



Data-driven verification and control moving from linear dynamical systems to nonlinear stochastic systems

9TH OF JULY 2023

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Data-driven Verification and Correct-by-Design Control

This talk:

How can you deal with the lack of environment and model knowledge in safety critical applications?

1. Direct data-driven control for linear dynamical systems
2. Approximate simulation relations for nonlinear stochastic systems with model uncertainty
3. Embedding environment uncertainty



[Amazon]



[TheVerge]



[Cda]



[BBC]

Contents

1. Direct data-driven approach for LTI systems
2. Approximate simulation relations for nonlinear stochastic systems with model uncertainty
3. Embedding environment uncertainty

Direct data-driven temporal logic control

True & unknown LTI system dynamics:

$$x(t + 1) = Ax(t) + Bu(t)$$

$$y(t) = Cx(t)$$

Specification in Signal Temporal Logic:

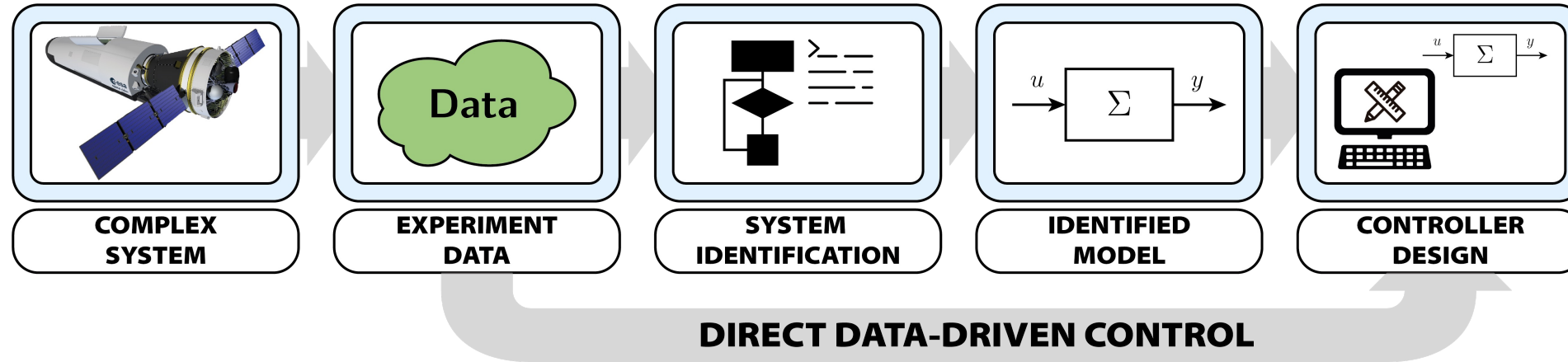
$$\varphi ::= \sigma \mid \neg\varphi \mid \varphi_1 \wedge \varphi_2 \mid \varphi_1 \vee \varphi_2 \mid \square_{[a,b]}\varphi \mid \varphi_1 \mathbf{U}_{[a,b]}\varphi_2, \quad (1)$$

Given a single finite data trace $w_{data} = (u_{data}, y_{data})$ design $u = \{u_0, u_1, y_2 \dots\}$ such that $y = \{y_0, y_1, y_2, \dots\}$ satisfies φ .

van Huijgevoort, B. C., Verhoek, C., Tóth, R., & Haesaert, S. (2023). Direct data-driven signal temporal logic control of linear systems. *arXiv preprint arXiv:2304.02297*.

Direct data-driven control: The idea

Achieve controller design directly from data



- Predictive control schemes (e.g., DeePC [3])
- State-feedback control [4]
- Dissipativity analysis [5]
- Noise handling & robustness guarantees [6]

[3] Coulson, Lygeros, Dorfler (2019) "Data-Enabled Predictive Control: In the Shallows of the DeePC," in *Proc. of the 2019 ECC*.

[4] Markovskiy & Rapisarda (2008) "Data-driven simulation and control," *Int. Journal of Control*.

[5] Romer et al. (2019) "One-shot verification of dissipativity properties from input-output data," *Control Systems Letters*.

[6] Berberich et al. (2021) "Data-Driven Model Predictive Control With Stability and Robustness Guarantees," *IEEE-TAC*

Direct data-driven temporal logic control

Model-based control STL

$$\arg \min_{\mathbf{u}} J(\mathbf{u}, \mathbf{y})$$

$$s. t. \quad \begin{aligned} x(t+1) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) \end{aligned}$$

$$\begin{aligned} \mathbf{y}_0 &= [y(0), y(1), y(2), \dots] \\ \mathbf{y}_0 &\models \varphi \end{aligned}$$

Model equations

Specification in Signal temporal logics
can be written as a MILP

Donzé, Alexandre, et al. "BluSTL: Controller Synthesis from Signal Temporal Logic Specifications." (2015)

Direct data-driven temporal logic control

$$\arg \min_{\mathbf{u}} J(\mathbf{u}, \mathbf{y})$$

s. t. Willems fundamental lemma



Replace model with data

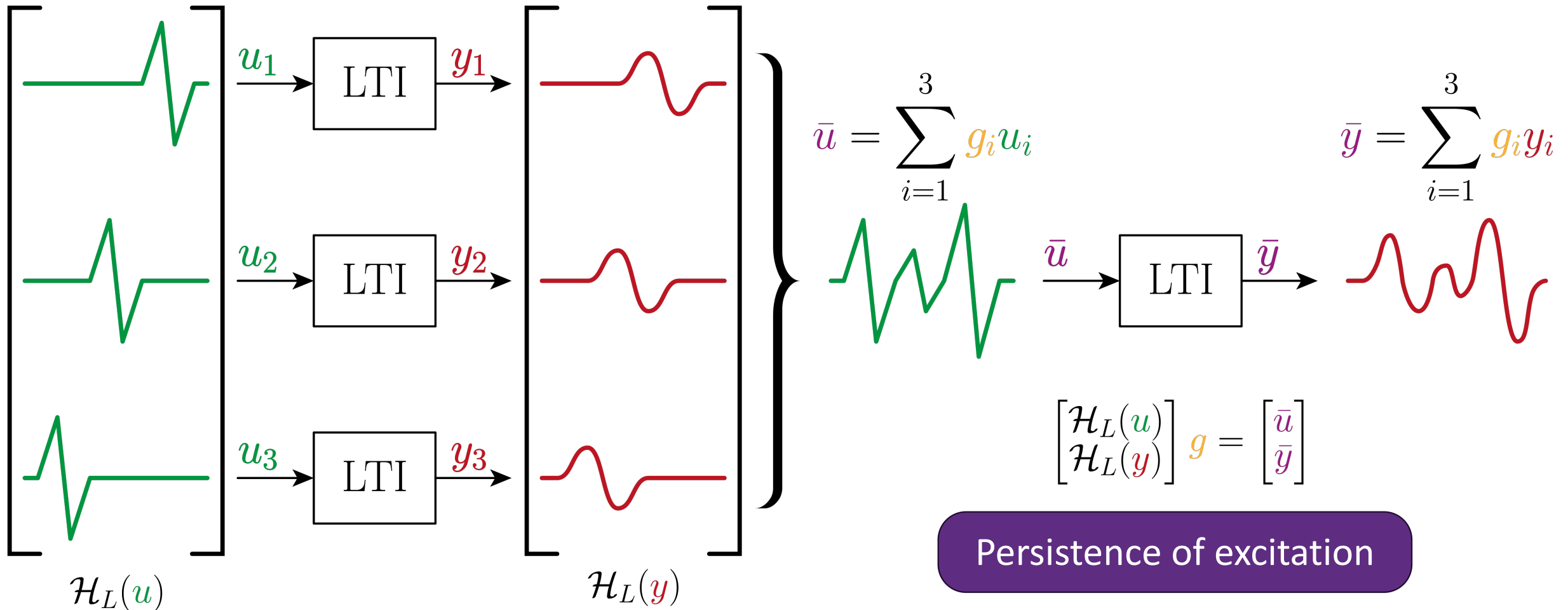
$$\mathbf{y}_0 = [y(0), y(1), y(2), \dots]$$

$$\mathbf{y}_0 \models \varphi$$

van Huijgevoort, B. C., Verhoek, C., Tóth, R., & Haesaert, S. (2023). Direct data-driven signal temporal logic control of linear systems. *arXiv preprint arXiv:2304.02297*.

Willems' Fundamental Lemma (main idea)

A behavioral approach to data-driven modeling



[1] Polderman, Willems (1998) "Introduction to Mathematical Systems Theory: A Behavioral Approach" Springer

[2] Willems et al. (2005) "A note on persistency of excitation" *Systems & Control Letters*

Direct data-driven temporal logic control

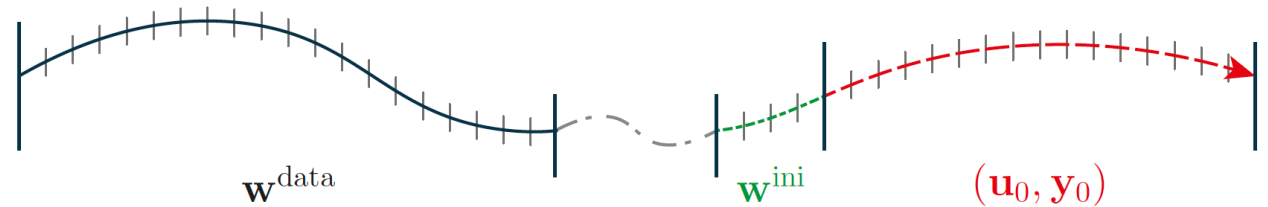
$$\arg \min_{\mathbf{u}} J(\mathbf{u}, \mathbf{y})$$

s. t. Willems fundamental lemma



Replace model with data

$$\mathbf{y}_0 = [y(0), y(1), y(2), \dots]$$
$$\mathbf{y}_0 \models \varphi$$



van Huijgevoort, B. C., Verhoek, C., Tóth, R., & Haesaert, S. (2023). Direct data-driven signal temporal logic control of linear systems. *arXiv preprint arXiv:2304.02297*.

