



# Reachability II

## (Hamilton-Jacobi)

DD2415 – Lecture 5 – Nov 2, 2024

# Last lectures

- Reachability on Graphs

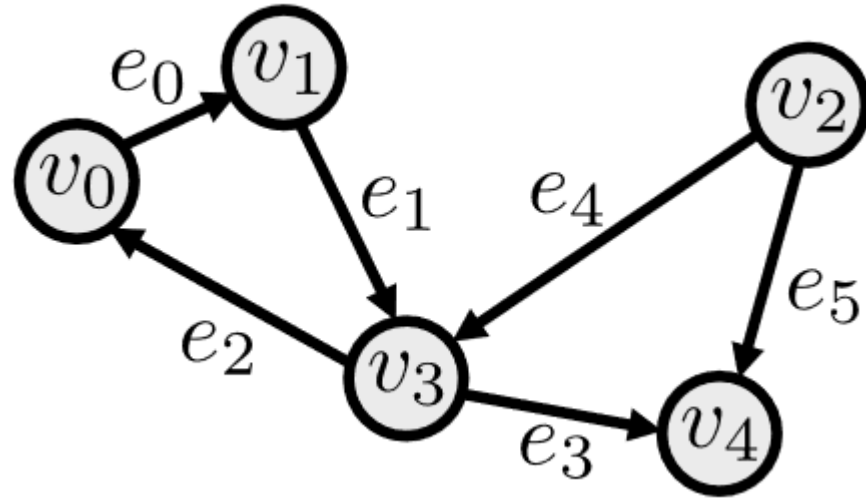


Fig: A Simple Digraph [Lec 3]

- Undisturbed linear systems

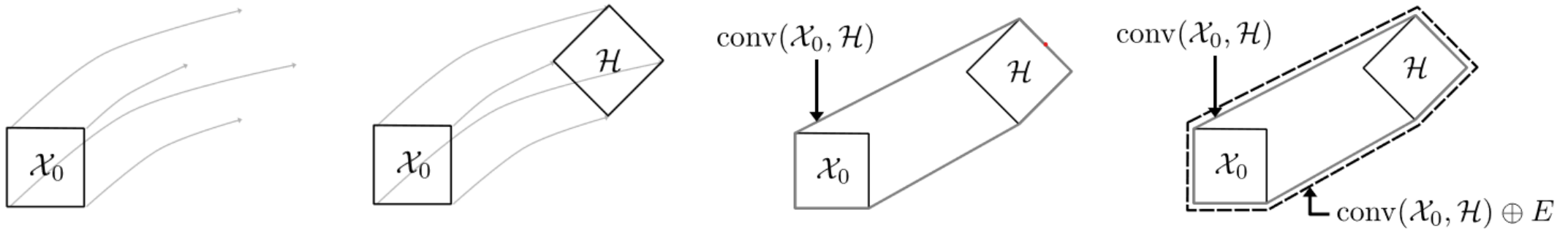


Fig: Algorithmic approach to FRS computation [Lec 3]

# Last lectures

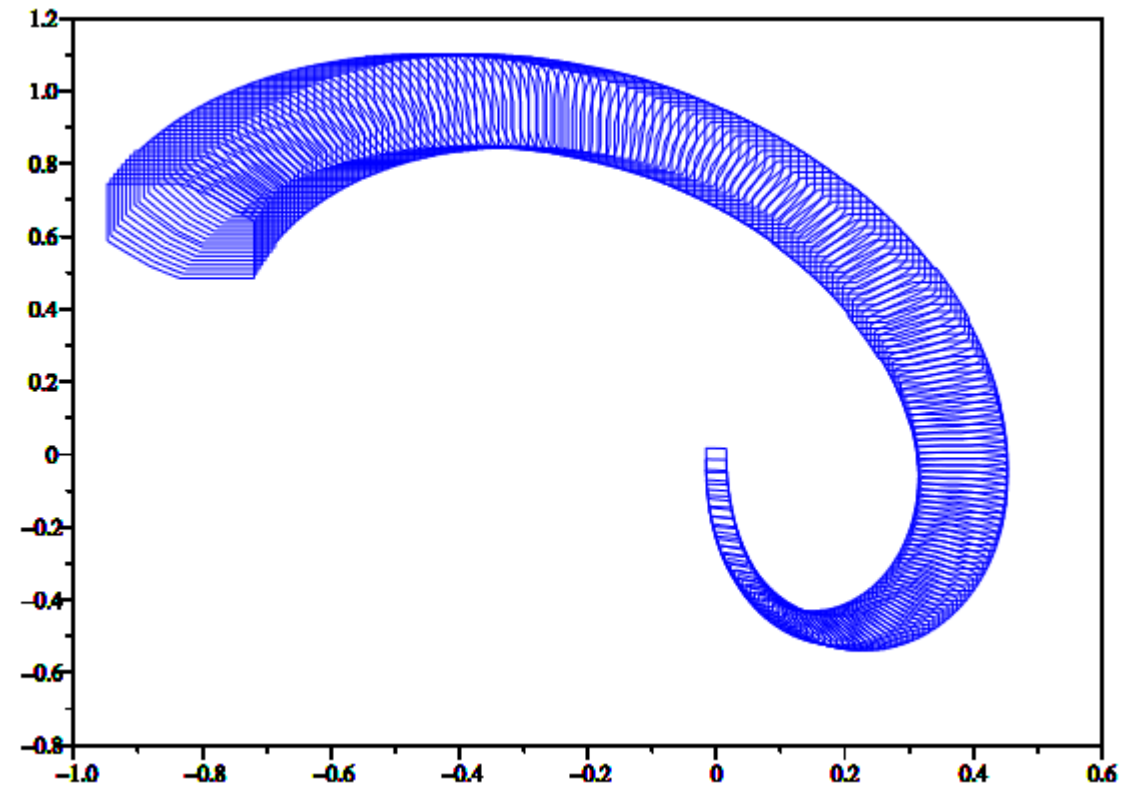
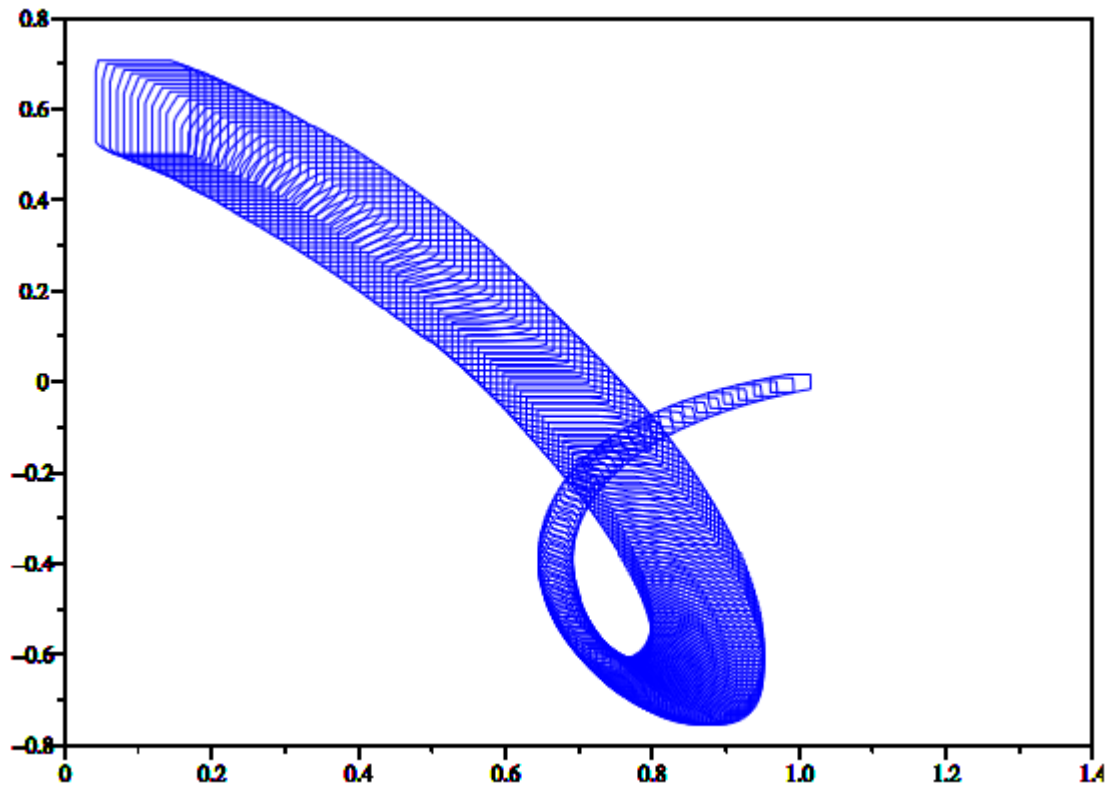


Fig: Projections of the reachable set [Lec 3]

# Slight Extensions on Last lectures

- What if we add a disturbance?
  - $\dot{x} = Ax + Bu + Cd$
  - The disturbance 'shrinks' the reachable set after every step
- The Minkowski difference
  - $A \ominus B = \{a - b \mid a \in A, b \in B\}$ ,  
where  $A \ominus B$  can be summed with  $B$  to recover  $A$
  - Zonotopes are not closed under this operator!
  - Polytope  $\leftrightarrow$  Zonotope conversions throughout!

