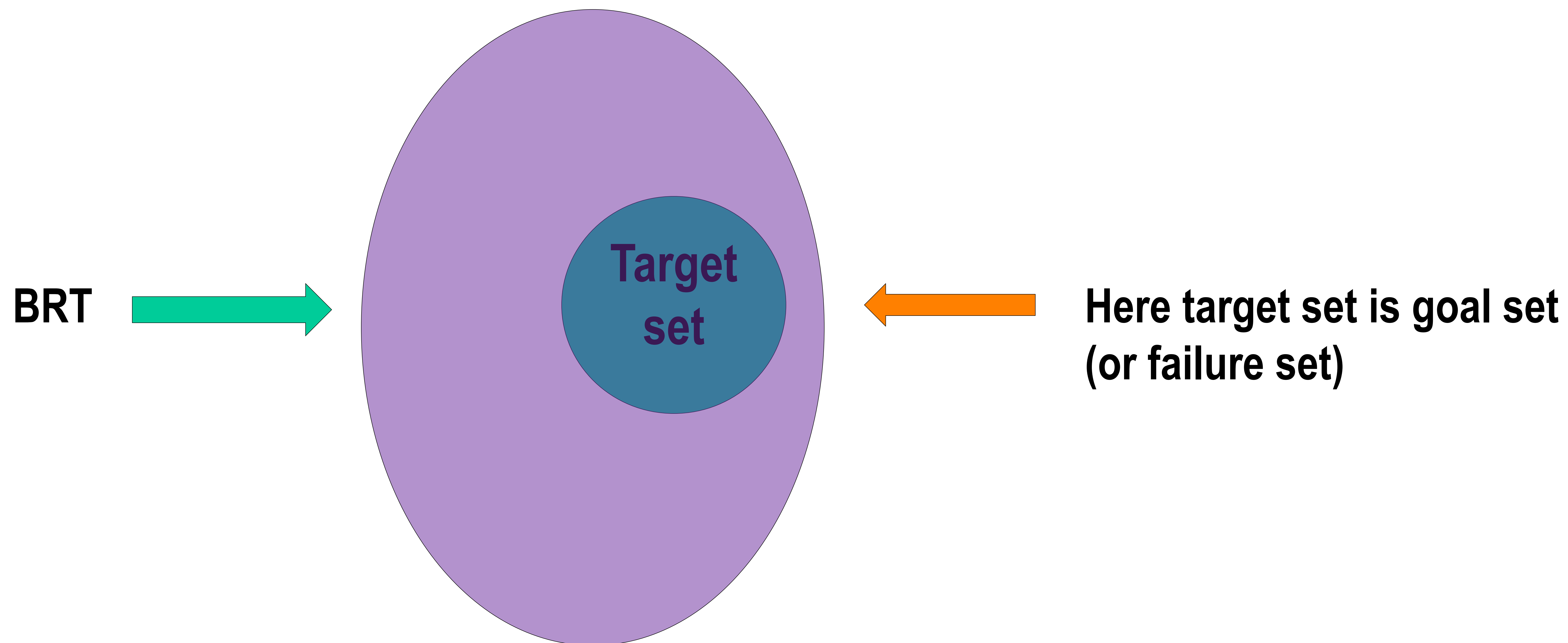
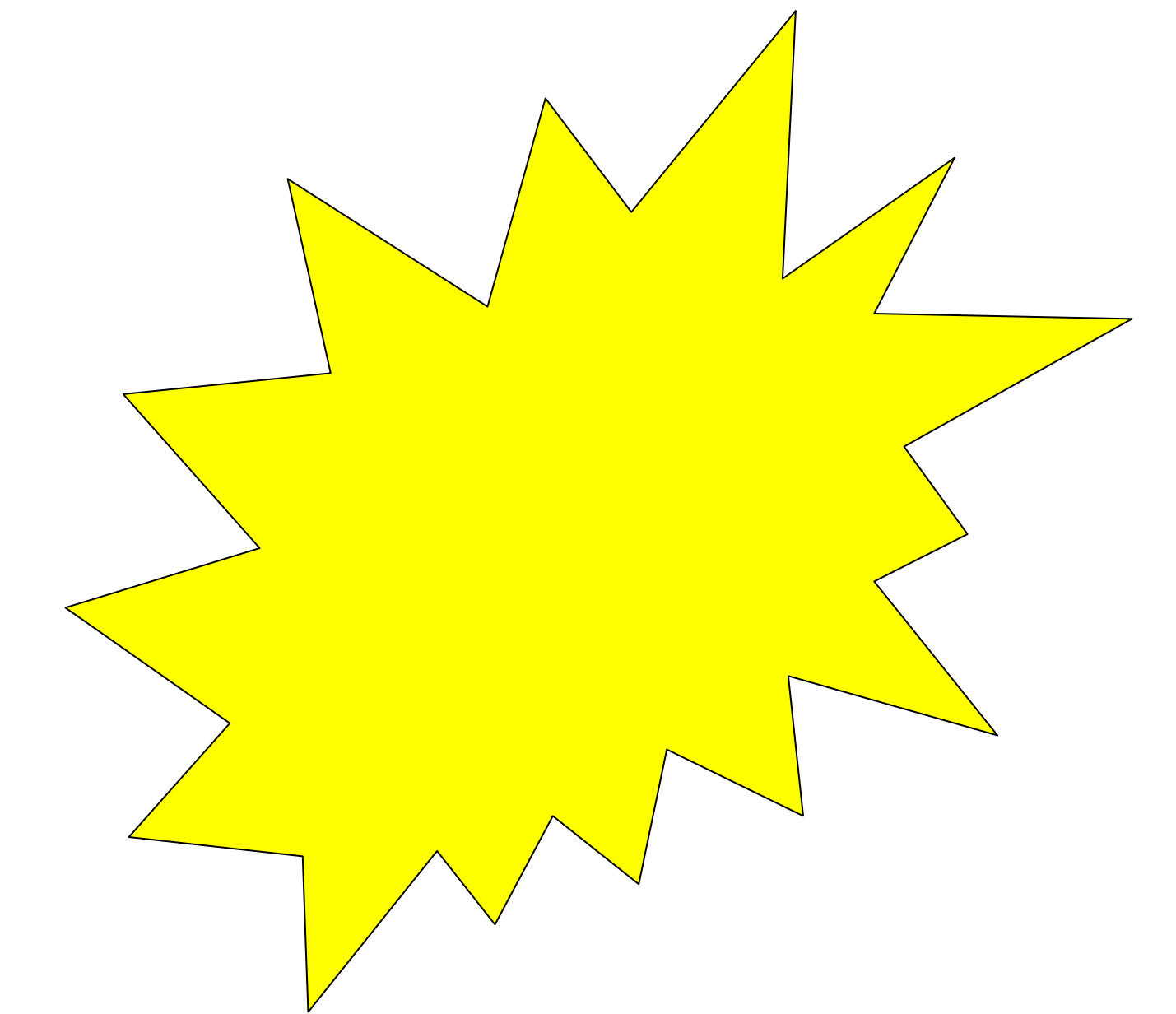
e.g. autonomous driving,
drone delivery,
legged robots for space exploration