Direct data-driven temporal logic control

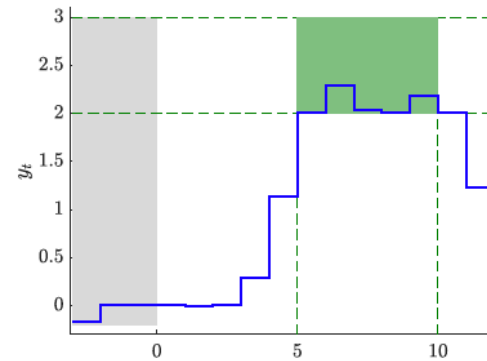
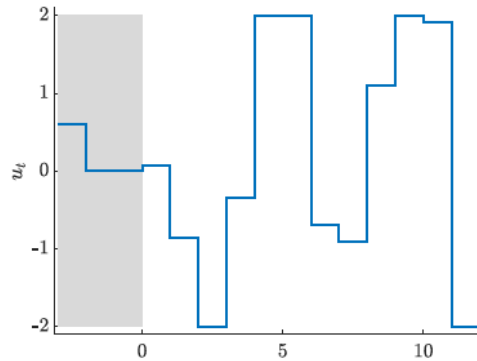
Car platoon case study



$$\varphi = \square_{[5,10]}(|y| \geq 2 \wedge |y| \leq 3).$$

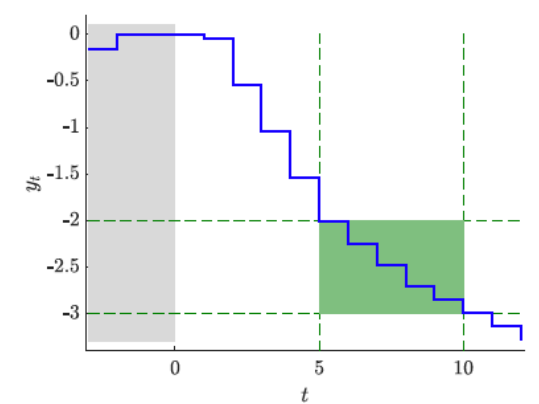
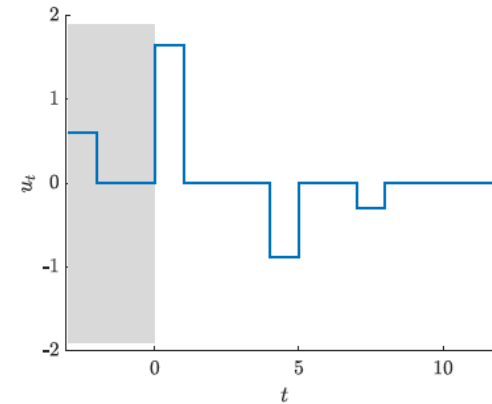
Minimize output & satisfy φ

$$J_1(\mathbf{u}_0, \mathbf{y}_0) = \|\mathbf{y}_{[0,L]}\|$$



Minimize output & satisfy φ

$$J_2(\mathbf{u}_0, \mathbf{y}_0) = \|\mathbf{u}_{[0,L]}\|$$



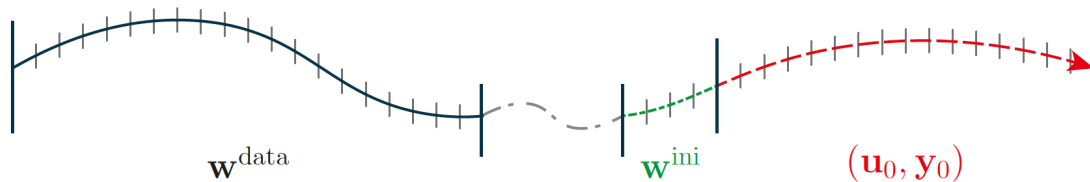
Direct data-driven temporal logic control

$$\arg \min_{\mathbf{u}} J(\mathbf{u}, \mathbf{y})$$

s. t. Willems fundamental lemma

$$\mathbf{y}_0 = [y(0), y(1), y(2), \dots]$$

$$\mathbf{y}_0 \models \varphi$$



Based on the fundamental Lemma

- Sound for LTI systems
(based on Willems fundamental lemma)
- Completeness based on persistence of excitation

van Huijgevoort, B. C., Verhoek, C., Tóth, R., & Haesaert, S. (2023). Direct data-driven signal temporal logic control of linear systems. *arXiv preprint arXiv:2304.02297*.

Applicability of fundamental lemma

Excellent results:

- Predictive control schemes (e.g., DeePC [3])
- State-feedback control [4]
- Dissipativity analysis [5]
- Noise handling & robustness guarantees [6]

$$\begin{bmatrix} \mathcal{H}_L(u^d) \\ \mathcal{H}_L(y^d) \end{bmatrix} g = \begin{bmatrix} \text{col}(\bar{u}) \\ \text{col}(\bar{y}) \end{bmatrix}$$

Generalizations:

- Linear Time-Varying (LTV), bilinear systems, stochastic linear systems [7-9]
- Wiener & Hammerstein, flat nonlinear, NARX systems [10-12]
- **Linear Parameter-Varying Systems [13]**

[7] Nortmann & Mylvaganam (2020) "Data-Driven Control of Linear Time-Varying Systems," in *Proc. of the CDC 2020*.

[8] Yuan & Cortés (2022) "Data-driven optimal control of bilinear systems," *IEEE Control Systems Letters*.

[9] Faulwasser et al. (2023) "Behavioral theory for stochastic systems? A data-driven journey from Willems to Wiener and back again," *Ann. Rev. in Control*.

[10] Berberich & Allgöwer (2020) "A trajectory-based framework for data-driven system analysis and control," in *Proc. of the ECC 2020*.

[11] Alsalti et al. (2021) "Data-Based System Analysis and Control of Flat Nonlinear Systems," in *Proc. of the CDC 2021*.

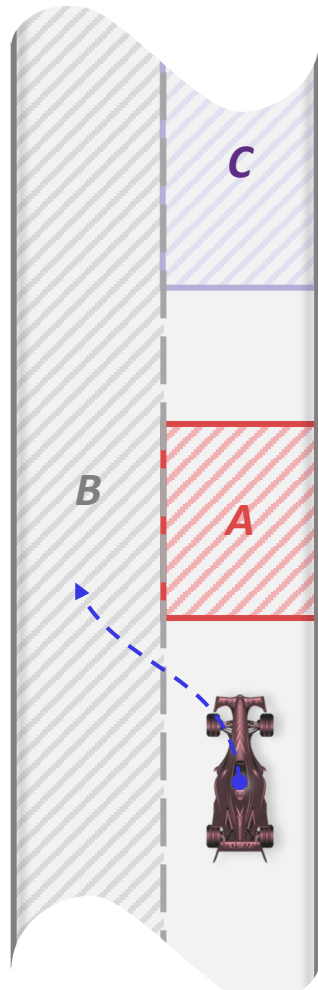
[12] Mishra et al. (2021) "Data-driven simulation for NARX systems," in *Proc. of the ESPC 2021*.

[13] Verhoek, Tóth, Haesaert, Koch (2021). "Fundamental Lemma for Data-Driven Analysis of Linear Parameter-Varying Systems." In *Proc. of the CDC 2021*.

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Verification and Correct-by-Design Control for Stochastic Systems



Stochastic system:

$$M: \begin{cases} x_{k+1} = f(x_k, u_k) + w_k \\ w_k \sim p_w(\cdot) \end{cases}$$

Specification:

$$\psi = (\neg A \text{ U } C) \wedge \bigcirc(B \rightarrow \diamond C)$$

LTL semantics: $\psi ::= p \mid \neg\psi \mid \psi_1 \vee \psi_2 \mid \psi_1 \wedge \psi_2 \mid \psi_1 \text{ U } \psi_2 \mid \bigcirc\psi$

Task:

Design controller such that controlled system exhibits specified behavior ψ with probability at least

