Compositional Verification and Runtime Monitoring for Learning-Enabled Autonomous Systems

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Problem

- Autonomous systems increasingly use Deep Neural Networks (DNNs) for perception
  - Need to be highly reliable
- Reasoning about “closed loop” autonomous systems is very difficult
  - High complexity of the DNN (thousands or millions of parameters)
  - Complexity of the high-definition cameras
  - Complexity of the environment, subject to random perturbations


Our Approach

Key idea:

- **Abstract** away the hard-to analyze components:
  - Perception DNN, camera, environmental dynamics
- Replace them with **probabilistic or worst-case abstractions**
- Model other components (controller, plant) using conventional techniques
- **System becomes amenable to formal verification with off-the-shelf tools**
- Approach is **compositional**
  - **Conventional components analyzed separately from perception components**

This talk:

- **Probabilistic (average-case) analysis**: provides probabilistic guarantees
- **Worst-case analysis**: provides strong (non-probabilistic) guarantees

Case Study: TaxiNet

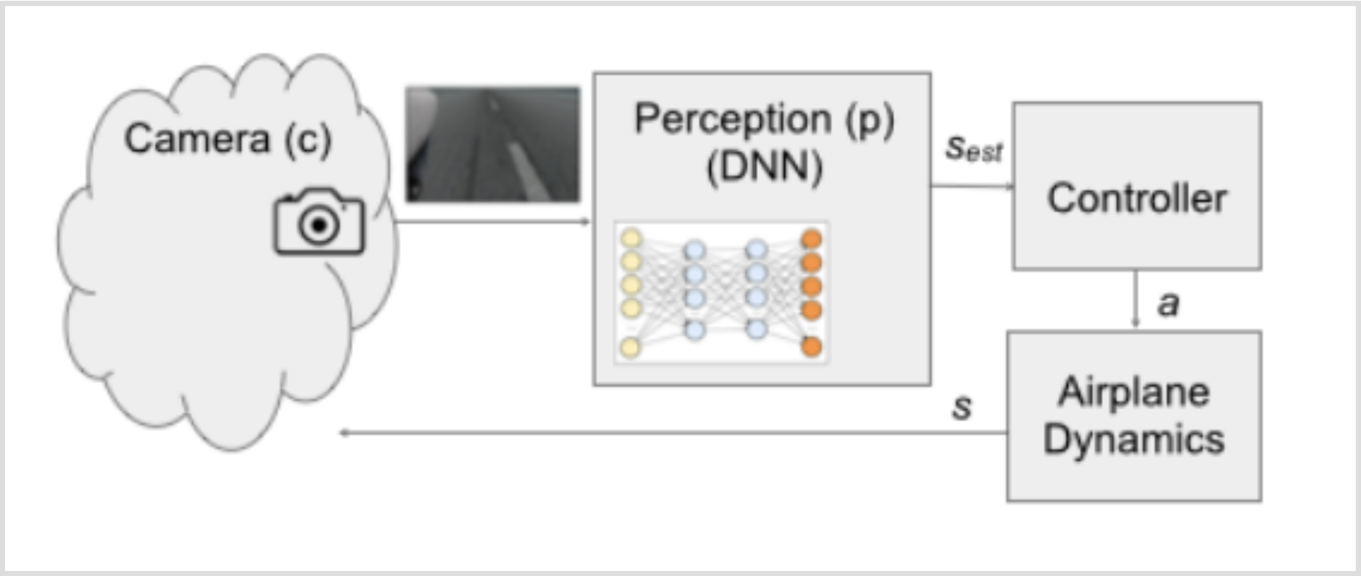
- Neural network designed to take a picture of the runway as input and return the plane's position w.r.t. the middle of the runway
- Returns two numerical outputs
  - Cross-track error (`cte`): The distance of the plane from the middle line
  - Heading error (`he`): The angle of the plane w.r.t. the runway

- Simple scenario:
  - From an initial state, keep straight line for a finite number of steps
- **Properties**:

  (Property 1) Airplane does not go off runway: **|`cte`| ≤ 8 meters**

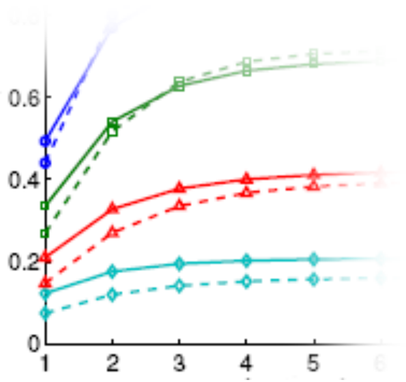
  (Property 2) Airplane does not turn more than certain degree: **|`he`| ≤ 35 degrees**

Autonomous Line Tracking System



- State ***s***: actual values of **(cte,he)**
- Estimated state $\boldsymbol{s_{est}}$: estimated values of **(cte,he)** as returned by the DNN

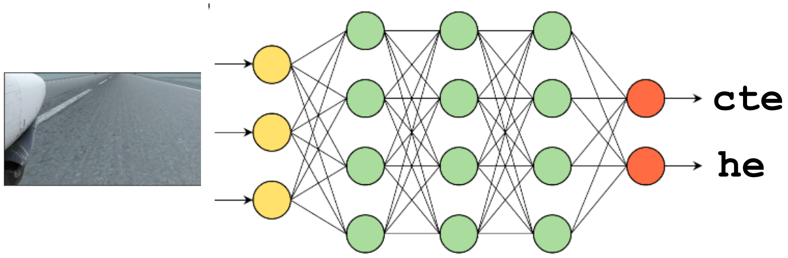
Discrete Models



- We build a discrete-state model of the system for analysis
  - Discrete controller
  - Discrete model of airplane dynamics
- **System state**: Real-valued (**`cte, he`**)
- **Discretize** system state (both actual and estimated) as dictated by controller logic
- The regression outputs of TaxiNet are discretized to view the model as a ***classifier*** which predicts the plane's position in discrete states

Discretized View of TaxiNet

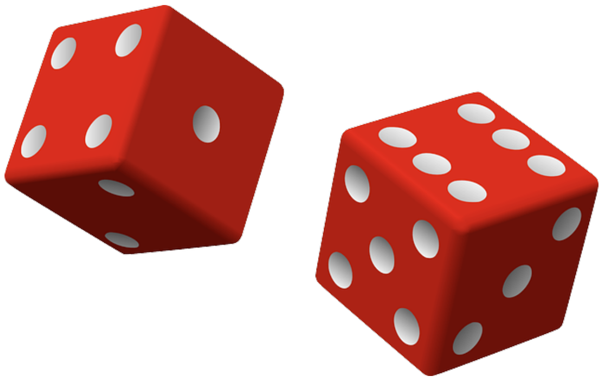
- Taxinet DNN model
  - Input images: RGB color images, 360 × 200 pixels
  - 24 layers CNN, 3 dense layers before output
  - Representative dataset with 11108 images
  - Mean Absolute Error (MAE): cte : 1.185, he: 7.86
- Discretization of outputs to view the model as a classifier
- Values outside the intervals: error states (encoded as “-1”)



$$\underline{\texttt{cte}} = \begin{cases} 3 \text{ if } -8.0 \text{ m} <= \texttt{cte} < -4.8 \text{ m} \\ 1 \text{ if } -4.8 \text{ m} <= \texttt{cte} < -1.6 \text{ m} \\ 0 \text{ if } -1.6 \text{ m} <= \texttt{cte} <= 1.6 \text{ m} \\ 2 \text{ if } 1.6 \text{ m} < \texttt{cte} <= 4.8 \text{ m} \\ 4 \text{ if } 4.8 \text{ m} < \texttt{cte} <= 8.0 \text{ m} \end{cases}$$

$$\underline{\texttt{he}} = \begin{cases} 1 \text{ if } -35.0^\circ <= \texttt{he} < -11.67^\circ \\ 0 \text{ if } -11.67^\circ <= \texttt{he} <= 11.66^\circ \\ 2 \text{ if } 11.66^\circ < \texttt{he} <= 35.0^\circ \end{cases}$$