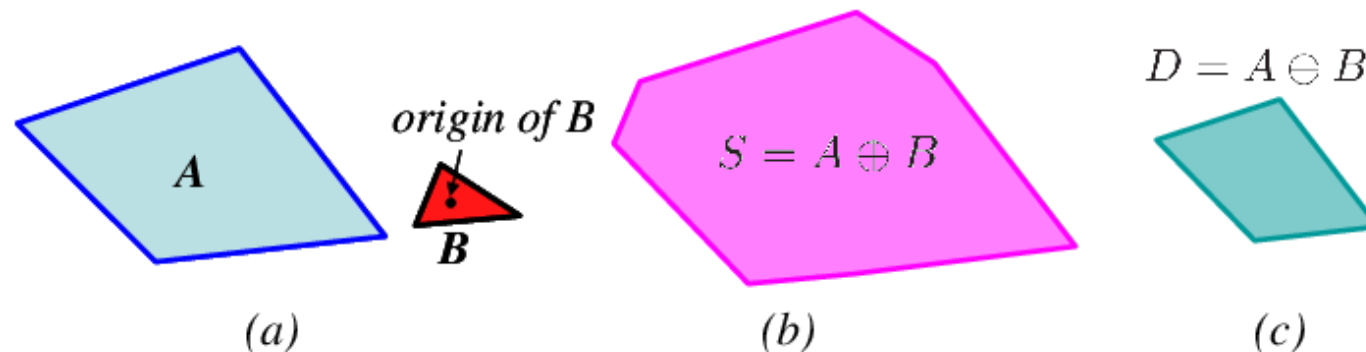


Fig: Minkowski difference of 2 polytopes [Bariki2010New]

# Today

1. Introduction
  - Reachability
  - Our Problem formulation
2. A Brief Intro into Optimal Control
  - Dynamic Programming
  - Hamilton-Jacobi-Bellman
3. Differential Control Problems
  - Zero-sum Differential Games
  - Hamilton-Jacobi-Isaacs
4. Solving the HJI equation
  - The Levelset method
5. Research in HJ Reachability

# Learning outcomes

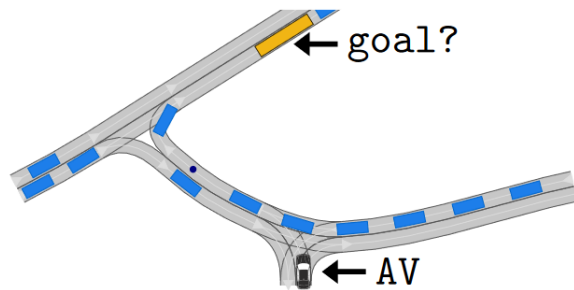
- Explain different flavours of reachability (BRS, BRT, Reach, Avoid) and how they are reflected in the final-value PDE
- Demonstrate the derivation of the HJB Equation and explain how this is used in optimal control
- Recall the relationship between HJB and HJI
- Demonstrate the ability to go from set-based to tube-based backwards reachability
- Demonstrate an intuitive understanding of the Levelset method for reachability computations

# Introduction

- Reachability
- Our Problem Formulation

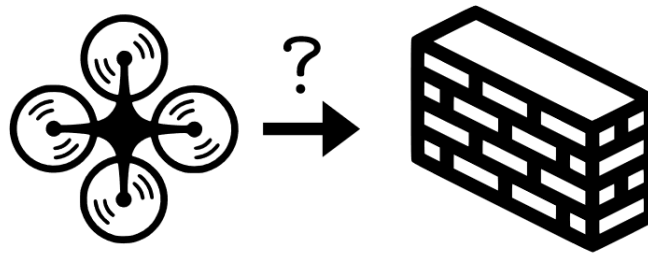
# Reachability in General Terms

- We want to:
  - Reach a goal
  - Avoid an unsafe region
  - both
- Achieve this despite:
  - Disturbances
  - "opponents"



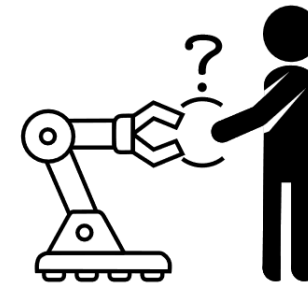
Can the AV reach the goal?

**Despite other drivers?**



Will the drone hit the wall?

**Despite the wind?**



Can the human reach the robot?

**Despite uncertainty?**



# Our Reachability Problem

- Some nonlinear dynamics model
- Leading to a system trajectory
- A goal set
- A finite time horizon

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

$$\Phi(t; x_0, u(\cdot), d(\cdot))$$

$$G(T)$$

$$t \in [0, T]$$

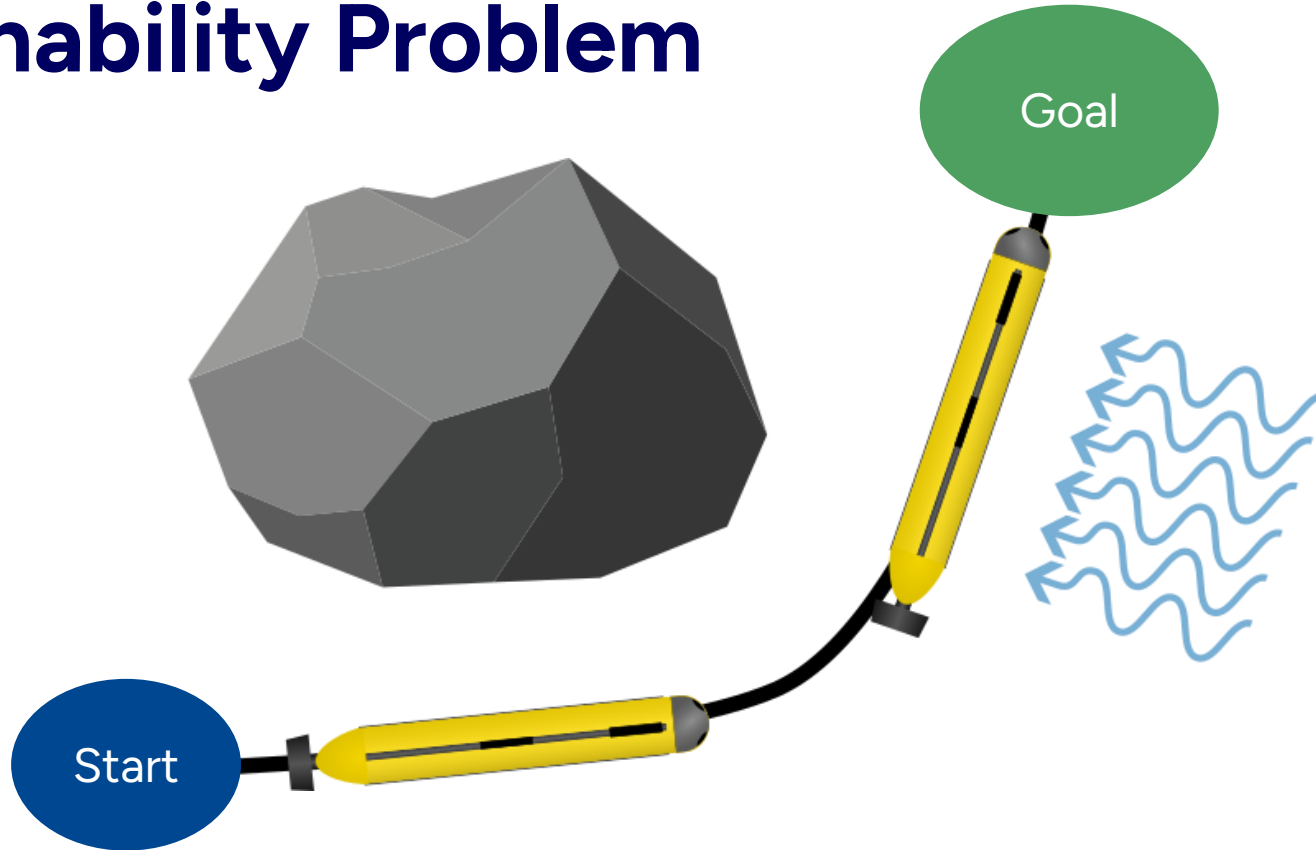


Fig: SAM (SMaRC, KTH)

Now we want to make statements about “reaching” states for a control action, for all disturbance actions

$$R_b(t) = \{x: \exists u(\cdot), \forall d(\cdot), \quad s.t. \Phi(T; x, u(\cdot), d(\cdot)) \in G(T)\}$$