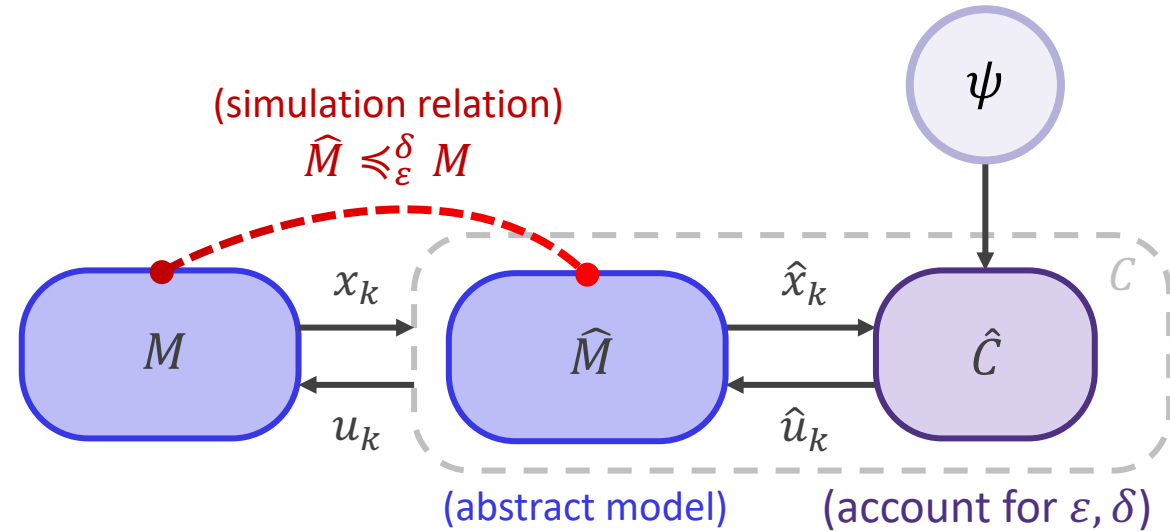
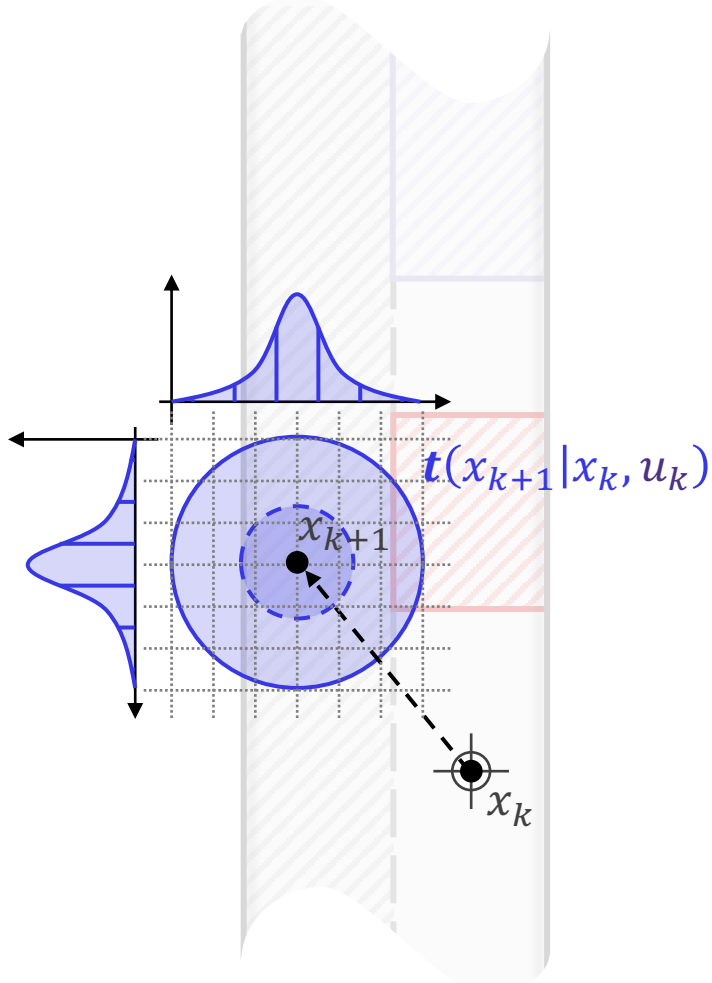
p_ψ .

✓ **Solvable for known continuous stochastic systems**

S. Haesaert & S. Soudjani (2020) *Robust dynamic programming for temporal logic control of stochastic systems*. TAC.

Correct-by-Design Control (Full Knowledge)

Abstraction-based solution



If ① $\hat{M} \preceq_{\epsilon}^{\delta} M$, then ② $\mathbb{P}\{C \times M \models \psi\} \geq \mathbb{P}\{\hat{C} \times \hat{M} \models \psi\} \geq p_{\psi}$

S. Haesaert & S. Soudjani (2020) *Robust dynamic programming for temporal logic control of stochastic systems. TAC.*

Toolbox “SySCoRe”

Temporal logic control for stochastic systems

- **Input:** Stochastic system model + specification
- **Output:** Robust policy + bounds on satisfaction probability

Features:

- ✓ Nonlinear stochastic dynamics
- ✓ (Arbitrary) unbounded support
- ✓ (Possibly) infinite horizon
- ✓ Unbounded scLTL specifications
- ✓ Model order reduction supported
- ✓ Exploits fast tensor computations

Toolbox: SySCoRe (v1 available)

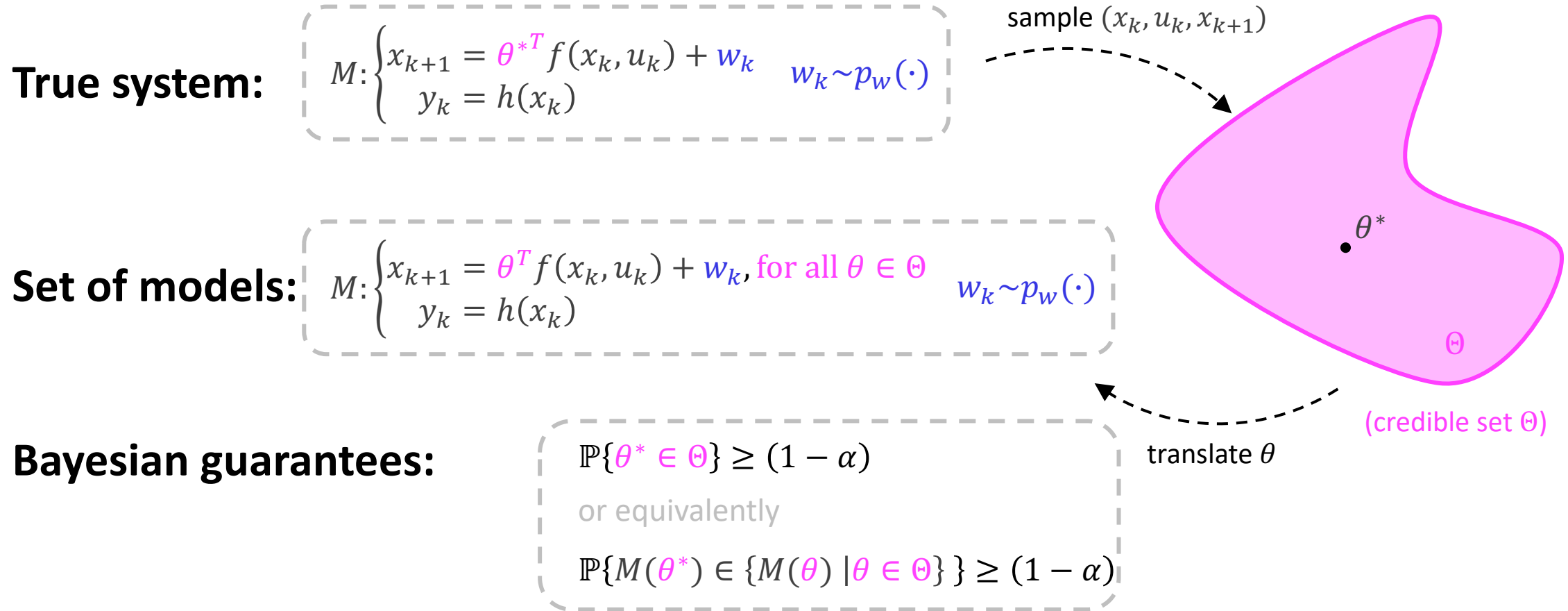
<https://github.com/BirgitVanHuijgevoort/SySCoRe-software>

Tool paper: B.C v. Huijgevoort et al. (2023) *SySCoRe: Synthesis via Stochastic Coupling Relations*. HSCC’23.

Friendly competition: ARCH-COMP22 Category Report: *Stochastic Models*. EPiC.

Collab. with Sadegh Soudjani’s group

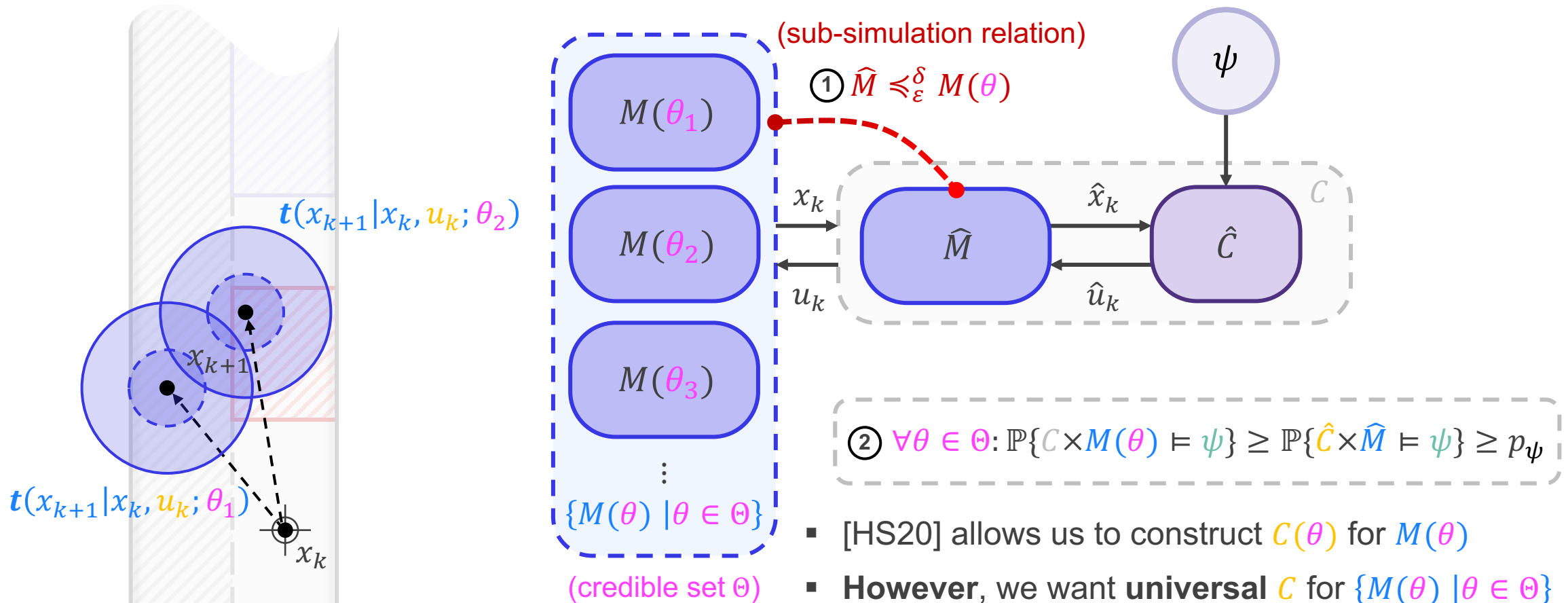
Correct-by-Design Control of Uncertain Systems



O. Schön et al. (2023) *Bayesian Approach to Temporal Logic Control of Uncertain Systems*.

Correct-by-Design Control of Uncertain Systems

Sub-Simulation Relations (SSR)



