

# An Introduction to Control Barrier Function

Theory and Application

Bolun Dai

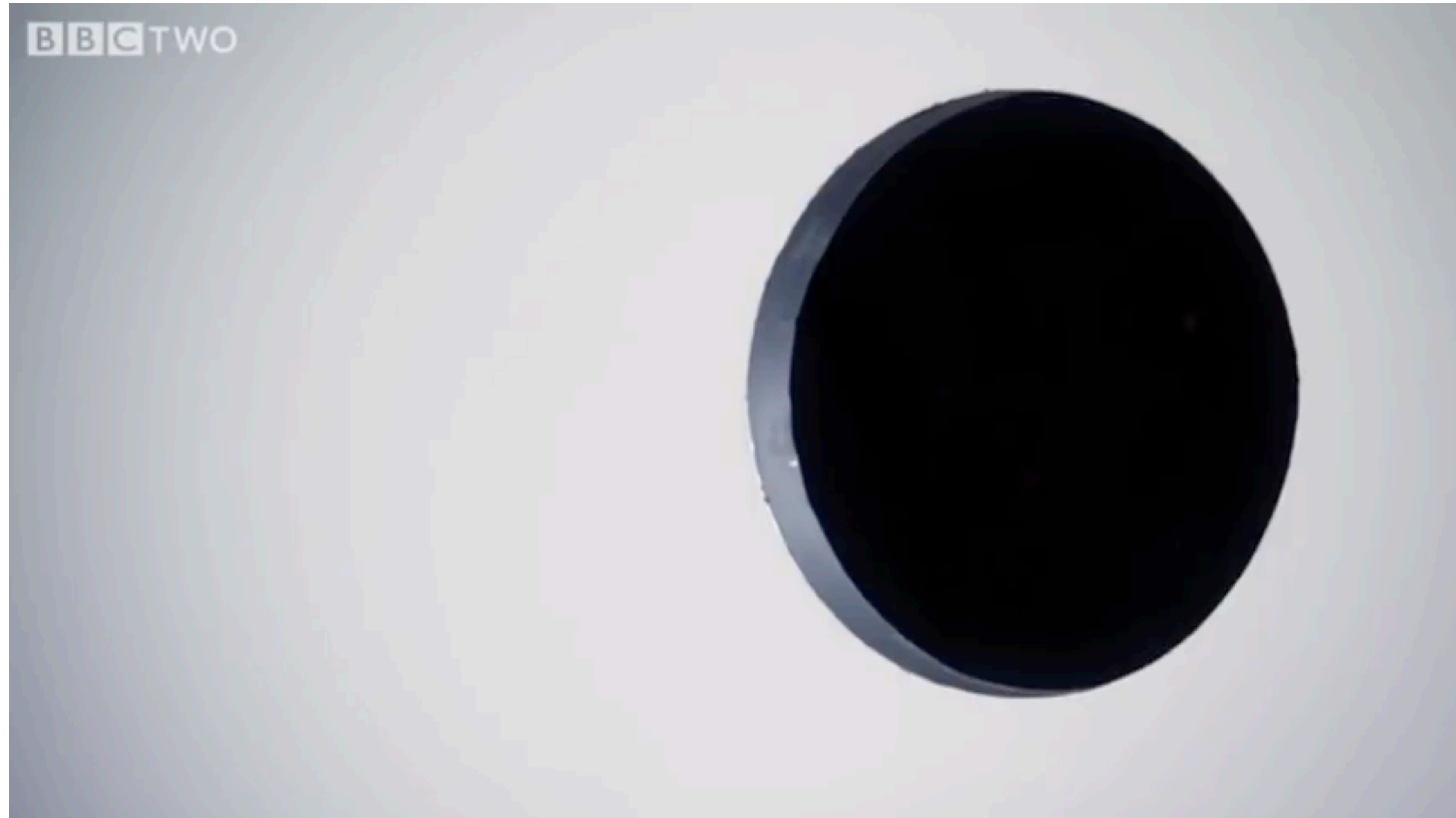
# Motivation

## Safe Control



# Motivation

## Agile Behavior Under Constraints



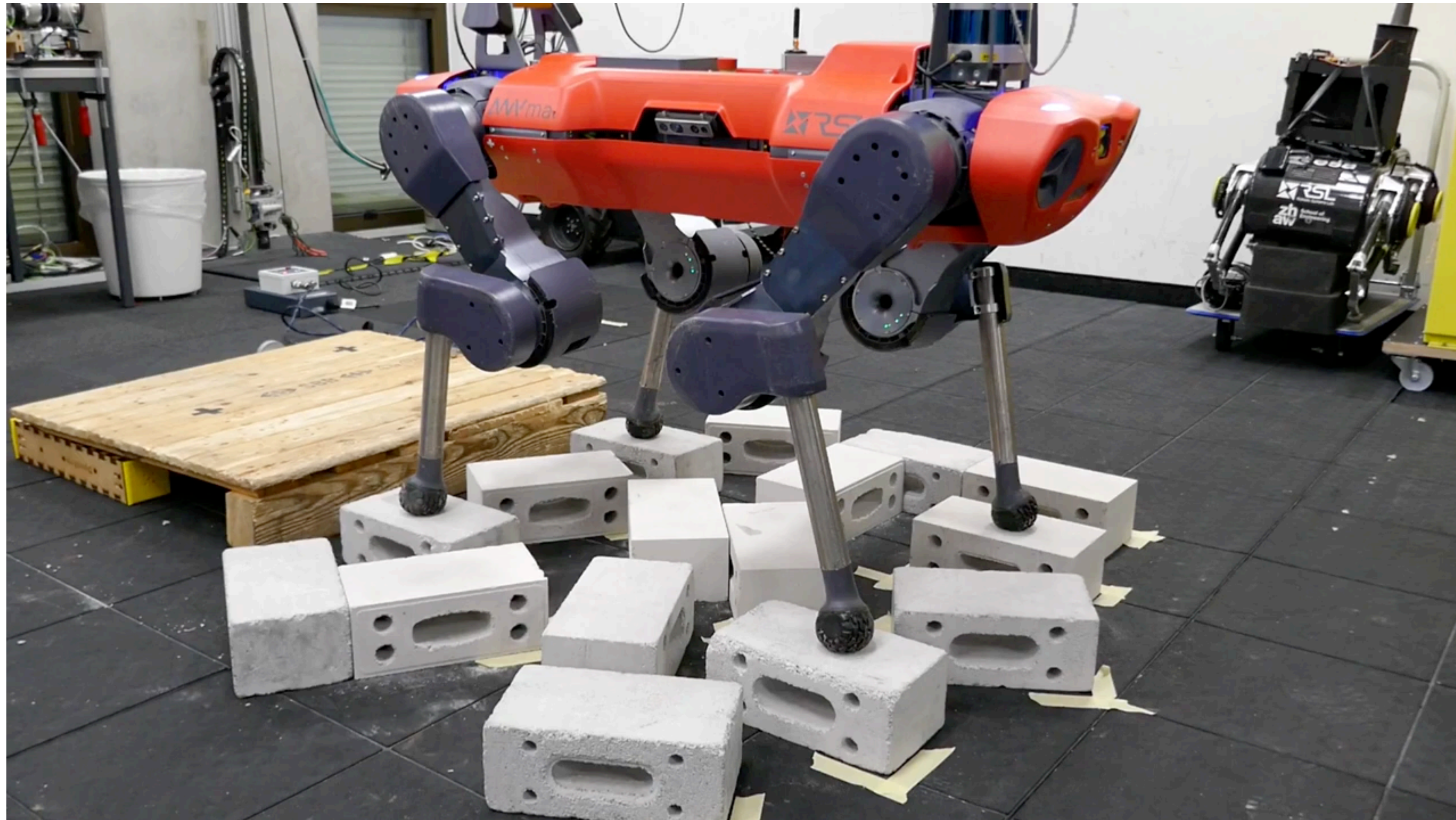
# Applications

## Bipedal Locomotion



# Applications

## Quadruped Locomotion



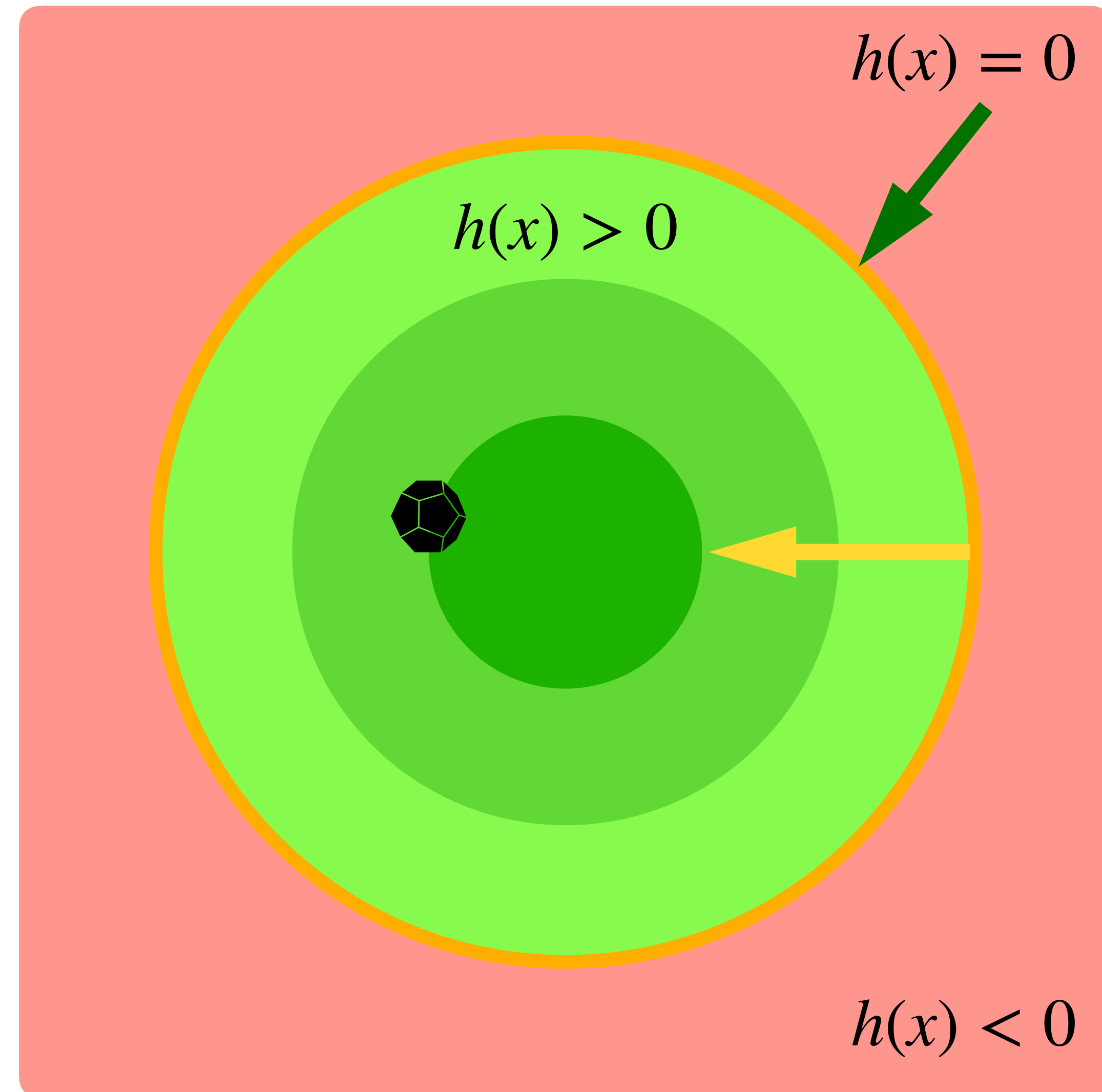
# Structure of this talk

- Control Barrier Function (CBF)
- CLF-CBF-QP
- CBF Example
- Exponential Control Barrier Function (ECBF)
- ECBF Example
- CBF Research

# Control Barrier Function (CBF)

## Nagumo's Invariance Principle

- $\mathcal{C} = \{x \in \mathbb{R}^n \mid h \geq 0\}$
- $\dot{h}(x) \geq 0, \forall x \in \partial\mathcal{C}$



# Control Barrier Function (CBF)

## Nagumo's Invariance Principle

- Given a dynamical system  $\dot{x} = f(x)$  with  $x \in \mathbb{R}^n$ , and assume that the safe set  $\mathcal{C}$  is the superlevel set of a smooth function  $h : \mathbb{R}^n \rightarrow \mathbb{R}$ ,

$$\mathcal{C} = \{x \in \mathbb{R}^n \mid h \geq 0\}$$

- then  $\mathcal{C}$  is forward invariant if and only if  $\dot{h}(x) \geq 0$  for all  $x \in \partial\mathcal{C}$ .



