

# Hamilton-Jacobi Reachability Analysis I

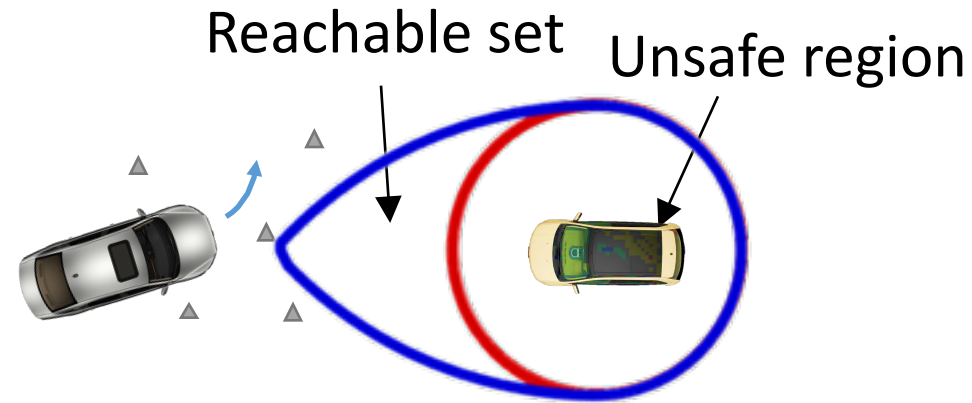
CMPT 419/983

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SFU Computing Science

16/10/2019

# Reachability Analysis: Avoidance



Assumptions:

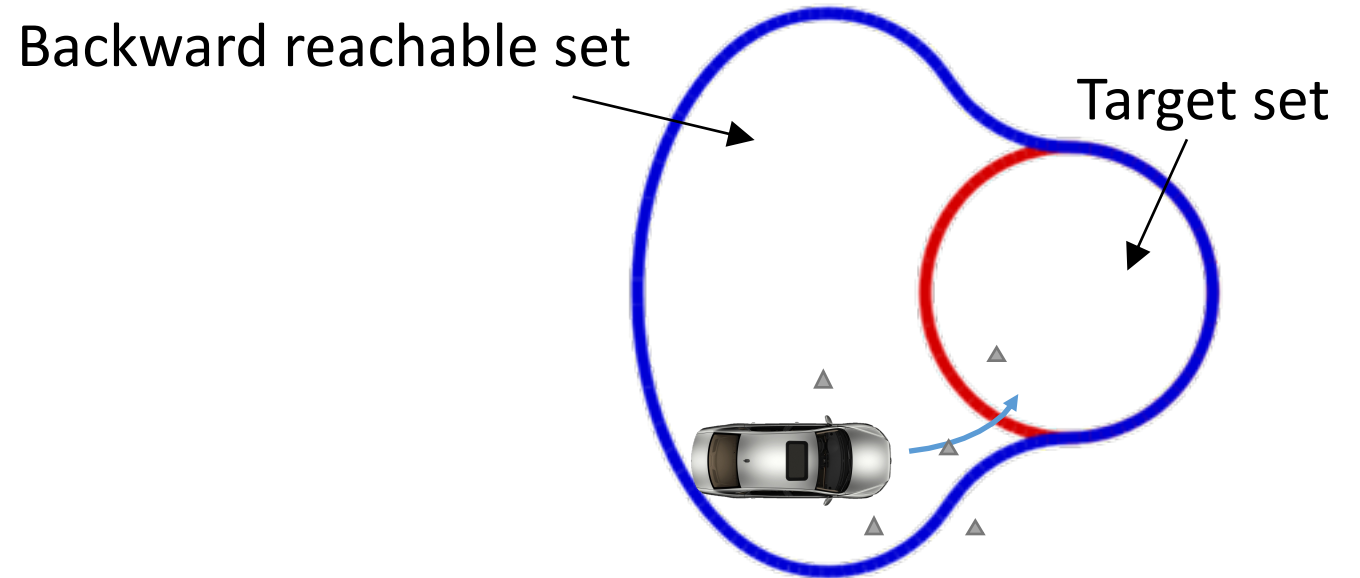
- Model of robot
- Unsafe region: Obstacle