O. Schön et al. (2022) *Correct-by-design control of parametric stochastic systems. CDC'22.*

Correct-by-Design Control of Uncertain Systems

Layered solution

Procedure:

1) Three layers of models: $M(\theta)$, \hat{M} , \tilde{M}

2) Two simulation relations:

$$\hat{M} \preceq_{\varepsilon_1}^{\delta_1} M(\theta) \text{ [O. Schön et al. (2022)]}$$

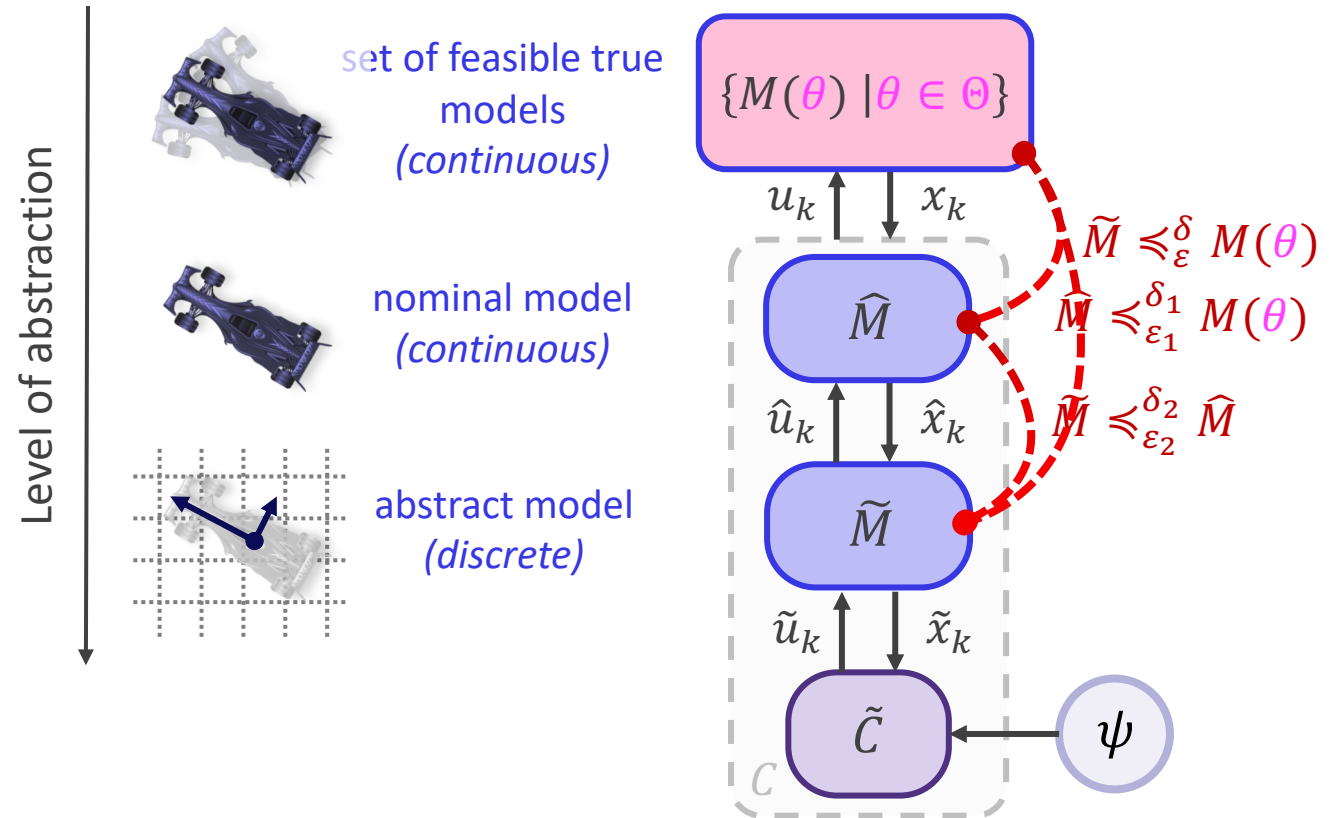
$$\tilde{M} \preceq_{\varepsilon_2}^{\delta_2} \hat{M} \text{ [S. Haesaert et al. (2017)]}$$

$$\rightarrow \tilde{M} \preceq_{\varepsilon}^{\delta} M(\theta), \quad \delta = \delta_1 + \delta_2, \quad \varepsilon = \varepsilon_1 + \varepsilon_2$$

3) Robust controller \tilde{C} for \tilde{M}

[S. Haesaert & S. Soudjani (2020)]

✓ Robust satisfaction probability for \mathcal{C} on $\{M(\theta) \mid \theta \in \Theta\}$



O. Schön et al. (2022) *Correct-by-design control of parametric stochastic systems. CDC'22.*

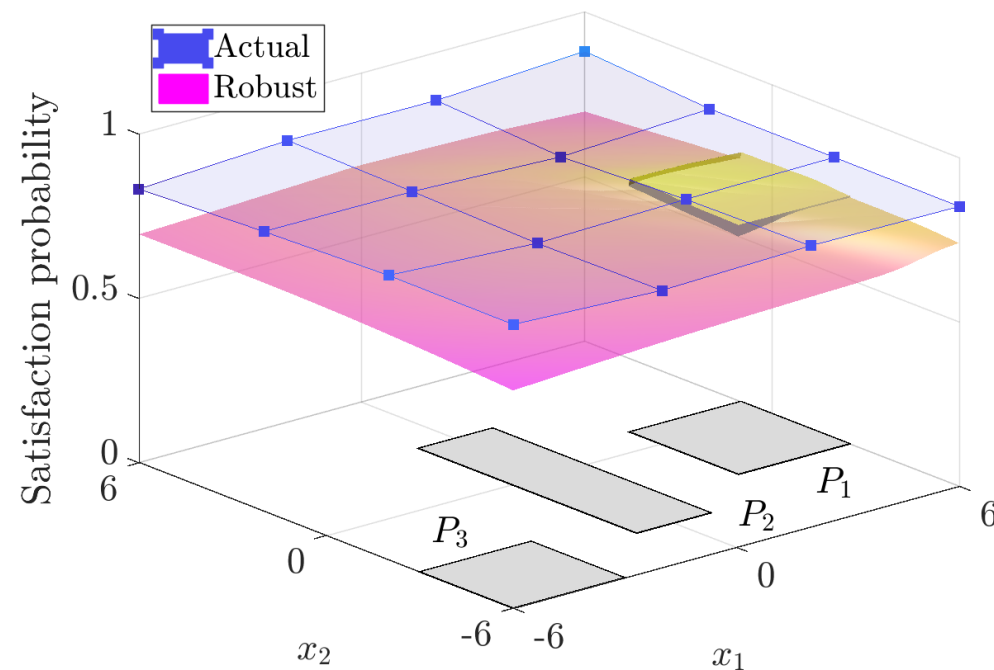
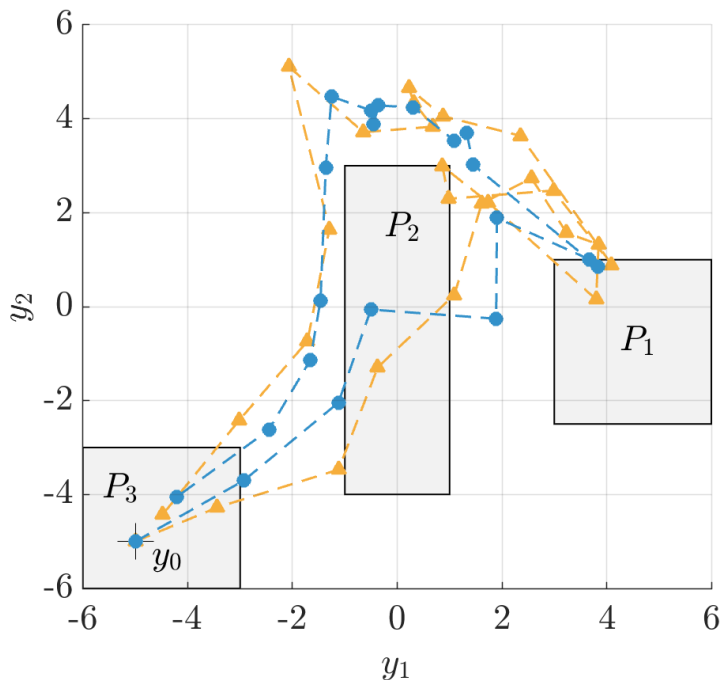
S. Haesaert & S. Soudjani (2020) *Robust dynamic programming for temporal logic control of stochastic systems. TAC.*

Collab. with Sadegh Soudjani's group

Numerical Results

Linear and nonlinear case studies

Applicable to linear and nonlinear system with Gaussian disturbances
 Varying amounts of data
 Lower bound on satisfaction probability



$$\psi = \diamond (P_1 \wedge (\neg P_2 \cup P_3))$$

$$M: \begin{cases} x_{k+1} = \theta^T [x_k; u_k] + w_k \\ y_k = x_k \end{cases} \quad w_k \sim p_w(\cdot)$$