# Control Barrier Function (CBF)

## Control Affine Systems

- Control affine systems have the form of

$$\dot{\mathbf{x}} = f(\mathbf{x}) + g(\mathbf{x})\mathbf{u}$$

- where  $\mathbf{x} \in \mathbb{R}^n$ ,  $f: \mathbb{R}^n \rightarrow \mathbb{R}^n$ ,  $g: \mathbb{R}^n \rightarrow \mathbb{R}^{n \times m}$  and  $\mathbf{u} \in \mathbb{R}^m$ . Control affine systems are very common, most mechanical systems are control affine

$$\begin{bmatrix} \dot{\mathbf{q}} \\ \ddot{\mathbf{q}} \end{bmatrix} = \begin{bmatrix} \dot{\mathbf{q}} \\ M^{-1}(C\dot{\mathbf{q}} + G) \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ M^{-1} \end{bmatrix} \mathbf{u}$$

# Control Barrier Function (CBF)

## Control Barrier Function

- For control affine systems  $\dot{\mathbf{x}} = f(\mathbf{x}) + g(\mathbf{x})\mathbf{u}$ , we have

$$\dot{h}(x) = \frac{\partial h(x)}{\partial x} \dot{x} = \frac{\partial h(x)}{\partial x} (f(x) + g(x)u) = L_f h(x) + L_g h(x)u$$

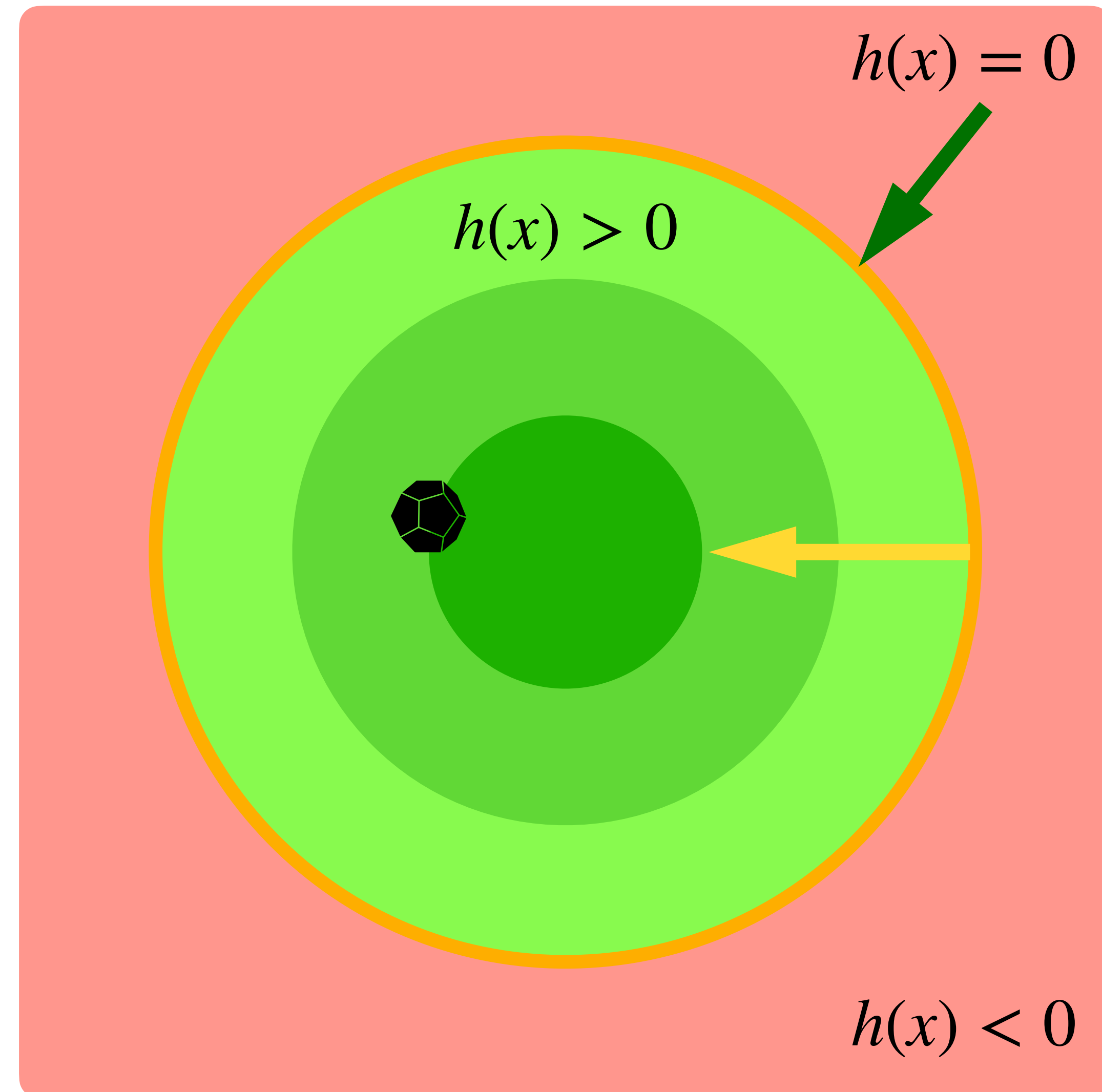
- which can be written using Lie derivatives

$$L_f h(x) = \frac{\partial h(x)}{\partial x} f(x), \quad L_g h(x) = \frac{\partial h(x)}{\partial x} g(x)$$

# Control Barrier Function (CBF)

Finding a control constraint using  $h(x)$

- What are the issues of using  $\dot{h}(x) \geq 0, \forall x \in \partial\mathcal{C}$  as a control constraint?
  - Abrupt behavior at the boundary, large control action.
- What are the issues of using  $h(x) \geq 0, \forall x \in \mathcal{C}$ ?
  - Too restrictive.



# Control Barrier Function (CBF)

## CBF Constraint

- For safe control, we can define a safe set  $\mathcal{C}$ , such that for a function  $h(\mathbf{x})$  it is always positive

$$\mathcal{C} = \{\mathbf{x} \mid h(\mathbf{x}) \geq 0\}$$

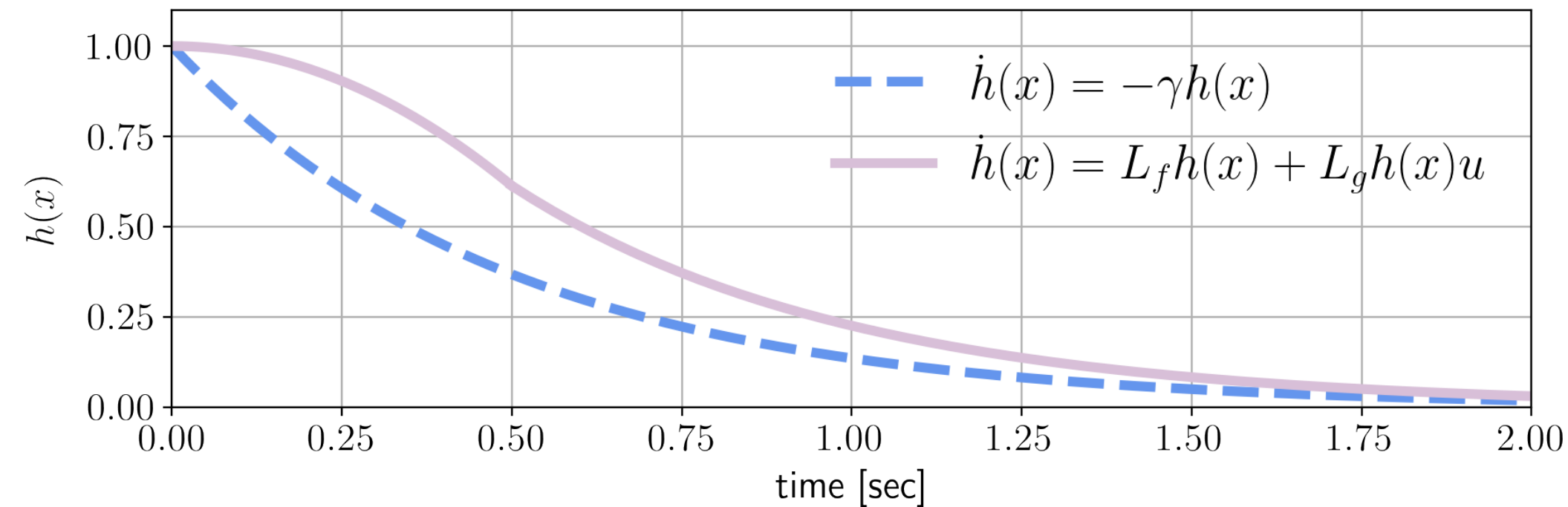
- If we can find a control  $\mathbf{u}$ , such that the safe set  $\mathcal{C}$  is forward invariant, we then have a valid CBF. This condition can be expressed using the inequality

$$\frac{\partial h}{\partial \mathbf{x}} \dot{\mathbf{x}} + \alpha(h(\mathbf{x})) = L_f h(\mathbf{x}) + L_g h(\mathbf{x}) \mathbf{u} + \alpha(h(\mathbf{x})) \geq 0$$

- The function  $\alpha(\cdot)$  is a class  $\mathcal{K}_\infty$  function.