Problem Formulation: Hamilton-Jacobi Reachability analysis



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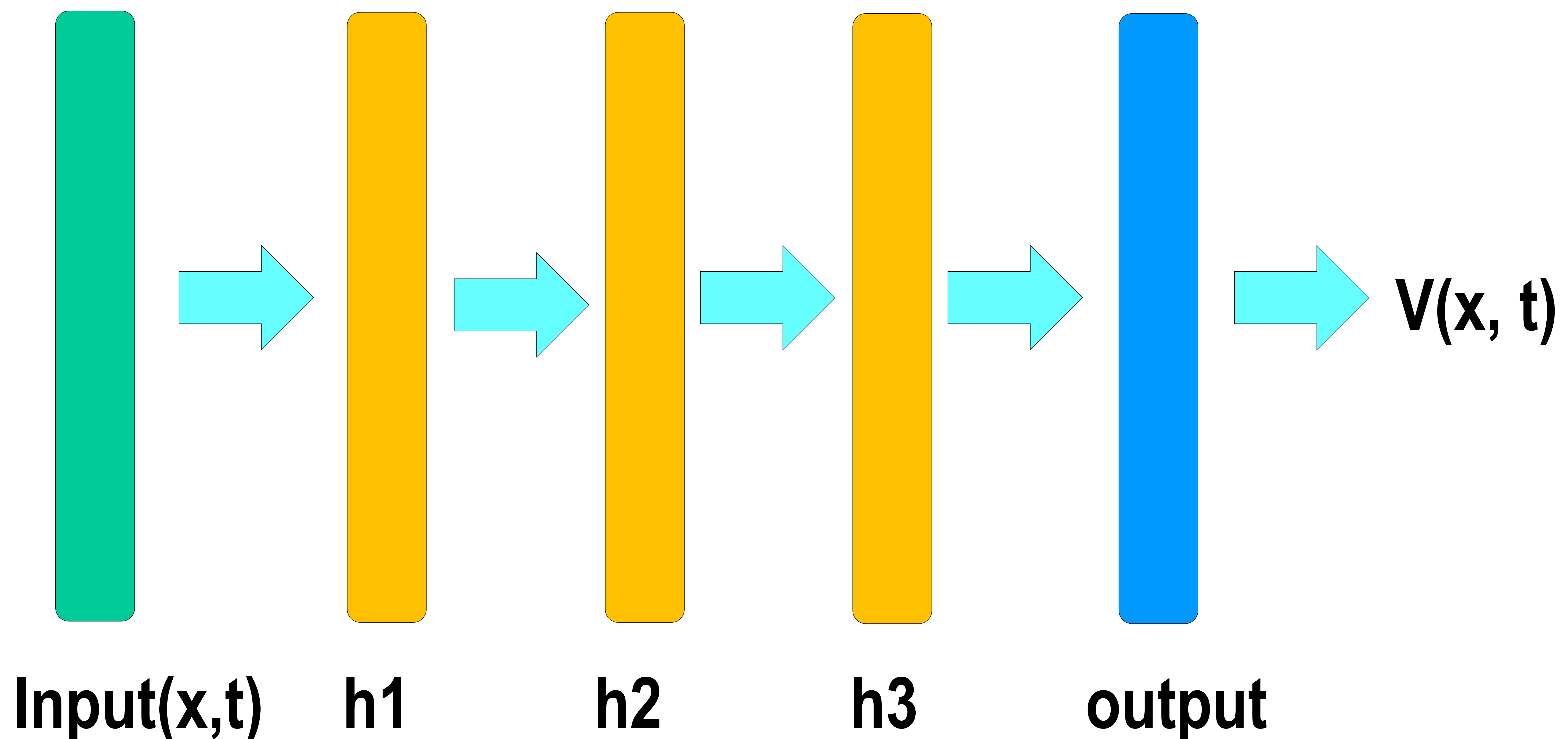
$$\mathcal{R}(T) = \{x_0: \exists u, s.t. \forall d, x(\cdot) \text{ satisfies } \dot{x} = f(x, u, d), x(0) = x_0; \exists t \in [0, T], s.t. x(t) \in \mathcal{L}\}$$

Project: improve the performance of DeepReach on high-dimensional systems by using different activation functions

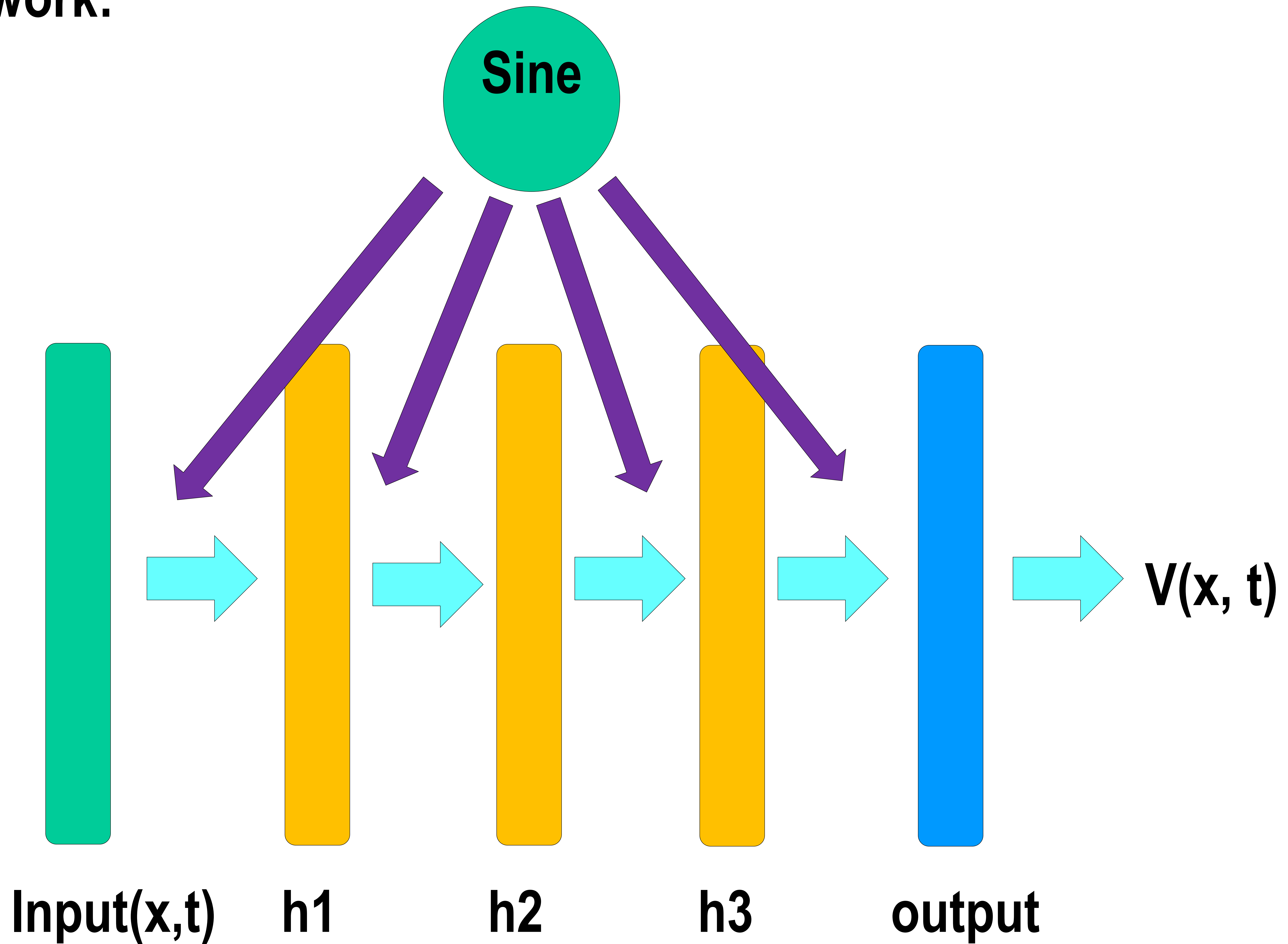
Related work:

DeepReach

- Multi-layer Perceptron with 5 layers
- Function approximation



Related work:

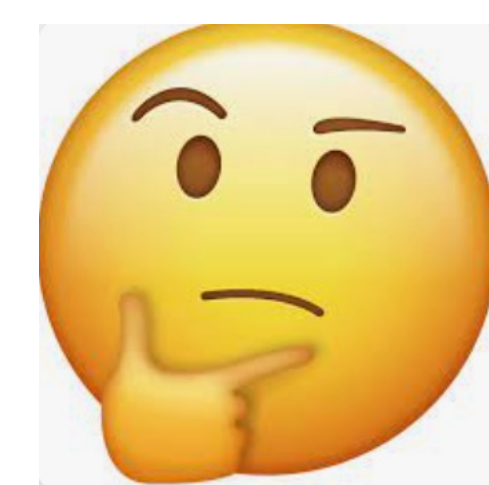


Related work:

Toolboxes to solve HJ Reachability:

- HelperOC (Matlab)
- DeepReach (Python)
- BEACLS (C++)
- Etc.