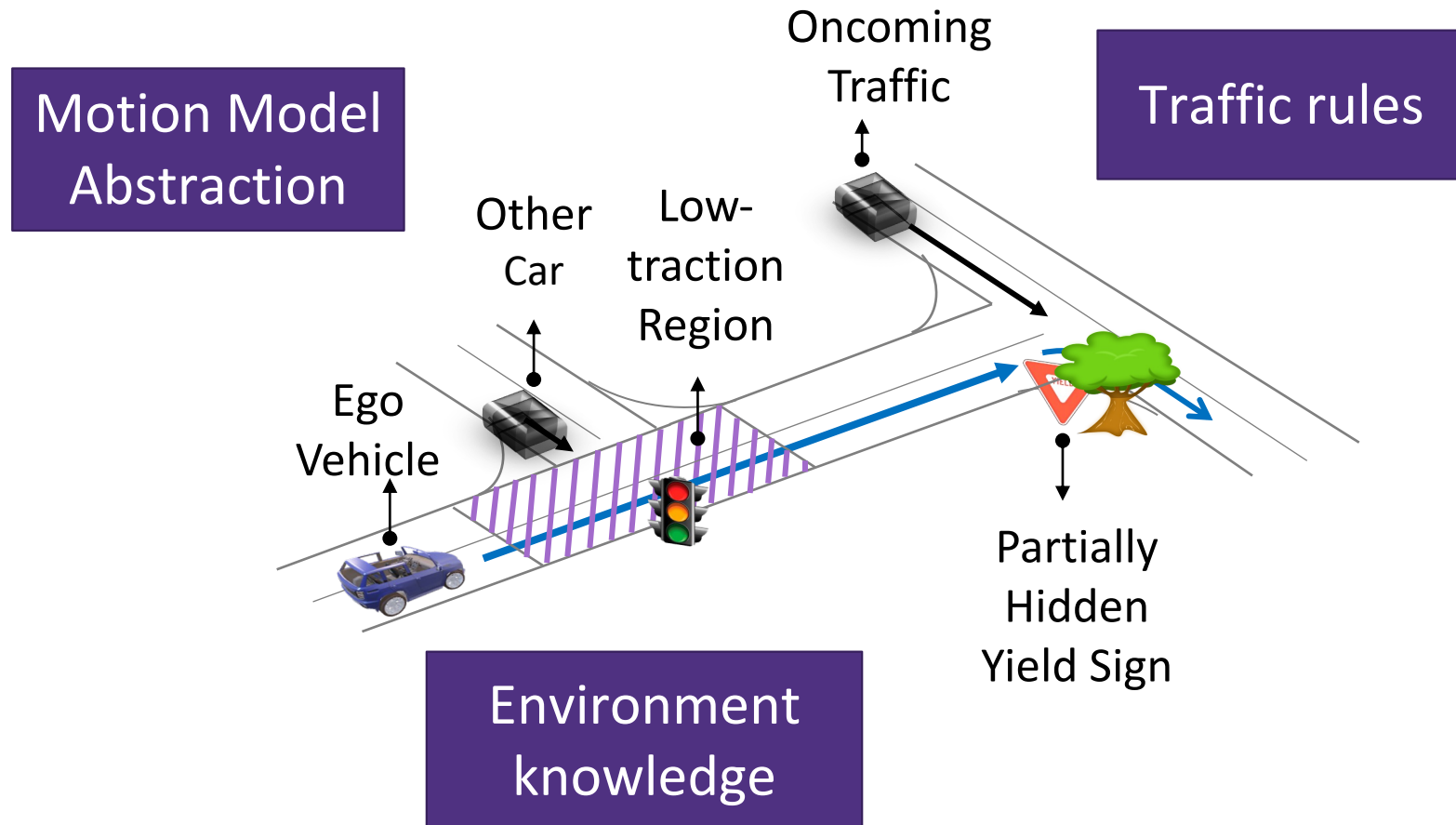
Computed with SySCoRe
<https://github.com/BirgitVanHuijgevoort/SySCoRe-software>

Collab. with Sadegh Soudjani's group

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Dealing with perception data and environment uncertainty

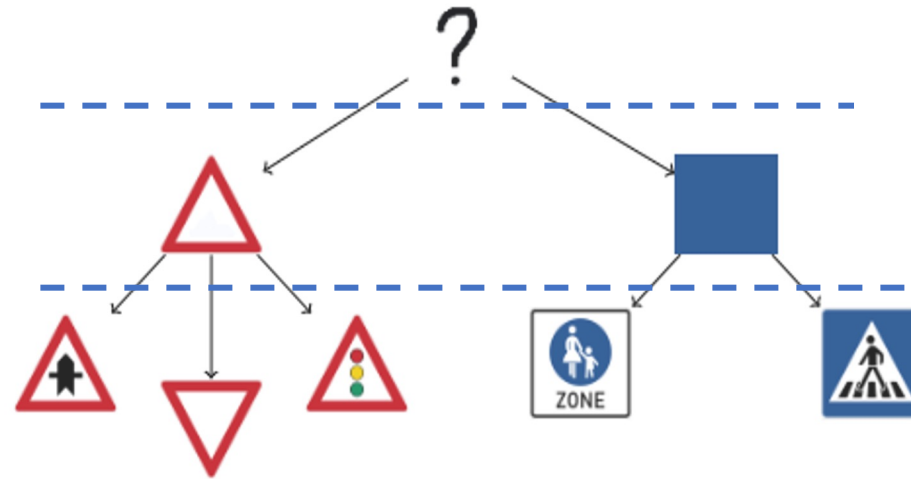
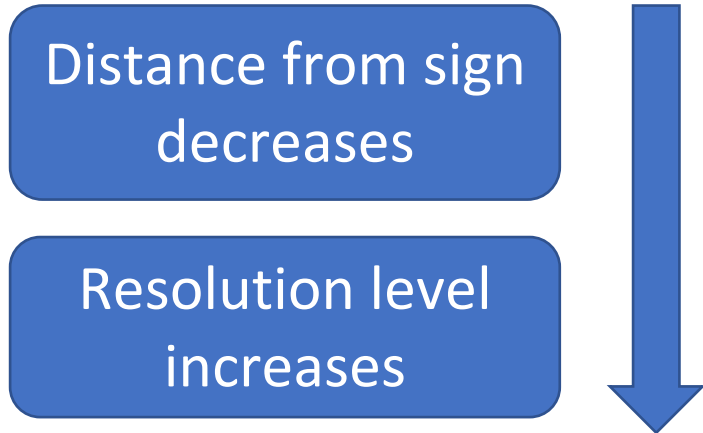


Incremental perception of environment

Uncertainty reduces while you get closer

Perception

Capture perception uncertainty dynamics as a symbolic finite state model



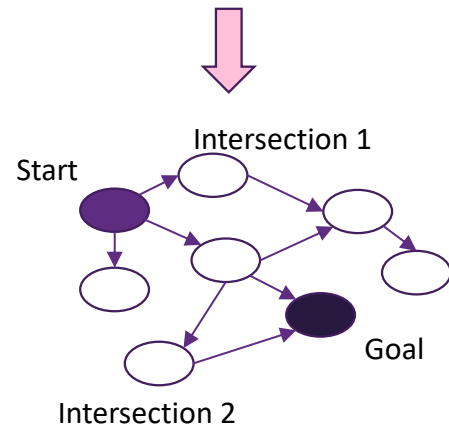
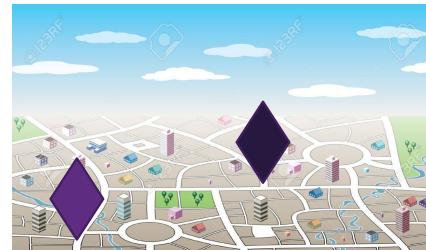
Dealing with incremental perception of environment

Traffic Rules

Traffic and safety rules as Temporal logic formula

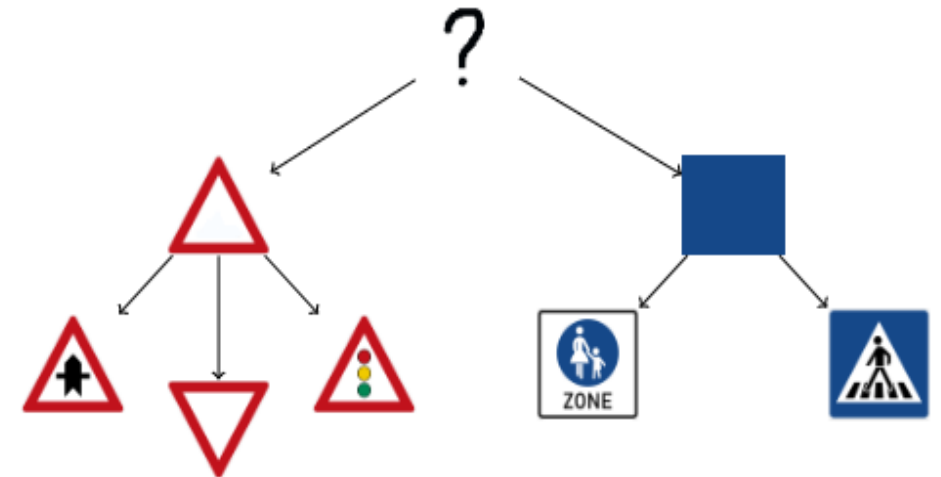
Encoded as GR(1) (Assume Guarantee) and solved with Omega / TuLiP