Control policy

Backward reachable set  
(States leading to danger)

# Reachability Analysis: Goal Reaching



- Model of robot
- Goal region



Control policy

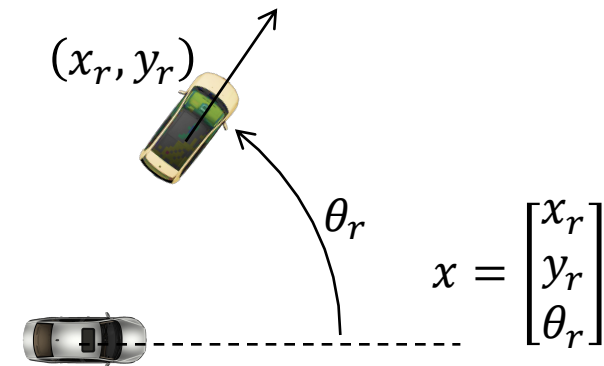
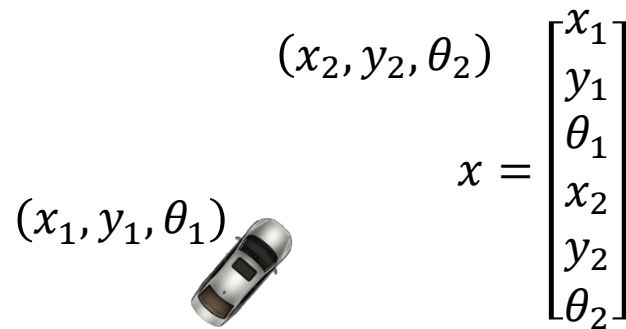
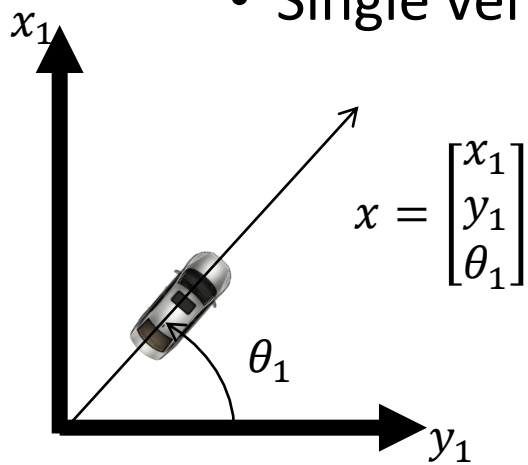
Backward reachable set  
(States leading to goal)

# Assumptions

- System dynamics:  $\dot{x} = f(x, u, d), t \leq 0$  (by convention, final time is 0)

- State  $x$

- Single vehicle, multiple vehicle, relative coordinates

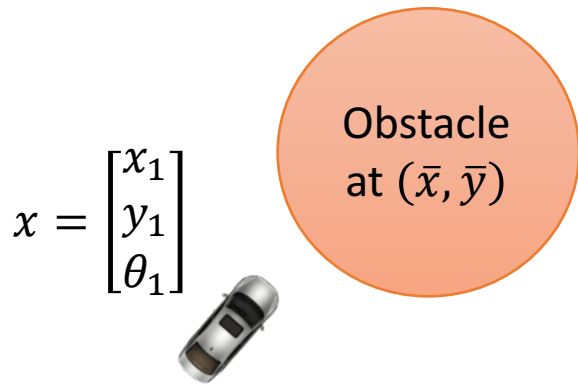


- Disturbance  $d$ : uncontrolled factors that affect the system, such as wind
  - Can be used to model other agents, when state includes them
  - Assume worst case