Why DeepReach?

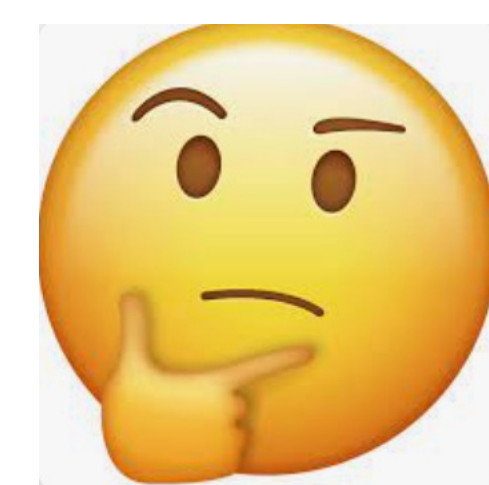


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Why DeepReach?



Its computation and memory cost don't scale exponentially with the dimensionality of the system, but with the complexity of the value function.

Related work:

Running example: air3D

**Framed by the relative dynamics between the two identical vehicles:
one pursuer, one evader:**

$$\dot{x}_1 = -v_e + v_p \cos x_3 + \omega_e x_2$$

$$\dot{x}_2 = v_p \sin x_3 - \omega_e x_1$$

$$\dot{x}_3 = \omega_p - \omega_e,$$

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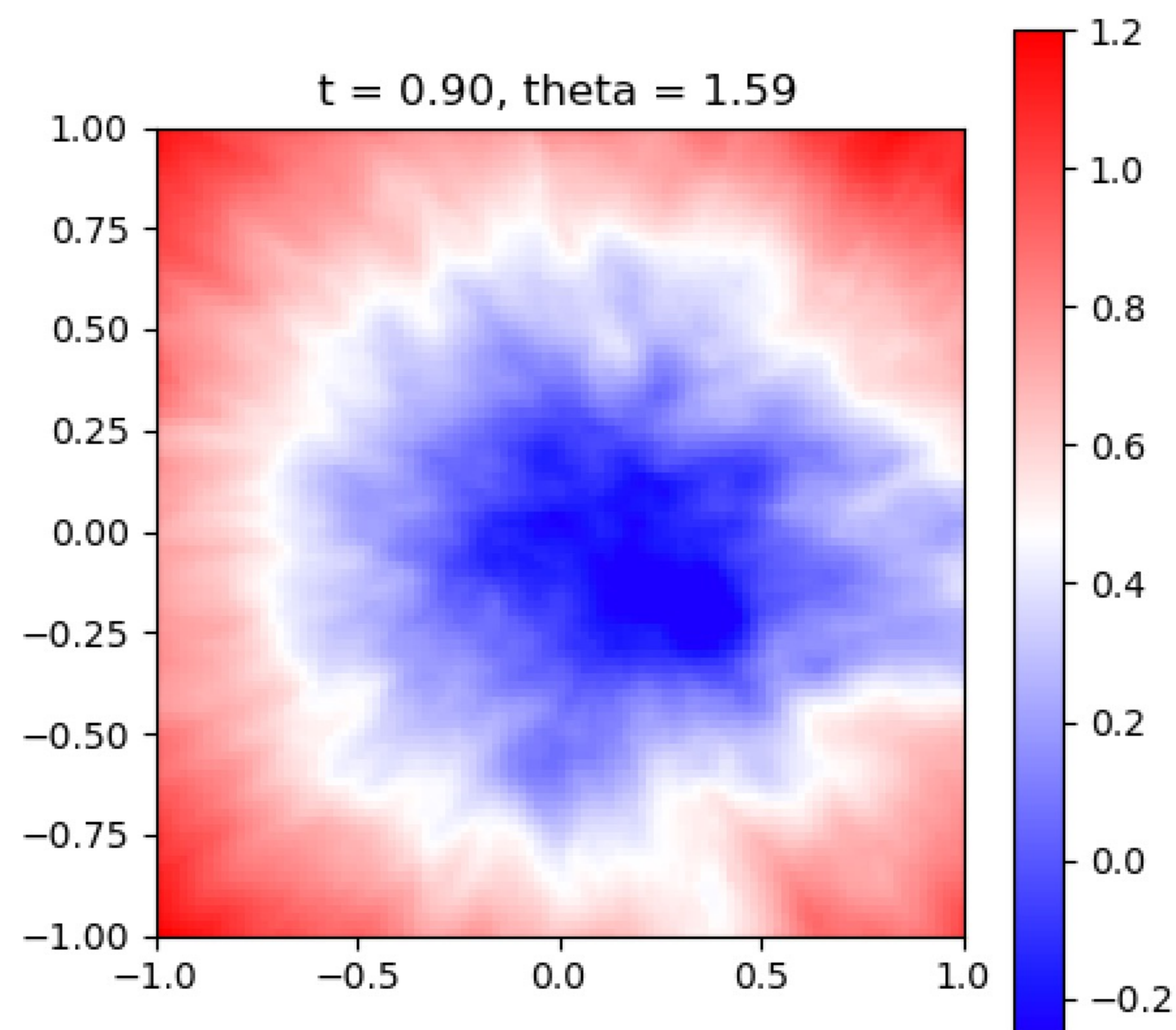
$$\dot{x}_3 = \omega_p - \omega_e,$$

Failure set: distance between the two vehicles \leq some constant

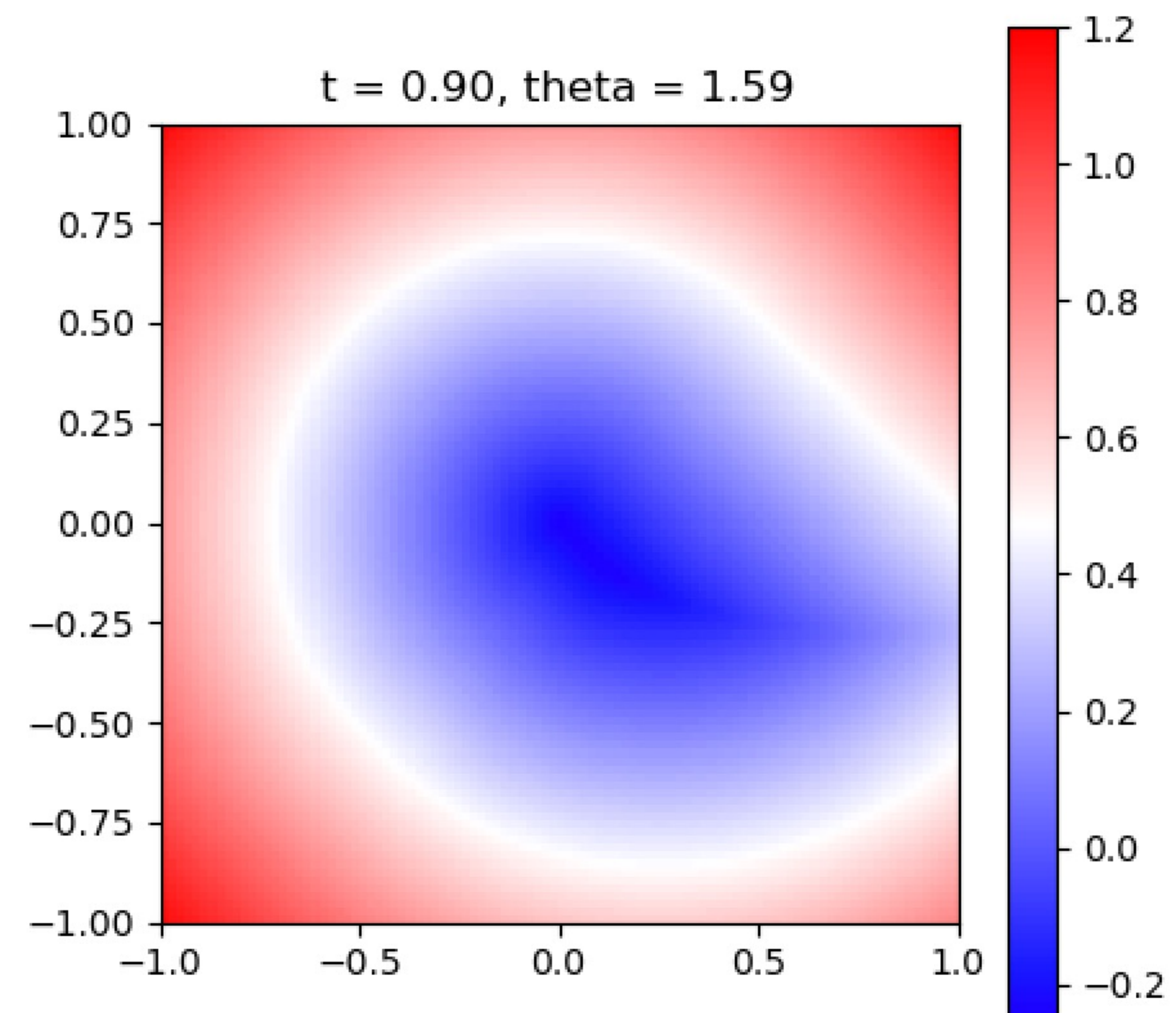
$$\mathcal{L} = \{x : \|(x_1, x_2)\| \leq \beta\}.$$