Motion Model Abstraction

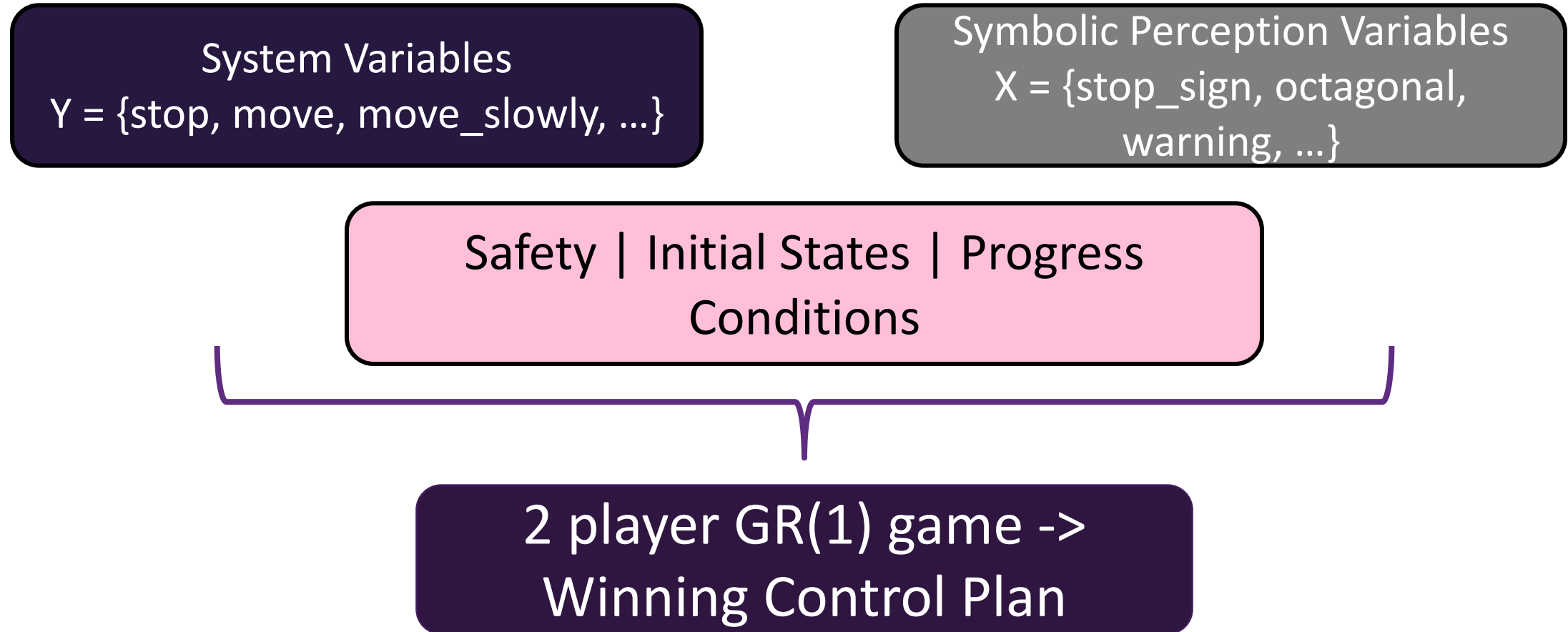


Perception

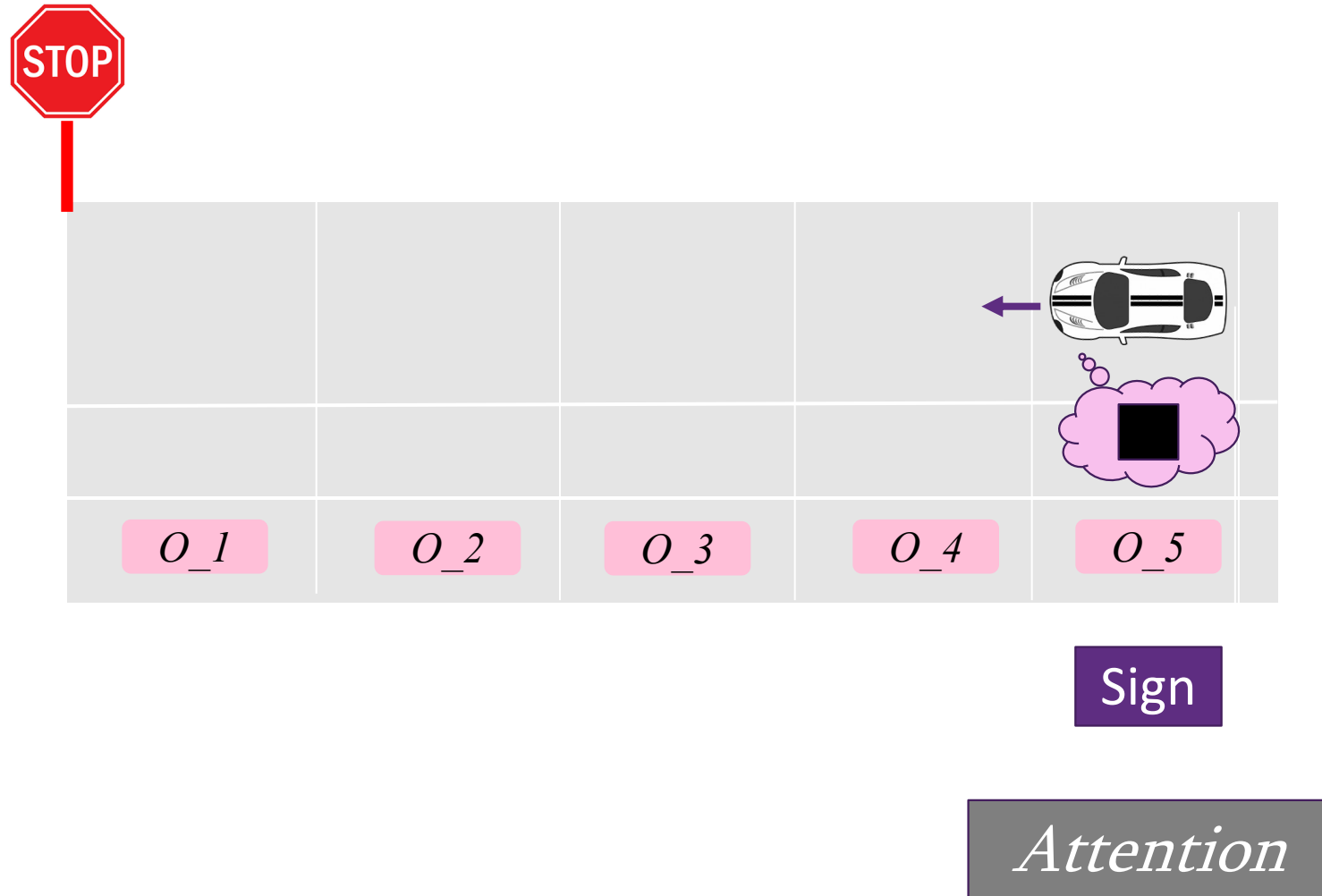
New finite symbolic models for incremental perception of the environment