# Control Barrier Function (CBF)

## CBF Constraint — Analogy to MTA

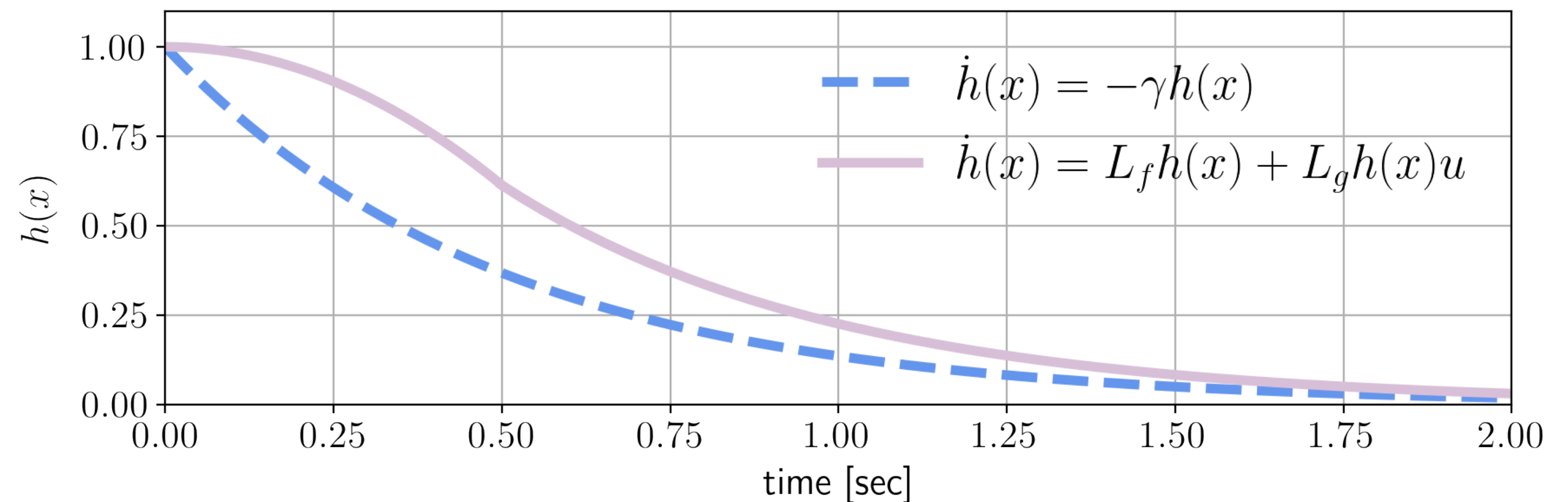


- You want to go to WSQ by taking either **A** or **C** train.
- **A** train is faster or equal to **C** train between each stop. (Assumption)
- If they start from **Jay St** at the same time, if **A** never reaches **West 4th**, **C** will never reach **West 4th**.
- If **C** reached **West 4th** then **A** definitely already reached **West 4th**.

# Control Barrier Function (CBF)

## CBF Constraint

- $L_f h(\mathbf{x}) + L_g h(\mathbf{x})\mathbf{u} \geq -\gamma h(\mathbf{x})$



- Assume that we have two functions:

$$\dot{h}(x) = -\gamma h(x) \text{ and } \dot{\bar{h}}(x) \geq -\gamma \bar{h}(x), \text{ and further we assume that } \bar{h}(x_0) = h(x_0)$$

$$\bar{h}(x_1) = \bar{h}(x_0) + \dot{\bar{h}}(x_0)dt \geq h(x_0) + \dot{h}(x_0)dt = h(x_1)$$

- Then it can be concluded that since  $\bar{h}(x) \geq h(x)$ , and  $h(x) = 0$  as time goes to infinity, we have  $\bar{h}(x) \geq 0$ .

# CLF-CBF-QP

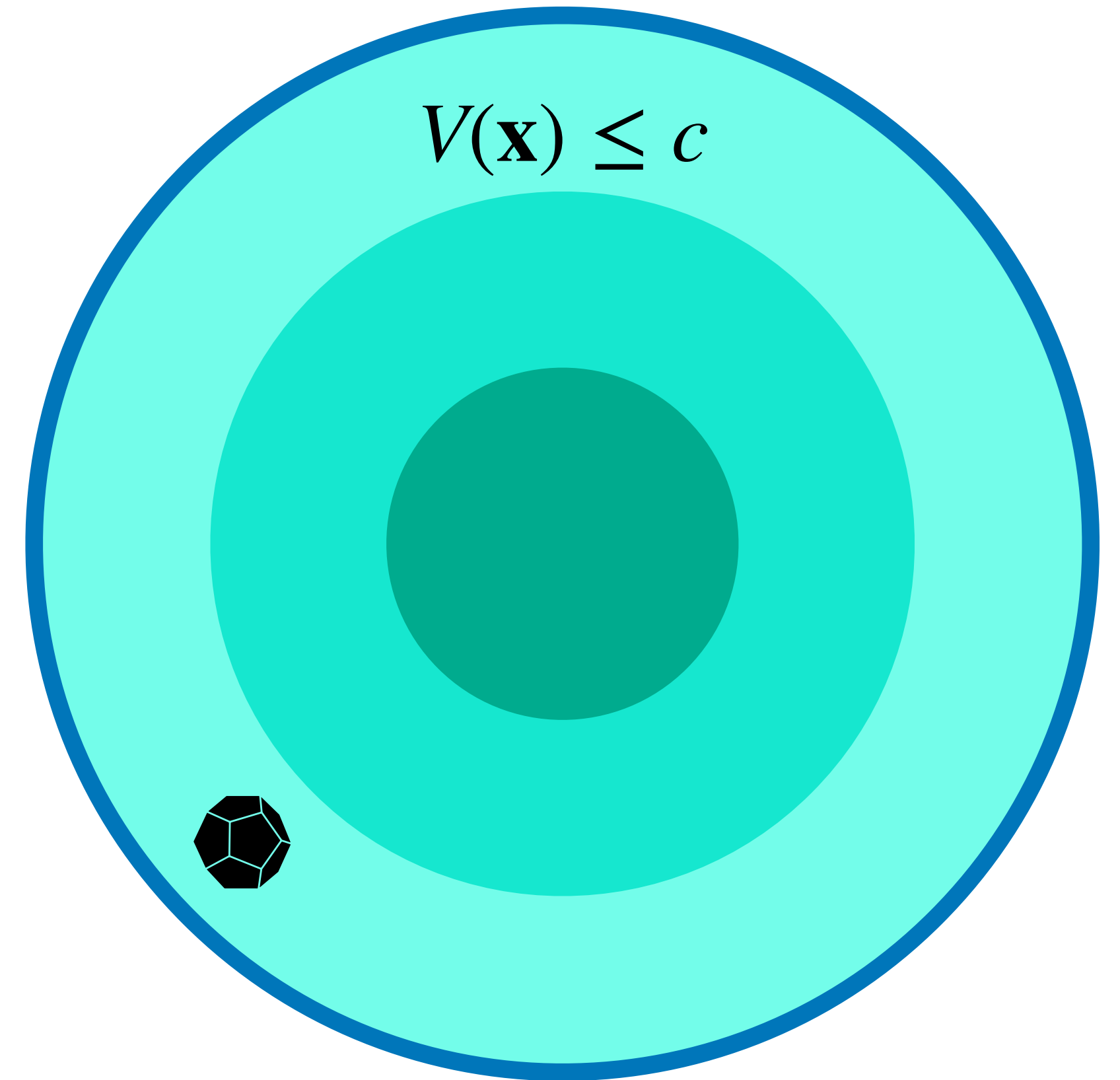
## Control Lyapunov Function (CLF)

- So far we have been looking at how to perform safe control. Another important quality a controller should possess is stability, i.e. the ability to drive a system from a nonzero state to a region around the origin and stay there.
- And similar to the concept of CBF, if there exist a CLF then the system is stable. A CLF is usually denoted using  $V(\mathbf{x})$ .

# CLF-CBF-QP

## Control Lyapunov Function (CLF)

- Some requirements for  $V(\mathbf{x})$ 
  - $\Omega_c := \{\mathbf{x} \in \mathbb{R}^n \mid V(\mathbf{x}) \leq c\}$  is a sub-level set of  $V(\mathbf{x})$
  - $V(\mathbf{x}) > 0, \forall \mathbf{x} \neq \mathbf{0}$ , and  $V(\mathbf{0}) = 0$
  - $\dot{V}(\mathbf{x}) \leq 0, \forall \mathbf{x} \in \Omega_c \setminus \{\mathbf{0}\}$
- Then we say  $V(\mathbf{x})$  is a local control Lyapunov function, and its region of attraction (ROA) is  $\Omega_c$ . And all of the states within its ROA can be asymptotically stabilized to  $\mathbf{0}$



$$\forall x_0 \in \Omega_c, \exists u(t), \text{ s.t. } \lim_{t \rightarrow \infty} x(t) = \mathbf{0}$$



# CLF-CBF-QP

## Control Lyapunov Function (CLF)

- Usually we want something faster than asymptotic stability, which is exponential stability.
- This can be achieved by enforcing the following constraint

$$\dot{V}(\mathbf{x}, \mathbf{u}) + \lambda V(\mathbf{x}) \leq 0$$

- Basically, this is saying that we want the CLF to decay faster than an exponential.

# CLF-CBF-QP

## QP Formulation

- Here  $\delta$  is a slack variable that relaxes the CLF constraint

$$\min_{\mathbf{u}, \delta} \mathbf{u}^T R \mathbf{u} + p \delta^2$$

subject to  $\mathbf{u} \in \mathcal{U}$

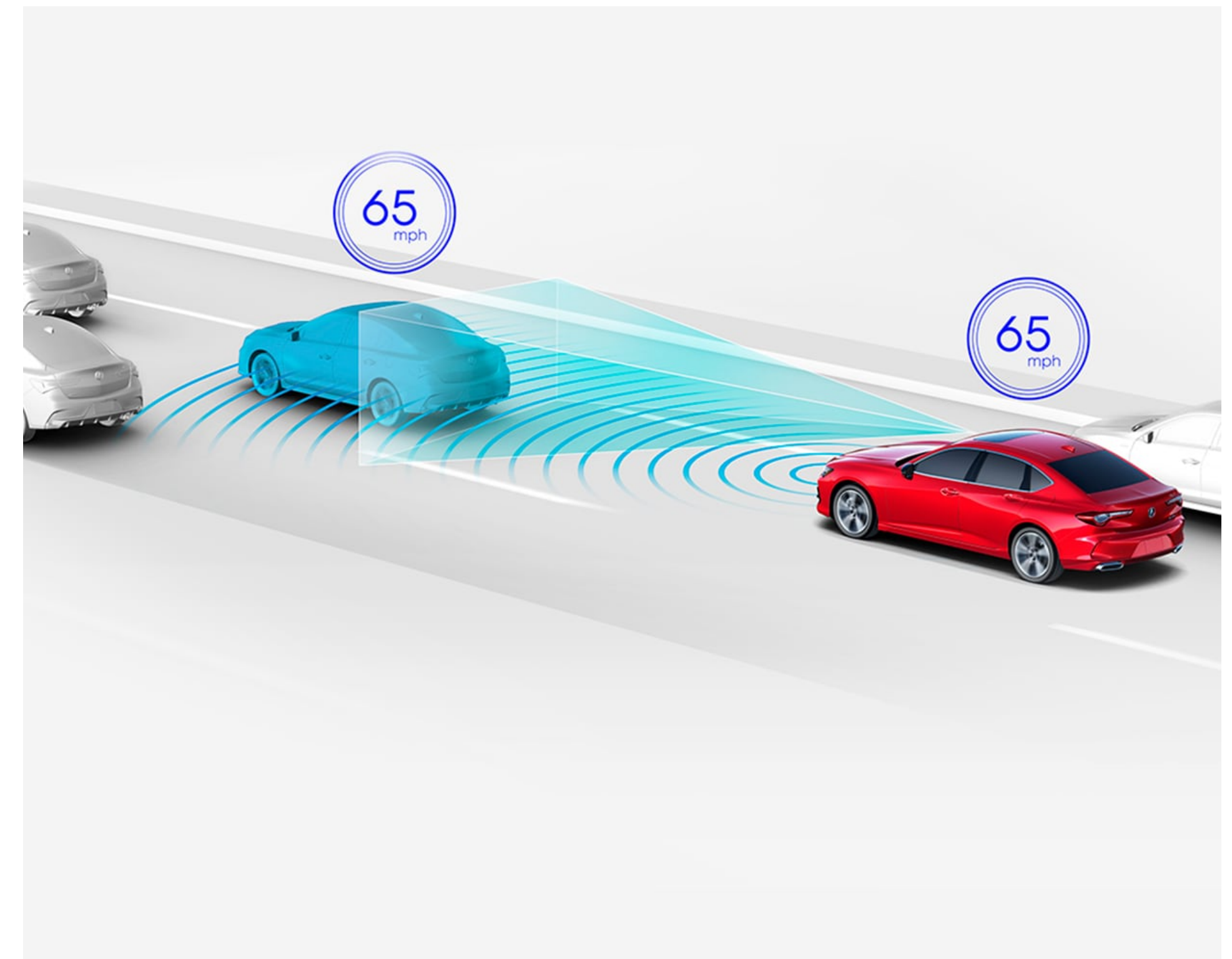
$$L_f h(\mathbf{x}) + L_g h(\mathbf{x}) \mathbf{u} + \gamma h(\mathbf{x}) \geq 0$$

$$L_f V(\mathbf{x}) + L_g V(\mathbf{x}) \mathbf{u} + \lambda V(\mathbf{x}) \leq \delta$$

