



Counterexample-Guided Synthesis of Perception Models and Control

University of California Berkeley

Shromona Ghosh*, Hadi Ravanbakhsh*, Sanjit A. Seshia

Abstract

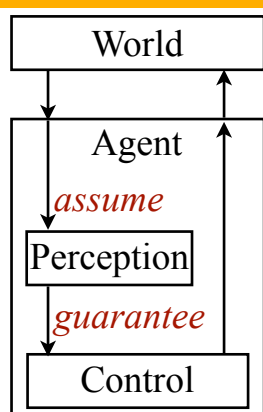
Goal: State of the art ML-based perception systems are still prone to errors. We need to design control modules for autonomous systems which are robust to perception errors.

Contributions:

- ◆ A novel counterexample-guided method to synthesize controllers robust to perception errors
- ◆ Data-driven inference of simple models of complex perception modules, including ML-based perception
- ◆ Two case studies:
 - ◆ Lane-keeping with a classical vision-based perception module
 - ◆ Automatic braking with a neural network-based perception module

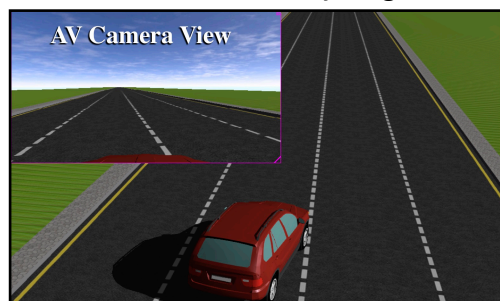
Approach

- ◆ **Common Approach:** Use assume-guarantee to decompose the system into perception and control modules. Design each component separately.
 - ◆ **Problem:** Currently we can't design provably correct perception modules
- ◆ **Our Approach:** Design a possibly faulty perception module. Afterwards, synthesize (a) assume-guarantee pairs for the perception module and (b) the control module



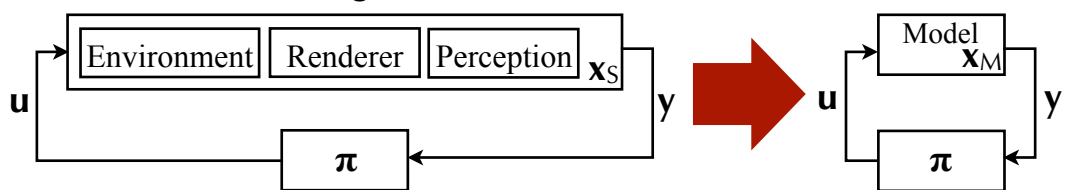
Problem

- ◆ **Simulation-based Verification:** Use high fidelity simulators for systematic safety analysis of autonomous agent in complex environments:
 - ◆ **Requirements:** Define all possible scenarios mathematically, e.g. **Scenic**
 - ◆ **Simulator:** We have access to internal state of the simulator and can enforce environment constraints by initializing the internal state.
 - ◆ **Verification:** We have a verification oracle that can systematically tests the closed-loop system and finds counterexamples. E.g. **VerifAI**
- ◆ **Problem:** Given a parameterized control policy, and a faulty perception module, find a set of parameters s.t. the closed-loop system in the simulator remains safe w.r.t. the requirements.



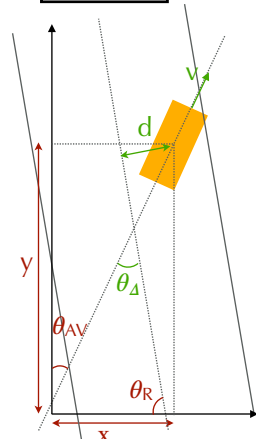
Assume-Guarantee through Modeling

Model for Control Design



Lane-keeping Example

- ◆ **Simulator state x_S :**
 - ◆ **Agent state:** x, y, θ_{AV}, v
 - ◆ **Environment variables:** Target lane on the map, Time of day, weather, marks on the ground, etc.
- ◆ **Model state x_M :** d, θ_{Δ}, v
- ◆ **Perception output y :** d', θ_{Δ}'
- ◆ **Control input u :** steering



