

Controller Synthesis and its Magical Futures

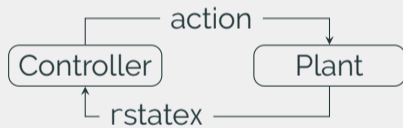
Anna Lukina

March 8, 2021

@ Synthesis of Models and Systems Seminar

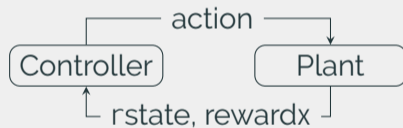


Controller Design



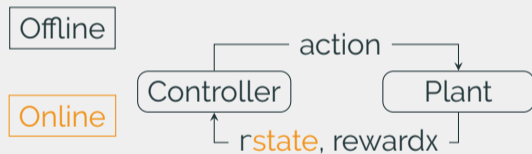
Controller Design via Deep RL

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 ensures
the plant satisfies ϕ

Deep RL

Optimizes performance

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

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-
sures the plant satisfies ϕ

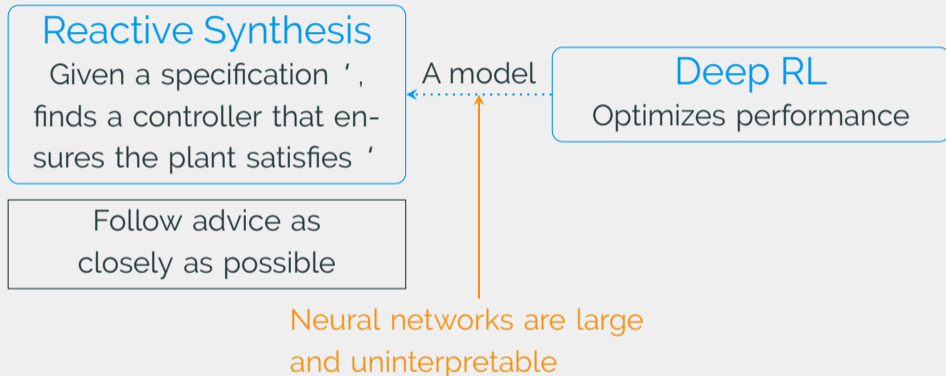
Follow advice as
closely as possible

A model

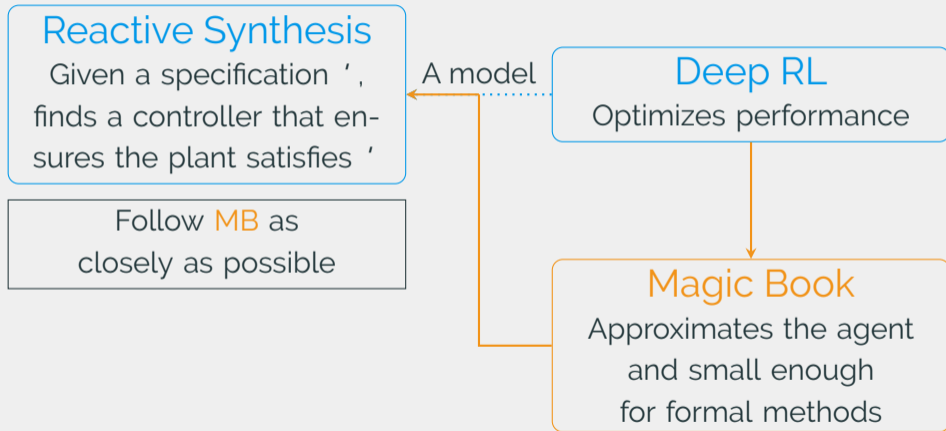
Deep RL

Optimizes performance

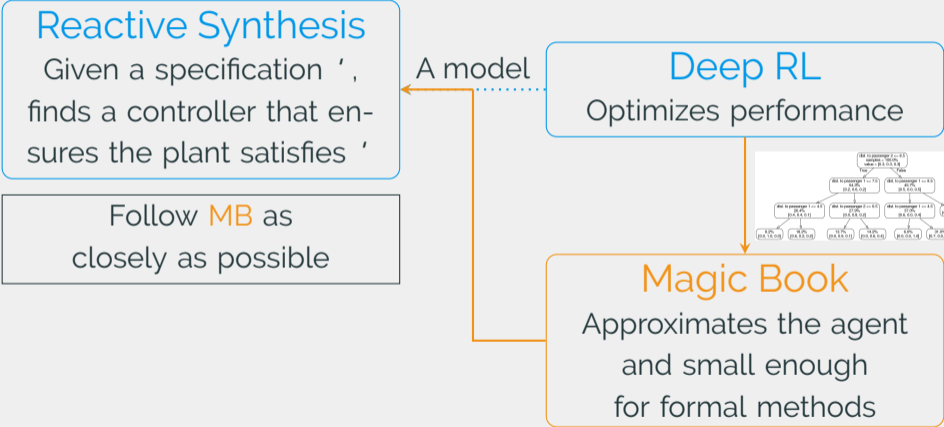
Formal Methods with a Touch of Magic [FMCAD 2020]