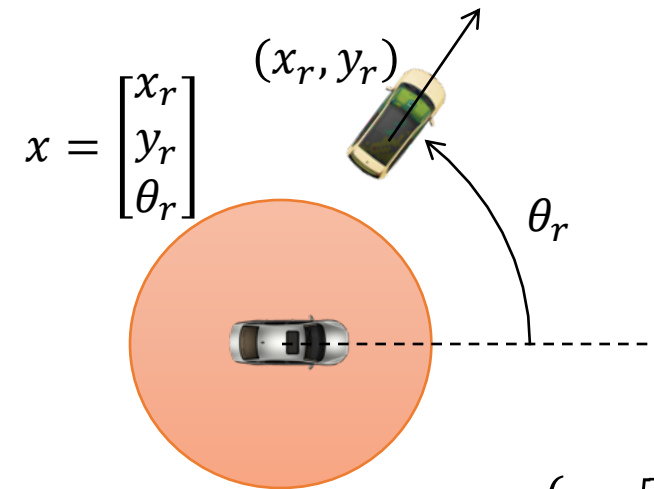


# Assumptions

- “Target set”,  $\mathcal{T}$ 
  - Can specify set of states leading to danger
  - Expressed through set notation



$$\mathcal{T} = \left\{ x: \sqrt{(x_1 - \bar{x})^2 + (y_1 - \bar{y})^2} \leq r \right\} \subseteq \mathbb{R}^3$$

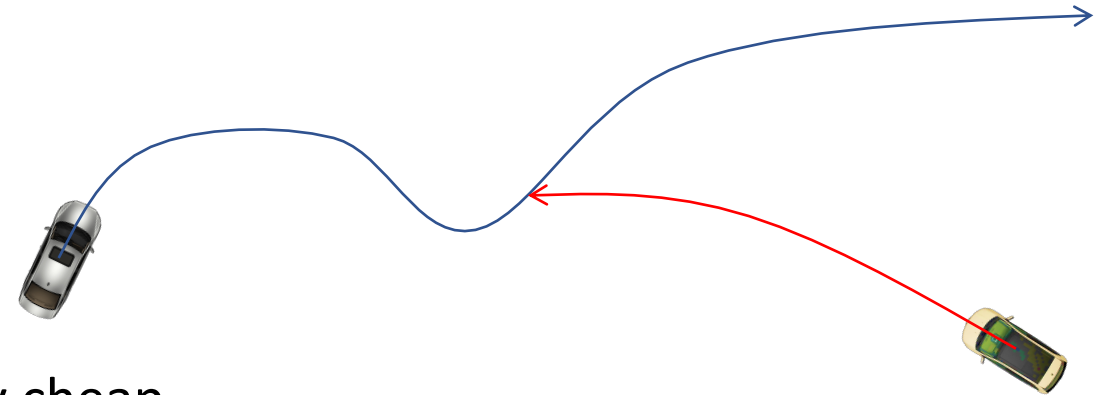


$$\mathcal{T} = \left\{ x: \sqrt{x_r^2 + y_r^2} \leq R \right\} \subseteq \mathbb{R}^3$$

# Information Pattern



- Control: chosen by “ego” robot
- Disturbances: chosen by other robot (or weather gods)
  - Assume worst case
- “Open-loop” strategies
  - Ego robot declares entire plan
  - Other robot responds optimally (worst-case)
  - Conservative, unrealistic, but computationally cheap
- “Non-anticipative” strategies
  - Other robot acts based on state and control trajectory up current time
  - Notation:  $d(\cdot) = \Gamma[u](\cdot)$
  - Disturbance still has the advantage: it gets to react to the control!



# Reachability Analysis

- Model of robot
- Unsafe region



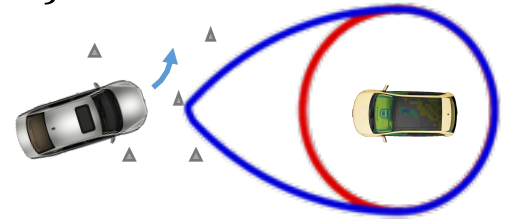
$$\mathcal{A}(t) = \{\bar{x} : \exists \Gamma[u](\cdot), \forall u(\cdot), \dot{x} = f(x, u, d), x(t) = \bar{x}, x(0) \in \mathcal{T}\}$$

Backward reachable set (States leading to danger)