Simulator Traces

- ◆ $y(i) = h_S(x_S(i))$
- ◆ $u(i) = \pi(y(i))$
- ◆ $x_S(i+1) = f_S(x_S(i), u(i))$

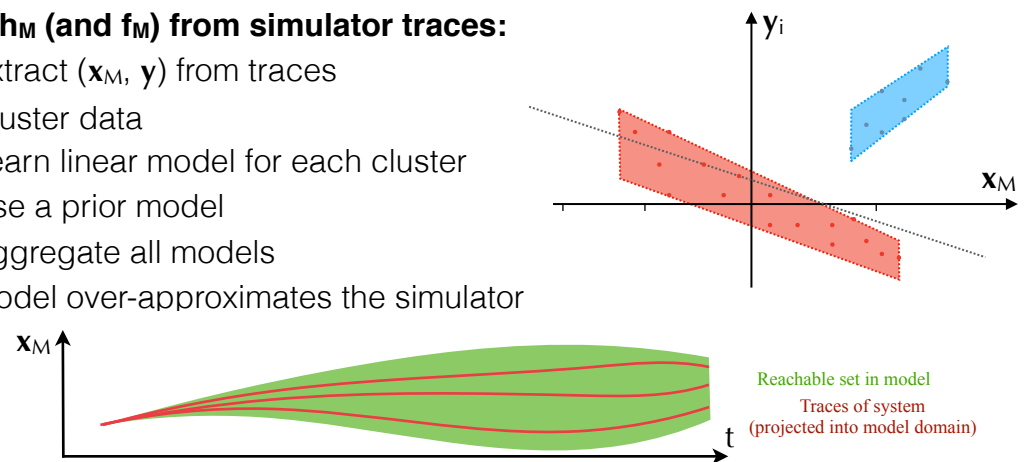
Model Traces

- ◆ $y(i) = h_M(x_M(i))$
- ◆ $u(i) = \pi(y(i))$
- ◆ $x_M(i+1) = f_M(x_M(i), u(i))$

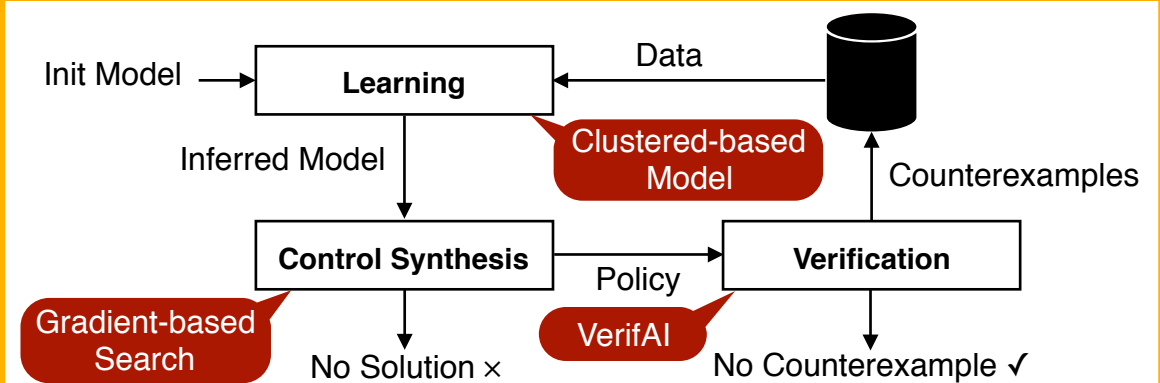
Inferring Sound Models

Infer h_M (and f_M) from simulator traces:

- ◆ Extract (x_M, y) from traces
- ◆ Cluster data
- ◆ Learn linear model for each cluster
- ◆ Use a prior model
- ◆ Aggregate all models
- ◆ Model over-approximates the simulator