# Our Reachability Problem



Now we want to make statements about “reaching” states for a control action, for all disturbance actions

$$R_b(t) = \{x: \exists u(\cdot), \forall d(\cdot), \quad s. t. \Phi(T; x, u(\cdot), d(\cdot)) \in G(T)\}$$

# To reiterate

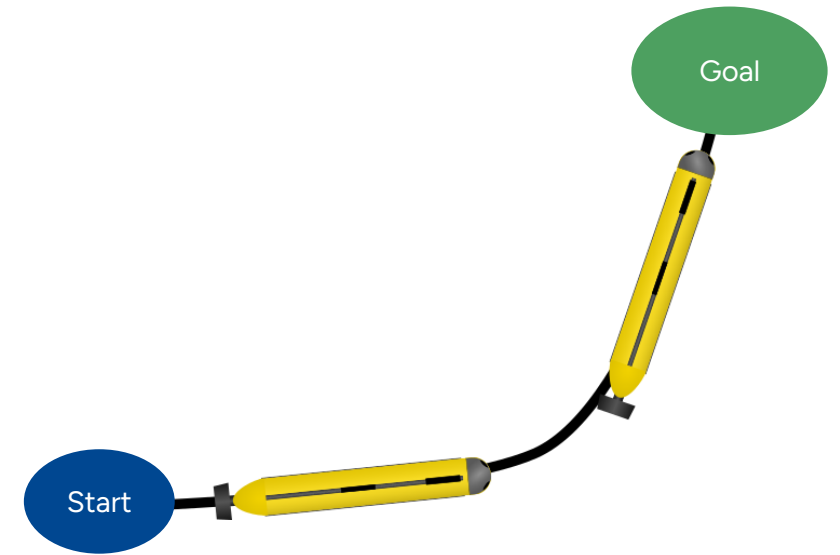
- We want to look at:
  - Disturbed nonlinear systems:  $\dot{x} = f(x, u, d)$   
for example, nonlinear control affine systems:  $\dot{x} = f(x) + g(x)u + h(x)d$
  - Backwards reachability!

# A brief intro to optimal control

- Dynamic Programming
- Hamilton-Jacobi-Bellman

# The Optimal Control Problem

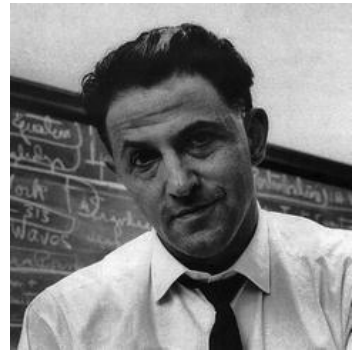
- Let's take a step back: undisturbed nonlinear system:  $\dot{x} = f(x, u)$
- The standard, fundamental (deterministic) problem of control:



$$\min_u \int_0^T \overbrace{L(x(t), u(t)) ds}^{\text{Running cost}} + \overbrace{l(x(T))}^{\text{Terminal (goal) cost}}$$
$$\text{s. t. } \left. \begin{array}{l} \dot{x} = f(x, u) \\ x(0) = x_0 \end{array} \right\} \begin{array}{l} \text{Dynamics constraints} \\ \text{Initial state constraint} \end{array}$$

- What are we trying to get the system to do?
- How do we solve something like this?
  - remember tutorial 0

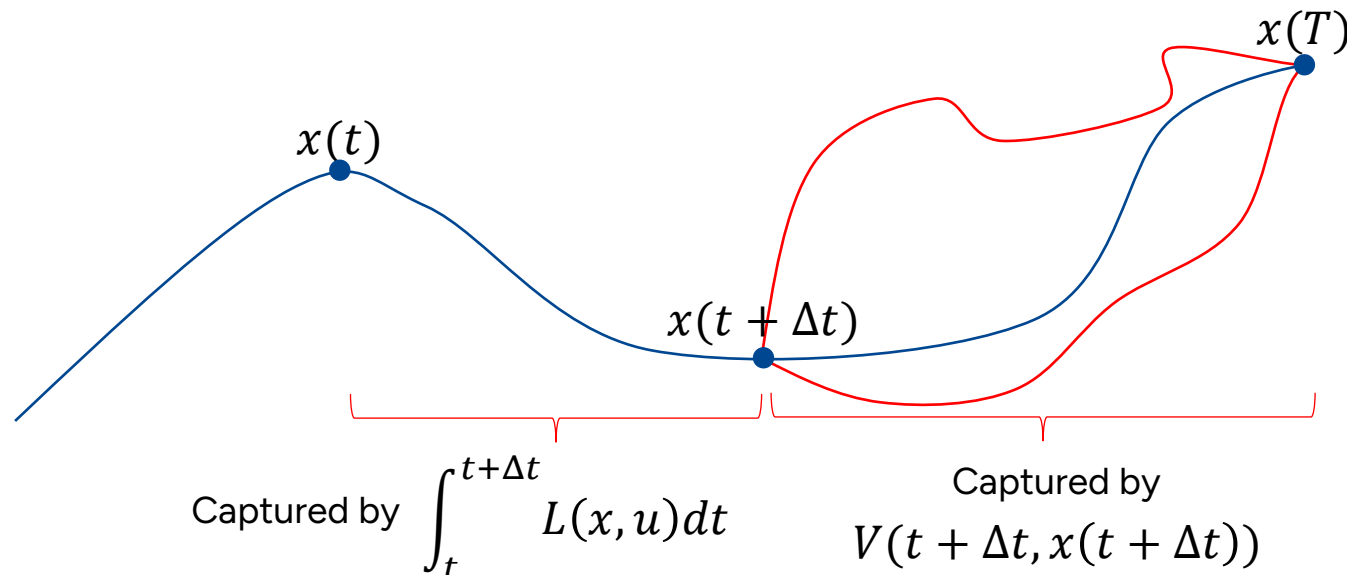
# Dynamic Programming



Richard Bellman

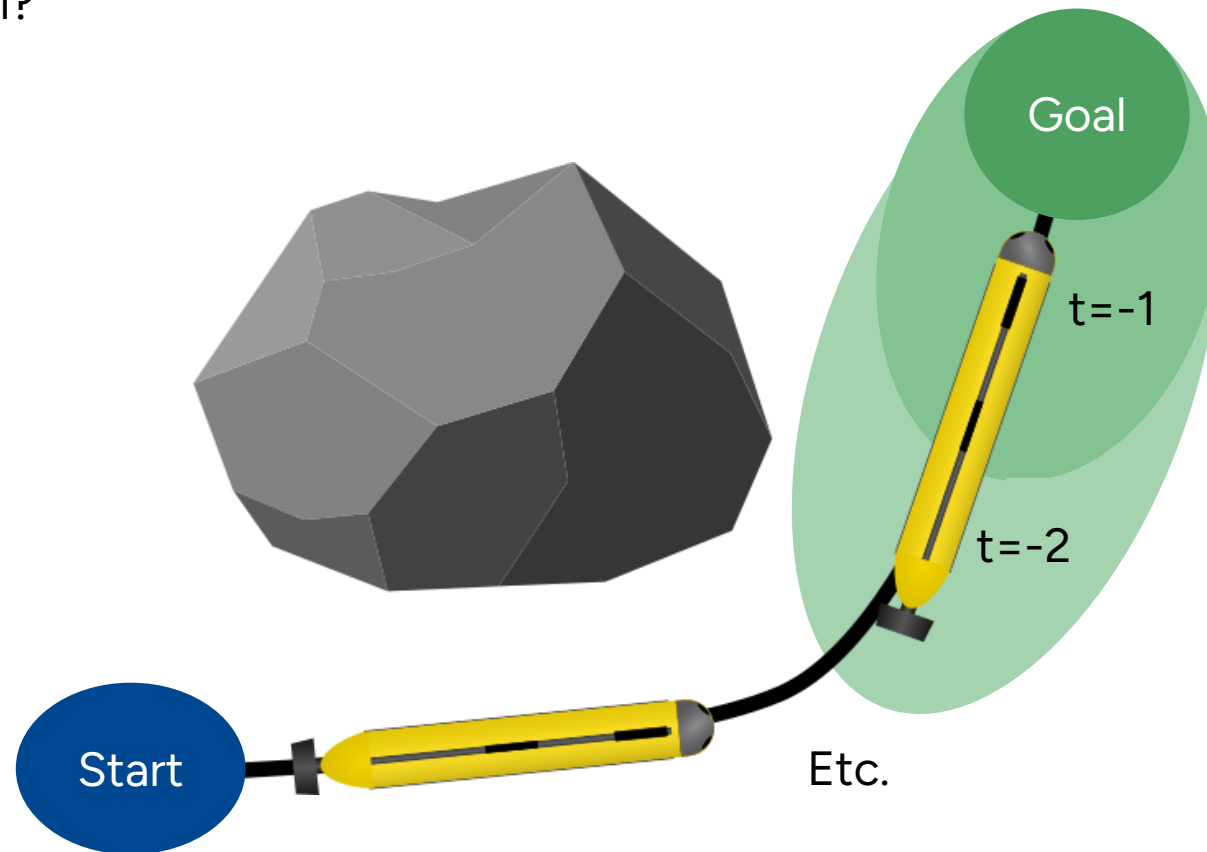
- Bellman's optimality principle:
  - The optimal state trajectory remains optimal at intermediate points in time!
  - Or in Bellman's own words:

"An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision."
- So we can iteratively solve the OCP, starting backwards in time



# Dynamic Programming

- So we can iteratively solve the OCP, starting backwards in time
- Why is this so useful?