Related work:

Running example: air3D



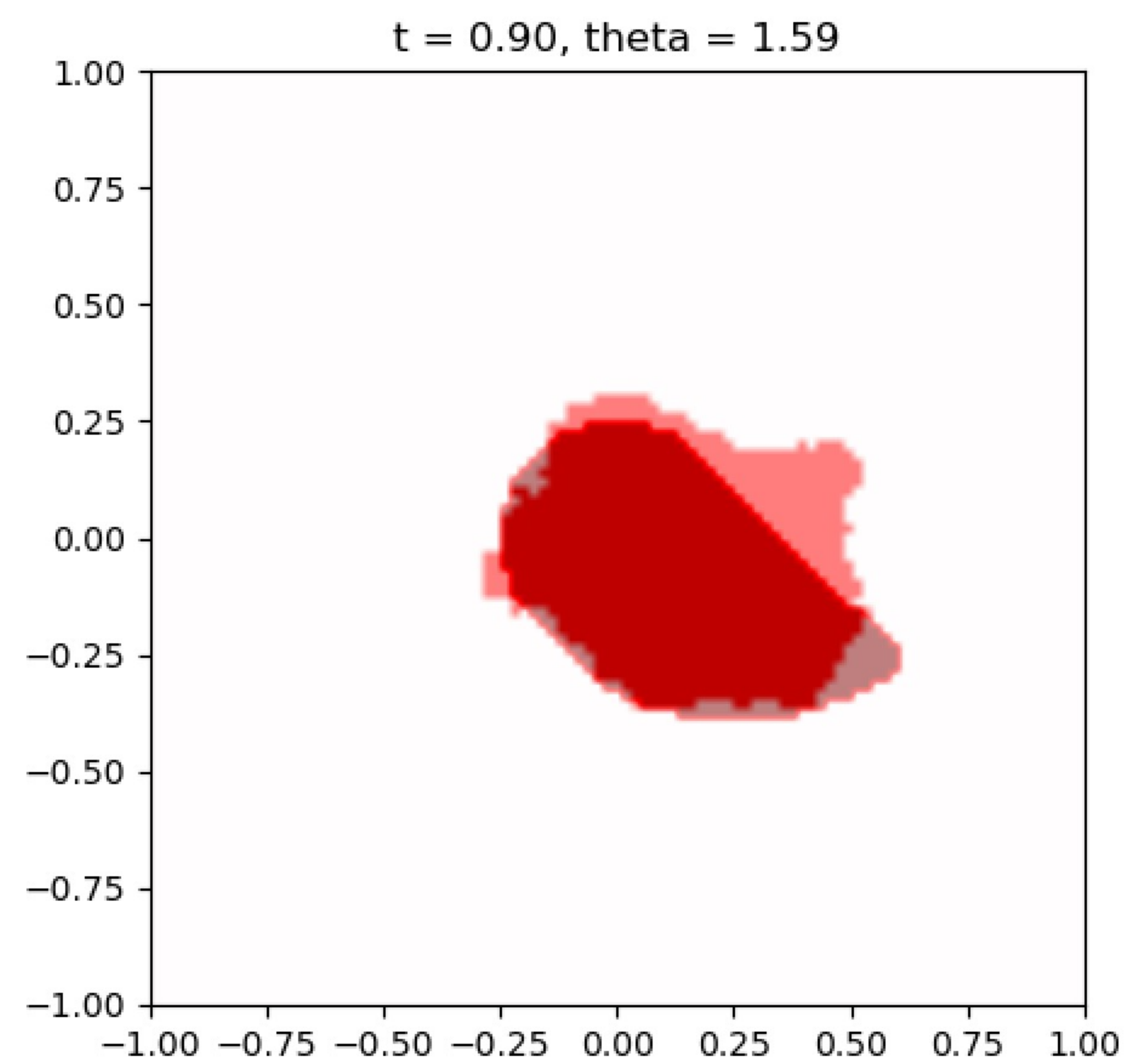
ReLU



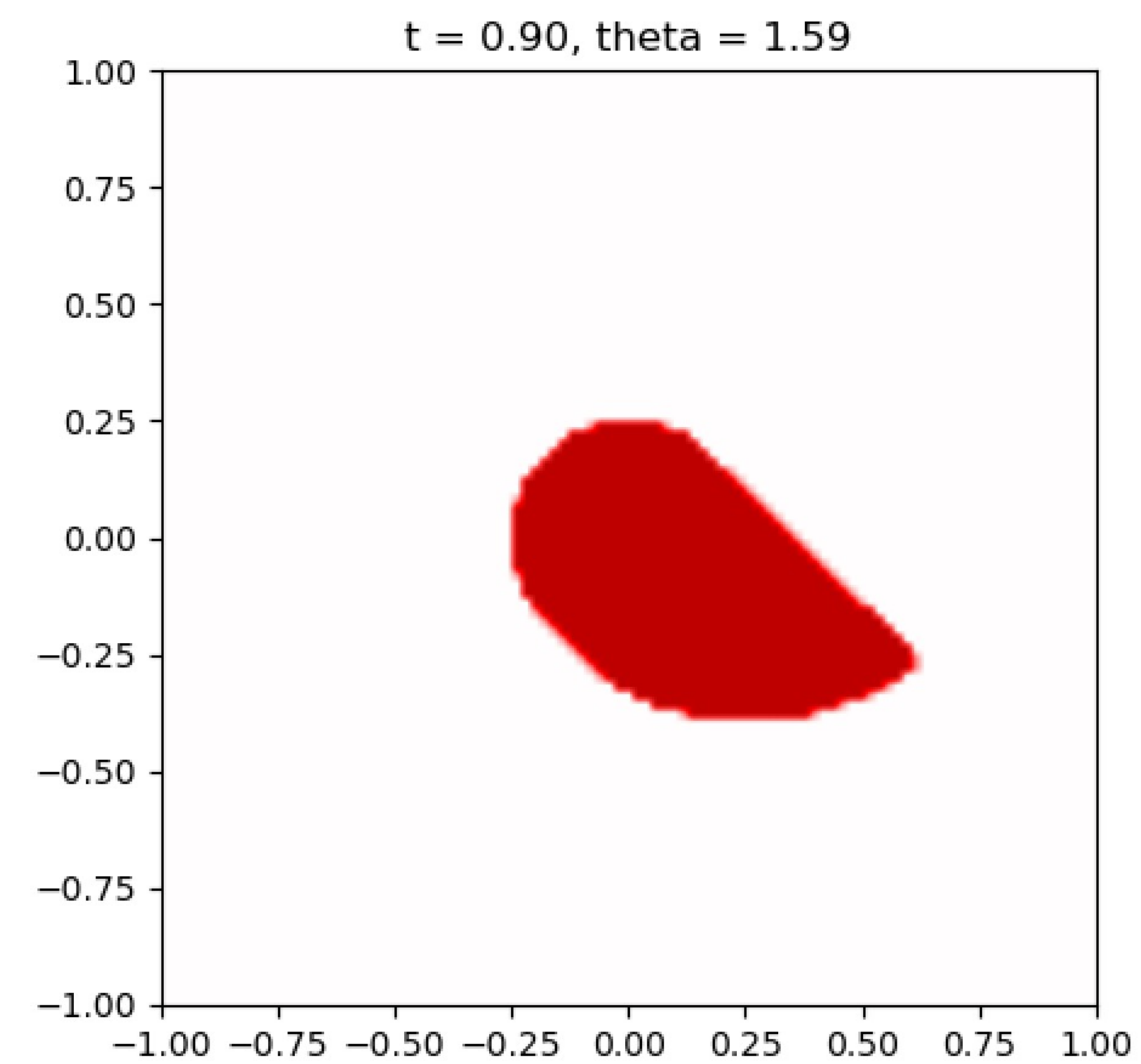
Sine

Related work:

Running example: air3D



ReLU



Sine

Proposed approach:

- How about using combination of Sine and ReLU?

Intuition:

Sine: better models the gradient, but harder to compute