# CBF Example

## Adaptive Cruise Control

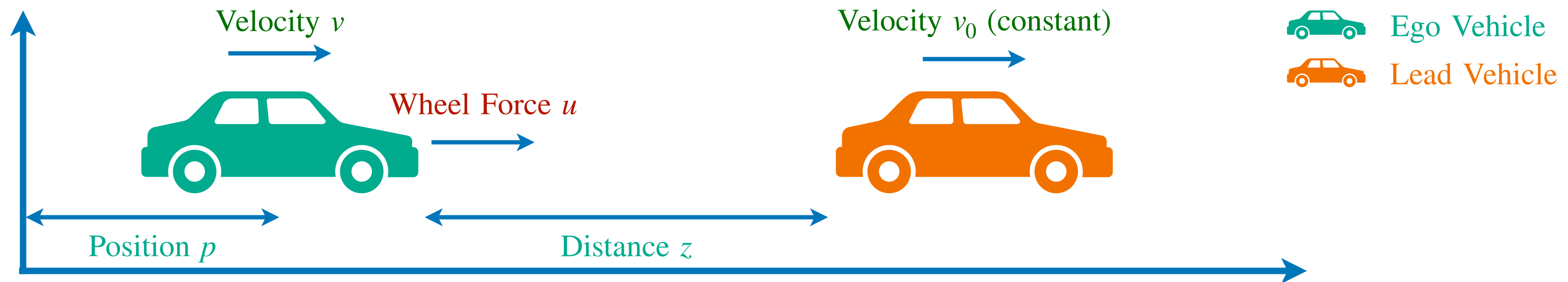
- Maintain a desired velocity while also keeping a safe distance with the leading vehicle.
- This example is borrowed from Jason Choi's guest lecture at UCSD.



<https://www.acura.com/tlx/modals/adaptive-cruise-control-with-low-speed-follow>

# CBF Example

## Adaptive Cruise Control — Problem Setup



- Dynamics:

$$\begin{bmatrix} \dot{p} \\ \dot{v} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} v \\ -\frac{1}{m}F_r(v) \\ v_0 - v \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m} \\ 0 \end{bmatrix} u$$

- $F_r(v) = f_0 + f_1v + f_2v^2$  is the rolling resistance

- Input constraints:  $-mc_dg \leq u \leq mc_dg$

- Stability Objective:  $v \rightarrow v_d$  ( $v_d$ : desired velocity)

- Safety Objective:  $z \geq T_h v$  ( $T_h$ : lookahead time)

# CBF Example

## Adaptive Cruise Control — Formulate CBF for $z \geq T_h v$

- One obvious choice of the CBF is  $h(\mathbf{x}) = z - T_h v$ , then we have the CBF constraint as

$$\dot{h}(\mathbf{x}, u) + \gamma h(\mathbf{x}) = \frac{T_h}{m}(F_r(v) - u) + (v_0 - v) + \gamma(z - T_h v) \geq 0$$

- If we neglect the effect of the rolling resistance and assuming we are applying the maximum force  $u = -c_d m g$ , we have

$$\dot{h}(\mathbf{x}, u) + \gamma h(\mathbf{x}) = T_h c_d g + v_0 - v + \gamma(z - T_h v) \geq 0$$

# CBF Example

Adaptive Cruise Control — Formulate CBF for  $z \geq T_h v$

$$\dot{h}(\mathbf{x}, u) + \gamma h(\mathbf{x}) = T_h c_d g + v_0 - v + \gamma(z - T_h v) \geq 0$$

- A CBF should be positive for all states in the safe set, which is defined by  $z \geq T_h v$ . We can see that the above function may be negative if  $v$  is large with respect to  $c_d$  and  $v_0$ .
- Note that the definition of the safe set did not specify an upper bound on the velocity  $v$ .
- The situation is when the distance  $z$  is larger than  $T_h v$ , but the vehicle cannot break to the same speed as the lead vehicle  $v_0$  before colliding.

# CBF Example

## Adaptive Cruise Control — Formulate CBF for $z \geq T_h v$

- A better choice of CBF is to incorporate the distance needed to slow down the vehicle to  $v_0$ , i.e. **distance  $>$  lookahead distance + distance to decelerate.**
- And under maximum deceleration, i.e.  $u = -c_d m g$ , we have the

$$\dot{h}(\mathbf{x}, u) = \frac{1}{m} T_h F_r(v) + T_h c_d g$$

- This value is always positive despite the choice of velocity  $v$ .

# CBF Example

## Adaptive Cruise Control — Parameters

```
dt = 0.02
sim_t = 20
x0 = [0, 20, 100]
```

```
params.v0 = 14
params.vd = 24
params.m = 1650
params.g = 9.81
params.f0 = 0.1
params.f1 = 5
params.f2 = 0.25
params.ca = 0.3
params.cd = 0.3
params.Th = 1.8
```

```
params.u_max = params.ca * params.m * params.g
params.u_min = -params.cd * params.m * params.g
```

```
params.clf.rate = 5 #  $\lambda$ 
params.cbf.rate = 5 #  $\gamma$ 
```

```
'''
```

Parameters are from

[https://github.com/HybridRobotics/CBF-CLF-Helper/  
blob/master/demos/run\\_cbf\\_clf\\_simulation\\_acc.m](https://github.com/HybridRobotics/CBF-CLF-Helper/blob/master/demos/run_cbf_clf_simulation_acc.m)