Probabilistic Analysis [CAV'23]



Probabilistic Abstraction for Perception

Probabilistic abstraction maps **actual** system states to (a distribution over) **predicted** states

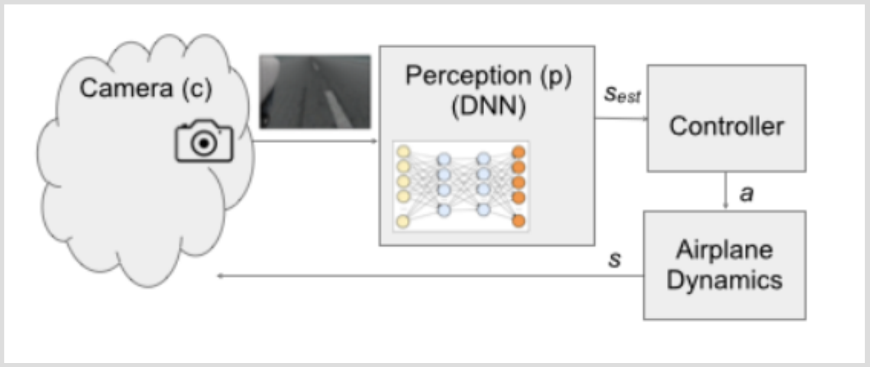
- Abstraction **linear** in the size of the output of the DNN, independent of the number of DNN parameters, the camera or the environment

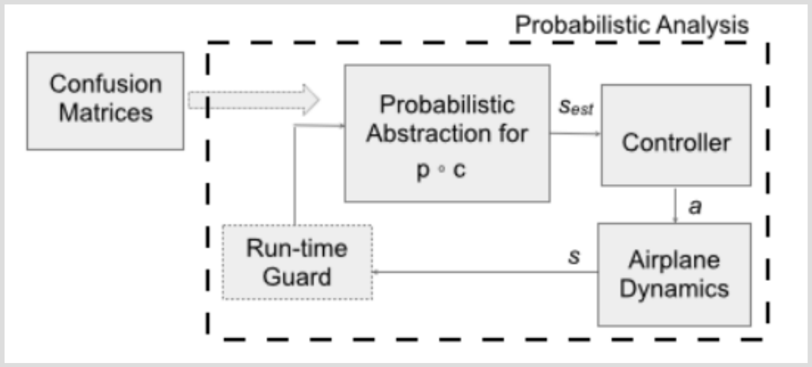
Why probabilistic view?

- Camera maps one 3D vehicle position to a distribution of images
- Different environment conditions (light, contrast, skid marks etc)

We leverage DNN-specific analysis (e.g., robustness) to define run-time guards

- Refine the abstraction and increase the safety of the system





Probabilistic Abstraction for Perception

Probabilistic abstraction:

- Maps every (discrete) system state to every (discrete) estimated state
- Transition probabilities estimated based on confusion matrices for perception DNN, measured on **“representative”** data set

State: (**`cte,he`**)

		Predicted		
	Total = 11108	**0**	**1**	**2**
Actual	**0**	4748	2139	148
	1	91	2010	0
	2	744	211	1017

Table 1: Confusion Matrix for **he**

DTMC code:

```
[] he=0 → 0.675: (he_est'=0) + 0.304: (he_est'=1) + 0.021: (he_est'=2);
[] he=1 → 0.043: (he_est'=0) + 0.957: (he_est'=1) + 0.0: (he_est'=2);
[] he=2 → 0.377: (he_est'=0) + 0.107: (he_est'=1) + 0.516: (he_est'=2);
```

DNN Checks as Run-time Guards

- Many techniques for DNN analysis
  - Robustness, safety, confidence, out-of-distribution detection, Prophecy, etc.
  - Can be black box or white box; complete or incomplete
  - How can we leverage these off-the-shelf analysis techniques to improve the safety of the overall system?
- Our approach
  - Uses DNN Checks as run-time guards
  - For inputs that pass the checks, the DNN is more likely to be correct/accurate.
  - For TaxiNet, we use rules extracted with Prophecy
  - Out of 11108 inputs, 9125 inputs (82.1%) pass the DNN check:

```
i:[0..M] init 0;
[]  pc=0 & i<M → 0.821: (v'=1) & (pc'=1) & (i'=0) + 0.179: (v'=0) & (i'=i+1);
```

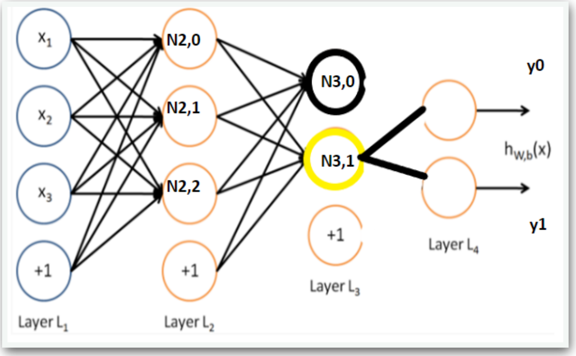
The abstract map for state variables he and cte is only computed for the inputs that pass the check (i.e., for v = 1) based on newly computed confusion matrices

Prophecy Rules as Run-time Guards

- Inferred automatically from DNN neuron activations [ASE'19]
  - Intent is to capture properties on the semantic features the network has learnt
  - Built with **decision-tree learning** over activations collected on training data, validated on test data
- Rule: Pre => Post
- Pre is a condition on neuron values at some layer; Post = "mis-prediction"

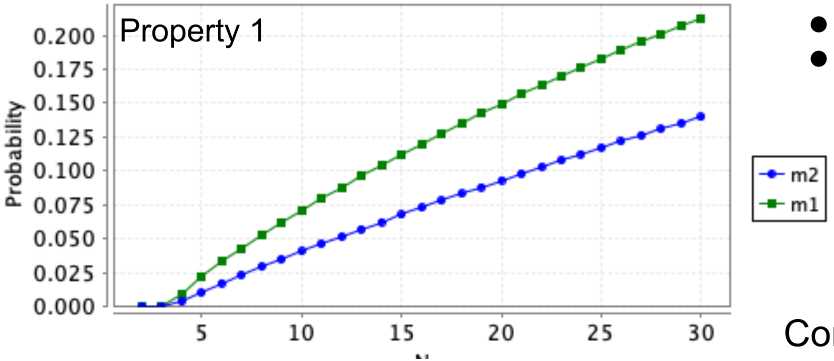
$$N_{1,85} <= -0.998 \ \wedge \ N_{2,50} <= 3.31 \ \wedge \ N_{1,84} <= -0.994 \ \wedge \ N_{1,15} > -0.999$$
$$\wedge \ N_{1,21} <= 1.711 \wedge N_{1,70} <= 11.088 \wedge N_{1,51} > -0.999 \wedge N_{1,21} > -0.637 \implies$$
$$|\mathtt{cte}^* - \mathtt{cte}| > 1.0 \ meters \ \vee \ |\mathtt{he}^* - \mathtt{he}| > 5 \ degrees$$