# Blackboard time

Let's see what we can do with this



# Hamilton-Jacobi-Bellman (HJB) PDE

$$V(t, x) = \min_u \int_0^T L(x(t), u(t)) ds + l(x(T))$$
$$s.t. \quad \dot{x} = f(x, u)$$

A continuous opt. problem

$$\frac{\partial V(t, x)}{\partial t} + \min_u \left\{ \frac{\partial V(t, x)}{\partial x} f(x, u) + L(x, u) \right\} = 0$$
$$s.t. \quad V(T, x(T)) = l(x(T))$$

A final-value PDE

- So what is  $V(t, x)$ ?
  - The “cost” of starting at  $(t, x)$ , under optimal control until  $T$
- Now how do we obtain a control signal?
  - Generally, we have to solve a (high-dimensional) PDE
  - But there are some cases for which this is trivial: Linear Dynamics, Quadratic Cost!

# Blackboard time

Let's derive a solveable representation!

# Differential Control Problems

- Zero-sum Differential Games
- Hamilton-Jacobi-Isaacs

# Games of Degree vs. Games of Kind

- Fundamentally, our problem is a yes/no problem...
  - Starting at this state  $(t, x)$ , will we reach the target within  $T$ ?

$$R(t) = \{x: \exists u(\cdot), \forall d(\cdot), \quad s.t. \Phi(T; x, u(\cdot), d(\cdot)) \in Goal\}$$

- We want to change our problem to a "how much" problem...
  - Starting at this state, what is the value of reaching the target?
  - Why do we want this?
- If we can formulate some 'game', then the control  $u(\cdot)$  and disturbance  $d(\cdot)$  can play against each other!
  - Zero-sum
  - Differential game

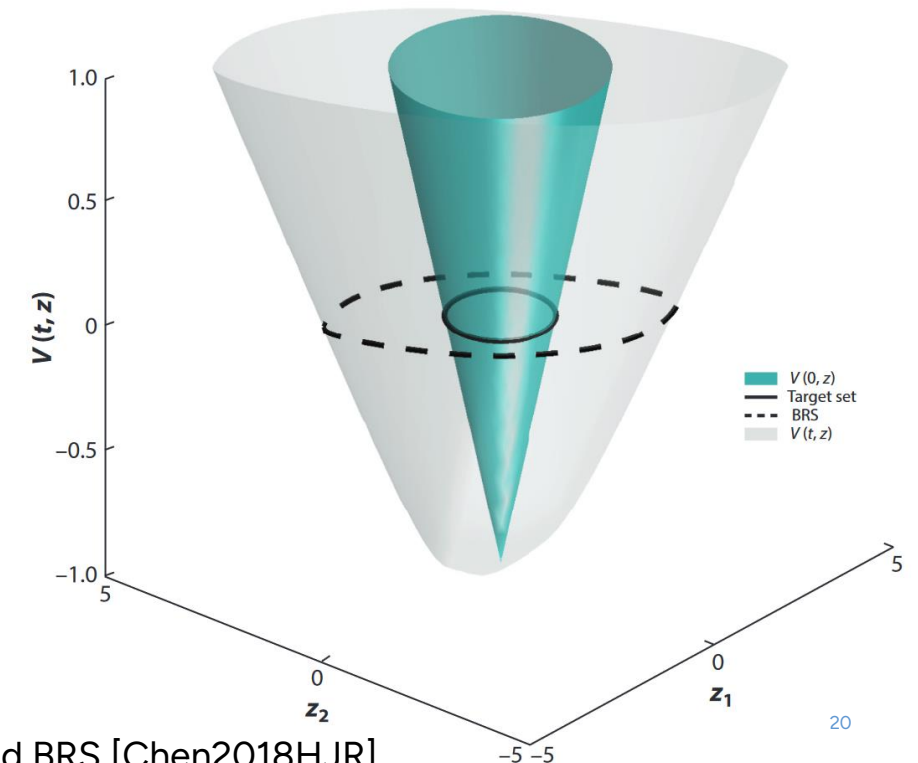


Fig: Zero-sublevel target set and BRS [Chen2018HJR]





Rufus Isaacs

# The Hamilton-Jacobi Isaacs Equation

$$V(t, x) = \min_u \int_0^T L(x(t), u(t), d(t)) ds + l(x(T))$$

$$s. t. \quad \dot{x} = f(x, u, d)$$

A continuous opt. problem

- How do we take care of the disturbance?
  - Assume the worst-case!

Lower-value

$$V(t, x) = \min_u \max_d \int_0^T L(x(t), u(t), d(t)) ds + l(x(T))$$

$$s. t. \quad \dot{x} = f(x, u, d)$$

A continuous opt. problem

- So what is  $V(t, x)$ ?
  - The "cost" of starting at  $(t, x)$  under optimal control and worst-case disturbance until  $T$

# The Hamilton-Jacobi Isaacs Equation

$$V(t, x) = \min_u \max_d \int_0^T L(x(t), u(t), d(t)) ds + l(x(T))$$

A continuous opt. problem

$s. t. \quad \dot{x} = f(x, u, d)$

$$\frac{\partial V(t, x)}{\partial t} + \min_u \max_d [\nabla V(t, x) f(x, u, d)] = 0$$

A final-value PDE  
Strict reachability

$s. t. \quad V(T, x(T)) = l(x(T))$

- So what is  $V(t, x)$ ?
  - The "cost" of starting at  $(t, x)$  under optimal control and worst-case disturbance until  $T$
  - We are interested in the sign of  $V(t, x)$  to answer reachability questions
- Now how do we obtain a control signal?
  - $u^* = \operatorname{argmin}_u \max_d [\nabla V(t, x) f(x, u, d)]$

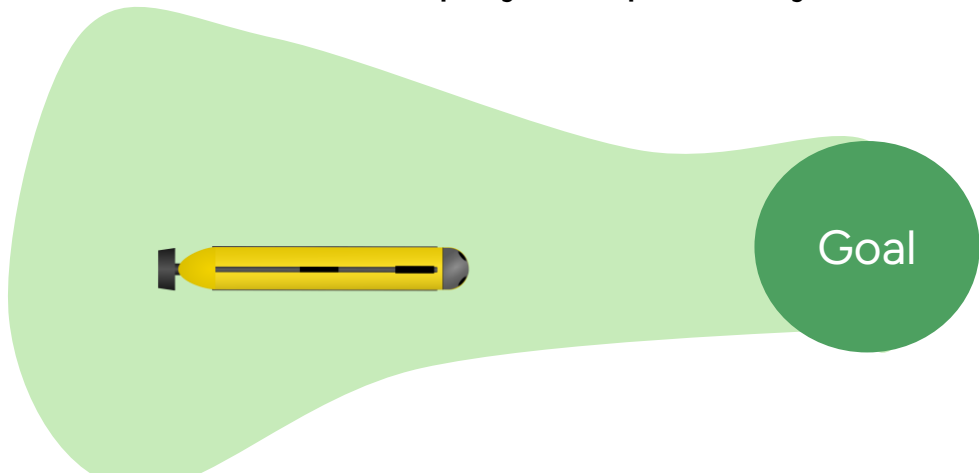
# Comparisons/equivalences between OCP and HJI

## Hamilton-Jacobi-Bellman

$$\frac{\partial V(t, x)}{\partial t} + \min_u [\nabla V(t, x) f(x, u)] = 0$$

s. t.  $V(T, x(T)) = l(x(T))$

"Standard" optimal control/reachability problem  
"One-player" optimality



## Hamilton-Jacobi-Isaacs

$$\frac{\partial V(t, x)}{\partial t} + \min_u \max_d [\nabla V(t, x) f(x, u, d)] = 0$$

s. t.  $V(T, x(T)) = l(x(T))$

Worst-case optimal control/reachability problem  
"Two-player" optimality





# The Hamilton-Jacobi Isaacs Equation

$$\frac{\partial V(t, x)}{\partial t} + \min_u \max_d [\nabla V(t, x) f(x, u, d)] = 0$$

*s. t.*  $V(T, x(T)) = l(x(T))$

A final-value PDE  
Strict reachability

- So what is  $V(t, x)$ ?
  - The "cost" of starting at  $(t, x)$  under optimal control and worst-case disturbance until  $T$
- What if we swap  $\min_u \max_d \dots$  to  $\max_u \min_d \dots$ 
  - Avoid the target set for all disturbances  $d(\cdot)$
- What if we swap  $\min_u \max_d \dots$  to  $\min_u \min_d \dots$ 
  - Reach the target set for some disturbance  $d(\cdot)$