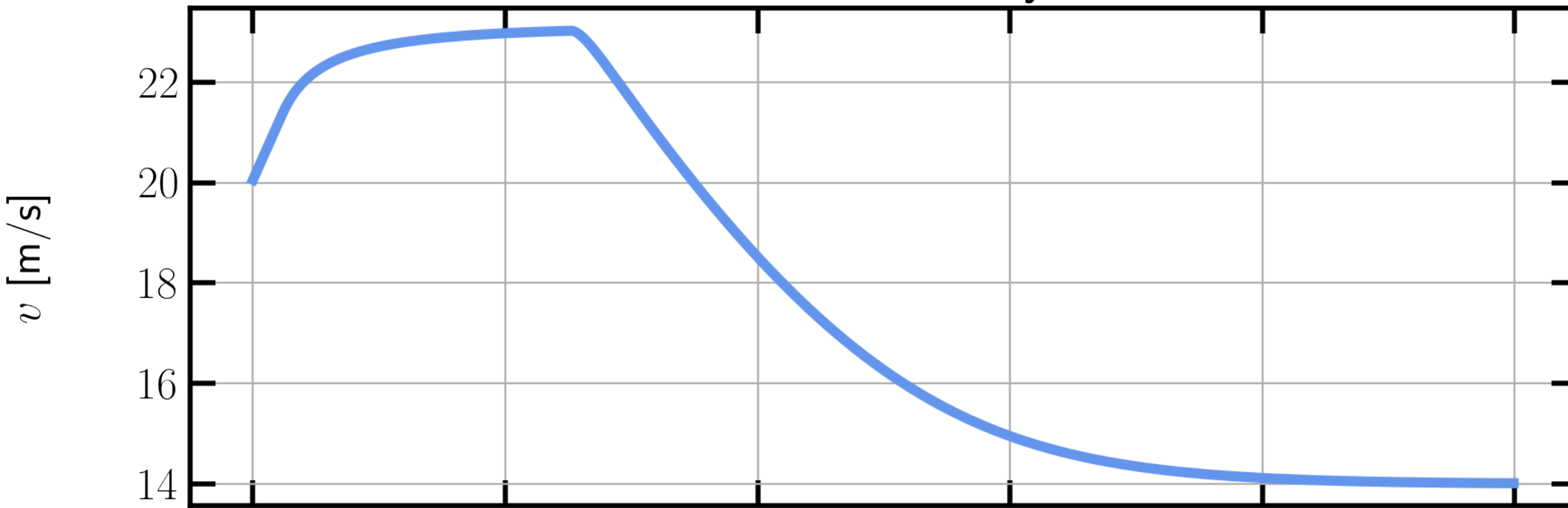
```
'''
```



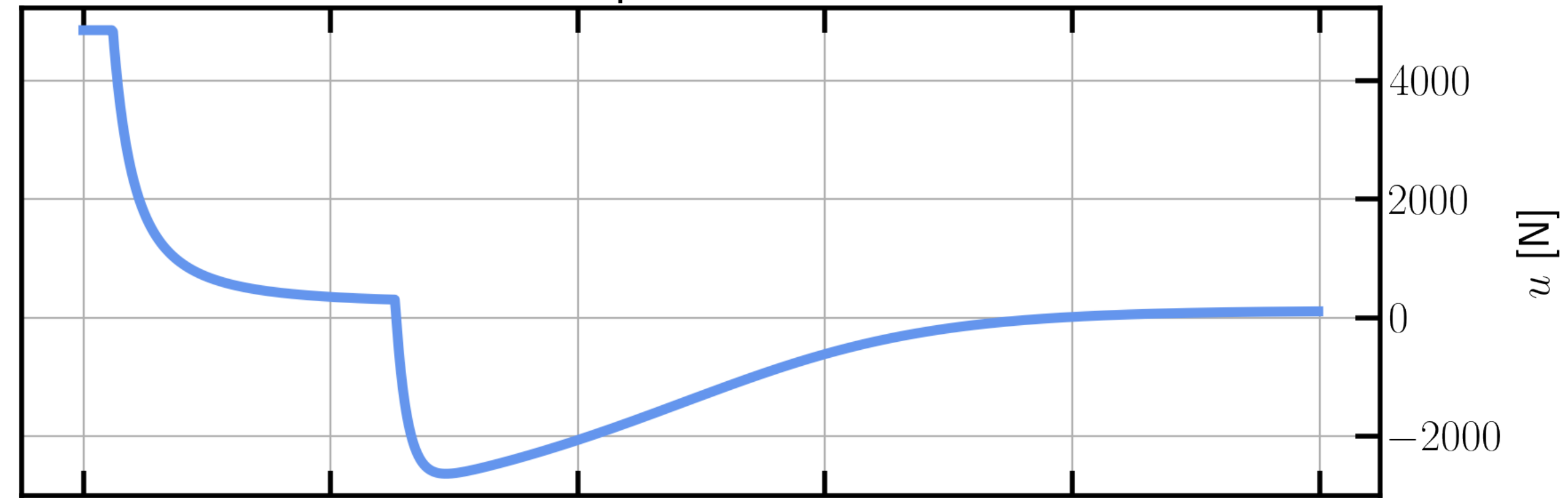
# CBF Example

## Results

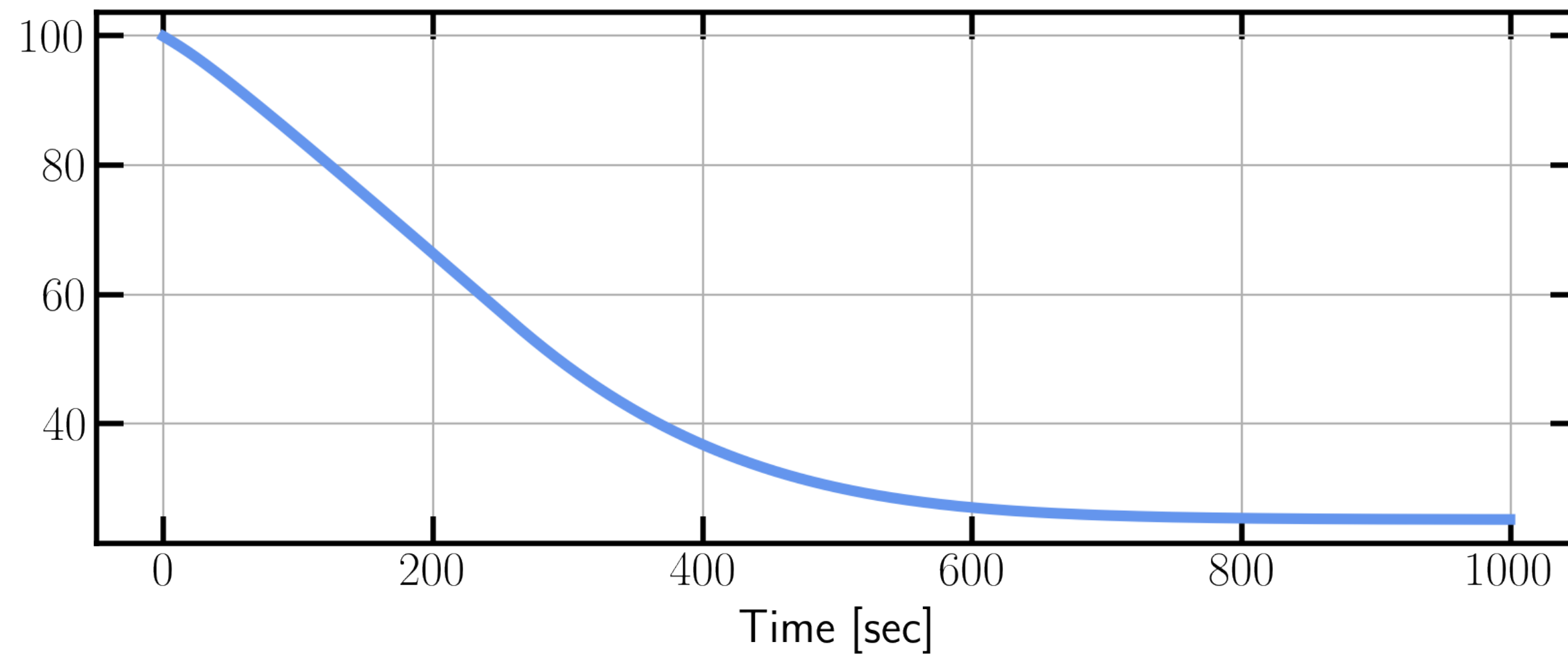
State - Velocity



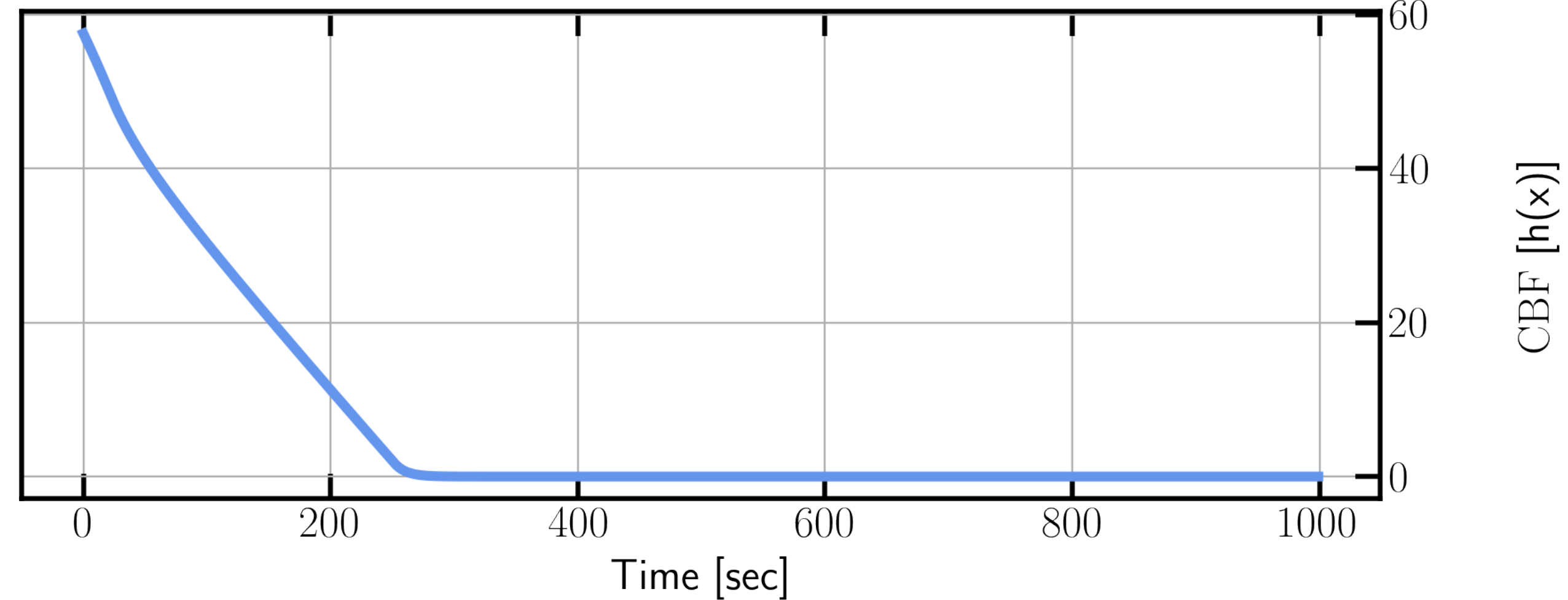
Control Input - Wheel Force



State - Distance to Lead Vehicle



CBF



# Exponential Control Barrier Function (ECBF)

## Motivation

- When writing the CBF constraint in the form of

$$L_f h(\mathbf{x}) + L_g h(\mathbf{x})\mathbf{u} + \alpha(h(\mathbf{x})) \geq 0$$

we need the derivative of the CBF  $\dot{\mathbf{x}}$  to be a function of the control  $\mathbf{u}$

- This might not always be the case, the most simple example is the double integrator system  $\ddot{\mathbf{x}} = \mathbf{u}$ , which can be seen as a point mass with acceleration control.

# Exponential Control Barrier Function (ECBF)

## Motivation — Double Integrator System

- Let us revisit what the CBF constraint does:
  - For a safe set  $\mathcal{C} = \{\mathbf{x} \mid h(\mathbf{x}) \geq 0\}$ , if we find the controls that satisfies

$$L_f h(\mathbf{x}) + \alpha(h(\mathbf{x})) \geq 0$$

then we can ensure that the double integrator system never exits the safe set.

- If we define  $d(\mathbf{x}) = L_f h(\mathbf{x}) + \alpha(h(\mathbf{x}))$ , then we can also have

$$d(\mathbf{x}) \geq 0$$

# Exponential Control Barrier Function (ECBF)

## Motivation — Double Integrator System

- We can view  $d(\mathbf{x})$  as the new CBF, since we can have the relationship

$$d(\mathbf{x}) \geq 0 \rightarrow h(\mathbf{x}) \geq 0$$

- This means that if we can find a control that ensures  $d(\mathbf{x}) \geq 0$ , then we can also ensure that  $h(\mathbf{x}) \geq 0$ .
- We can see  $d(\mathbf{x})$  as the new CBF and do what we did for CBFs with relative degree one using another class  $\mathcal{K}_\infty$  function  $\beta(\cdot)$

$$\dot{d}(\mathbf{x}) + \beta(d(\mathbf{x})) \geq 0 \rightarrow d(\mathbf{x}) \geq 0 \rightarrow h(\mathbf{x}) \geq 0$$

# Exponential Control Barrier Function (ECBF)

## Motivation — Double Integrator System

- Since  $d(\mathbf{x}) = \dot{h}(\mathbf{x}) + \alpha(h(\mathbf{x}))$ , we can write it as

$$d(\mathbf{x}) = h_{\mathbf{x}}\dot{\mathbf{x}} + \alpha(h(\mathbf{x}))$$

- Then we have its time derivative as

$$\dot{d}(\mathbf{x}) = h_{\mathbf{xx}}\dot{\mathbf{x}}^2 + h_{\mathbf{x}}\ddot{\mathbf{x}} + \frac{d\alpha(h(\mathbf{x}))}{dt} = h_{\mathbf{xx}}\dot{\mathbf{x}}^2 + h_{\mathbf{x}}\mathbf{u} + \frac{d\alpha(h(\mathbf{x}))}{dt}$$

# ECBF Example

## System Dynamics

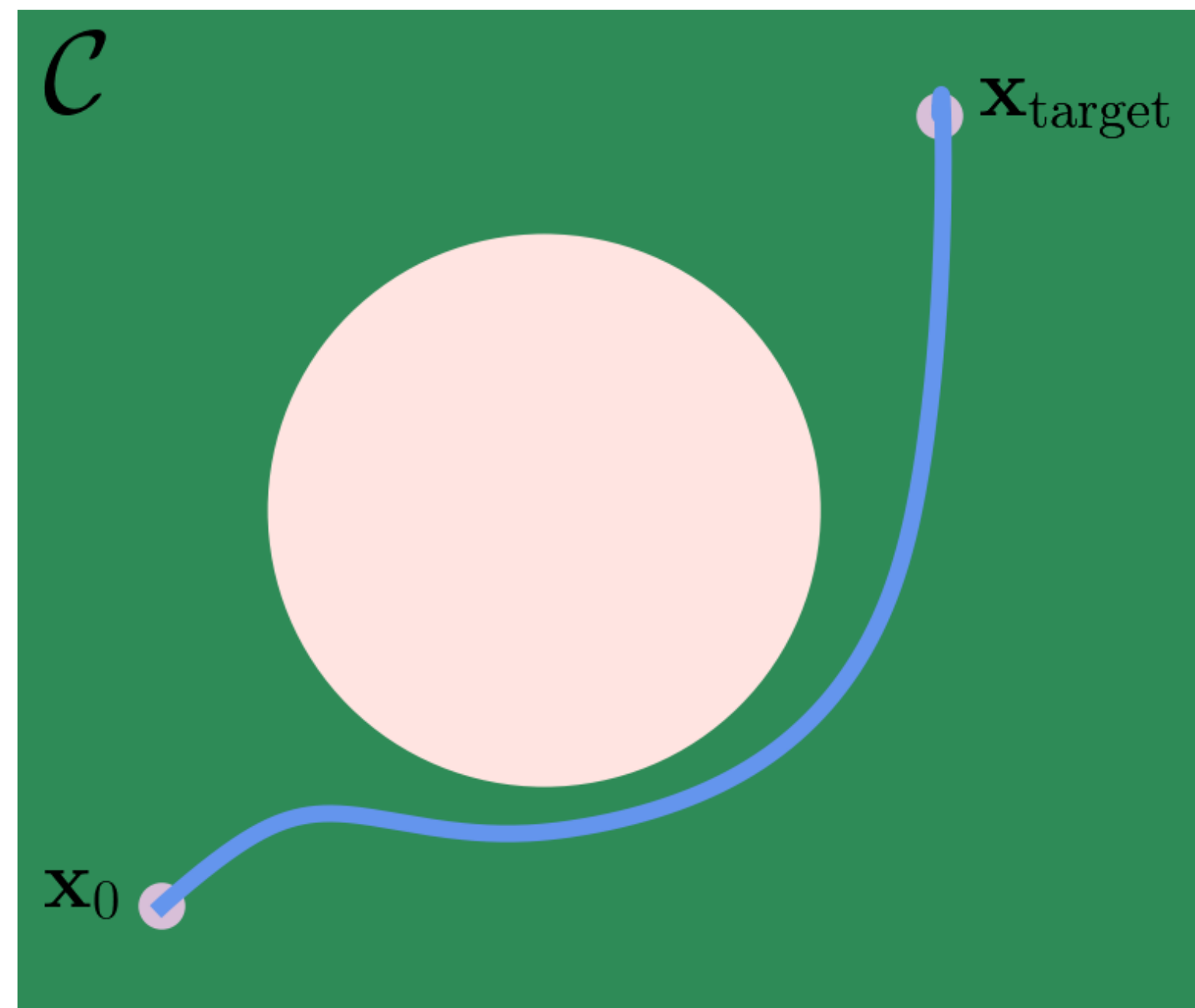
- We use the system dynamics of a double integrator

$$\dot{\mathbf{x}} = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \ddot{x} \\ \ddot{y} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} u_x \\ u_y \end{bmatrix}$$