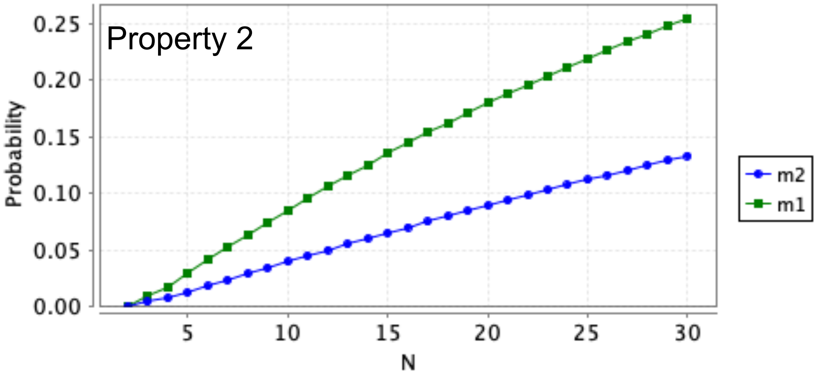
- If an input satisfies Pre it is considered to violate the runtime check
- Can be evaluated efficiently during forward pass of DNN
- If the check is violated M times, go to "abort" state
  - e.g., hand over control to the pilot



(N3,0 = 0 /\ N3,1 > 0) => y0 < y1 (label 1)

Experiments with PRISM





Analyzed two models:

- m1 (no run-time guard)
- m2 (with run-time guard)
  - Rules characterizing inputs where the model gives mis-predictions
  - A rule is of the form **Pre => Post**
  - Pre is a condition in the latent space; Post is a condition on the output
  - An input passes the guard if it is not “rejected” by the rule
  - Extracted using **Prophecy** from the dense layers of the model

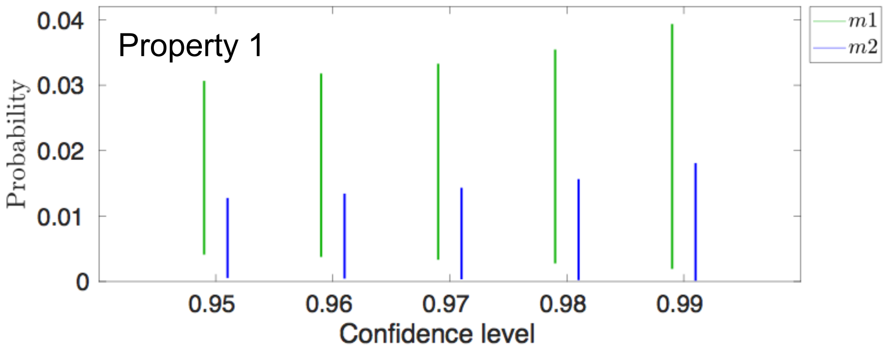
Controller and dynamics are the same for both models

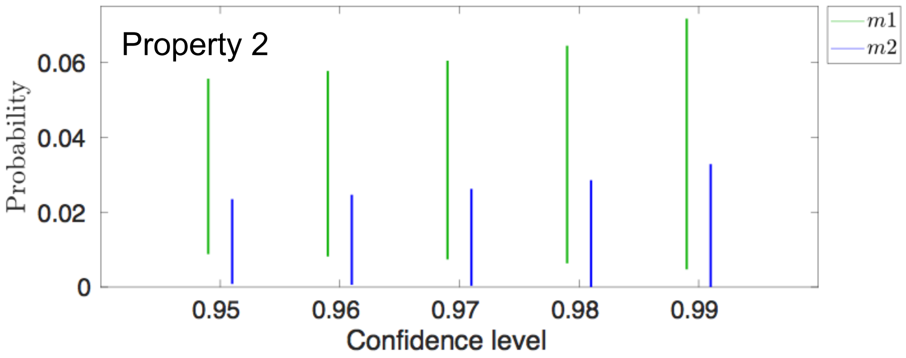
(Property 1) **P =?[F (`cte` = −1)]**

(Property 2) **P =?[F (`he` = −1)]**

Experiments with FACT: Confidence Interval Analysis

- Probabilistic abstractions based on empirical estimates of probabilities
  - Lack **statistical guarantees;** can be off from true probabilities
- We compute **confidence intervals**
  - For the transition probabilities
  - For the probability that the safety properties are satisfied
- FACT tool:
  - Synthesizes a $(1 - \delta)$-**confidence interval** $[a, b] \subseteq [0, 1]$ for the probability that a property φ is satisfied, given a set of observations (based on confusion matrices)



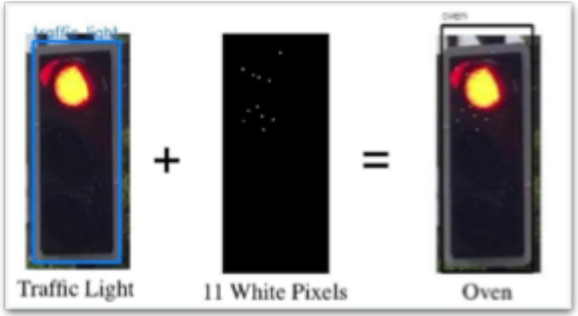


Summary

- Experiments demonstrate the feasibility of our approach
  - Analysis of DNN working side-by-side with conventional components (controller, dynamics)
  - Abstraction **separates** the concerns of DNN and conventional system development and evaluation
  - Analysis incorporates accuracy/confusion matrices results in the system-level analysis
- We provide **probabilistic guarantees**
  - Address gaps of quantitative evaluation for future AI certification
- Experiments show benefit of the run-time guards
- *Improved performance of the DNN translates into improved safety*

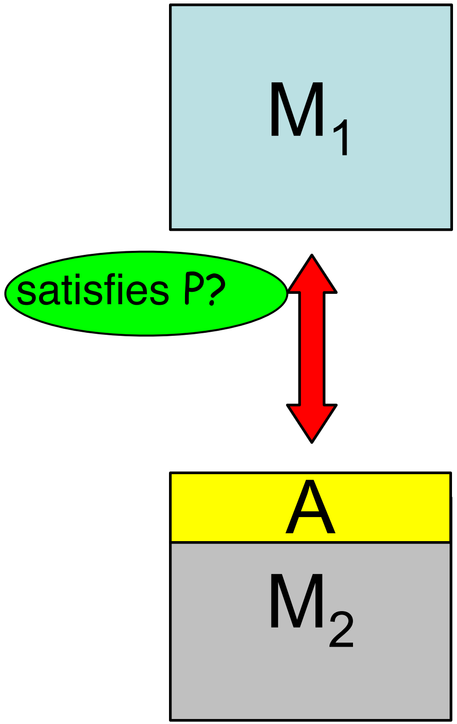
Discussion

- What about adversarial examples?
  - Use local robustness certifiers (such as CMU's Gloro) as run-time guards
- What about out-of-distribution inputs?
  - Use out-of-distribution detectors as run-time guards
- What about other rare events?
  - "Smarter" sampling, e.g. stratified sampling
- What if the data set is not "representative"?
  - **"Average-case" analysis**; the system should be safe at least in this average case!
  - Parametric probabilistic analysis: instead of using probabilities empirically derived from confusion matrices, generate them automatically from the analysis of the closed-loop system with **parametric** model for perception



Compositional Worst-Case Analysis

Compositional Verification



does system made up of M_1 and M_2 satisfy property P?