# Blackboard time

Different flavours of HJI Reachability

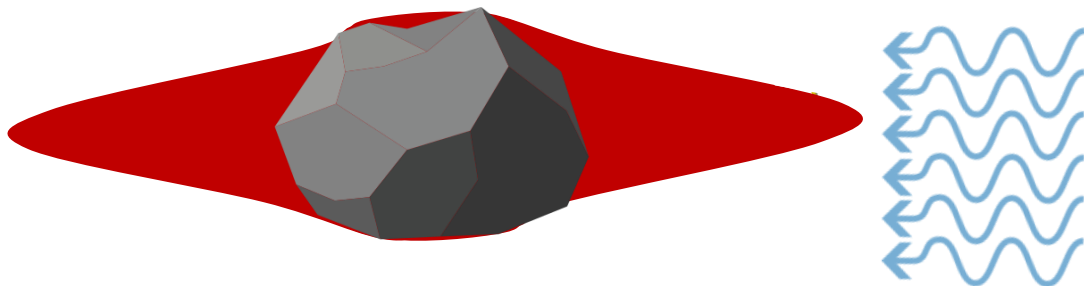
# Different Perspectives

## Avoid Set

$$R(t) = \{x: \exists d, \forall u(\cdot): \Phi(T; x, u(\cdot), d[u](\cdot)) \in Obs\}$$

$$\begin{aligned} \frac{\partial V(t, x)}{\partial t} + \max_u \min_d [\nabla V(t, x) f(x, u, d)] &= 0 \\ \text{s.t.} \quad V(T, x(T)) &= l(x(T)) \end{aligned}$$

Enter G(t): You will collide at T

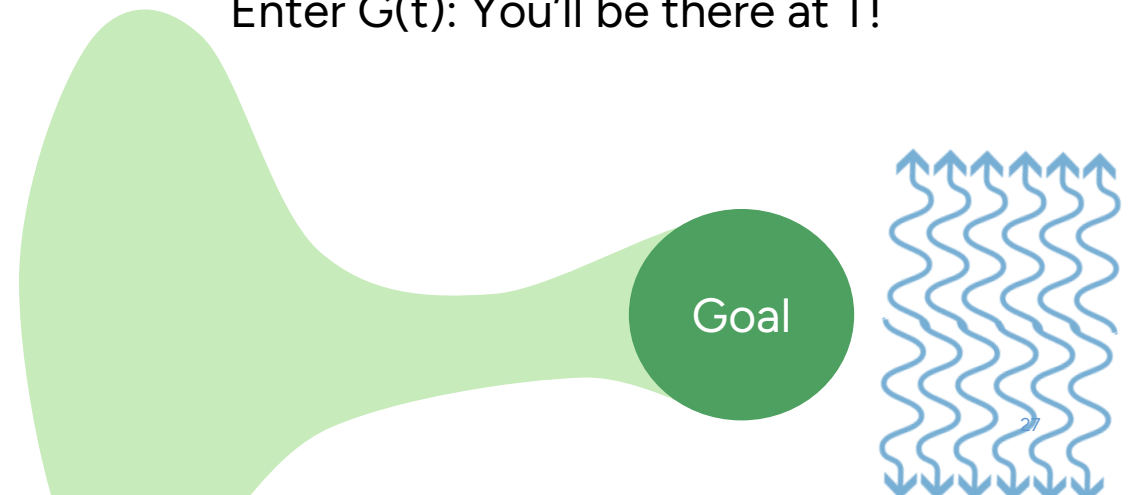


## Reach Set

$$R(t) = \{x: \forall d, \exists u(\cdot): \Phi(T; x, u(\cdot), d[u](\cdot)) \in Goal\}$$

$$\begin{aligned} \frac{\partial V(t, x)}{\partial t} + \min_u \max_d [\nabla V(t, x) f(x, u, d)] &= 0 \\ \text{s.t.} \quad V(T, x(T)) &= l(x(T)) \end{aligned}$$

Enter G(t): You'll be there at T!



# Solving all of this

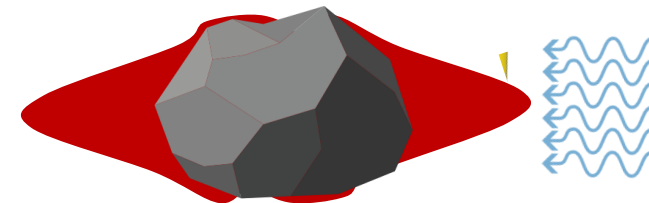
- The Levelset method

# The Levelset Method

- What do we need to solve the HJI Equation?
  - We need a value-function  $V(t, x)$  that, for any  $x \in X$  and  $t \in [0, T]$  captures whether we reach the goal/obstacle
- What do we have?
  - (high-dimensional ) nonlinear dynamics,  $\dot{x} = f(x, u, d)$
  - A control player and a disturbance player,  $\min_u \dots$  and  $\max_d \dots$
- At the end, regardless of reach/avoid, helper/opposer
  - We need to solve a PDE...
  - But these are awful PDEs to analytically solve ☹

$$\frac{\partial V(t, x)}{\partial t} + \max_u \min_d [\nabla V(t, x) f(x, u, d)] = 0$$

s. t.  $V(T, x(T)) = l(x(T))$



# Blackboard time

# Different Perspectives

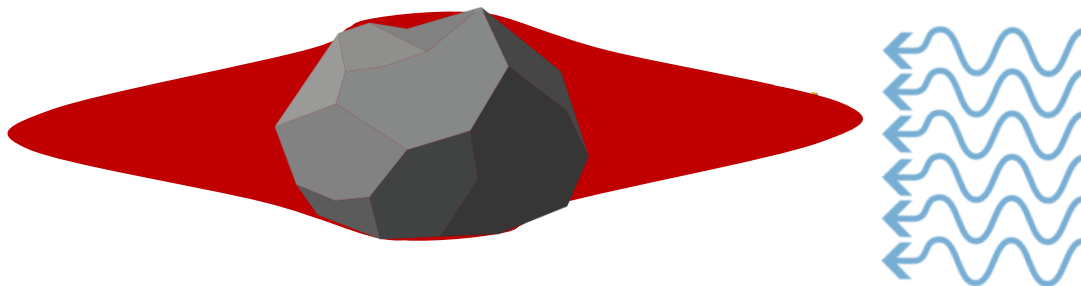
## Avoid Set

$$R(t) = \{x: \exists d, \forall u(\cdot): \Phi(T; x, u(\cdot), d[u](\cdot)) \in Obs\}$$

$$\frac{\partial V(t, x)}{\partial t} + \max_u \min_d [\nabla V(t, x) f(x, u, d)] = 0$$

s. t.  $V(T, x(T)) = l(x(T))$

Enter G(t): you'll collide at t=T



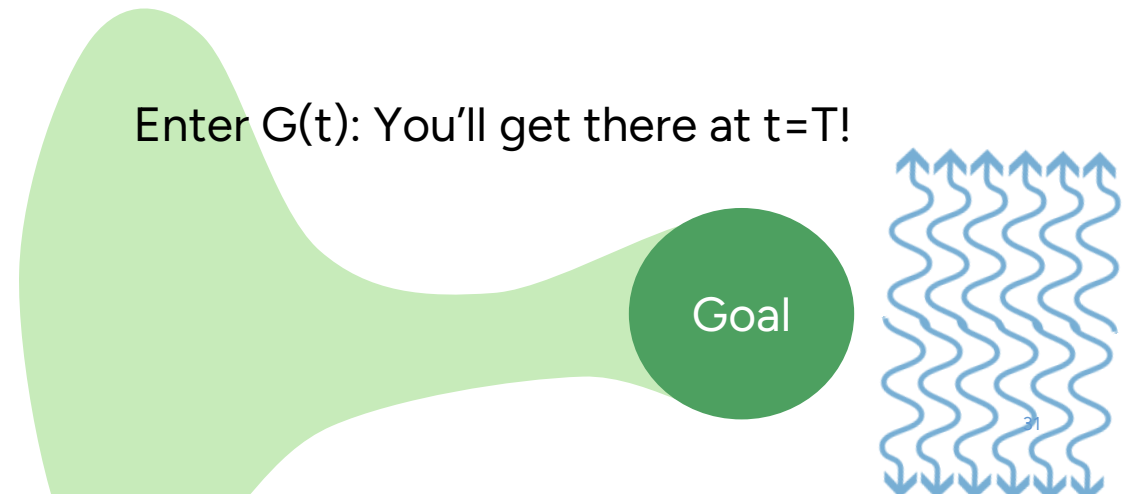
## Reach Set

$$R(t) = \{x: \forall d, \exists u(\cdot): \Phi(T; x, u(\cdot), d[u](\cdot)) \in Goal\}$$

$$\frac{\partial V(t, x)}{\partial t} + \min_u \max_d [\nabla V(t, x) f(x, u, d)] = 0$$

s. t.  $V(T, x(T)) = l(x(T))$

Enter G(t): You'll get there at t=T!