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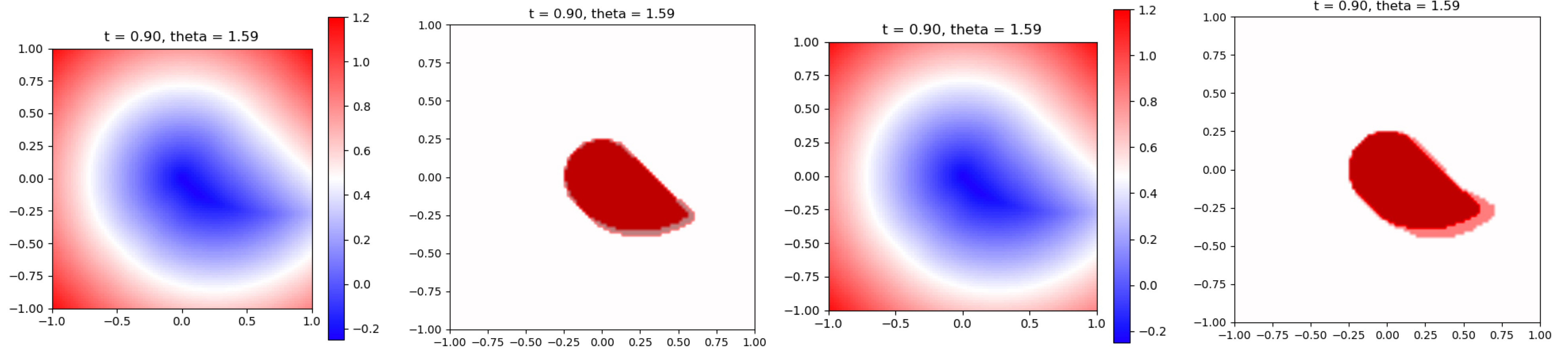
Sine: better models the gradient, but harder to compute

ReLU: less accurate gradient, first derivative is piecewise constant, but less computational cost

$\max(0, \max(0, \max(0, x)))$ vs $\sin(\sin(\sin(x)))$

Results:

Running example: air3D

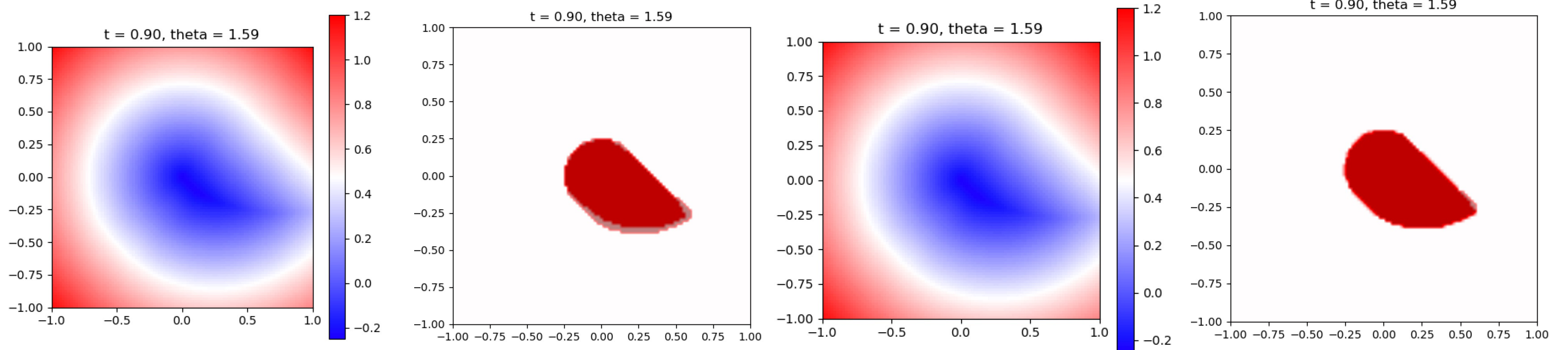


rrrs1

srrr1

Results:

