

Controller Synthesis and its Magical Futures

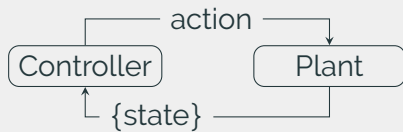
Anna Lukina

March 8, 2021

@ Synthesis of Models and Systems Seminar

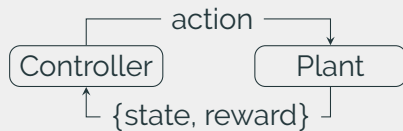


Controller Design



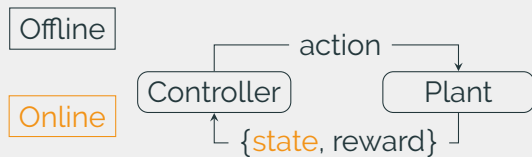
Controller Design via Deep RL

Offline



Goal: maximize expected rewards

Controller Design via Deep RL



Goal: maximize expected rewards

What if the agent has never seen this state offline?

Key Contributions

Current research focus: reliable design of learned systems via combination of formal methods and machine learning

(FMCAD-20) **Formal Methods with a Touch of Magic.** Alizadeh Alamdari, Avni, Henzinger, **Lukina**.

(ECAI-20) **Outside the Box: Abstraction-Based Monitoring of Neural Networks.** Henzinger, **Lukina**, Schilling.

(ATVA-17) **Attacking the V: on the Resiliency of Adaptive-Horizon MPC.** Smolka, Tiwari, Esterle, **Lukina**, Yang, Grosu.

(TACAS-17) **ARES: Adaptive Receding-Horizon Synthesis of Optimal Plans.** **Lukina**, Esterle, Hirsch, Bartocci, Yang, Tiwari, Smolka, Grosu.

A Touch of Magic ✨

Formal Methods with a Touch of Magic [FMCAD 2020]

Reactive Synthesis

Given a specification φ ,
finds a controller that en-
sures the plant satisfies φ

Deep RL

Optimizes performance

Formal Methods with a Touch of Magic [FMCAD 2020]

Reactive Synthesis

Given a specification φ ,
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sures the plant satisfies φ

No performance guarantee

Deep RL

Optimizes performance

No correctness guarantee

Formal Methods with a Touch of Magic [FMCAD 2020]

Reactive Synthesis

Given a specification φ ,
finds a controller that en-
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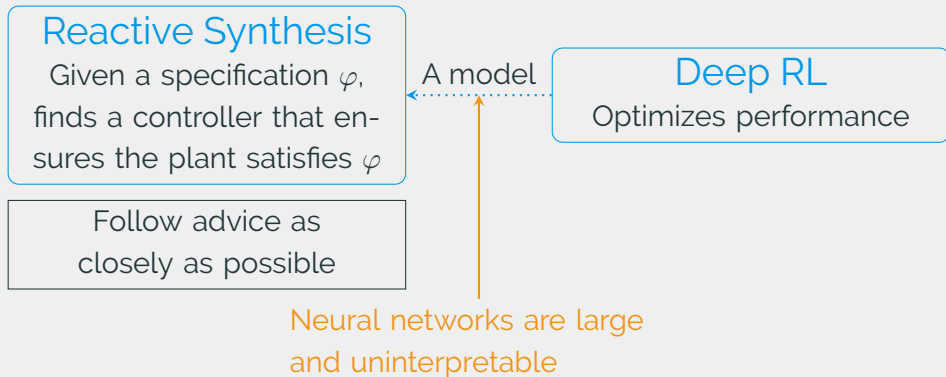
Follow advice as
closely as possible