Control policy

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

$$u^*(t, x)$$



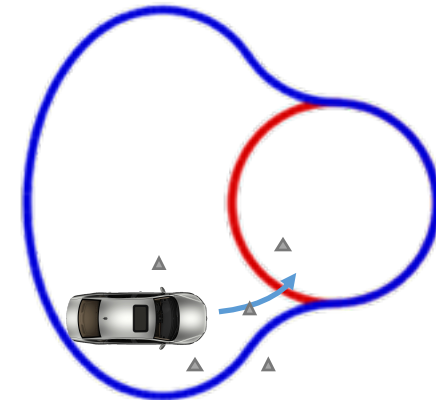
- Model of robot
- Goal region



Control policy

Backward reachable set (States leading to goal)

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



# Reachability Analysis

States at time  $t$  satisfying the following:

there exists a disturbance such that for all control, system enters target set at  $t = 0$

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

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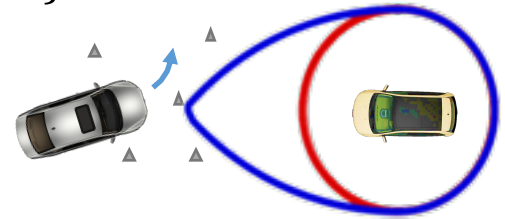


Backward reachable set (States leading to danger)

Control policy

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

$$u^*(t, x)$$



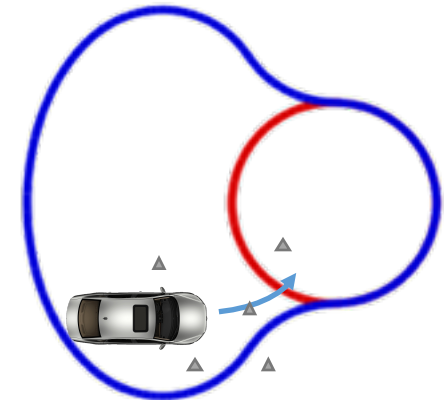
- Model of robot
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Control policy

Backward reachable set (States leading to goal)

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States at time  $t$  satisfying the following:

for all disturbances, there exists a control such that system enters target set at  $t = 0$

# Computing Reachable Sets: Hamilton-Jacobi Approach

- **Start from continuous time dynamic programming**
- Observe that disturbances do not affect the procedure
- Remove running cost
- Pick final cost intelligently

# Dynamic Programming: Continuous Time

$$\begin{aligned} & \text{minimize}_{u(\cdot)} \underbrace{l(T, x(T))}_{\text{Final cost}} + \underbrace{\int_0^T c(x(t), u(t)) dt}_{\text{Running cost}} \\ & \text{subject to } \dot{x}(t) = f(x(t), u(t)) \end{aligned}$$

Cost functional,  $J(x(\cdot), u(\cdot))$

Dynamic model

$$x(t) \in \mathbb{R}^n, u(t) \in \mathbb{R}^m, x(0) = x_0$$

- Let  $J(t, x(t)) = l(T, x(T)) + \int_t^T c(x(t), u(t)) dt$ 
  - $V(0, x(0)) = \min_{u(\cdot)} J(0, x(0))$  is what we want
- Strategy:
  - make a “discrete time” argument with  $\Delta t$
  - Let  $\Delta t \rightarrow 0$

# Dynamic Programming: Continuous Time

- Let  $J(t, x(t)) = \int_t^T c(x(s), u(s)) ds + l(x(T))$  "Cost to go"

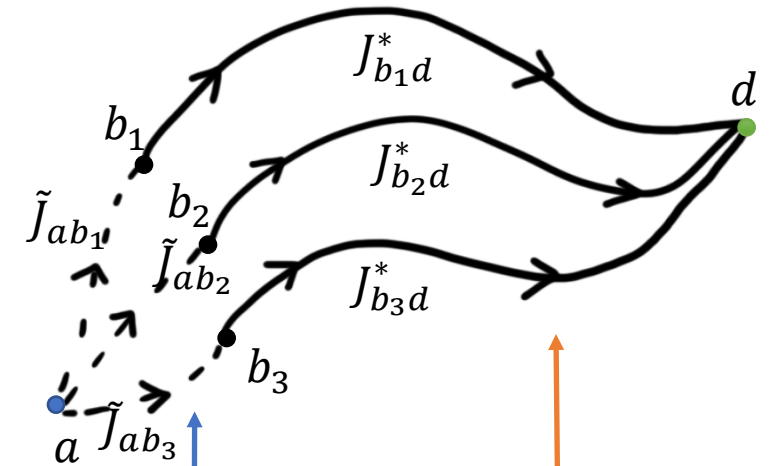
$$V(t, x(t)) = \min_{u_{[t,T]}(\cdot)} \left[ \int_t^T c(x(s), u(s)) ds + l(x(T)) \right]$$