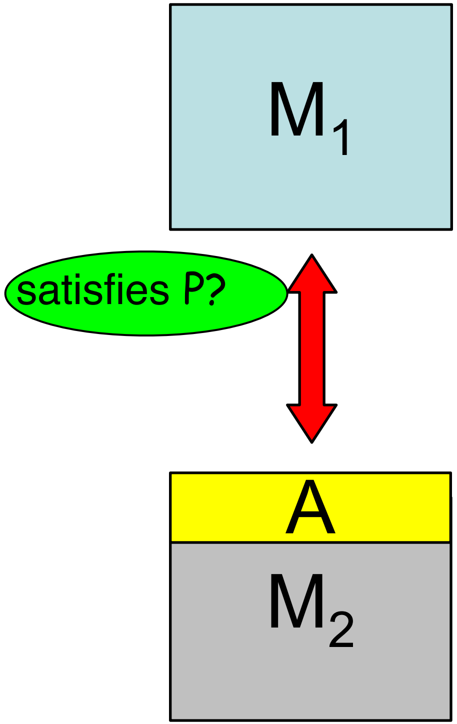
- check P on entire system: too many states!
- use the natural decomposition of the system into its components to break-up the verification task
- check components in isolation
- does M_1 satisfy P?

typically a component is designed to satisfy its requirements in specific contexts / environments

- assume-guarantee reasoning [Jones 83, Pnueli 85]

introduces assumption A representing M_1's “context” at the level of its interactions with the component

Assume-Guarantee Reasoning



reason about triples:

$$\langle A\rangle\ M\ \langle P\rangle$$

the formula is *true* if whenever M is part of a system that satisfies A, then the system must also guarantee P

simplest assume-guarantee rule

$$\frac{\begin{array}{c}\langle A\rangle\ M_1\ \langle P\rangle \\ \langle \mathit{true}\rangle\ M_2\ \langle A\rangle\end{array}}{\langle \mathit{true}\rangle\ M_1 \parallel M_2\ \langle P\rangle}$$

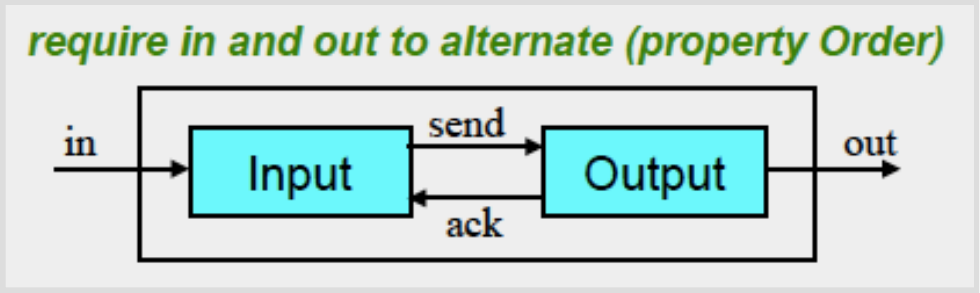
"discharge" the assumption

we synthesize the assumption automatically [ASE'02,TACAS'03]

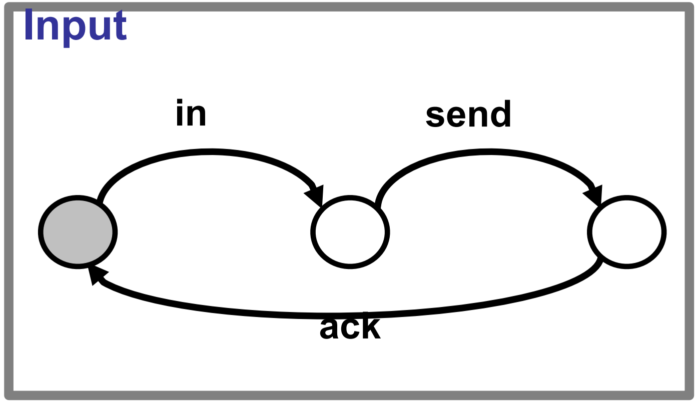
Formalisms

- components modeled as finite state machines (FSM)
  - FSMs assembled with parallel composition operator "||"
  - Synchronizes shared actions, interleaves remaining actions
- a safety property P is a FSM
  - P describes all legal behaviors
  - P_{err} – complement of P
    - make deterministic & complete P with an "error" state;
    - bad behaviors lead to error
  - component M satisfies P iff error state unreachable in $(M \mid\mid P_{err})$
- assume-guarantee reasoning
  - assumptions and guarantees are FSMs
  - $\langle A \rangle\ M\ \langle P \rangle$ holds iff error state unreachable in $(A \mid\mid M \mid\mid P_{err})$

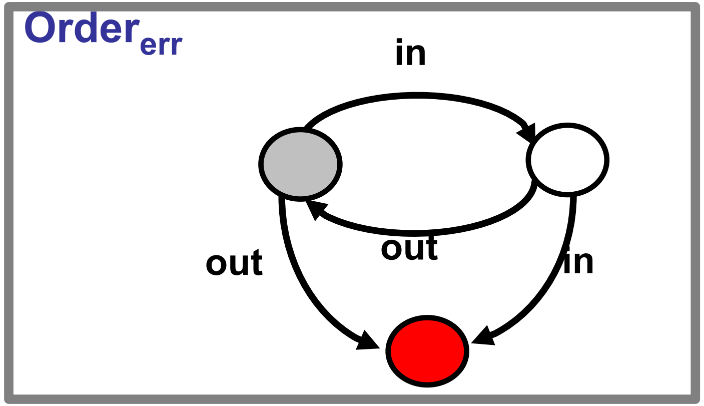
Example



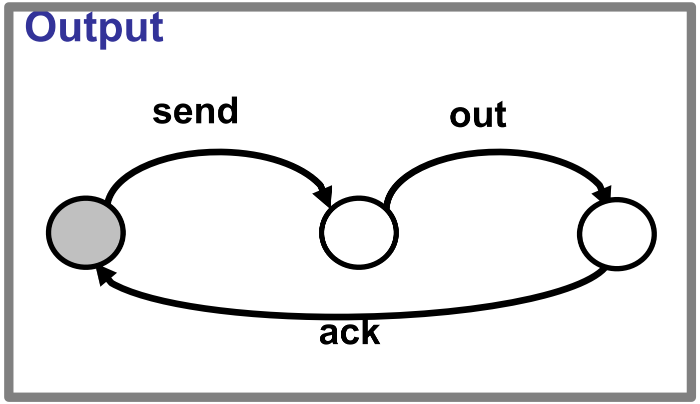
require in and out to alternate (property Order)
in
send
Input
Output
out
ack