Counter-example Guided Search

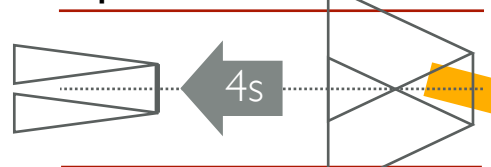


Case Study: Lane-keeping

Problem

- ◆ **Policy:** $\pi : p_1 \theta_{\Delta} + p_2 d$
- ◆ **Perception:** θ_{Δ}' and v' are accurate, but d' is inaccurate

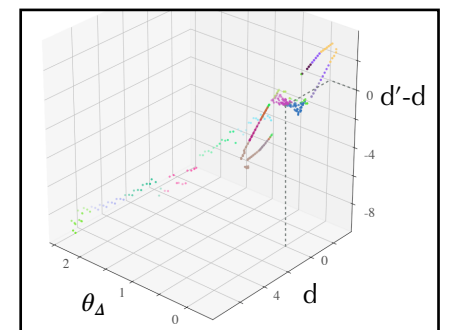
Specification:



- ◆ **Modeling:** $d' \in h_M(d, \theta_{\Delta}, v)$

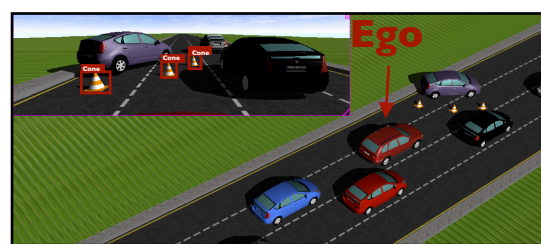
Counterexample-guided Search

- ◆ 1st itr: $p_1 = -0.5, p_2 = -0.8 \times$
 - ◆ **VerifAI** finds counterexamples
- ◆ 5th itr: $p_1 = -3.93, p_2 = -0.63 \checkmark$



Case Study: Automatic Braking

- ◆ **Problem:** Brake after cone detection, avoiding crash



- ◆ **Environment Parameters:** traffic speed, color of broken car, orientation of broken car...

Model state x_M :

- ◆ d : distance to cones
- ◆ v : speed

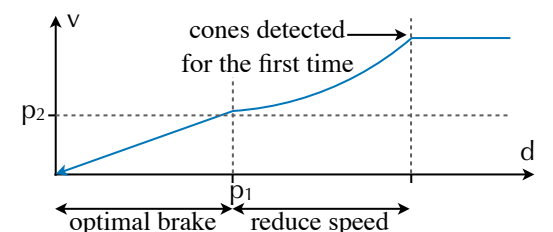
- ◆ **Perception:** v' is accurate, d' is not: use size of detection boxes to measure distance to cones

- ◆ **Control input:** thrust

- ◆ **Modeling:** $d' \in h_M(d, v)$

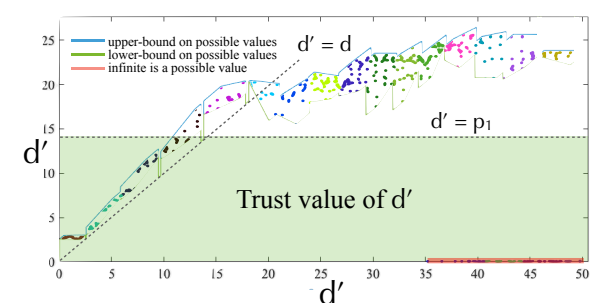
Policy:

- ◆ if $d' > p_1$, reduce speed to p_2
- ◆ if $d' \leq p_1$, use both v' and d'



Counterexample-guided Search

- ◆ 1st itr: easy to find counterexamples \times
- ◆ 2nd itr: only ew counterexamples. In all cases the color of broken car and cones color are similar \times
- ◆ 3rd itr: no counterexample \checkmark



Acknowledgement

This work is supported in part by NSF grants CPS-1545126 (VeHICaL), CCF-1837132, by the DARPA Assured Autonomy grant, and by Berkeley Deep Drive.