"Value function", " $J^*(t, x(t))$ "

Write out time interval explicitly for clarity

- Dynamic programming principle:

$$V(t, x(t)) = \min_{u_{[t,t+\delta]}(\cdot)} \left[ \underbrace{\int_t^{t+\delta} c(x(s), u(s)) ds}_{\text{cost over } \delta} + \underbrace{V(t + \delta, x(t + \delta))}_{\text{value at } t+\delta} \right]$$



- Approximate integral and Taylor expand  $V(t + \delta, x(t + \delta))$
- Derive Hamilton-Jacobi partial differential equation (HJ PDE)

# Dynamic Programming: Continuous Time

- Approximations for small  $\delta$ :

$$V(t, x(t)) = \min_{u_{[t, t+\delta]}(\cdot)} \left[ \underbrace{\int_t^{t+\delta} c(x(s), u(s)) ds}_{c(x(t), u(t))\delta} + \underbrace{V(t + \delta, \overbrace{x(t + \delta)}^{x(t) + \delta f(x, u)})}_{V(t, x(t)) + \left(\frac{\partial V}{\partial x}\right)^\top \delta f(x(t), u(t)) + \frac{\partial V}{\partial t} \delta} \right]$$

- Omit  $t$  dependence...

$$V(t, x) = \min_u \left[ c(x, u)\delta + V(t, x) + \left(\frac{\partial V}{\partial x}\right)^\top \delta f(x, u) + \frac{\partial V}{\partial t} \delta \right]$$

Assume constant  $u_{[t, t+\delta]}$  → Optimization over a vector, not a function!

- $V(t, x)$  does not depend on  $u$

$$V(t, x) = V(t, x) + \min_u \left[ c(x, u)\delta + \left(\frac{\partial V}{\partial x}\right)^\top \delta f(x, u) + \frac{\partial V}{\partial t} \delta \right]$$



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$$0 = \frac{\partial V}{\partial t} \delta + \min_u \left[ c(x, u)\delta + \left(\frac{\partial V}{\partial x}\right)^\top \delta f(x, u) \right]$$

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# Computing Reachable Sets: Hamilton-Jacobi Approach

- Start from continuous time dynamic programming
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# Dynamic Programming: Continuous Time (with disturbances and $T = 0$ )

- Let  $J(t, x(t)) = \int_t^0 c(x(s), u(s), d(s))ds + l(x(T))$  "Cost to go"

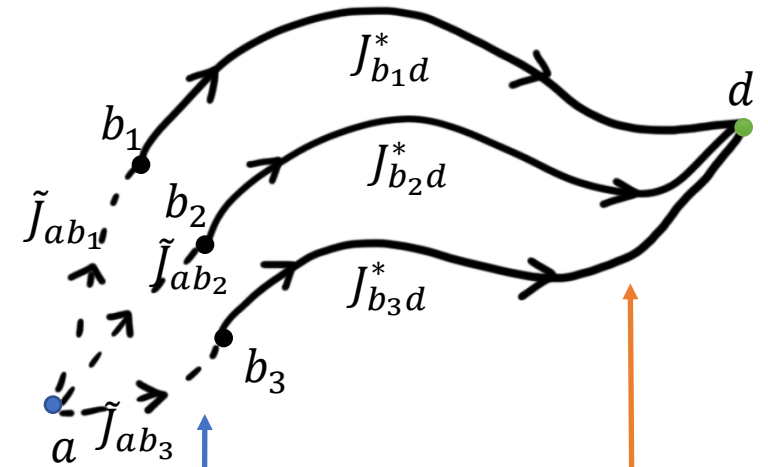
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Worst-case disturbance -- do the opposite of the control