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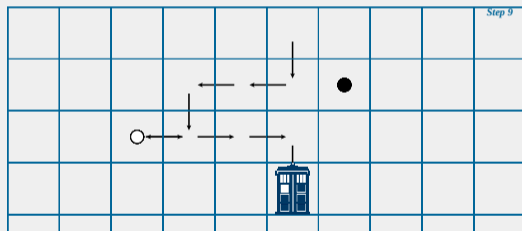


Formal Methods with a Touch of Magic [FMCAD 2020]



Verification of the Magic Book [FMCAD 2020]

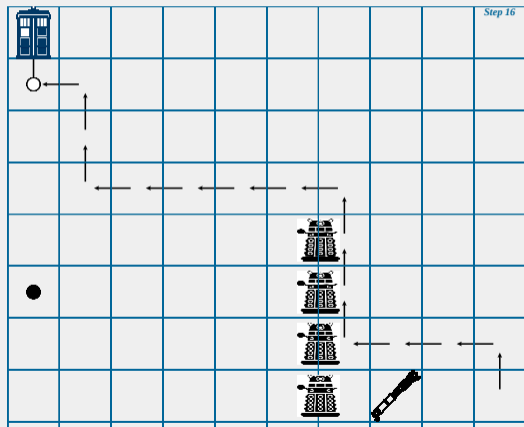
- ' "the taxi never enters a loop in which no passenger is collected"



A state at time i : $r x_0^i; y_0^i; \dots; x_k^i; y_k^i$

Control Synthesis by the Magic Book [FMCAD 2020]

' "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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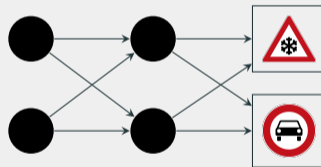
"Passenger 2 is collected first": $\bigwedge_{j \in \{1,3\}} (x_j^i \wedge y_j^i \rightarrow x_j^0 \wedge y_j^0)$

$$x_2^i \wedge y_2^i \rightarrow x_2^0 \wedge y_2^0$$

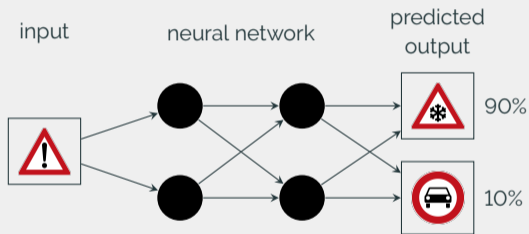
Bound	Passenger 2	
	runtime	succ. ratio
6	0.25 s	85 %
7	0.30 s	87.2 %
8	0.36 s	89.9 %
9	0.47 s	82.2 %

Reaction to Novel Input Classes

neural network



Reaction to Novel Input Classes

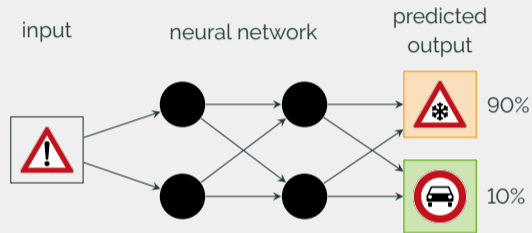


Must output "do not know"

Outside the Box

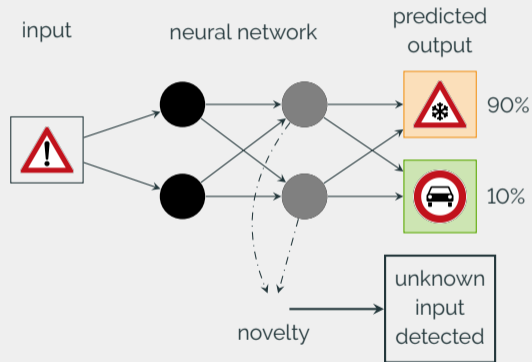
Abstraction-Based Monitoring of Neural Networks