Approach

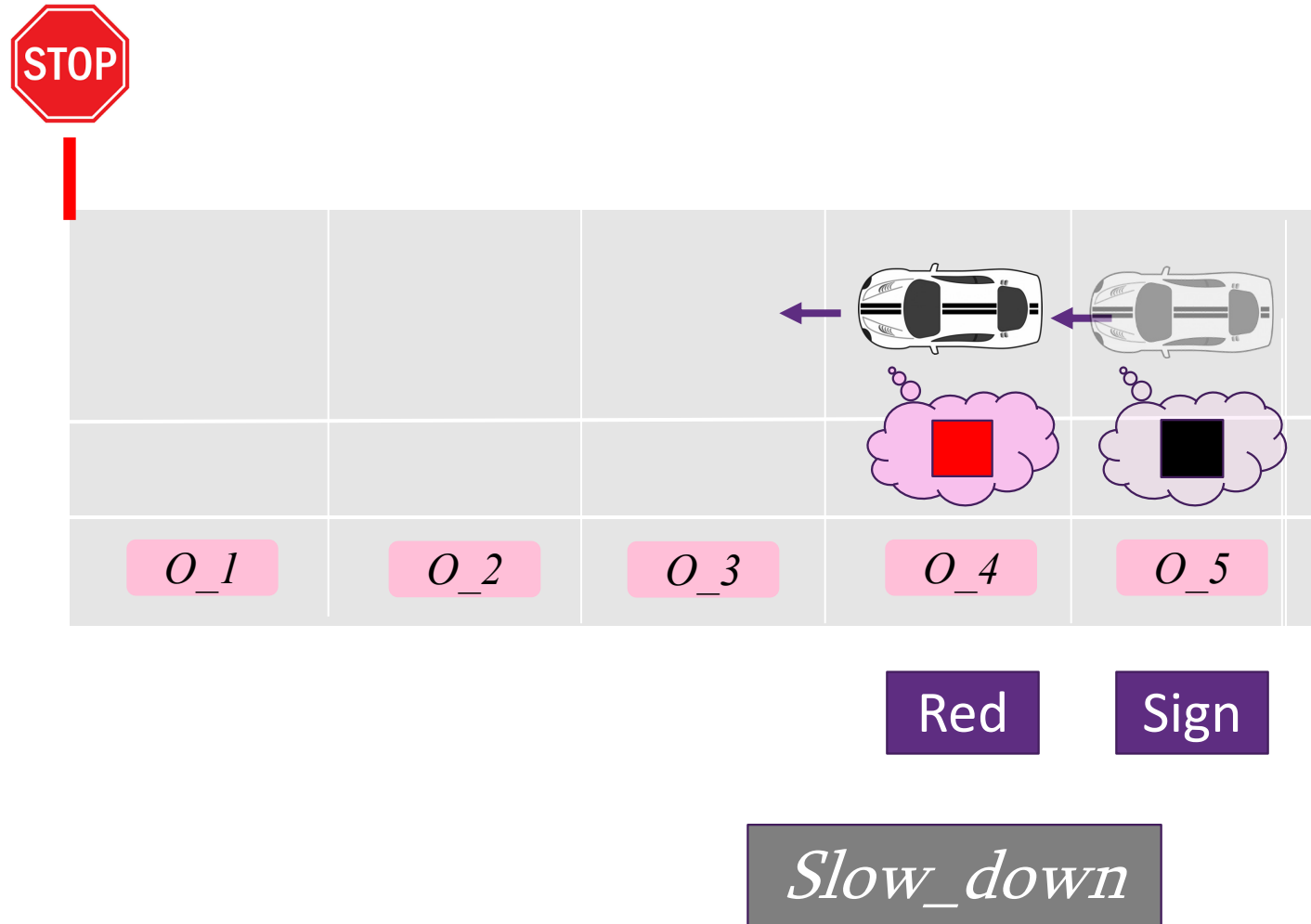


Simulation

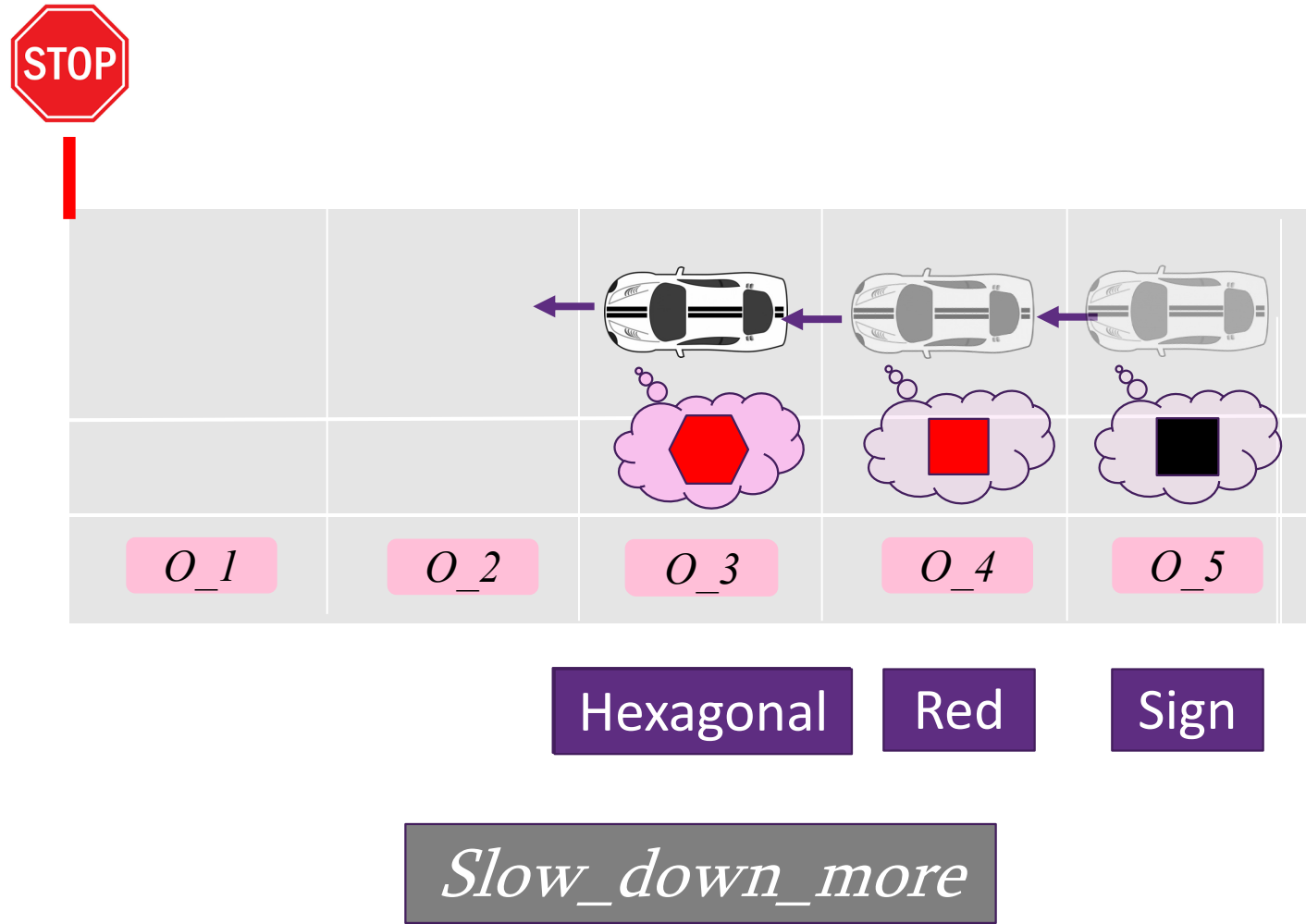


Kamale, Disha, Sofie Haesaert, and Cristian-Ioan Vasile. "Cautious Planning with Incremental Symbolic Perception: Designing Verified Reactive Driving Maneuvers." ICRA 2023

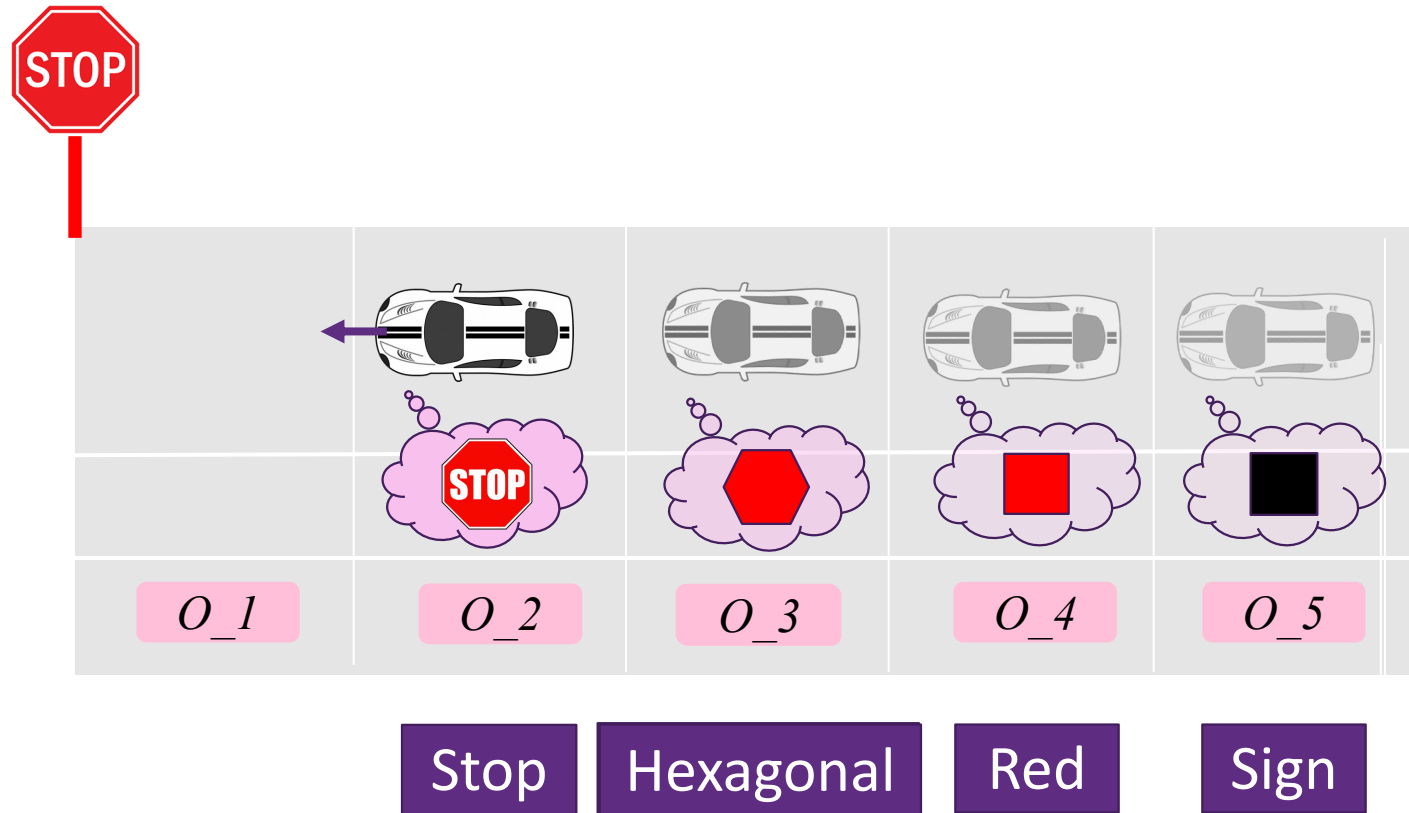
Simulation



Simulation

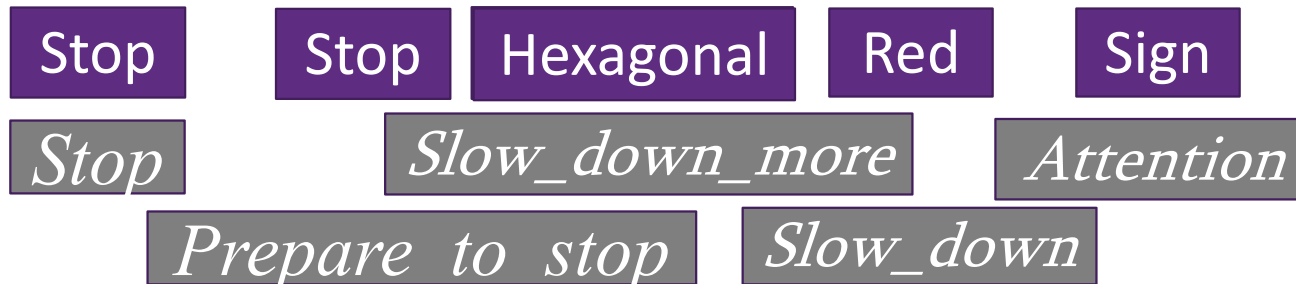
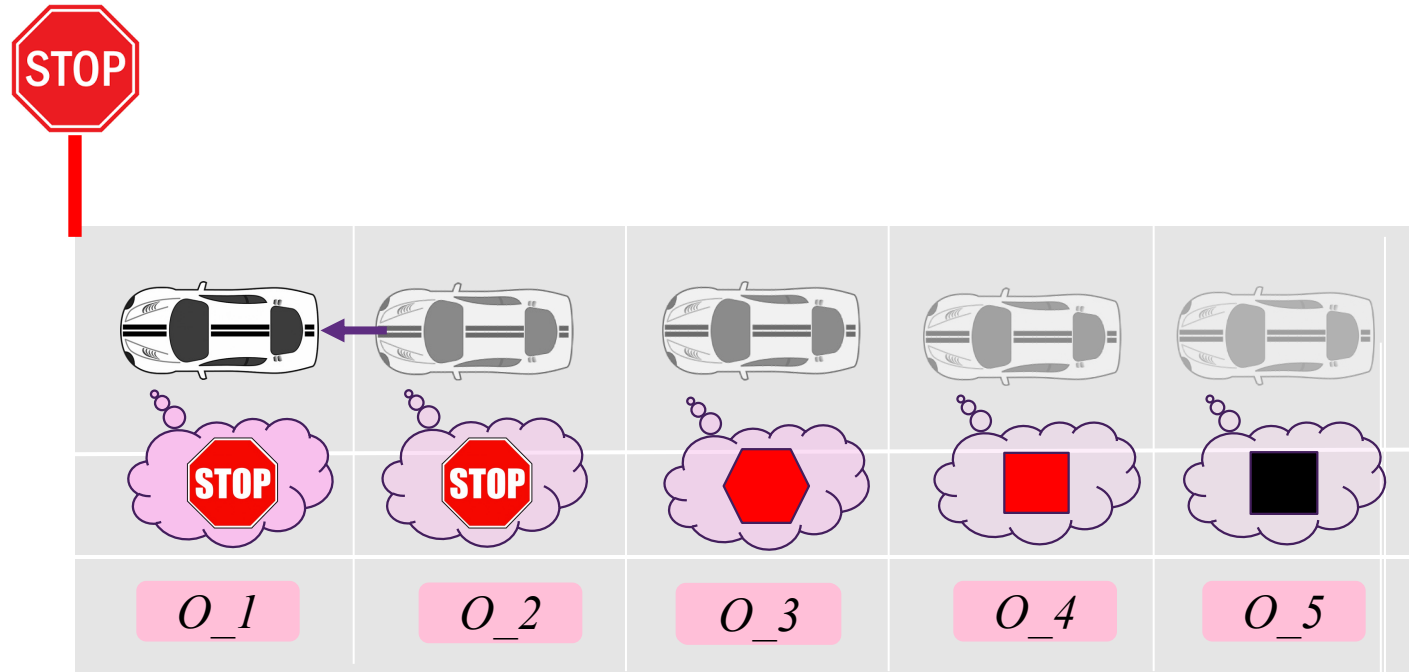