- Dynamic programming principle:

$$V(t, x(t)) = \min_{\Gamma[u](\cdot)} \max_{u(\cdot)} \left[ \underbrace{\int_t^{t+\delta} c(x(s), u(s), d(s))ds}_{\text{blue bracket}} + \underbrace{V(t + \delta, x(t + \delta))}_{\text{orange bracket}} \right]$$

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$$V(t, x) = \max_u \min_d \left[ c(x, u, d)\delta + V(t, x) + \left( \frac{\partial V}{\partial x} \right)^\top \delta f(x, u, d) + \frac{\partial V}{\partial t} \delta \right]$$

- Assume constant  $u$  and  $d \rightarrow$  Optimization over vectors, not functions!
- Order of max and min reverse: disturbance has the advantage

- $V(t, x)$  does not depend on  $u$  or  $d$

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# Dynamic Programming: Continuous Time (with disturbances and $T = 0$ )

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# Computing Reachable Sets: Hamilton-Jacobi Approach

- Start from continuous time dynamic programming
- Observe that disturbances do not affect the procedure
- **Remove running cost**
- **Pick final cost intelligently**

# Remove Running Cost, Pick Final Cost

- Hamilton-Jacobi Equation

- $0 = \frac{\partial V}{\partial t} + \max_d \min_u \left[ c(x, u, d) + \left( \frac{\partial V}{\partial x} \right)^\top f(x, u, d) \right], \quad V(0, x) = l(x)$

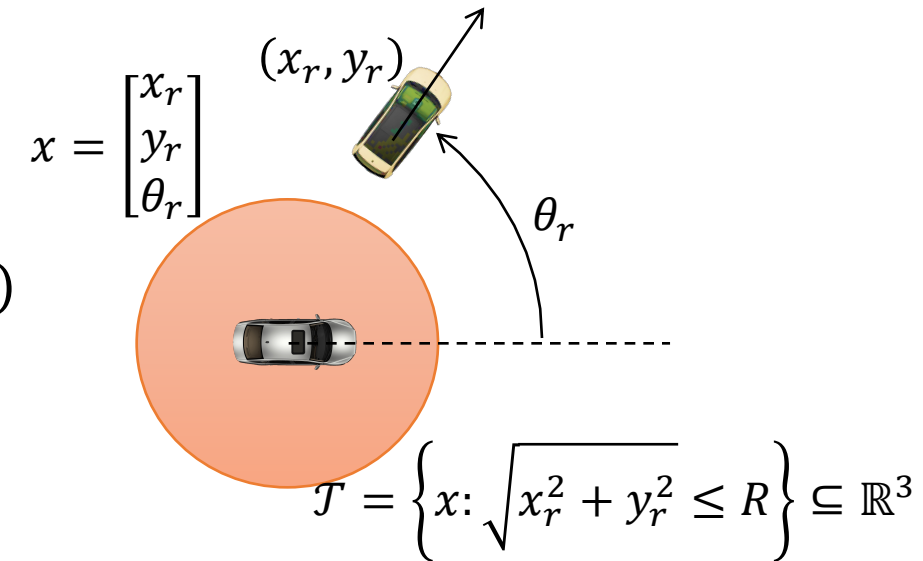
- Remove running cost

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- Pick final cost such that

- $x \in \mathcal{T} \Leftrightarrow l(x) \leq 0$

- Example: If  $\mathcal{T} = \left\{ x: \sqrt{x_r^2 + y_r^2} \leq R \right\} \subseteq \mathbb{R}^3$ , we can pick  $l(x_r, y_r, \theta_r) = \sqrt{x_r^2 + y_r^2} - R$