[ECAI 2020]



Abstraction-Based Monitoring of Neural Networks

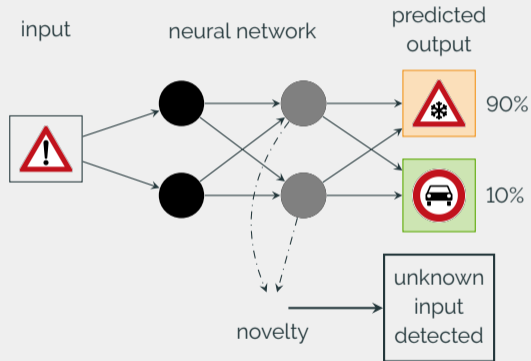
[ECAI 2020]



box abstraction

Abstraction-Based Monitoring of Neural Networks

[ECAI 2020]

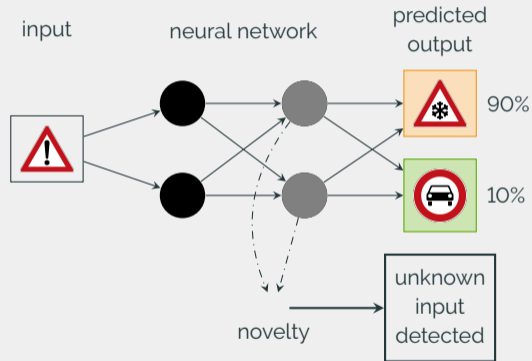


box abstraction

1. Computationally **cheap**

Abstraction-Based Monitoring of Neural Networks

[ECAI 2020]

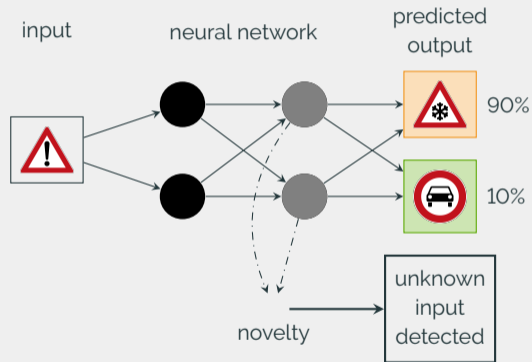


box abstraction

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

Abstraction-Based Monitoring of Neural Networks

[ECAI 2020]

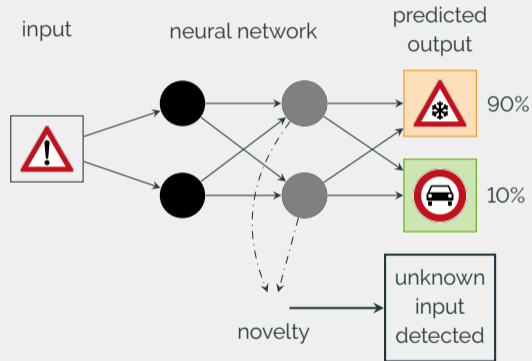


box abstraction

1. Computationally **cheap**
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3. Data and model **independent**

Abstraction-Based Monitoring of Neural Networks

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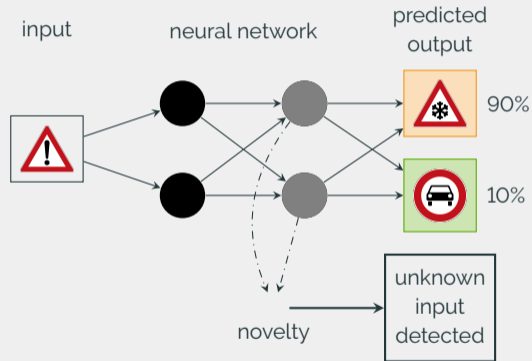


box abstraction

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4. **Easy** to integrate

Abstraction-Based Monitoring of Neural Networks

[ECAI 2020]



box abstraction

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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¹<https://pjreddie.com/darknet/yolo/>

²<https://rpubs.com/dgolicher/yolo>

Open Problems

Verification Learning

Scalability:

- Dimensionality of the input for controllers.
- Control synthesis for POMDPs.

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Run-time performance vs. guarantees:

- Real-time performance in self driving.
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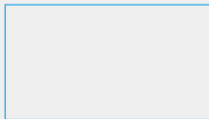
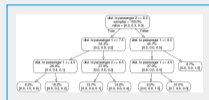
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How to make model checkers generate good-for-learning counterexamples?

How to use statistical model checking for learned controllers?