Simulation

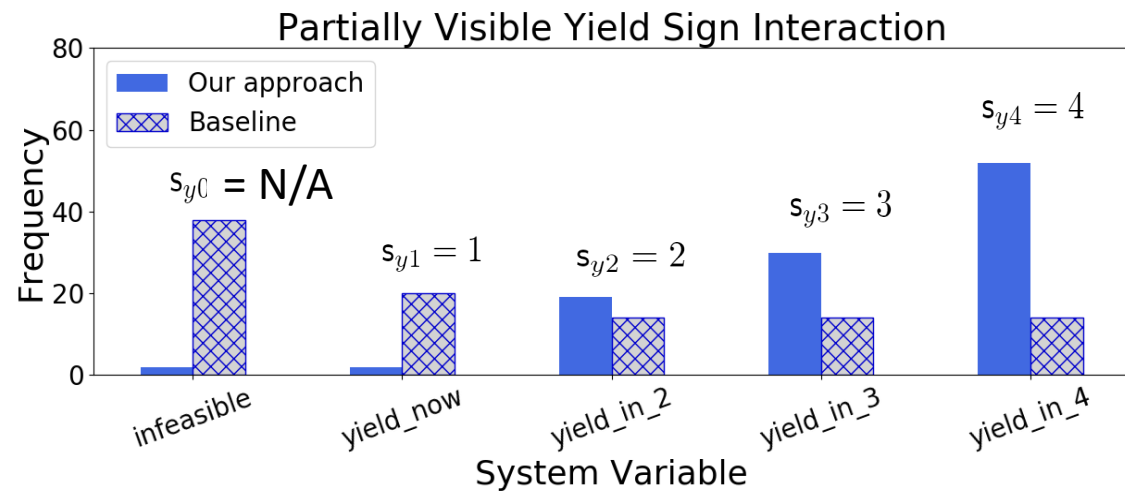
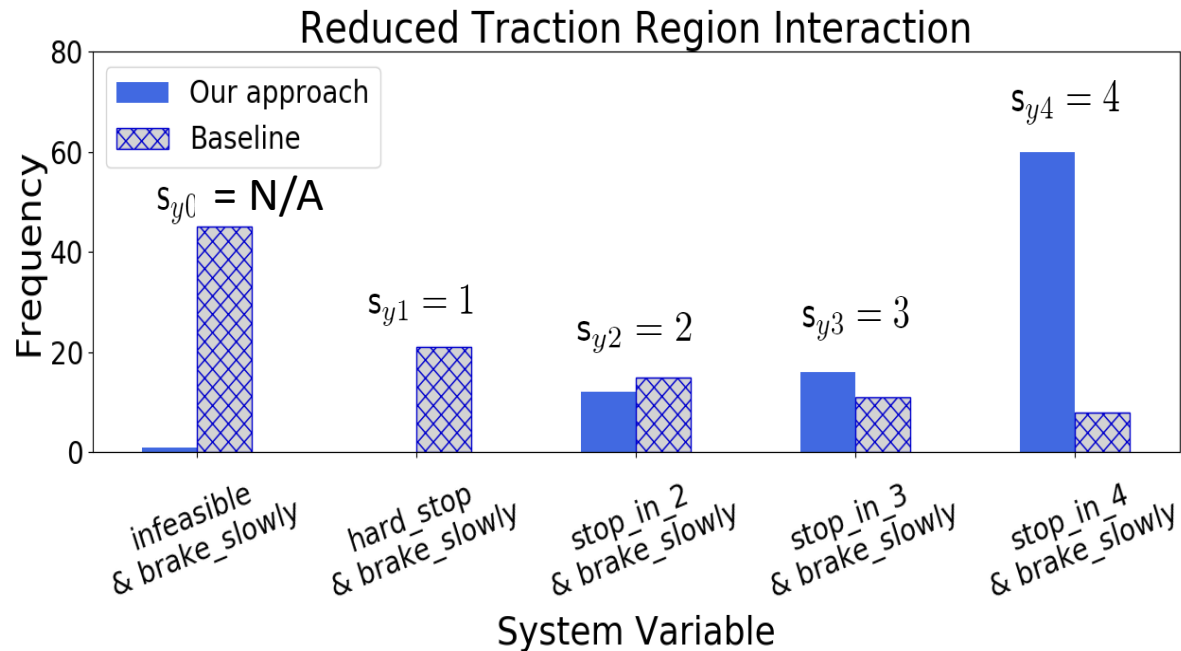
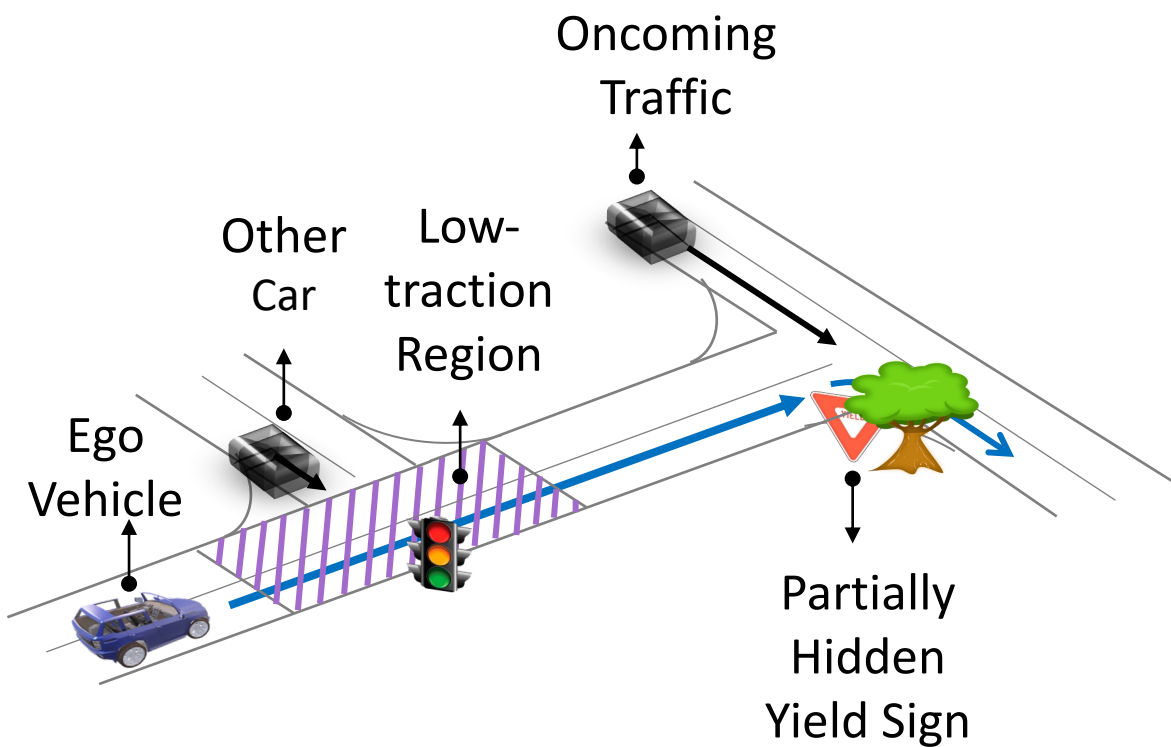


Prepare to stop

Simulation



Simulation

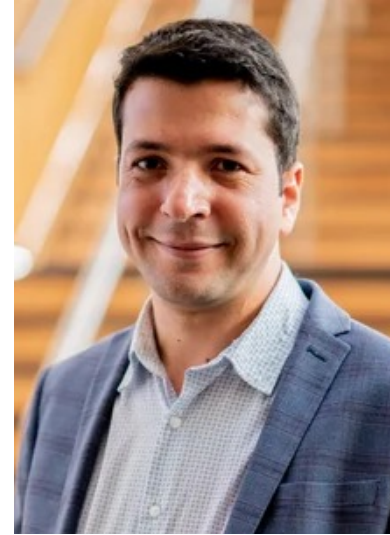


Future work

1. Dealing with partially observable stochastic systems with parametric uncertainty
2. Combining actively getting data and verified control into 1 computable online approach with temporal logic guarantees for stochastic systems
3. Risk-awareness based on perception data and environment uncertainty

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- Sadegh Soudjani (Newcastle university)
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- Roland Toth (TU Eindhoven)



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- [Kamale 2022] Kamale, Disha, Sofie Haesaert, and Cristian-Ioan Vasile. "Cautious Planning with Incremental Symbolic Perception: Designing Verified Reactive Driving Maneuvers." arXiv preprint arXiv:2209.09818 (2022).