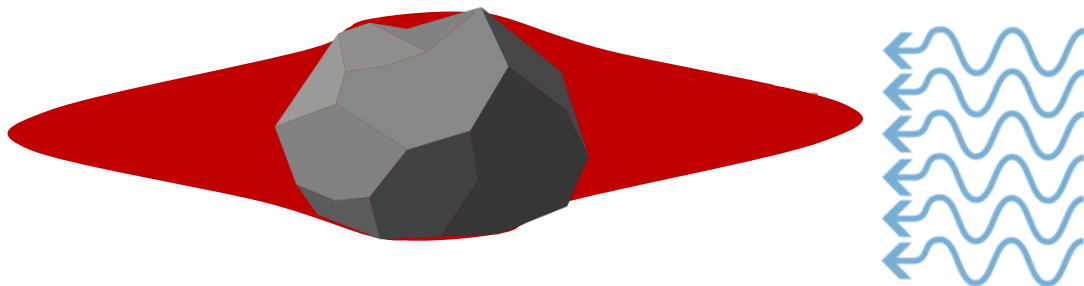
# Different Perspectives

## Avoid Tube

$$R(t) = \{x: \exists d, \forall u(\cdot), \exists \tau \in [0, T]: \\ \Phi(\tau; x, u(\cdot), d[u](\cdot)) \in Obs\}$$

$$\frac{\partial V(t, x)}{\partial t} + \min\{0, \max_u \min_d [\nabla V(t, x) f(x, u, d)]\} = 0 \\ s.t. \quad V(T, x(T)) = l(x(T))$$

Enter G(t): you'll collide at some  $t \in [0, T]$



## Reach Tube

$$R(t) = \{x: \forall d, \exists u(\cdot), \exists \tau \in [0, T]: \\ \Phi(\tau; x, u(\cdot), d[u](\cdot)) \in Goal\}$$

$$\frac{\partial V(t, x)}{\partial t} + \min\{0, \min_u \max_d [\nabla V(t, x) f(x, u, d)]\} = 0 \\ s.t. \quad V(T, x(T)) = l(x(T))$$

Enter G(t): You'll get there at some  $t \in [0, T]$





# Different Perspectives

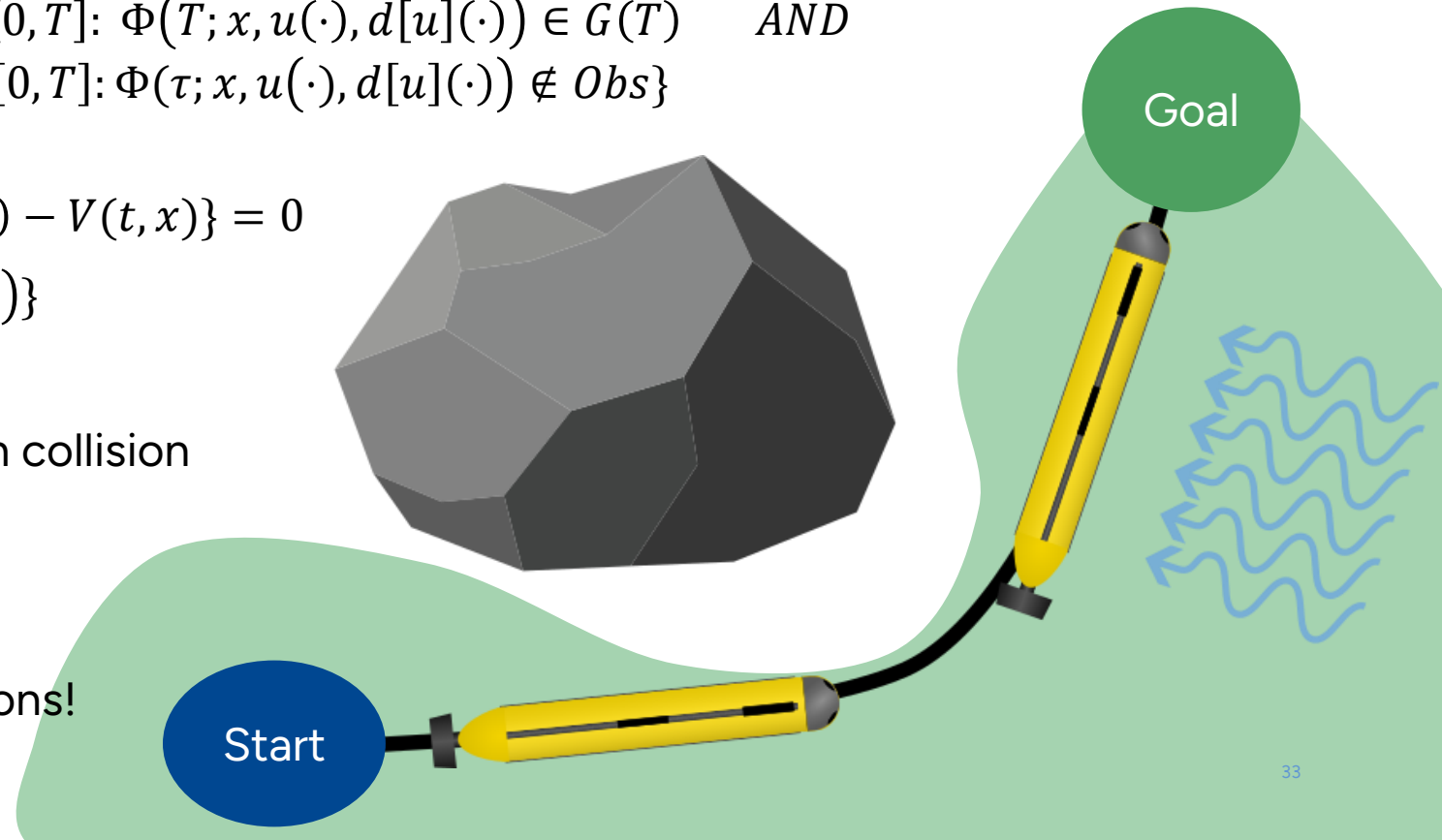
## Reach-Avoid Tube

$$R(t) = \{x: \exists u, \forall d, \\ \exists t \in [0, T]: \Phi(T; x, u(\cdot), d[u](\cdot)) \in G(T) \quad \text{AND} \\ \forall \tau \in [0, T]: \Phi(\tau; x, u(\cdot), d[u](\cdot)) \notin Obs\}$$

$$\begin{aligned} \max\{ \frac{\partial V}{\partial t} + \min\{0, \min_u \max_d [\nabla V f(x, u, d)]\}, g(x) - V(t, x) \} &= 0 \\ \text{s.t.} \quad V(T, x(T)) &= \max\{l(x(T)), g(x(T))\} \end{aligned}$$

$g(x)$  = a function s.t.  $g(x) \geq 0$  if the state is in collision

Enter  $R(t)$ : You'll get there without collisions!



# The Levelset Method

- A set-based perspective on solving a PDE
  - Evolution of the set backwards in time
- We have to define a grid of the state-space
  - What does this allow us to do?
    - Arbitrary shapes of goals and obstacles
  - What does this mean for high-dimensional systems?
    - Curse of dimensionality!
  - What does this mean for the accuracy of our solution?
    - Only under- or over-approximations
- We solve for discrete points in time
  - What does this mean for the accuracy of our solution?
    - Again, only under- or over-approximations
- It is "trivial" to consider time-varying obstacles