Input
in
send
ack

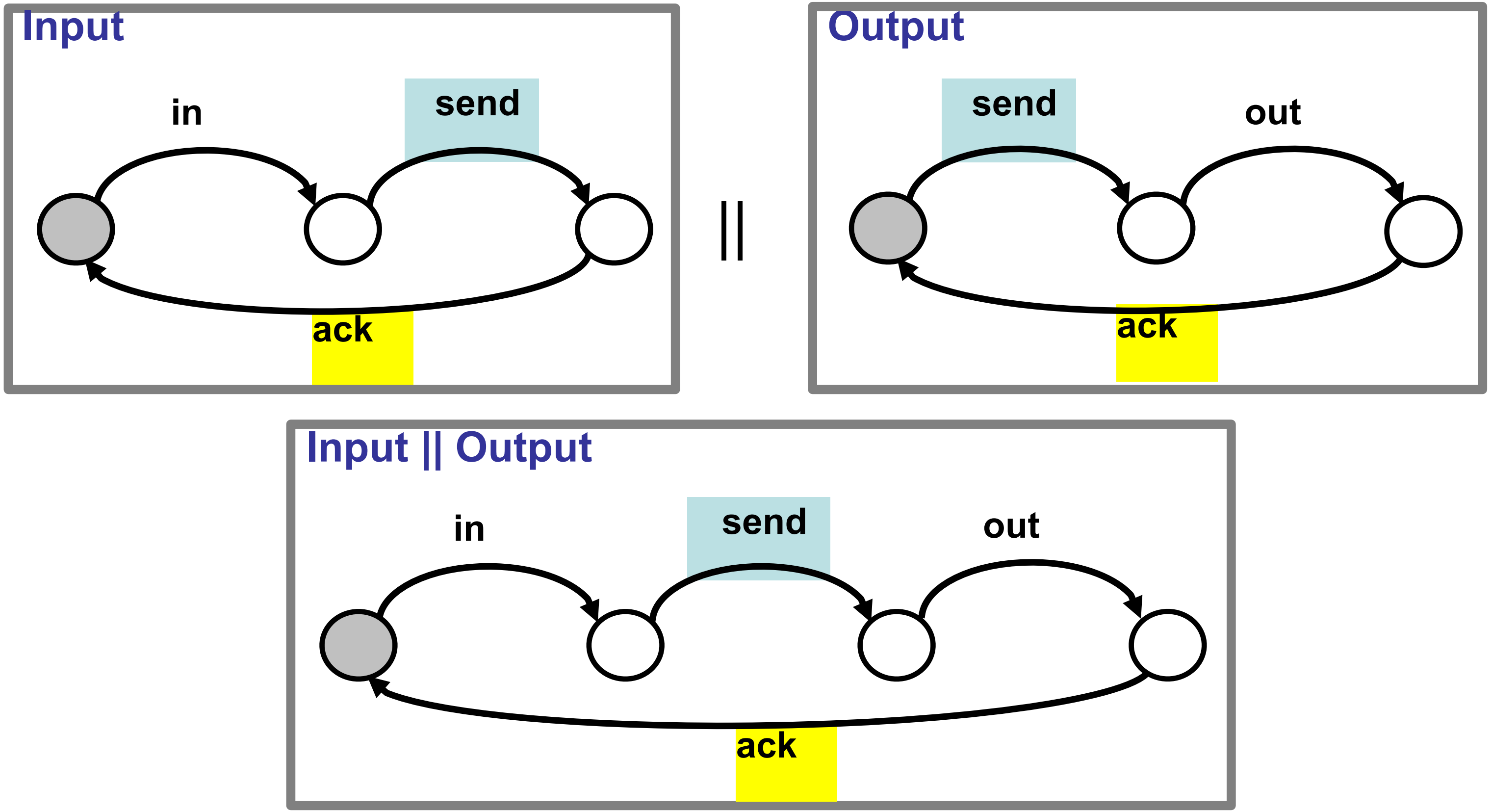


Order$_{err}$
in
out
out
in

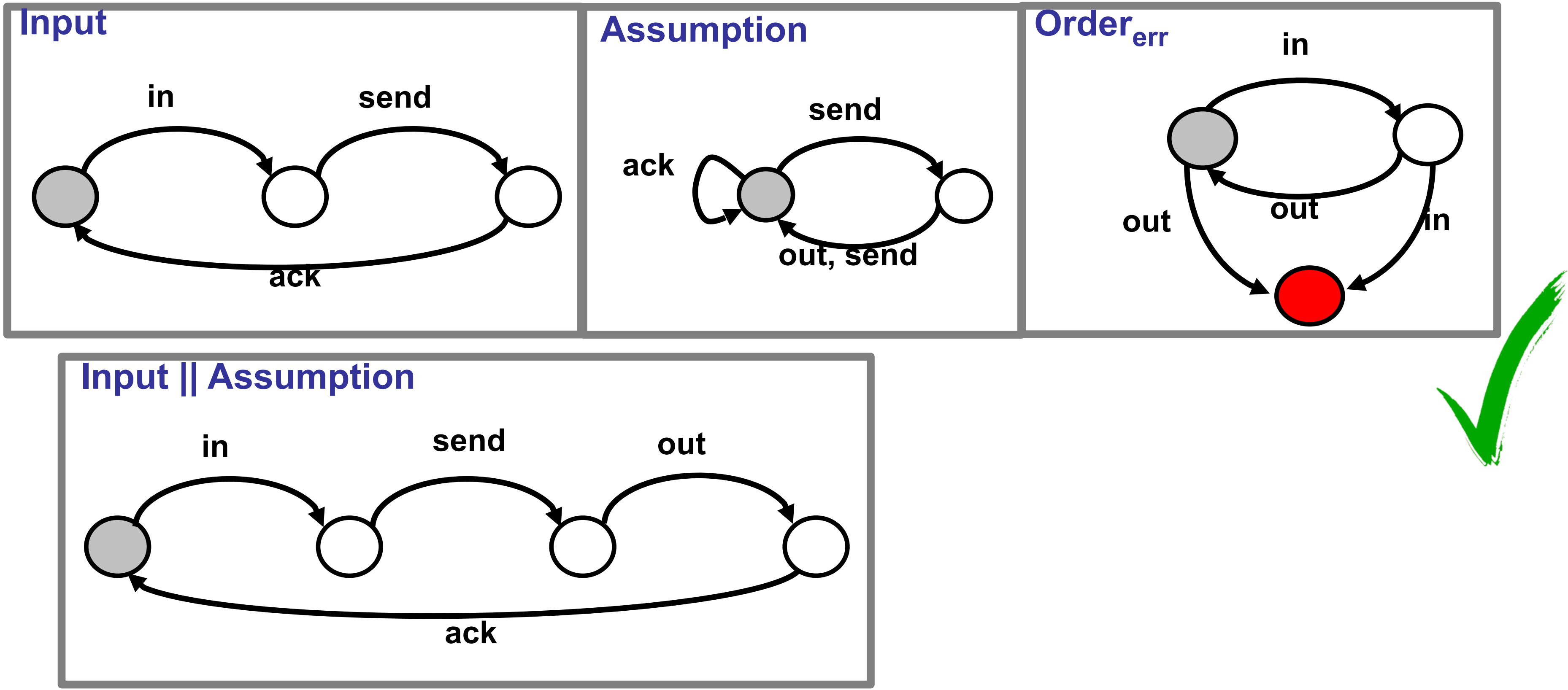


Output
send
out
ack

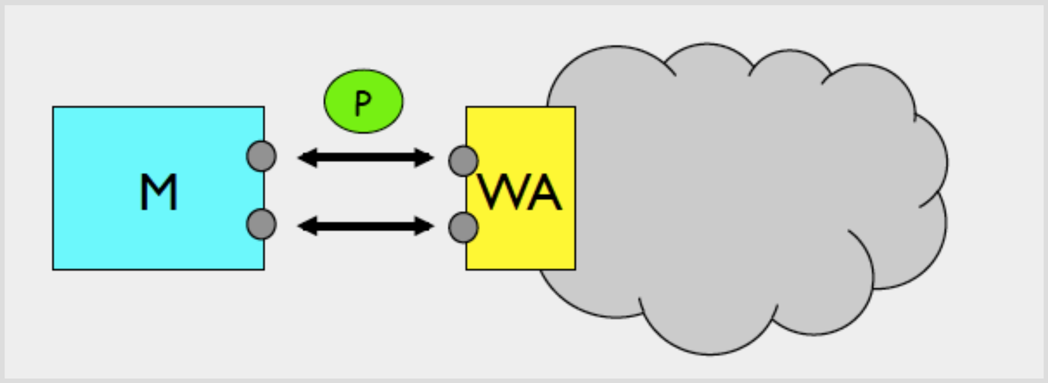
Parallel Composition



Assume-Guarantee Reasoning



Weakest Assumption [ASE'02]