Running example: air3D

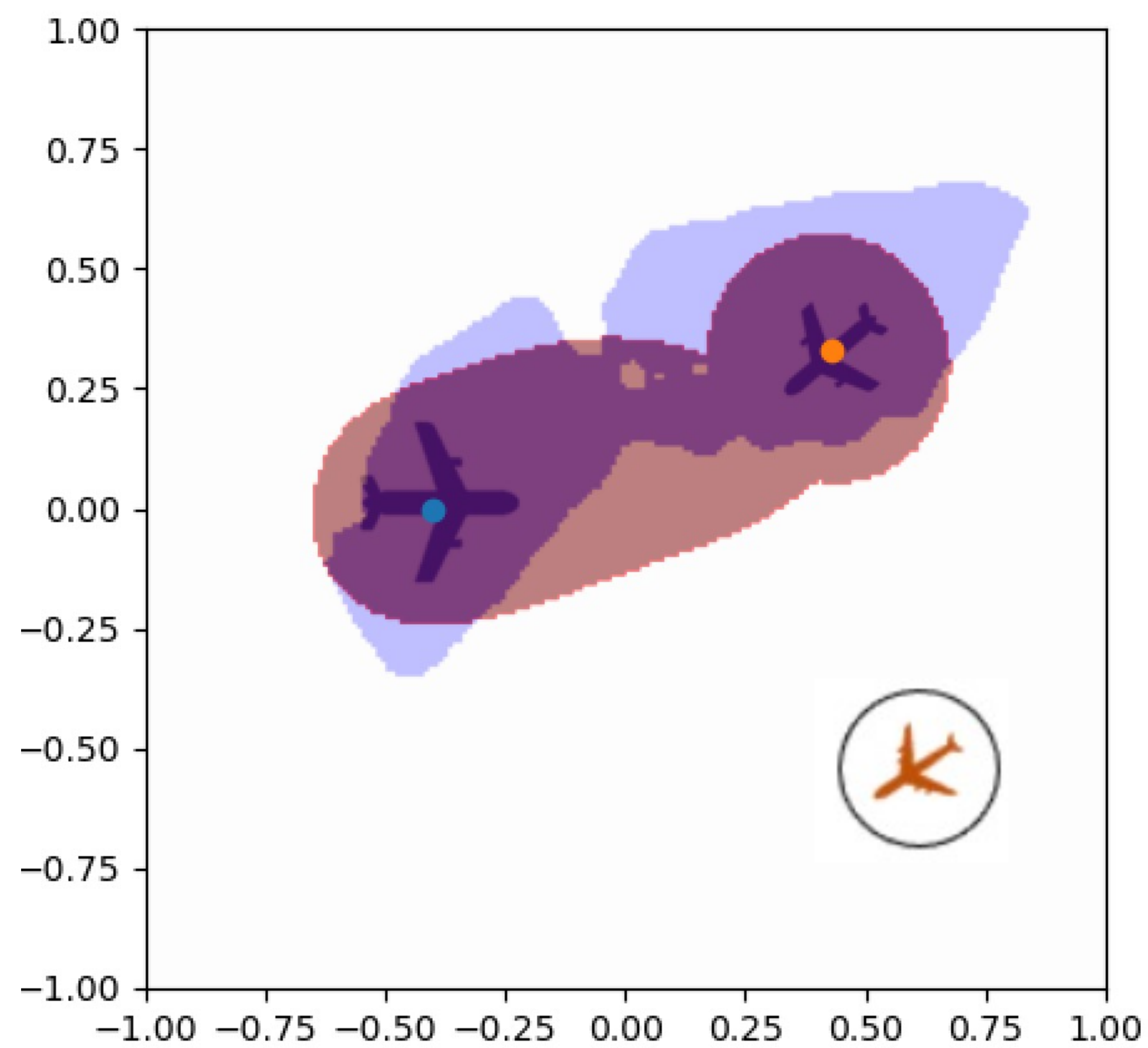


srsrl

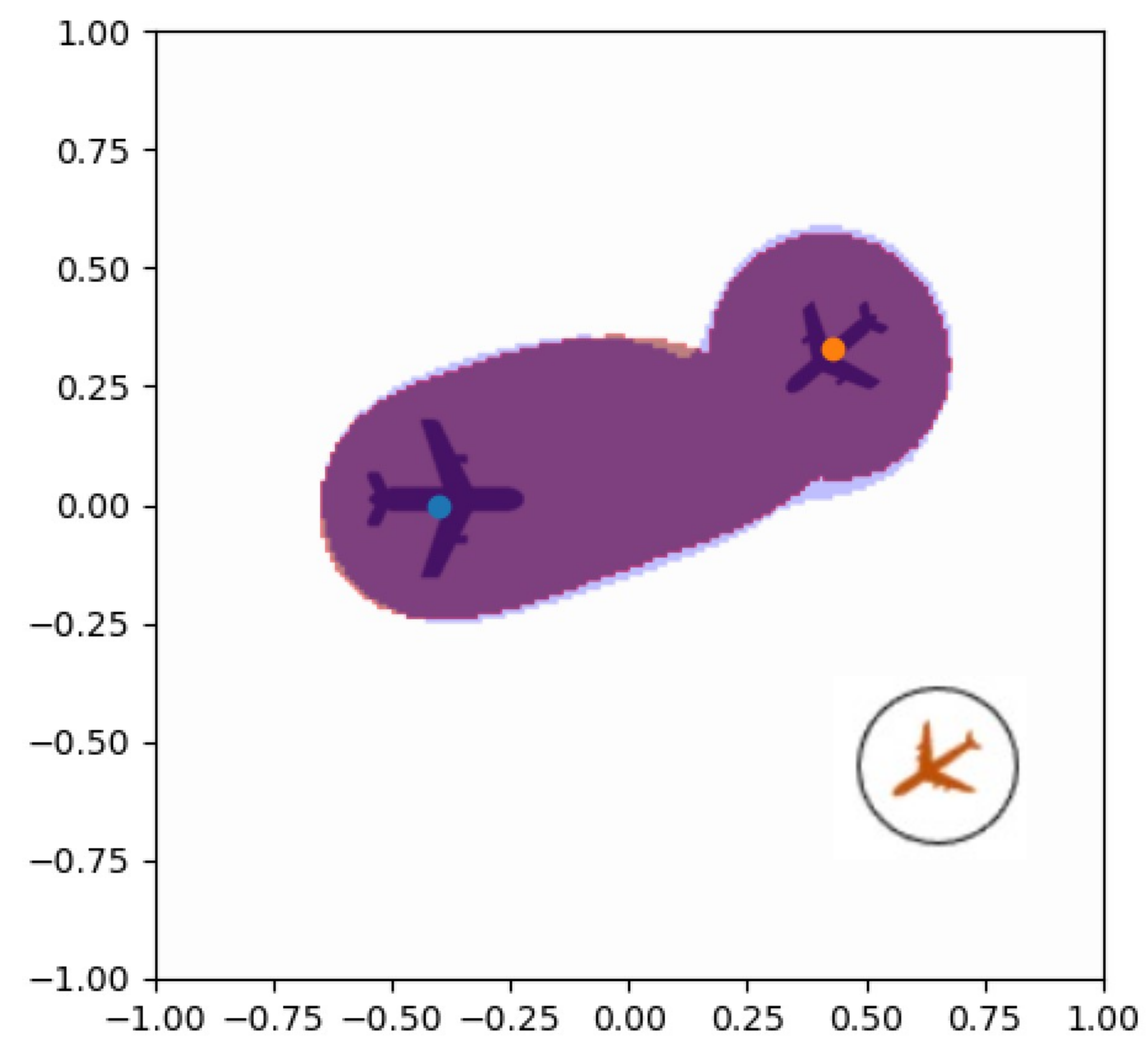
ssrsrl

Results:

Running example: 9D three-vehicle collision (2Evaders, 1Pursuer)