# Pick Final Cost

- Pick final cost such that

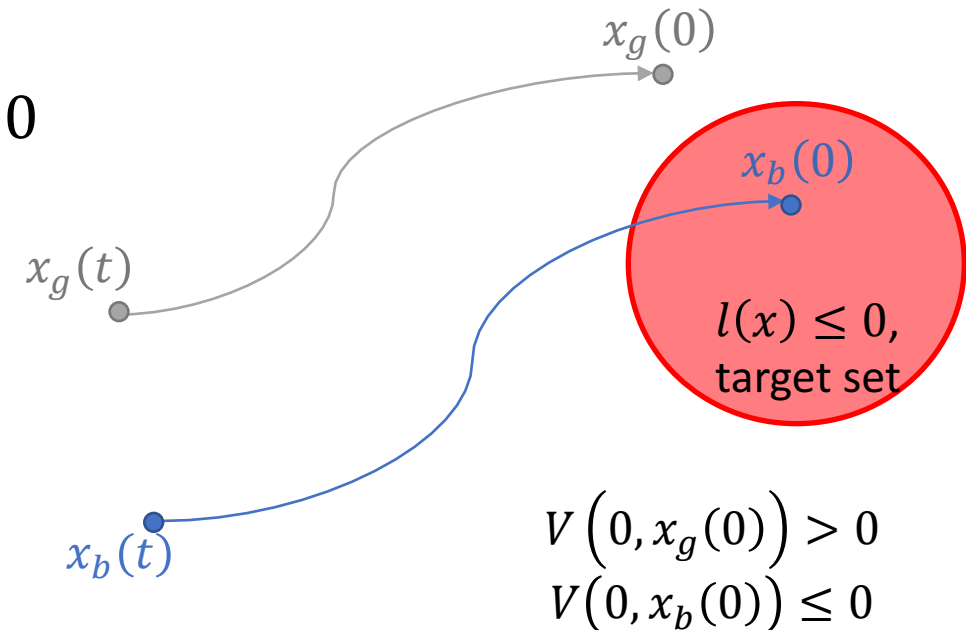
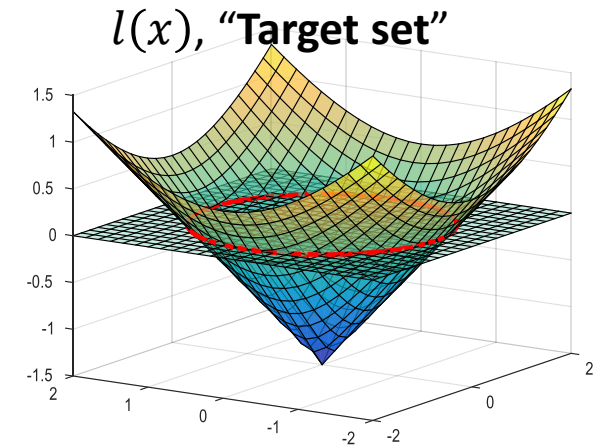
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- If  $\mathcal{T} = \{x: \sqrt{x_r^2 + y_r^2} \leq R\} \subseteq \mathbb{R}^3$ , we can pick  $l(x_r, y_r, \theta_r) = \sqrt{x_r^2 + y_r^2} - R$

- Why is this correct?

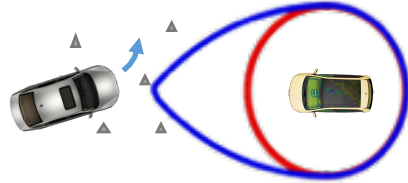
- Final state  $x(0)$  is in  $\mathcal{T}$  if and only if  $l(x(0)) \leq 0$
  - To avoid  $\mathcal{T}$ , control should maximize  $l(x(0))$ 
    - Worst-case disturbance would minimize

- $V(t, x) = \min_{\Gamma[u]} \max_u l(x(0))$



# Reaching vs. Avoiding

- Avoiding danger



- BRS definition

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

- Value function

$$V(t, x) = \min_{\Gamma[u]} \max_u l(x(0))$$

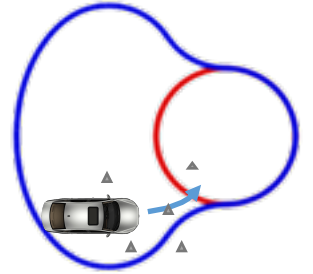
- HJ PDE

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

- Optimal control

$$u^* = \arg \max_u \min_d \left( \frac{\partial V}{\partial x} \right)^\top f(x, u, d)$$