- Inputs: Component M, property P, interface (alphabet) of M || P_{err} with its context
- Output: Weakest environment assumption WA such that ⟨WA⟩ M ⟨P⟩ holds
- Weakest assumption:
  - prevents component to go to error (safe)
  - is as permissive as possible
  - uses only interface actions

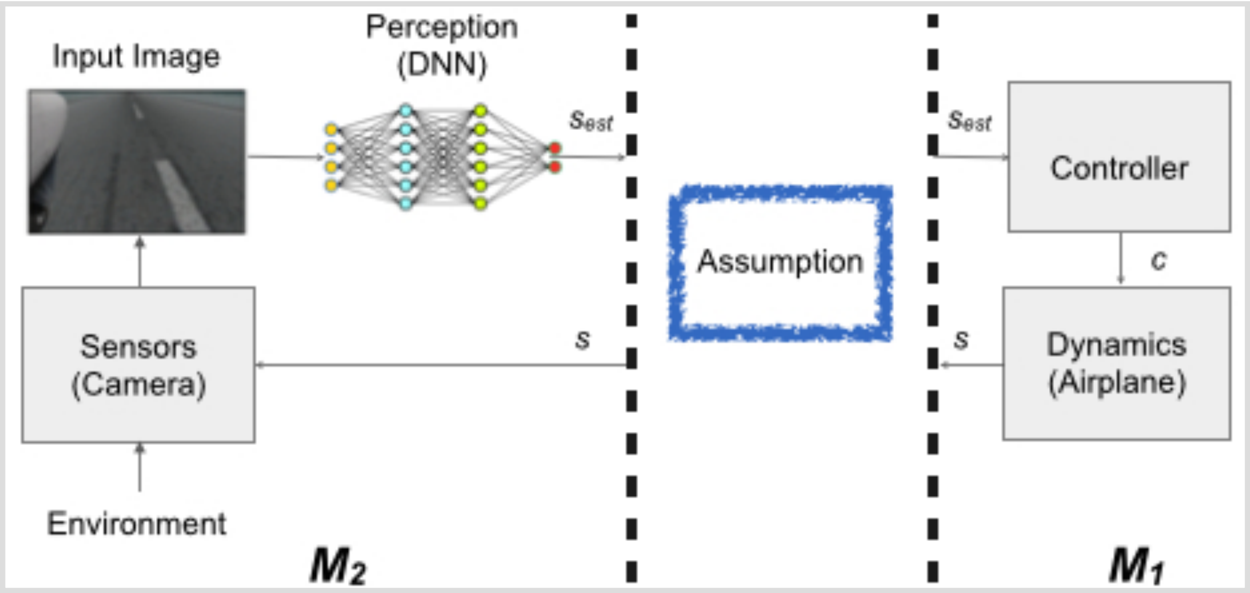
Giannakopoulou, D., Pasareanu, C.S., Barringer, H.: Assumption generation for software component verification. [ASE'02]

Weakest Assumption and Assume-Guarantee Reasoning

- Weakest assumption for M and P
  - for all environment components N: $\langle true \rangle\ M \| N\ \langle P \rangle$ iff $\langle true \rangle\ N\ \langle WA \rangle$
- Let's use WA (for M_1 and P) in the rule
  - if both $\langle WA \rangle\ M_1\ \langle P \rangle$ and $\langle true \rangle\ M_2\ \langle WA \rangle$ hold then $\langle true \rangle\ M_1 \| M_2\ \langle P \rangle$ holds
  - if $\langle true \rangle\ M_2\ \langle WA \rangle$ does not hold then $\langle true \rangle\ M_1 \| M_2\ \langle P \rangle$ does not hold

$$\frac{\begin{array}{c}\langle A \rangle\ M_1\ \langle P \rangle \\ \langle \mathit{true} \rangle\ M_2\ \langle A \rangle\end{array}}{\langle \mathit{true} \rangle\ M_1 \parallel M_2\ \langle P \rangle}$$

Assume-Guarantee Reasoning for the TaxiNet System



Property: safe operation. |`cte`| ≤ 8 meters and |`he`| ≤ 35 degrees

Compositional Analysis

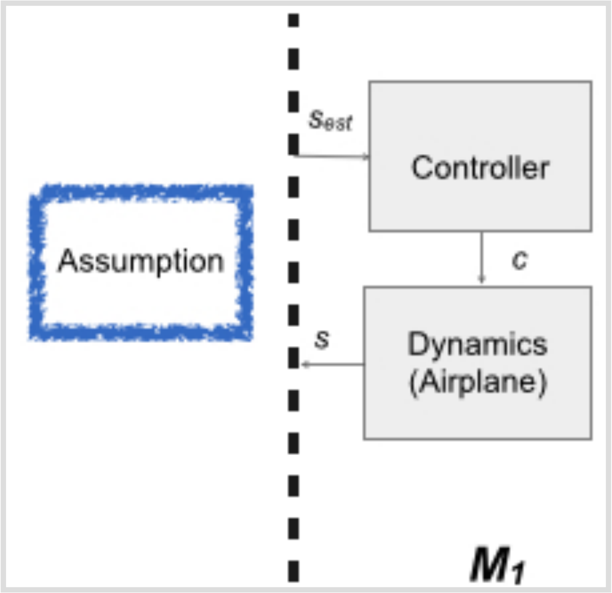
Optimistic View:

- Analyze the system assuming **ideal perception**
- Fix all errors due to controller and dynamics logic

Pessimistic View:

- Analyze the system in the **absence** of the DNN
- Implicit **worst-case** behavior: estimates can be arbitrarily wrong
- Accounts for **all possible** perturbations in the environment, distribution shifts, etc.
- Compute weakest assumption: [ASE'02] with small modifications

Assumption encodes all the DNN behaviors that **guarantee** that the autonomous system satisfies the property!



Property

How to “discharge” the assumption?

Formal verification is difficult (impossible?)

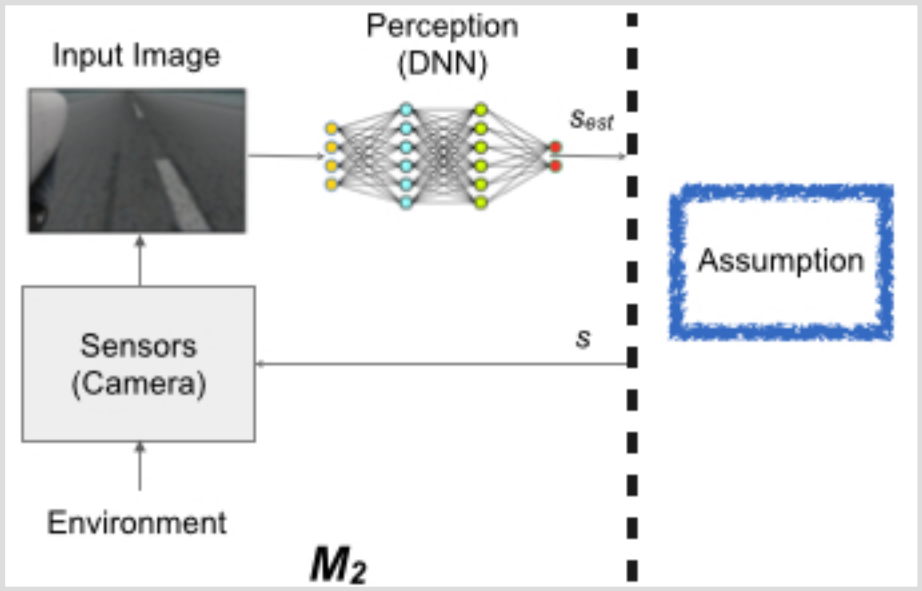
- DNN size (millions/billions of parameters)
- Modeling of all the possible environment conditions

Solution: run-time monitoring!