# ECBF Example

## Find CBF

- The task is to reach a target position without colliding with an obstacle



# ECBF Example

## ECBF

- We can see a natural choice of the CBF is

$$h(\mathbf{x}) = x^2 + y^2 - r^2$$

- However, since we are controlling the acceleration, the CBF has relative degree two. Thus, an ECBF needs to be used

$$\bar{h} = \dot{h}(\mathbf{x}, \mathbf{u}) + \gamma h(\mathbf{x}) = 2x\dot{x} + 2y\dot{y} + \gamma(x^2 + y^2 - r^2)$$



# ECBF Example

## CBF-QP

- Assuming that for each state we have a stabilizing controller  $\bar{\mathbf{u}} \sim \pi(\mathbf{x})$ , then we can write the CBF-QP as

$$\begin{aligned} & \min_{\mathbf{u}} \quad \|\mathbf{u} - \bar{\mathbf{u}}\|^2 \\ & \text{subject to} \quad \mathbf{u} \in \mathcal{U} \\ & \quad \quad \quad L_f h(\mathbf{x}) + L_g h(\mathbf{x})\mathbf{u} + \alpha(h(\mathbf{x})) \geq 0 \end{aligned}$$

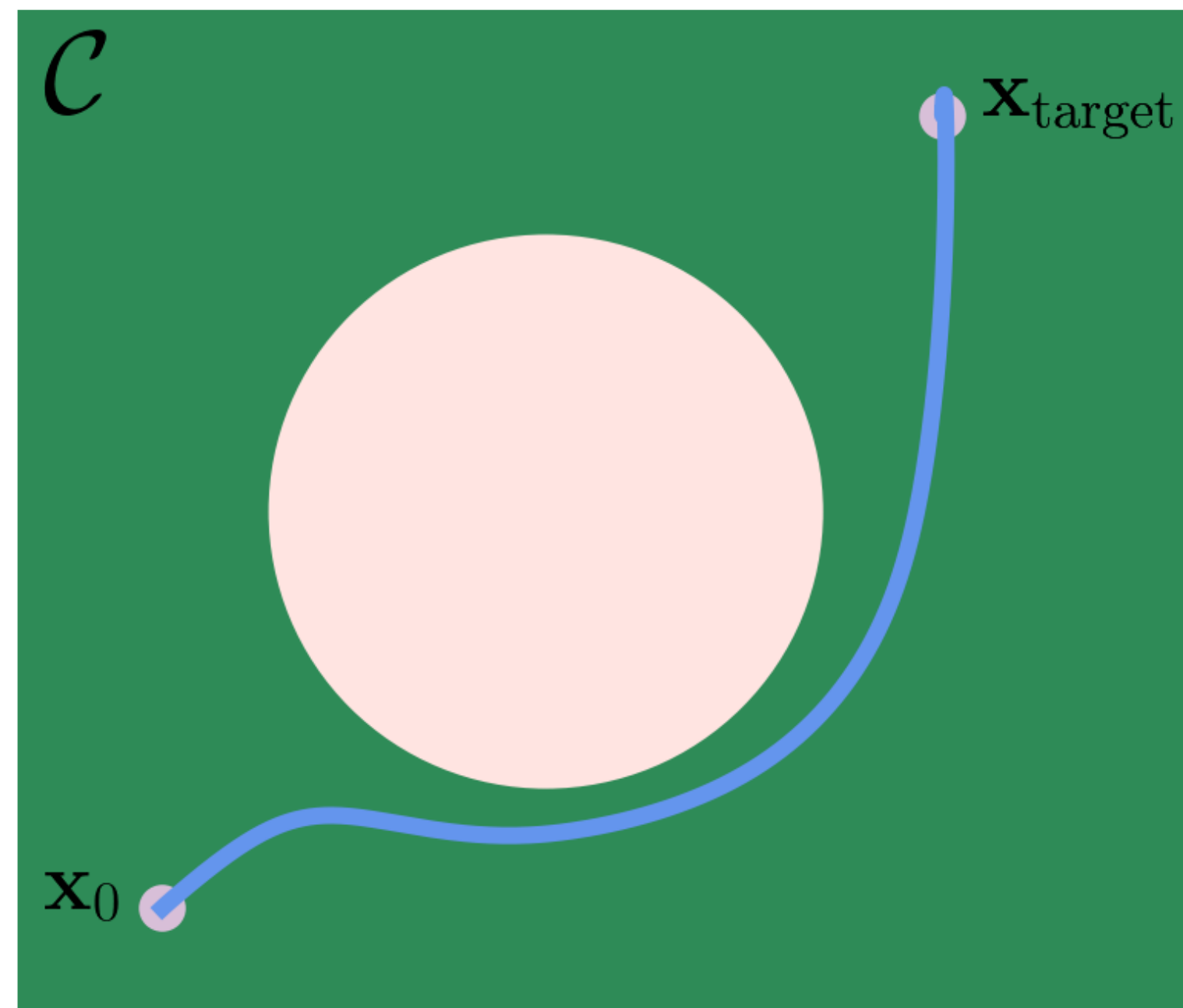
- The system is assumed to be control affine

$$\dot{\mathbf{x}} = f(\mathbf{x}) + g(\mathbf{x})\mathbf{u}$$

# ECBF Example

## Results

- Along with a stabilizing controller generated using LQR, we have the following motion.



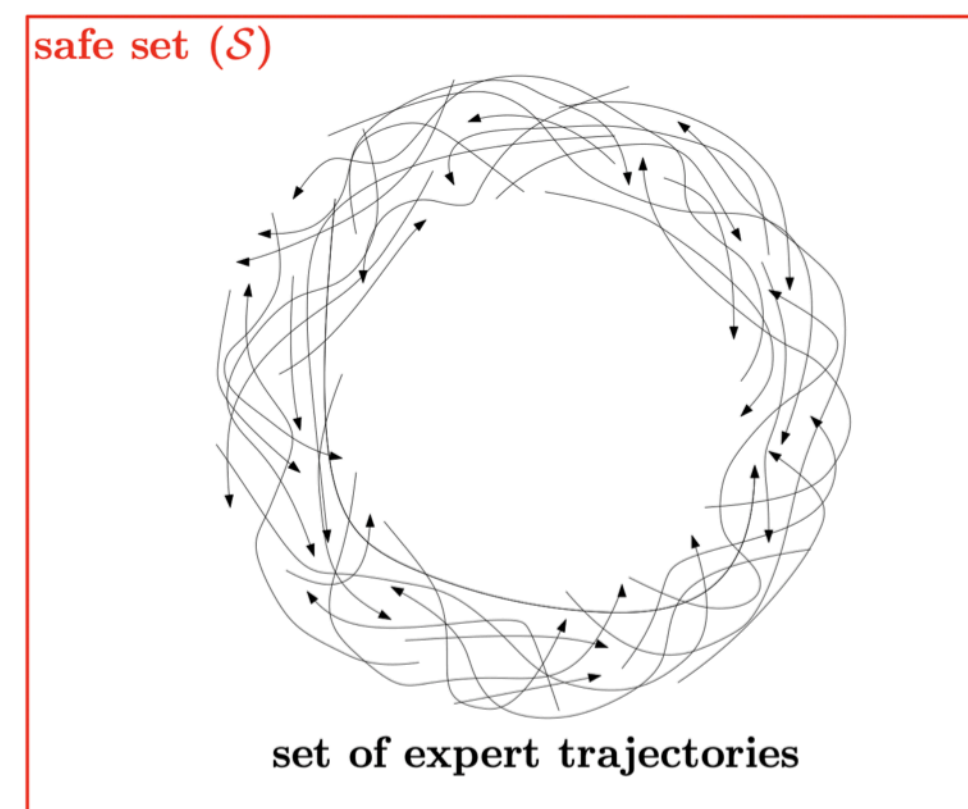
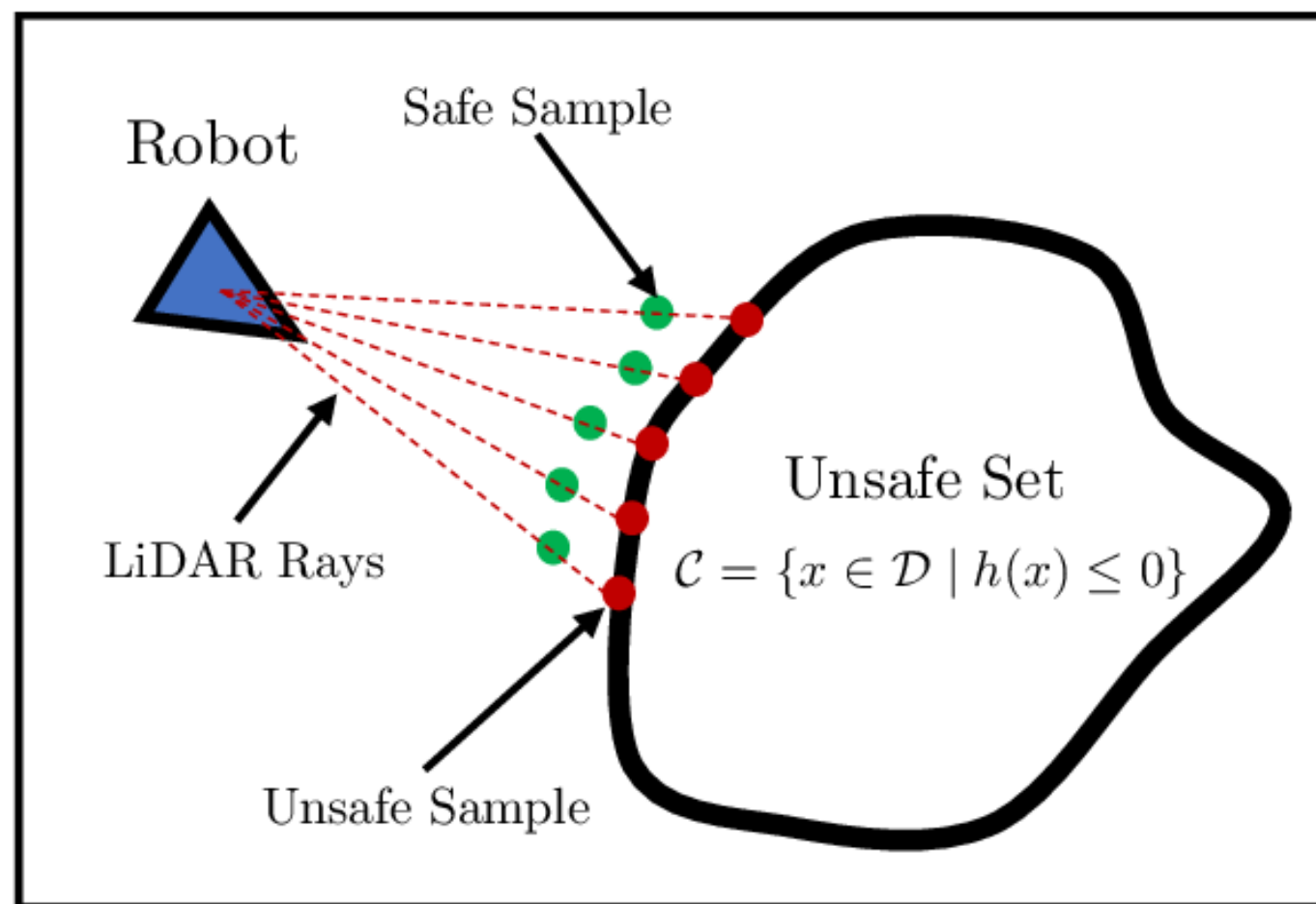
# CBF Research