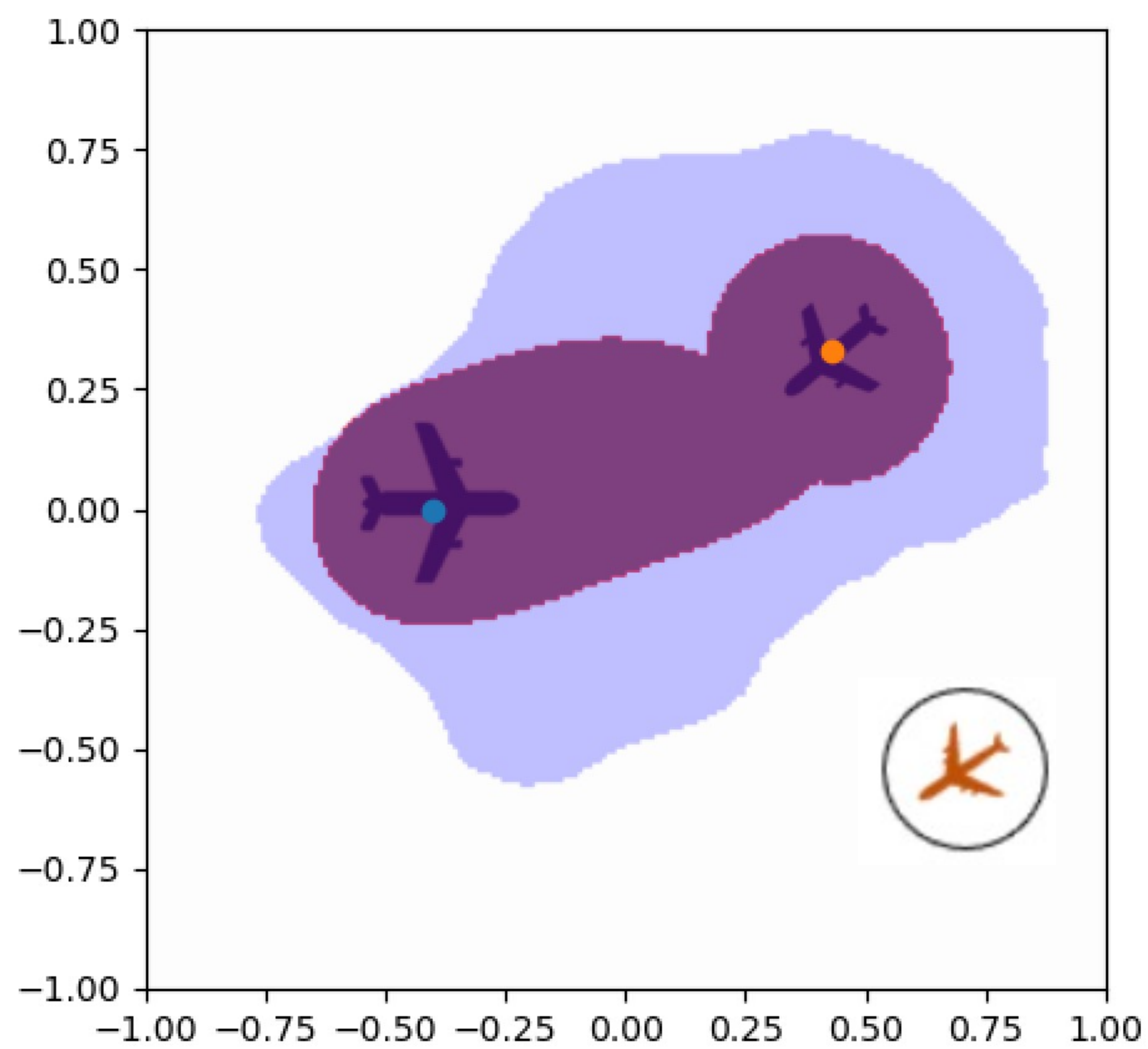
rrrri



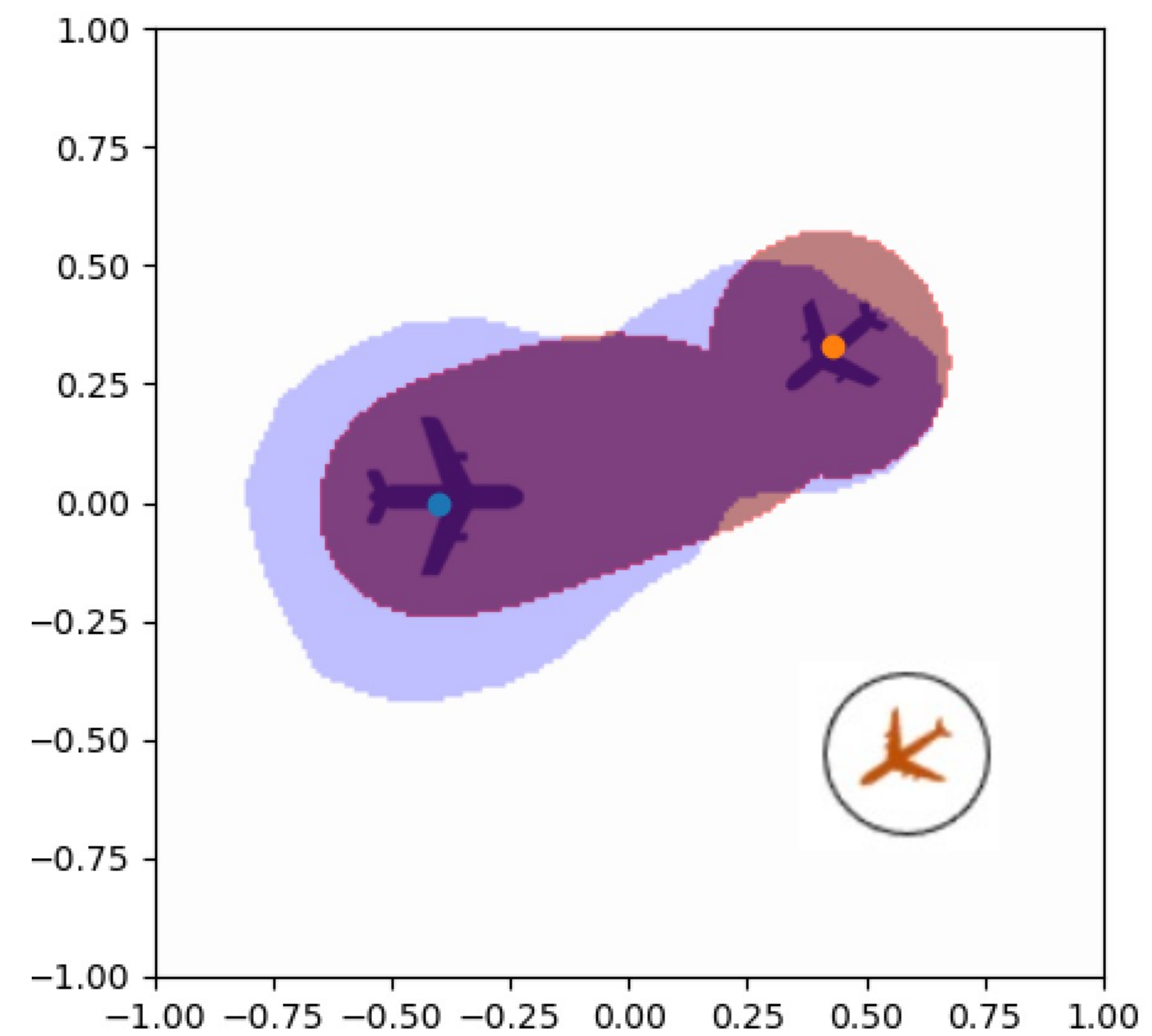
ssssl

Results:

Running example: 9D three-vehicle collision (2Evaders, 1Pursuer)