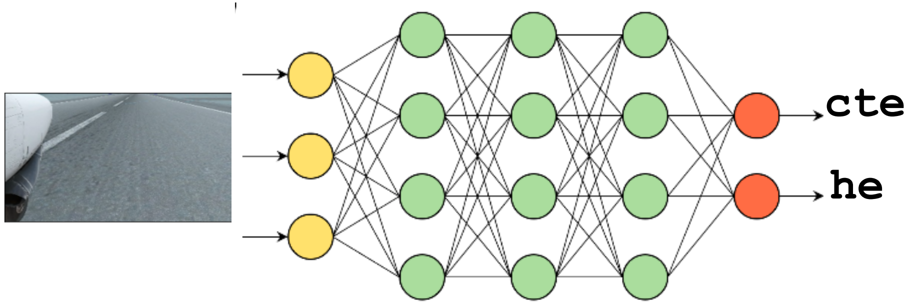
- Monitor DNN outputs
- Go to “safe fail state” if assumption is violated

Extract local properties from assumption

- More natural for DNNs
- Guide training and testing of the DNN



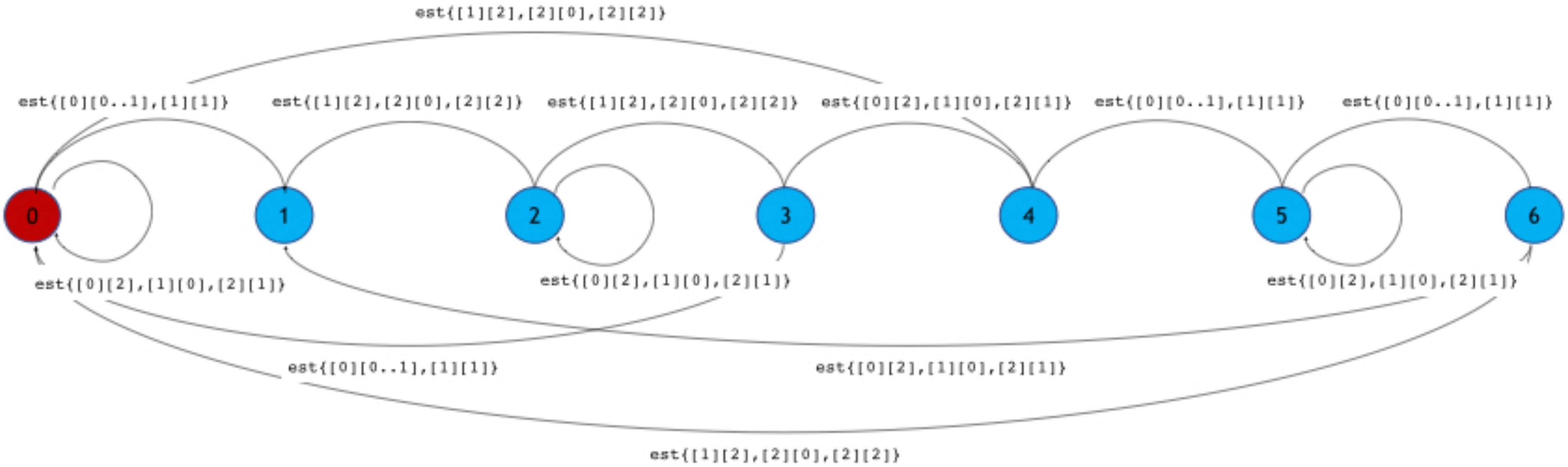
Discretized View of the DNN TaxiNet



$$\underline{\texttt{cte}} = \begin{cases} 0 \text{ if } \texttt{cte} \in [-8, -2.7) \\ 1 \text{ if } \texttt{cte} \in [-2.7, 2.7] \\ 2 \text{ if } \texttt{cte} \in (2.7, 8] \end{cases}$$

$$\underline{\texttt{he}} = \begin{cases} 1 \text{ if } \texttt{he} \in [-35, -11.67) \\ 0 \text{ if } \texttt{he} \in [-11.67, 11.66] \\ 2 \text{ if } \texttt{he} \in (11.66, 35.0] \end{cases}$$

Assumptions for Run-Time Monitoring



- Set alphabet to be only in terms of **estimates**
- Generated assumption defines allowable **temporal behavior** over the DNN outputs

Extracting Local Properties

```
Assumption_TaxiNet_Err = Q0 ,
Q0 = ( est {[0][0..1] , [1][1]} → Q1
  | est {[0][2] , [1][0] , [2][1]} → Q8
  | est {[1][2] , [2].{[0] , [2]}} → Q9 ) ,
Q1 = ( act [2][2] → Q3 ) ,
Q3 = ( est {[0][0..2] , [1][0..1] , [2][1]} → ERROR
  | est {[1][2] , [2].{[0] , [2]}} → Q4 ) ,
Q4 = ( act [2][0] → Q5 ) ,
Q5 = ( est {[0][0..1] , [1][1]} → ERROR
  | est {[0][2] , [1][0] , [2][1]} → Q4
  | est {[1][2] , [2].{[0] , [2]}} → Q6 ) ,
Q6 = ( act [1][1] → Q7 ) ,
Q7 = ( est {[1][2] , [2].{[0] , [2]}} → ERROR
  | est {[0][0..1] , [1][1]} → Q8
  | est {[0][2] , [1][0] , [2][1]} → Q9 ) ,
Q8 = ( act [1][0] → Q0 ) ,
Q9 = ( act [0][1] → Q10 ) ,
Q10 = ( est {[0][2] , [1].{[0] , [2]} , [2][0..2]} →
ERROR
  | est {[0][0..1] , [1][1]} → Q11 ) ,
Q11 = ( act [0][0] → Q12 ) ,
Q12 = ( est {[1][2] , [2].{[0] , [2]}} → ERROR
  | est {[0][2] , [1][0] , [2][1]} → Q11
  | est {[0][0..1] , [1][1]} → Q13 ) ,
Q13 = ( act [1][2] → Q14 ) ,
Q14 = ( est {[0][0..1] , [1][1]} → ERROR
  | est {[0][2] , [1][0] , [2][1]} → Q1
  | est {[1][2] , [2].{[0] , [2]}} → Q8 ) .
```

Assumption only restricts incorrect DNN behavior!
When actuals are [2][2], estimates [0][0..2] , [1][0..1] , [2][1] lead to error.

Local Properties

"When actuals are [2][2], estimates [0][0..2] , [1][0..1] , [2][1] lead to error."

$$(cte_* \in [2.7, 8) \wedge he_* \in (11.66, 35.0]) \Rightarrow ((cte \in [-2.7, 2.7] \wedge he \in (11.66, 35.0]) \vee (cte \in [2.7, 8) \wedge he \in [-11.67, 11.66]) \vee (cte \in [2.7, 8) \wedge he \in (11.66, 35.0]))$$

cte_*, he_* = actuals
cte , he = estimates

- Extracted local properties tolerate some output values that are different than the ground truth, as they don't affect safety of the overall system
- Could be used for DNN testing and training; relaxed training objective allows increased flexibility during training
- DNN verification?