A model

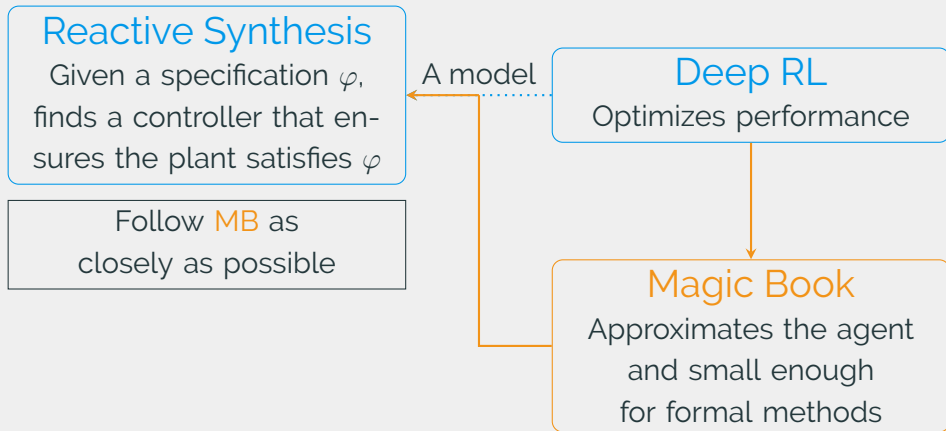
Deep RL

Optimizes performance

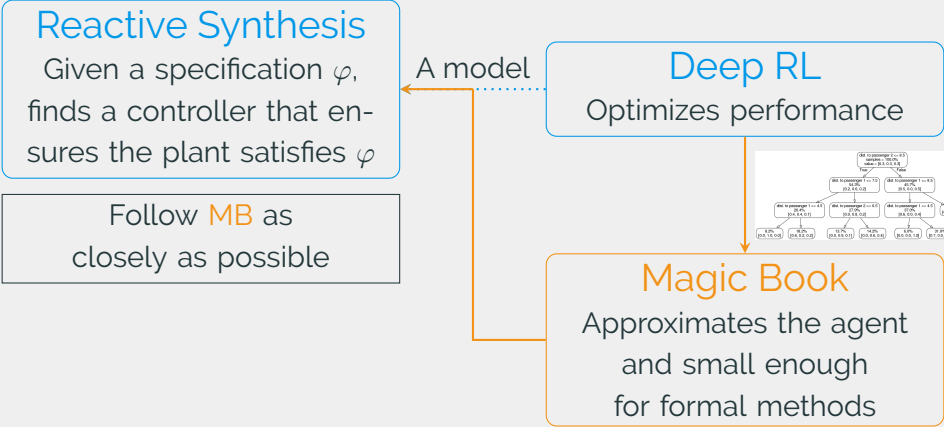
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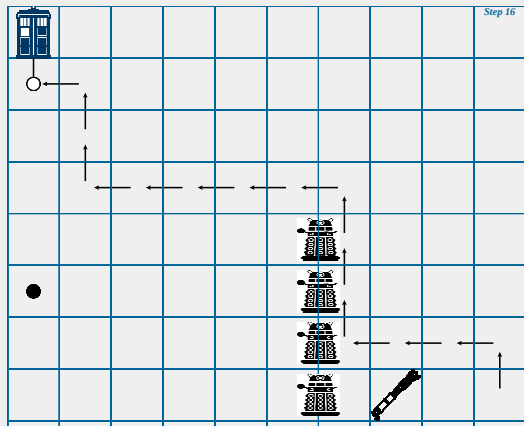


Formal Methods with a Touch of Magic [FMCAD 2020]



Control Synthesis by the Magic Book [FMCAD 2020]

φ : "reach a gas station every t time steps"



Performance and Explainability [FMCAD 2020]

Num. of collected passengers	RF(5,6)	Wizard
Avg. performance	154	159
Max. performance	194	200
Synthesis avg. performance	96	-

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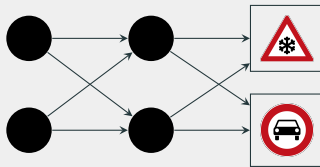
"Passenger 2 is collected first": $\bigwedge_{1 \leq i \leq \ell} (x_j^i = x_j^0 \wedge y_j^i = y_j^0) \forall j = 1, 3$

$$\neg(x_2^\ell = x_2^0 \wedge y_2^\ell = y_2^0)$$

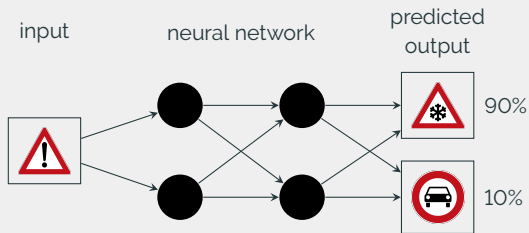
Bound	Passenger 2	
	runtime	succ. ratio
6	0.25 s	85 %
7	0.30 s	87.2 %
8	0.36 s	89.9 %
9	0.47 s	82.2 %

Reaction to Novel Input Classes

neural network

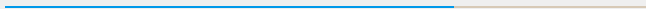


Reaction to Novel Input Classes



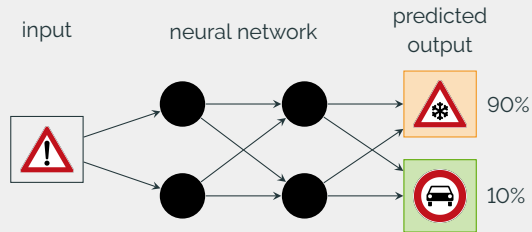
Must output "do not know"

Outside the Box



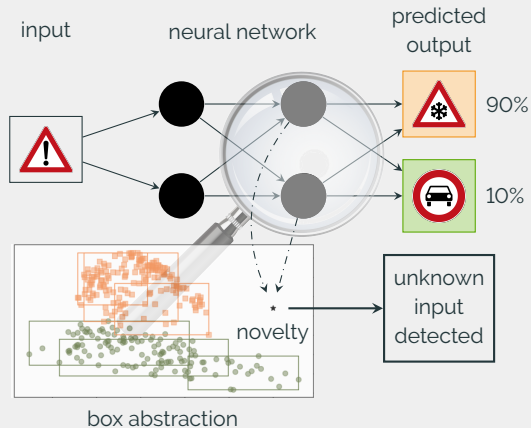
Abstraction-Based Monitoring of Neural Networks

[ECAI 2020]