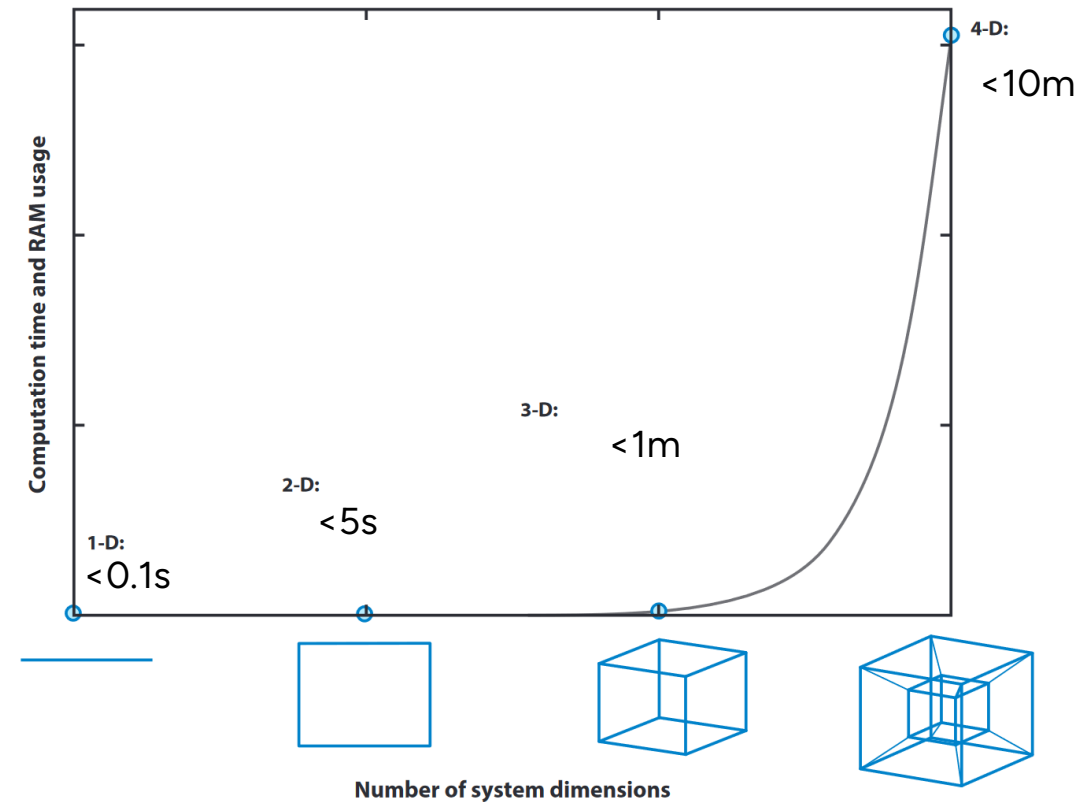


Fig: Computational complexity of HJ Reachability  
adapted from [Chen2018HJR]

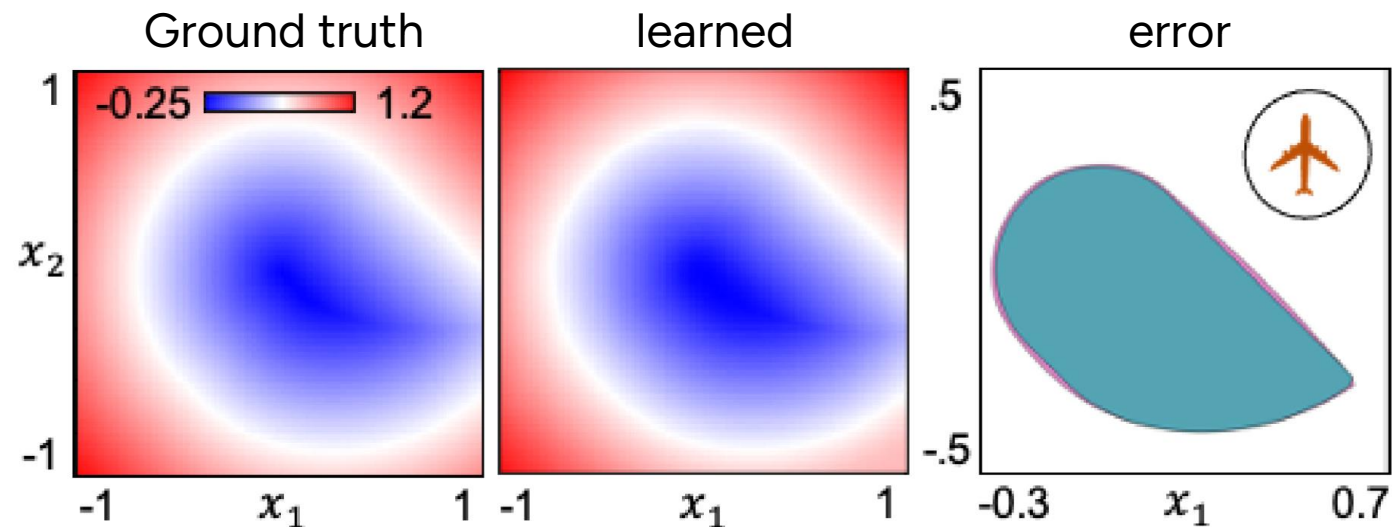
# Research on HJ Reachability

- Fundamentally, we need to solve a PDE
  - So lots of research on speeding up (approximate) methods



# Research on HJ Reachability

- “DeepReach: A Deep Learning Approach to High-Dimensional Reachability” (Bansil & Tomlin, 2021)
- Conditioned on a goal/obstacle state, can we learn
  - $V(t, x) = NN(t, x)$ , in a self-supervised way (supervised by HJI value iteration)!
  - $Loss(x_i, t_i, \theta) = ||V_\theta(t_i, x_i) - l(x_i)||1(t_i = T) + \lambda ||\min\{\frac{\partial V_\theta(t_i, x_i)}{\partial t} + \max_u \min_d \{\nabla V(t_i, x_i) f(x, u, d)\}, l(x_i) - V_\theta(t_i, x_i)\}||$
- Extensions for statistical guarantees with conformal prediction



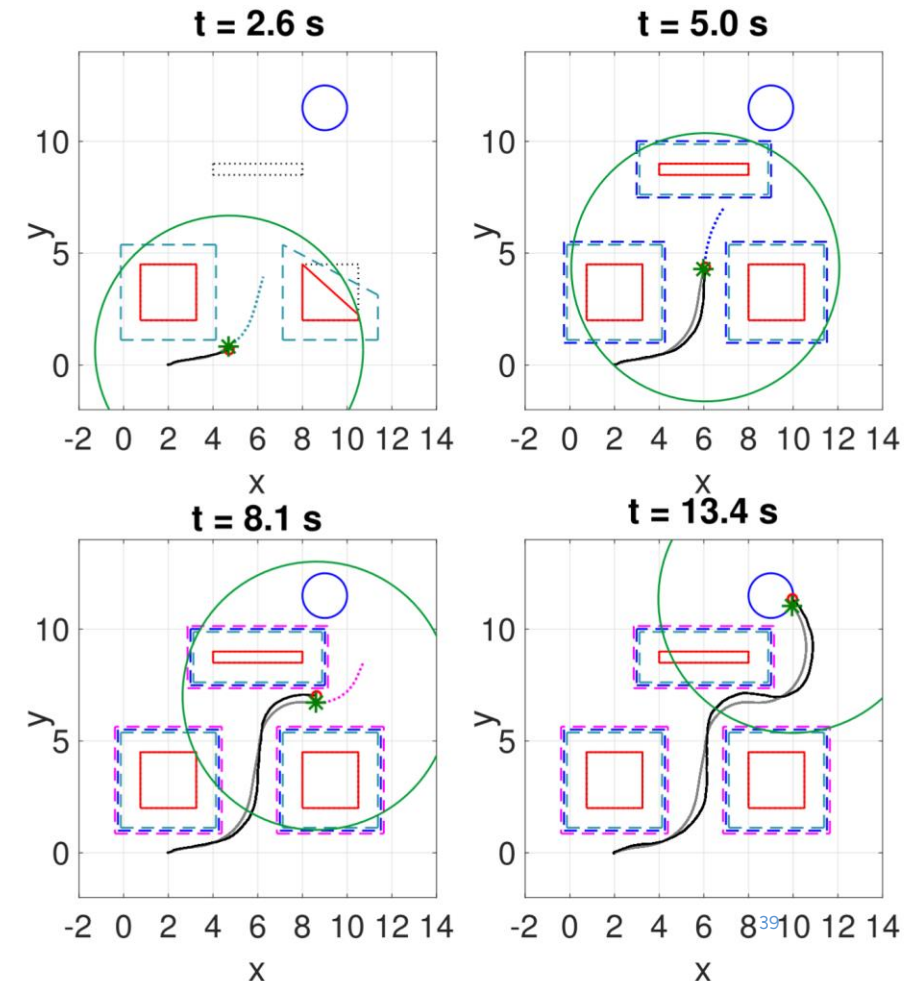
# Research with HJ Reachability

- We can use HJ Reachability for
  - computing safe sets and plan with them!
  - Computing value functions and use them as backup controllers

# Research with HJ Reachability

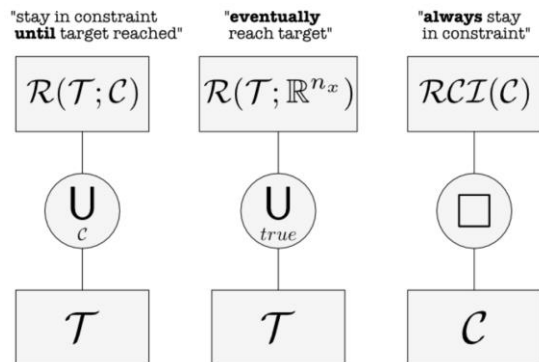
- FaSTrack: a Modular Framework for Fast and Guaranteed Safe Motion Planning (Herbert, Chen, Han, Bansal, Fisac & Tomlin, 2017)

1. Define a simplified model of a complex dynamical model
2. Define tracking dynamics of the simplified and complex model
3. Offline reachability computation on these tracking dynamics
  1. Pursuit-evasion game between planner and tracker
  2. Tracker is pursuing the planner: what is the max tracking error?
4. Bloating obstacles for planning and safe controller look-up tables