- Reaching a goal



- BRS definition

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

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- Optimal control

$$u^* = \arg \min_u \max_d \left( \frac{\partial V}{\partial x} \right)^\top f(x, u, d)$$

# Optimal Control and Disturbance

- Example: Scalar control and disturbance affine system
  - Dynamics:  $\dot{x} = f(x) + \sum_i g_i(x)u_i + \sum_j h_j(x)d_j, x \in \mathbb{R}$
  - Control and disturbance constraints:  $u_i \in [\underline{u}_i, \bar{u}_i], d_j \in [\underline{d}_j, \bar{d}_j]$

$$\frac{\partial V}{\partial t} + \min_{\{u_i \in [\underline{u}_i, \bar{u}_i]\}} \max_{\{d_j \in [\underline{d}_j, \bar{d}_j]\}} \left[ \left( \frac{\partial V}{\partial x} \right)^\top f(x, u, d) \right] = 0$$

$$\frac{\partial V}{\partial t} + \min_{\{u_i \in [\underline{u}_i, \bar{u}_i]\}} \max_{\{d_j \in [\underline{d}_j, \bar{d}_j]\}} \left[ \frac{\partial V}{\partial x} \left( f(x) + \sum_i g_i(x)u_i + \sum_j h_j(x)d_j \right) \right] = 0$$

$$\frac{\partial V}{\partial t} + \min_{\{u_i \in [\underline{u}_i, \bar{u}_i]\}} \max_{\{d_j \in [\underline{d}_j, \bar{d}_j]\}} \left[ \frac{\partial V}{\partial x} f(x) + \sum_i \frac{\partial V}{\partial x} g_i(x)u_i + \sum_j \frac{\partial V}{\partial x} h_j(x)d_j \right] = 0$$

$$u_i = \begin{cases} \underline{u}_i, & \frac{\partial V}{\partial x} g_i(x) \geq 0 \\ \bar{u}_i, & \frac{\partial V}{\partial x} g_i(x) < 0 \end{cases}$$

$$d_j = \begin{cases} \underline{d}_j, & \frac{\partial V}{\partial x} h_j(x) < 0 \\ \bar{d}_j, & \frac{\partial V}{\partial x} h_j(x) \geq 0 \end{cases}$$

# Optimal Control and Disturbance

- Easy to compute for many common types of control and disturbance constraints
- Interval constraints: easy -- see last slide
- Polytopic constraints: easy -- test all vertices
- Other: ideally, need analytic expression
  - Optimization needs to be done at every grid point!

$$\text{Eg. } \frac{\partial V}{\partial t} + \min_u \max_d \left[ \left( \frac{\partial V}{\partial x} \right)^\top f(x, u, d) \right] = 0$$

# Terminology

- Minimal backward reachable set
  - $\mathcal{A}(t) = \{\bar{x}: \exists \Gamma[u](\cdot), \forall u(\cdot), \dot{x} = f(x, u, d), x(t) = \bar{x}, x(0) \in \mathcal{T}\}$
  - Control minimizes size of reachable set
- Maximal backward reachable set
  - $\mathcal{R}(t) = \{\bar{x}: \forall \Gamma[u](\cdot), \exists u(\cdot), \dot{x} = f(x, u, d), x(t) = \bar{x}, x(0) \in \mathcal{T}\}$
  - Control maximizes size of reachable set
- Minimal and maximal backward reachable tube
  - $\bar{\mathcal{A}}(t) = \{\bar{x}: \exists \Gamma[u](\cdot), \forall u(\cdot), \dot{x} = f(x, u, d), x(t) = \bar{x}, \exists s \in [t, 0], x(s) \in \mathcal{T}\}$
  - $\bar{\mathcal{R}}(t) = \{\bar{x}: \forall \Gamma[u](\cdot), \exists u(\cdot), \dot{x} = f(x, u, d), x(t) = \bar{x}, \exists s \in [t, 0], x(s) \in \mathcal{T}\}$