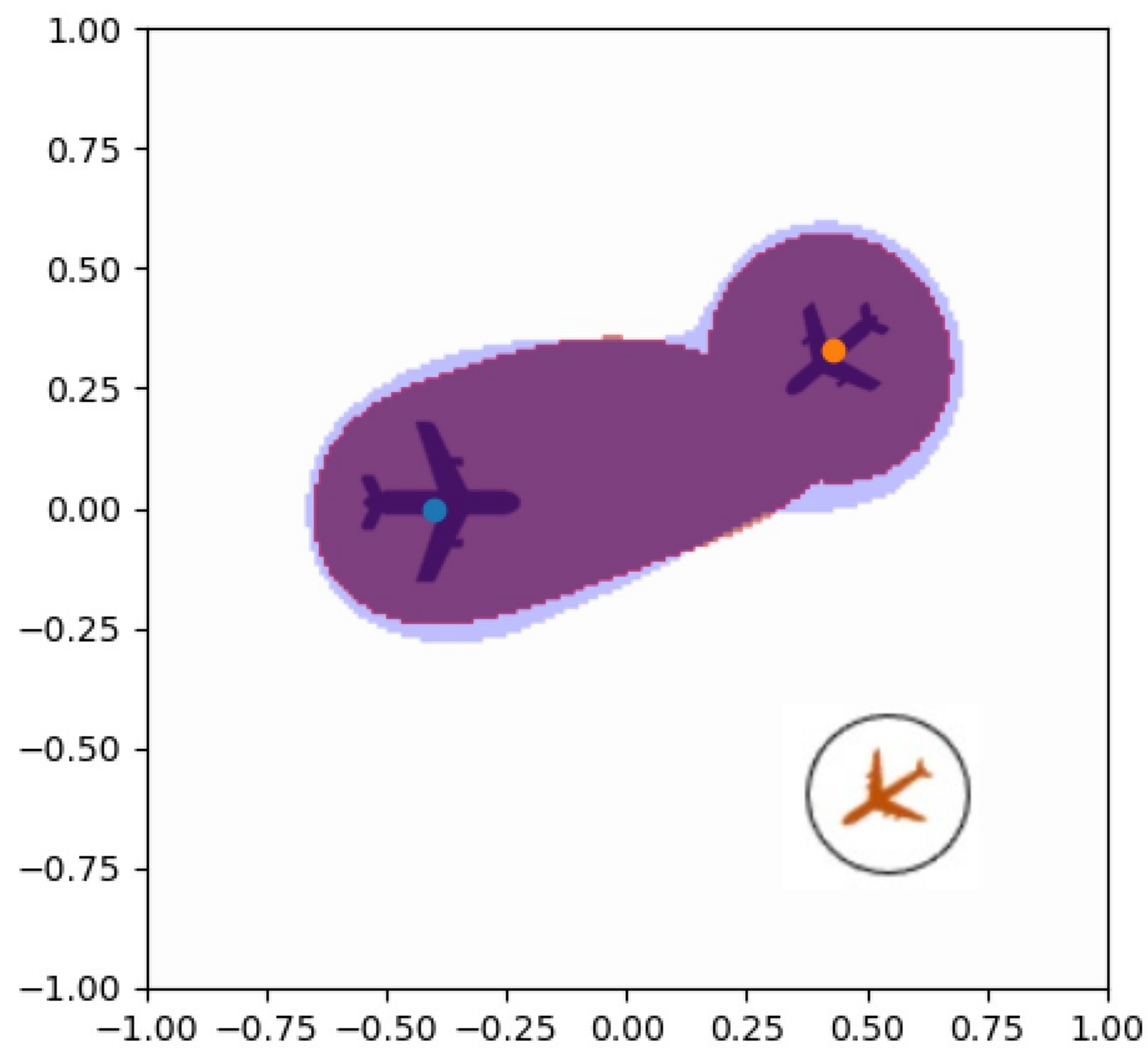
rrrsl



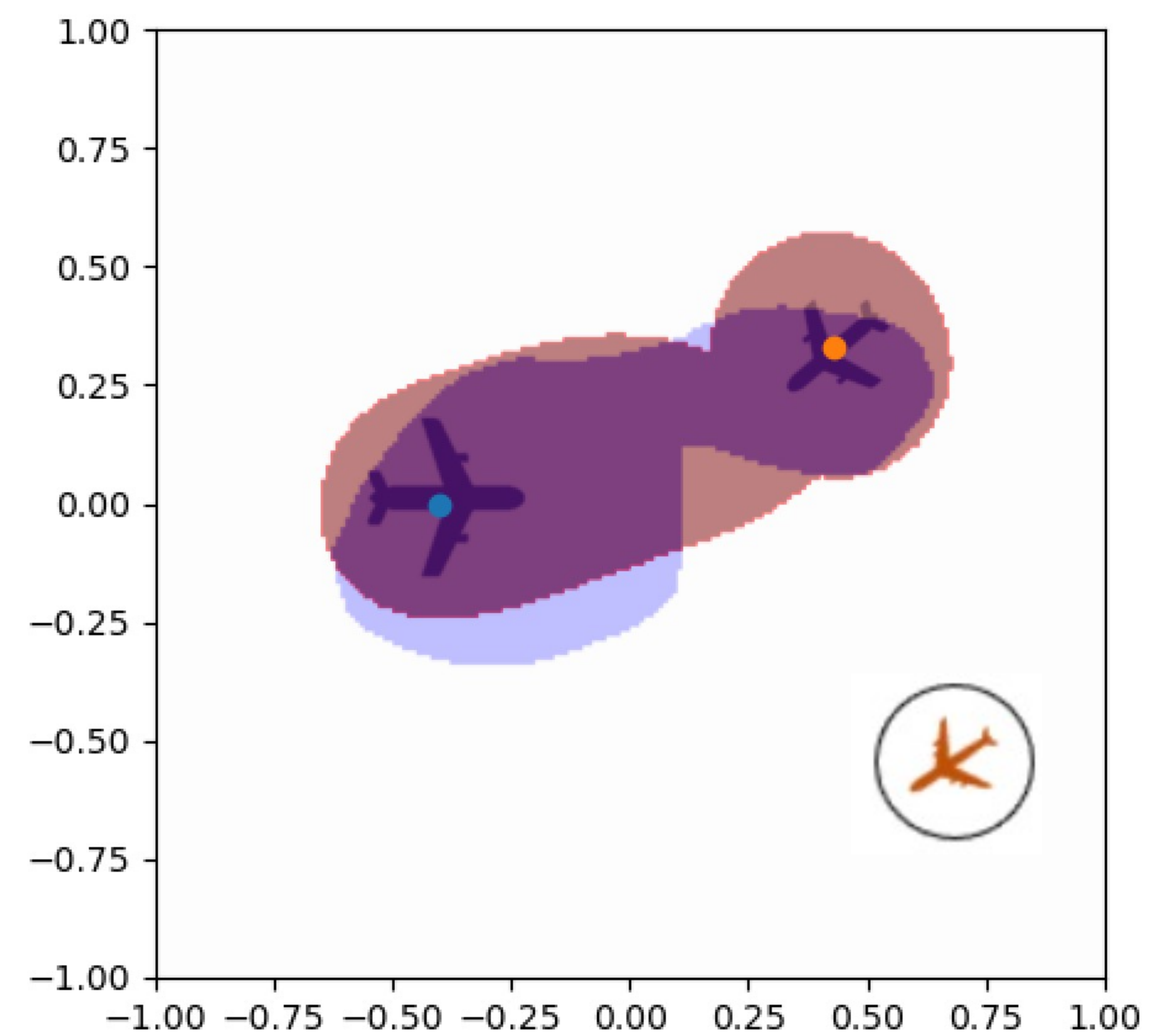
srrrl

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ssrsl



rsrsl

Analysis:

- The graphs provide some visual information about the BRTs, but it relies on our intuition and is not constructive.

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- The graphs provide some visual information about the BRTs, but it relies on our intuition and is not constructive.
- Question: how to quantify the accuracy of BRTs?

Useful tools from the paper below:

A. Lin and S. Bansal, "Generating Formal Safety Assurances for High-Dimensional Reachability,"

Scenario Optimization – violation rate:

1. Sample a state $x \in X$ uniformly randomly and apply u^* and d^* to generate trajectory $\xi_{x,t}^{u,d}(s)$ for $s \in [0, T_f]$
2. If it meets any of the following two conditions, we mark it as a violation

1)

$$\exists x \in BRT^C \wedge s \in [0, T_f] : \xi_{x,t}^{u,d}(s) \in T$$

2)

$$\exists x \in BRT : \forall s \in [0, T_f], \xi_{x,t}^{u,d}(s) \notin T$$

Scenario Optimization – δ -level:

- the maximum learned value of an empirically unsafe initial state under the induced policy $\tilde{\pi}$

$$\delta_{\tilde{V}, \tilde{\pi}} := \max_{x \in X} \left\{ \tilde{V}(x, 0) : J_{\tilde{\pi}}(x, 0) \leq 0 \right\}$$

- Intuitively, the **violation rate** measures how often the model deviates from the true BRT, and **δ -level** measures how far away the worst violating state is from the true BRT.

Results:

- We want to compute the **violation rate** the BRTs we obtained from the experiments

Activation	Violation Rate	δ -level
ssrsl	0.189	0.441
ssssl	0.190	0.550
rsrsl	0.211	0.891
rrrsl	0.213	0.803
rrrri	0.235	0.999
srrri	0.271	0.916

Limitations:

- **For various systems of different dimensions, we might get different empirical results. Therefore, no naive conclusions can be drawn.**

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- **For various systems of different dimensions, we might get different empirical results. Therefore, no naive conclusions can be drawn.**
- **Only some combinations of Sine and ReLU are experimented with, while others remain unknown. Need a more systematic way of examining the influence of activation on the accuracy of BRTs.**

Summary:

- 1. We explored several combinations of Sine and ReLU in DeepReach on 3D and 9D systems.**

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- 1. We explored several combinations of Sine and ReLU in DeepReach on 3D and 9D systems.**
- 2. Based on the plots and violation rates, adding layers of sine activation helps learn more accurate value functions, thus better BRTs. However, the results cannot be generalized to other systems.**

Future work/directions:

1. Explore other hyperparameters and architecture of DeepReach

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- 1. Explore other hyperparameters and architecture of DeepReach**
- 2. Implement error correction to reduce the error rates of BRTs obtained from DeepReach**