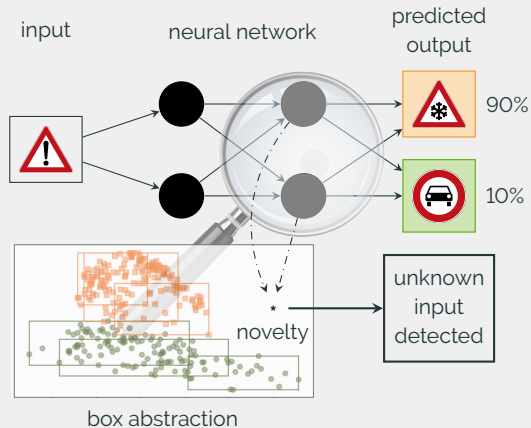
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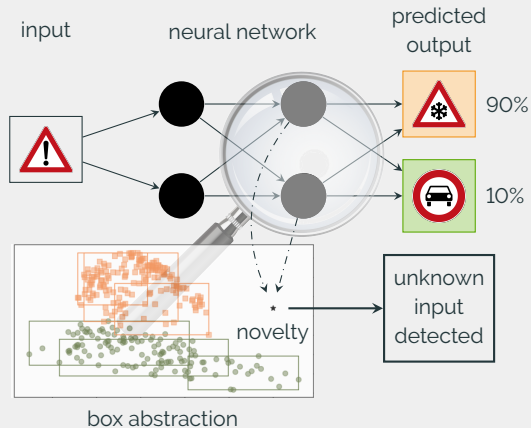
[ECAI 2020]



1. Computationally **cheap**

Abstraction-Based Monitoring of Neural Networks

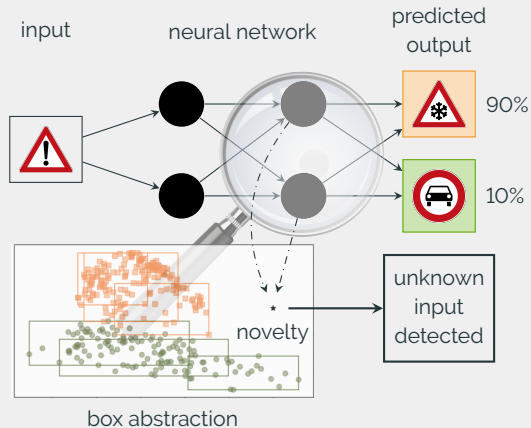
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1. Computationally **cheap**
2. **Effective** in detecting novelties

Abstraction-Based Monitoring of Neural Networks

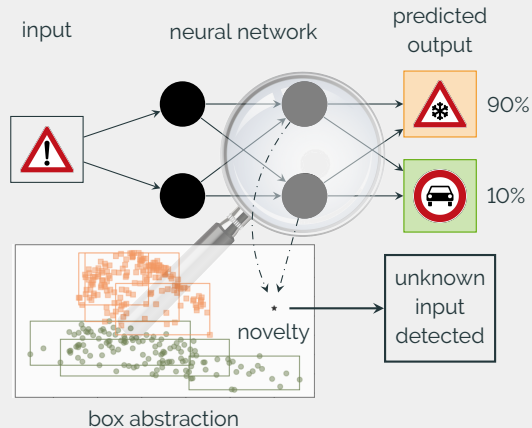
[ECAI 2020]



1. Computationally **cheap**
2. **Effective** in detecting novelties
3. Data and model **independent**

Abstraction-Based Monitoring of Neural Networks

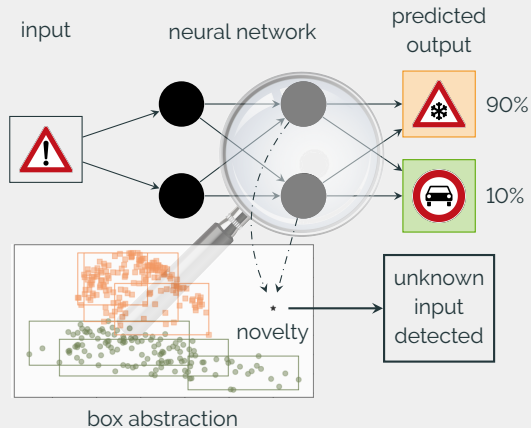
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Abstraction-Based Monitoring of Neural Networks

[ECAI 2020]



1. Computationally **cheap**
2. **Effective** in detecting novelties
3. Data and model **independent**
4. **Easy** to integrate
5. **Flexible** to user configuration

Neural Networks in Dynamic Environments

Real-time object detection with neural networks¹:

¹<https://pjreddie.com/darknet/yolo/>

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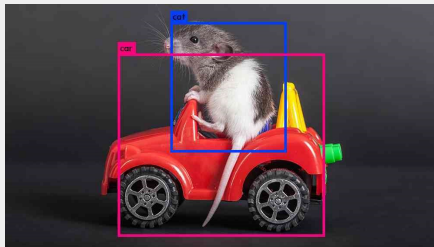


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²<https://rpubs.com/dgolicher/yolo>

Open Problems

Verification Learning

Scalability:

- Dimensionality of the input for controllers.
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How to make model checkers generate good-for-learning counterexamples?

How to use statistical model checking for learned controllers?