Evaluation

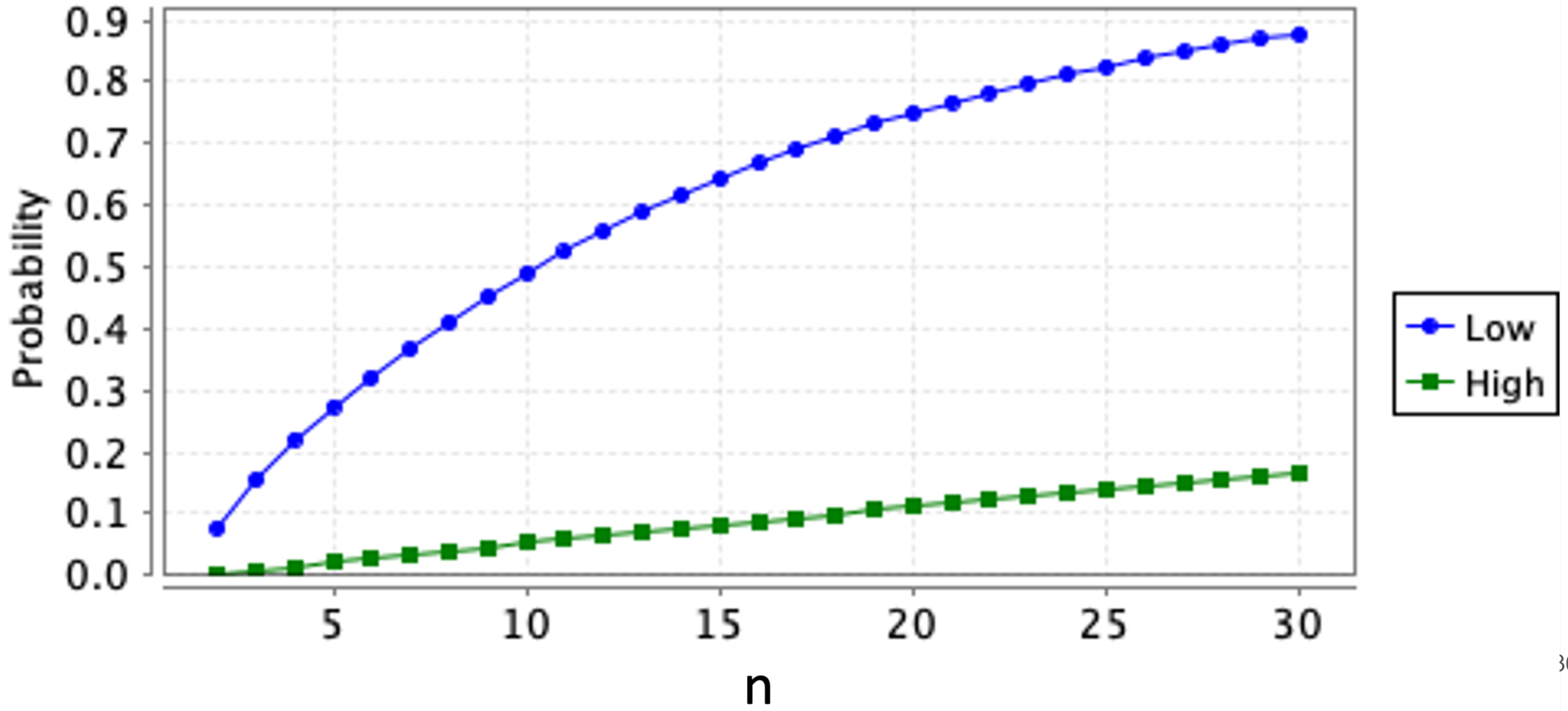
- Scalability
  - Assumptions for increasing alphabet sizes (increasing number of DNN outputs)
  - Used LTSA tool
- Permissiveness of run-time monitor
  - Run-time monitor blocks system when assumption is violated
  - Safe but prevents the system to operate
  - Used Prism to compute probability of assumption violation for two DNN models (high vs low accuracy)

Assumptions for Increasing Alphabet Sizes

MaxCTE	Assump. size	M_1 size	Time (sec.)	Memory (KB)
2	7	99	0.079	9799
4	13	261	0.126	10556
6	19	495	0.098	9926
14	43	2151	0.143	13324
30	91	8919	0.397	31056
50	151	23859	2.919	45225
100	301	92709	81.529	132418

Our approach can handle DNN classifiers with **hundreds** of of outputs

Probability of Assumption Violation



Summary

- Presented worst-case analysis approach for autonomous systems with DNN-based perception
- Generated “weakest assumptions” on DNN behavior that **guarantee** safety properties
- Can be used as run-time monitors
- Extracted local specifications on DNN behavior; can be used for training and testing

Future work:

- Systems with multiple perception components (camera and LIDAR)
  - Decompose global assumption into component-wise assumptions
- Incremental techniques for assumption generation
- Neuro-symbolic techniques for DNN training, as guided by assumptions and local properties
- Assumptions for LLMs?

Related Work

- Proving safety properties of autonomous systems with low-dimensional sensor readings
  - *Ivanov, R., Weimer, J., Alur, R., Pappas, G.J., Lee, I.: Verisig: verifying safety properties of hybrid systems with neural network controllers. (2019)*
  - *Ivanov, R., Jothimurugan, K., Hsu, S., Vaidya, S., Alur, R., Bastani, O.: Compositional learning and verification of neural network controllers. (2021)*
  - Intractable for systems that use rich sensors producing high-dimensional inputs such as images
- More closely related works build models based on the analysis of the perception components
  - *Katz, S.M., Corso, A.L., Strong, C.A., Kochenderfer, M.J.: Verification of image-based neural network controllers using generative models. (2022)*
  - *Shoukry, Y.: Nnlander-verif: A neural network formal verification framework for vision-based autonomous aircraft landing. (2022)*
  - *P,H.,Deka,N.,D'Souza,D.,Lodaya,K.,Prabhakar,P.:Verification of camera-based autonomous systems.(2023)*
  - They either do not provide guarantees or do not scale to large networks
- Falsification techniques
  - *Dreossi, T., Donzé, A., Seshia, S.A.: Compositional falsification of cyber-physical systems with machine learning components. (2019)*
  - *Ghosh, S., Pant, Y.V., Ravanbakhsh, H., Seshia, S.A.: Counterexample-guided synthesis of perception models and control. (2021)*
  - They do not provide guarantees
- Most closely related approach
  - *Hsieh, C., Li, Y., Sun, D., Joshi, K., Misailovic, S., Mitra, S.: Verifying controllers with vision-based perception using safe approximate abstractions. (2022)*
  - Builds abstractions of the DNN components as guided by system-level safety properties.
  - Does not provide strong system-level guarantees
  - Provides a probabilistic result that measures empirically how close a real DNN is to the abstraction
- Probabilistic verification
  - *Incer, I., Badithela, A., Graebener, J., Mallozzi, P., Pandey, A., Yu, S.J., Benveniste, A., Caillaud, B., Murray, R.M., Sangiovanni-Vincentelli, A., et al.: Pacti: Scaling assume-guarantee reasoning for system analysis and design. (2023)*
  - They either do not incorporate DNN-specific analysis
- Safe shielding
  - *Alshiekh, M., Bloem, R., Ehlers, R., Könighofer, B., Niekum, S., Topcu, U.: Safe reinforcement learning via shielding (2017)*
  - Does not consider complex DNN
  - Our assumptions monitor DNN outputs instead of controller actions (as in shielding); can prevent errors earlier
  - Further, local specifications enable DNN testing and training

Thank you!