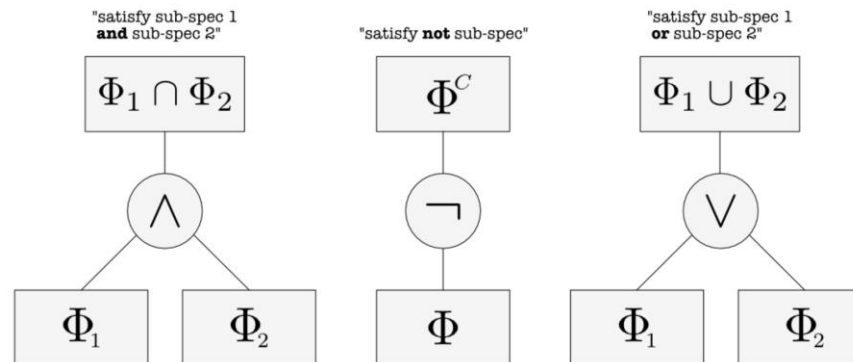


# Research with HJ Reachability

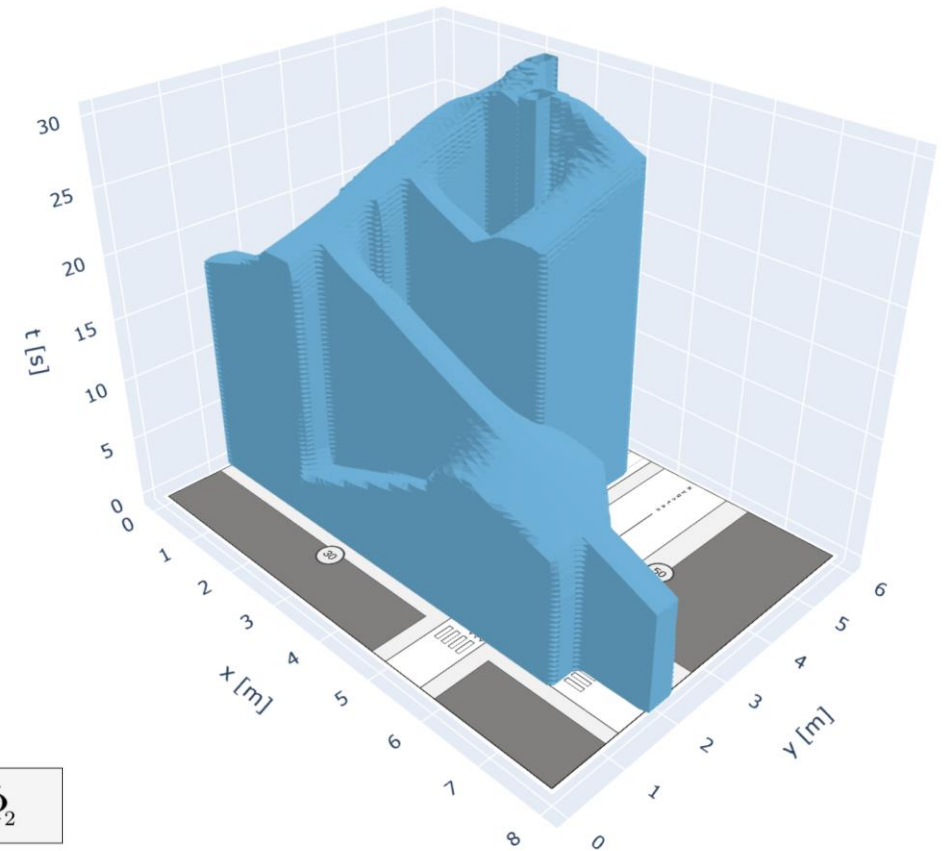
- “Guaranteed Completion of Complex Tasks via Temporal Logic Trees and Hamilton-Jacobi Reachability” (Jiang, Arfvidsson, He, Chen, Johansson, 2024)
- Convert a high-level specification (e.g. do this and this or that and that) to a tree of reachable sets
- If you start in a valid region, you are guaranteed to satisfy the overall specification



Reachability Branches



Set Operation Branches





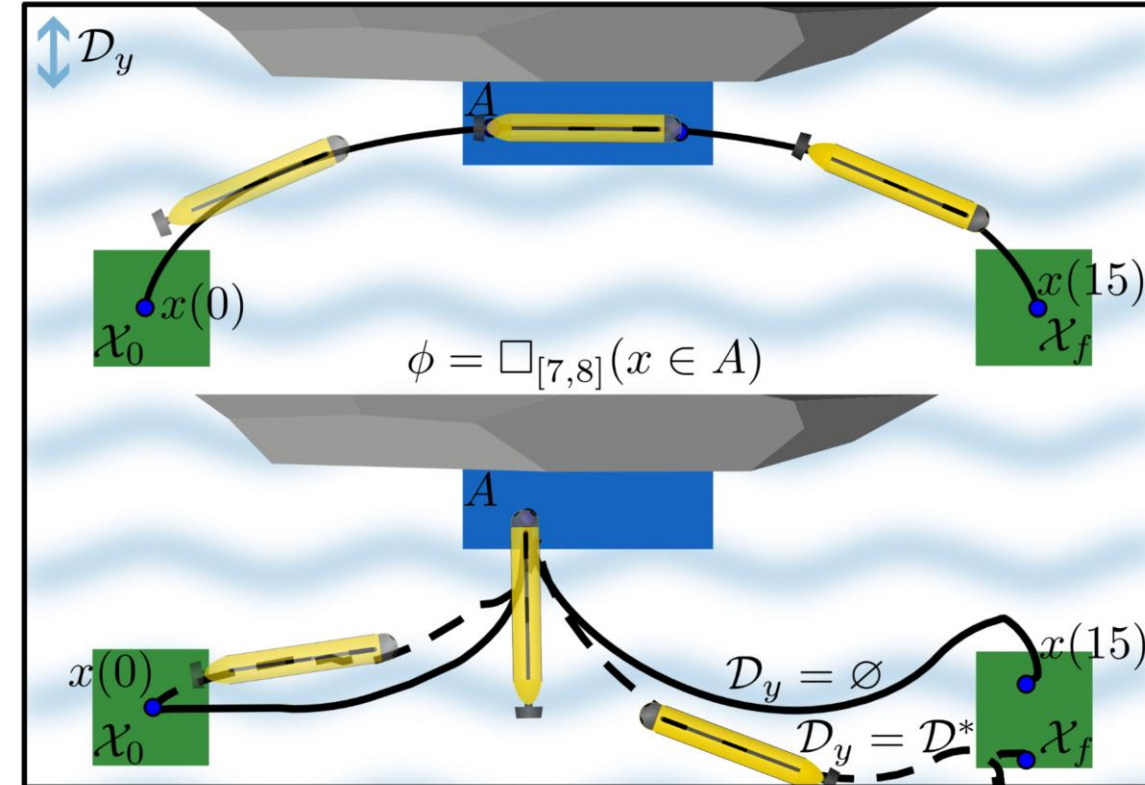
# Research with HJ Reachability

- “Robust STL Control Synthesis under Maximal Disturbance Sets” (Verhagen, Lindemann, Tumova, 2024)

- We have some high-level specification  $\phi$ 
  - E.g. Always, between 7 and 8 seconds, be at location A
  - Always, Eventually, AND, OR
- Which “trajectory” permits the largest disturbance set  $D, d \in D$

$$\begin{aligned} & \max D \\ & \text{s.t. } \Phi(t_0, X_0, u(\cdot) \in U, d(\cdot) \in D) \models \phi \end{aligned}$$

- Generally, no closed-form approach
- Iterative HJI computations (specific algs. per operator)





# References

- [Barki2010New]: Barki, H., Denis, F., & Dupont, F. (2010, June). A new algorithm for the computation of the Minkowski difference of convex polyhedra. In *2010 Shape Modeling International Conference* (pp. 206-210). IEEE.
- [Chen2018HJR]: Chen, M., & Tomlin, C. J. (2018). Hamilton–jacobi reachability: Some recent theoretical advances and applications in unmanned airspace management. *Annual Review of Control, Robotics, and Autonomous Systems*, 1(1), 333-358. **Good review paper!**
- [Chen2018Decomposition]: Chen, M., Herbert, S. L., Vashishtha, M. S., Bansal, S., & Tomlin, C. J. (2018). Decomposition of reachable sets and tubes for a class of nonlinear systems. *IEEE Transactions on Automatic Control*, 63(11), 3675-3688.
- [Bansal2017HJR]: Bansal, S., Chen, M., Herbert, S., & Tomlin, C. J. (2017, December). Hamilton-jacobi reachability: A brief overview and recent advances. In *2017 IEEE 56th Annual Conference on Decision and Control (CDC)* (pp. 2242-2253). IEEE. **Good review paper!**