## Directions

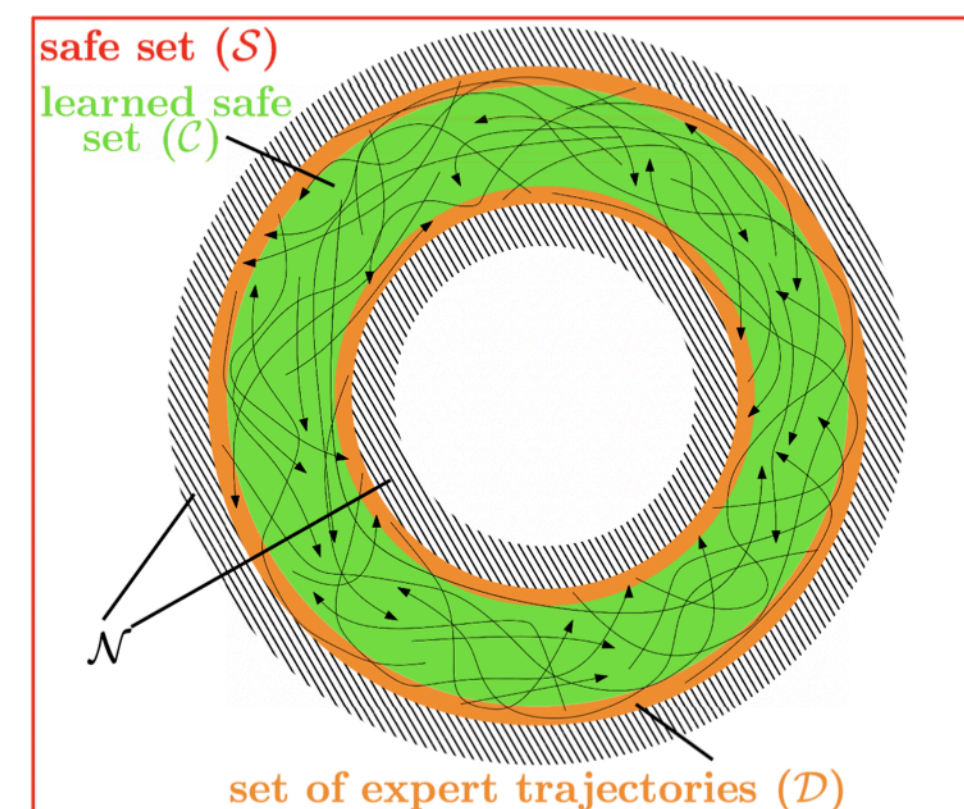
- Synthesis CBFs from data
- CBF with model uncertainty
- CBF for new dynamical systems
- Application to new areas

# CBF Research

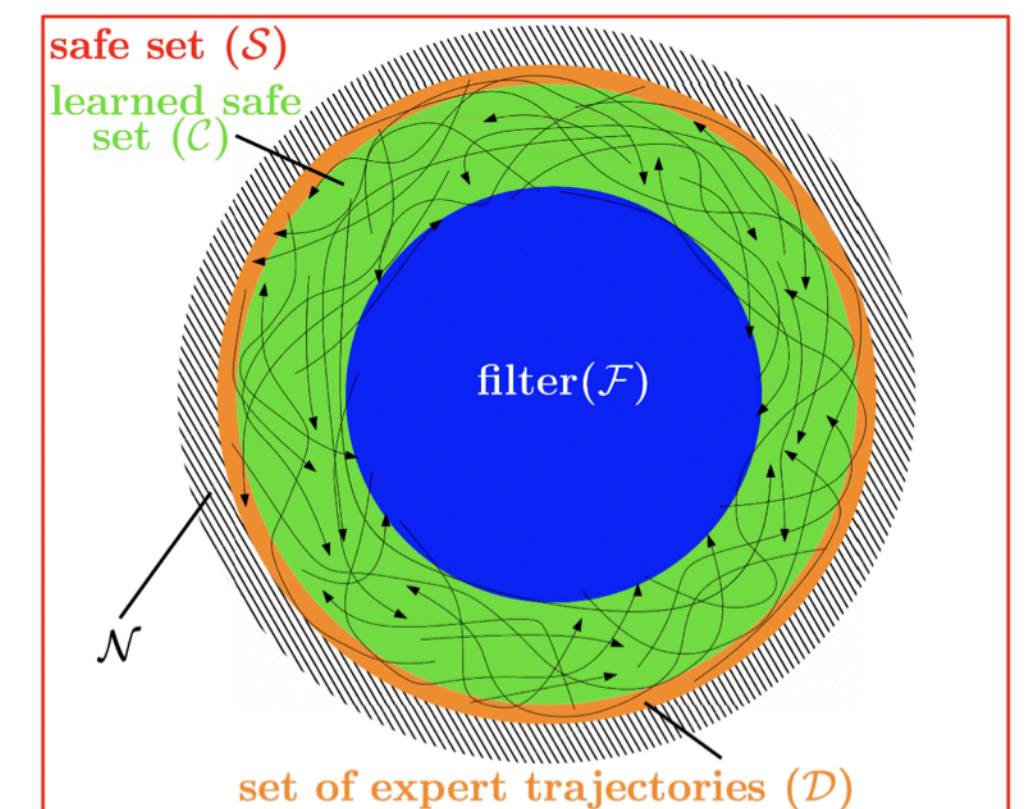
## Synthesis CBFs from Data



(a) Problem setup.



(b) Desired result.



(c) Control barrier filter.

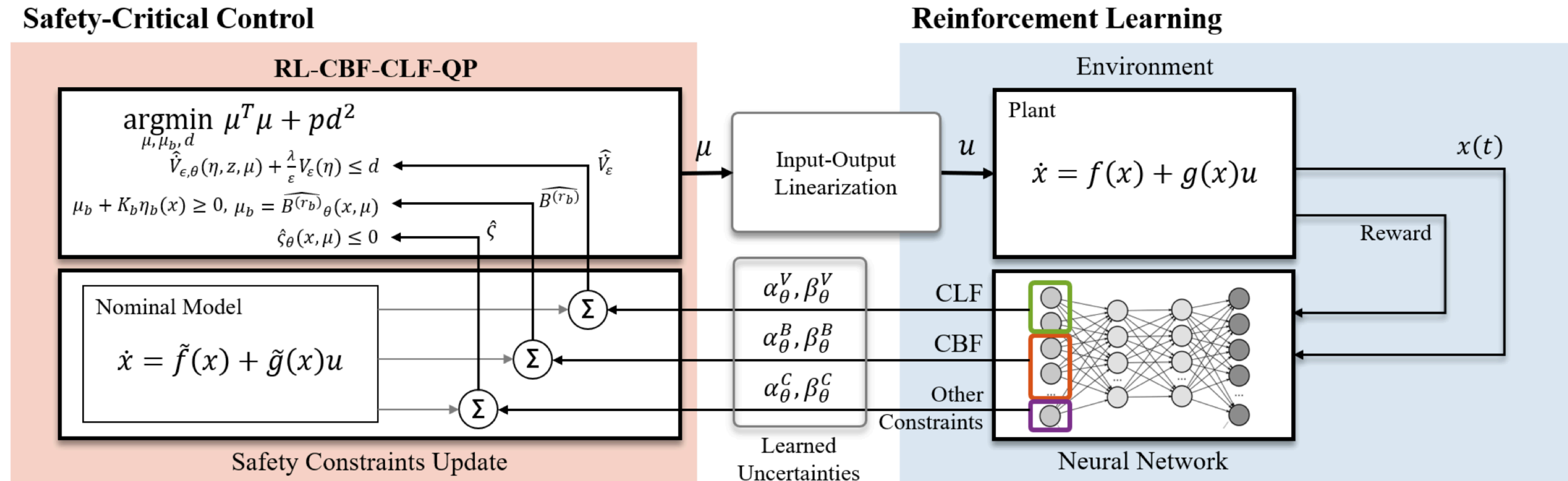
Srinivasan et al., IROS 2020

Robey et al., CDC 2020

- *Learning Safe Multi-Agent Control with Decentralized Neural Barrier Certificates*, Qin et al., ICLR 2021

# CBF Research

## CBF with Model Uncertainty

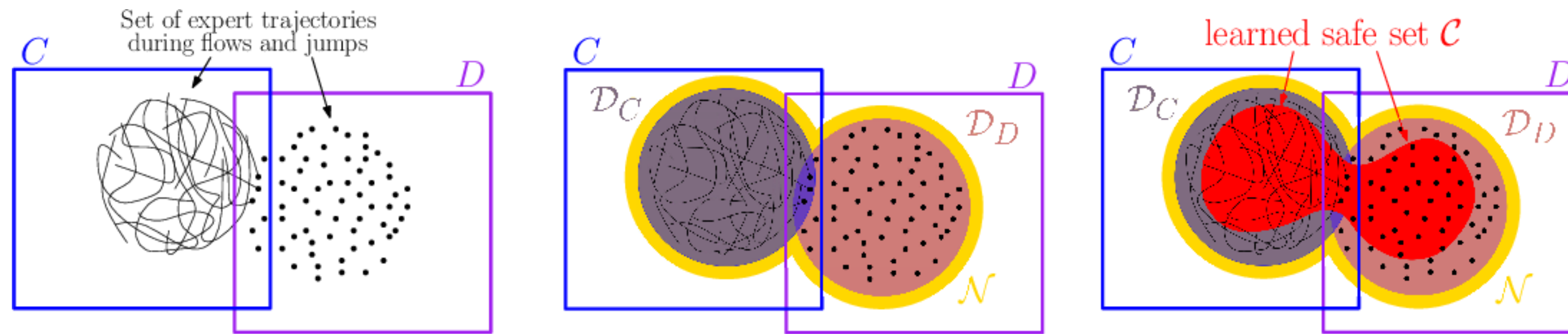


Choi et al., RSS 2020

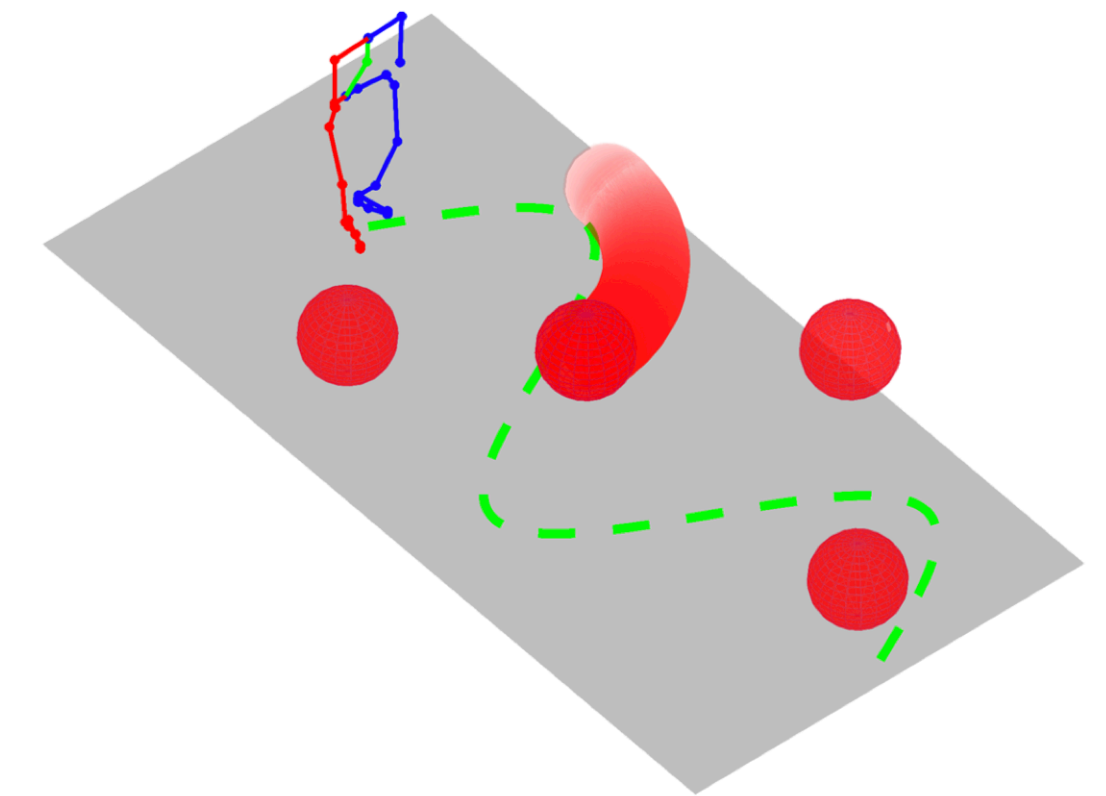
- *Learning for Safety Critical Control with Control Barrier Functions*, Taylor et al., L4DC 2020
- *End-to-End Safe Reinforcement Learning through Barrier Functions for Safety Critical Continuous Control Tasks*, Cheng et al., AAI 2019

# CBF Research

## CBF for New Dynamical Systems



Robey et al., CoRL 2020

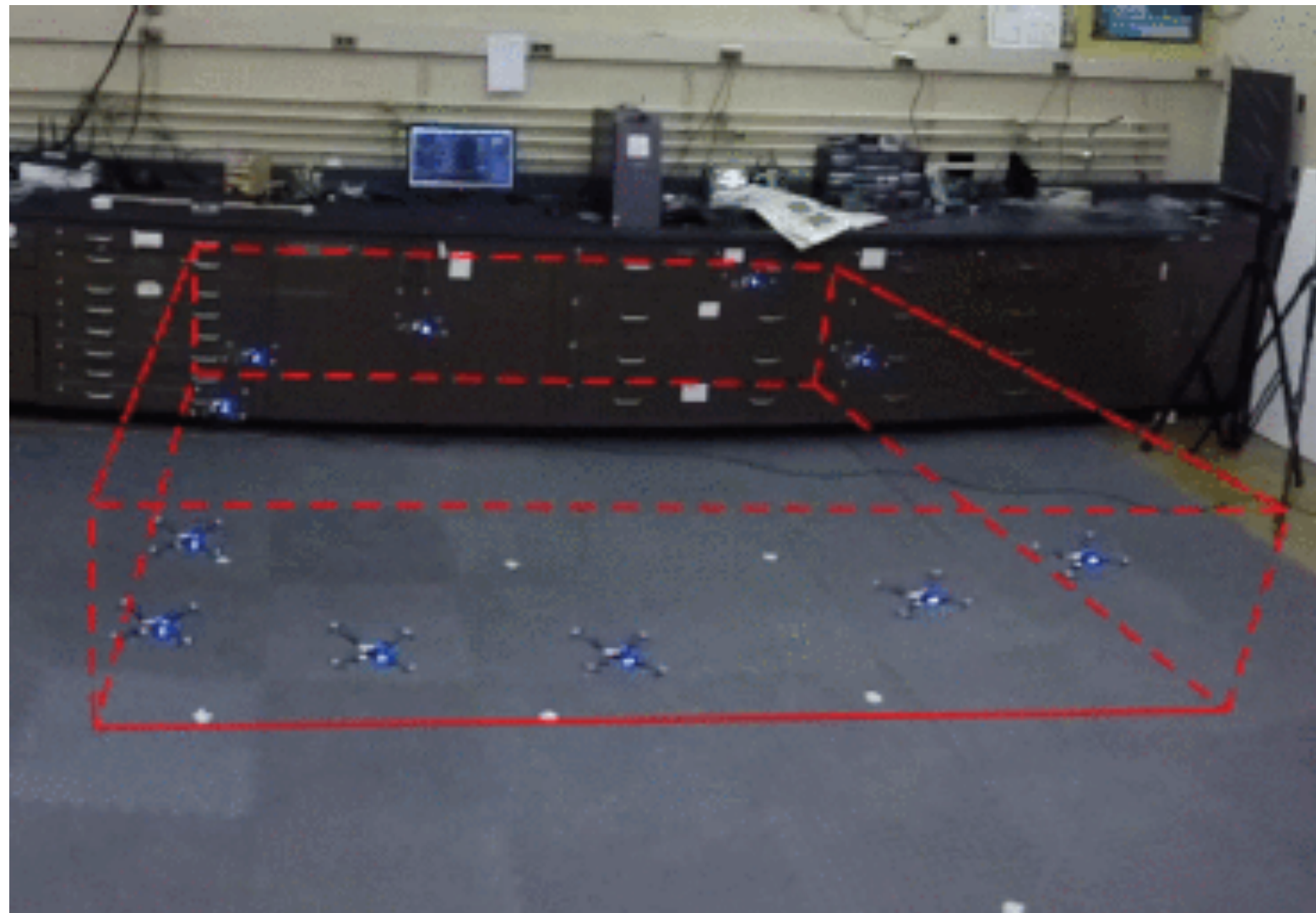


Agrawal et al., RSS 2017

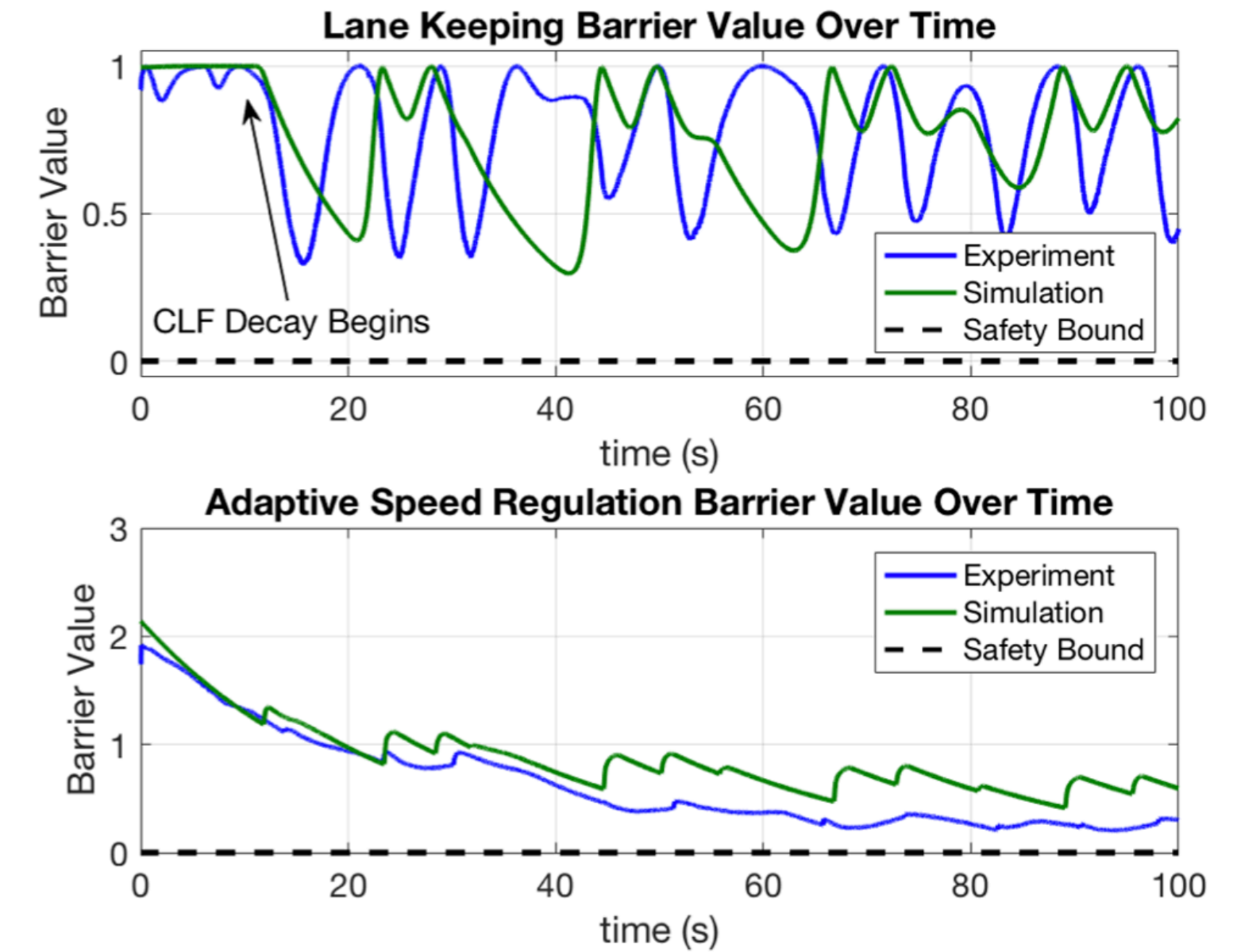
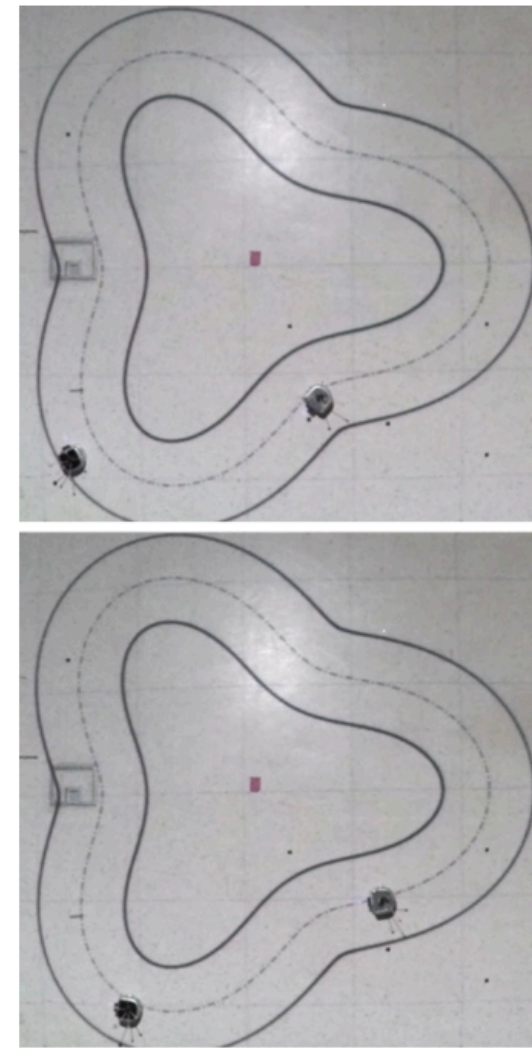
- *Exponential Control Barrier Functions for enforcing high relative-degree safety-critical constraints*, Nguyen et al., ACC 2016

# CBF Research

## Applications to New Systems



Xu et al., ICRA 2018



Xu et al., CCTA 2017

- *Constraint-driven coordinated control of multi-robot systems*, Notomista et al., ACC 2019