Ensuring Safety in Deep Reinforcement Learning for Systems

The whiRL Approach

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Objectives

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- Introduce **whiRL**, a platform designed for verifying DRL policies in systems, leveraging recent advancements in deep neural network verification and scalable model checking techniques.
- Demonstrate the utility of **whiRL** by applying it to verify natural requirements in learning-augmented systems in real-world environments like Internet congestion control, adaptive video streaming, and job scheduling in compute clusters.

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- However, as DRL policies make decisions, they often do so in ways that are challenging to understand and interpret. The decision-making process is obscured within complex neural networks. This obscurity raises a fundamental question: Can we trust these policies to make safe decisions?

How is it different to DNN Verification?

- **Single Invocation:** DNN verification tools typically focus on a single invocation of the DNN. In DRL, where DNNs are invoked repeatedly and their behavior evolves over time, this limitation is restrictive.

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- **Scalability:** The NP-complete nature of DNN verification results in exponential worst-case complexity, making DRL verification via DNN-style approaches highly challenging.

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Opportunities

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- Formal verification offers a systematic, mathematical approach to assess whether a given system, in this case, DRL policies, satisfies predefined requirements or exposes specific vulnerabilities.
- In this presentation, we will delve into the details of how formal verification, through the whiRL platform, can help us ensure the safety and reliability of learning-augmented systems, and we'll illustrate its application in real-world scenarios.

Aurora

A DRL Congestion Controller

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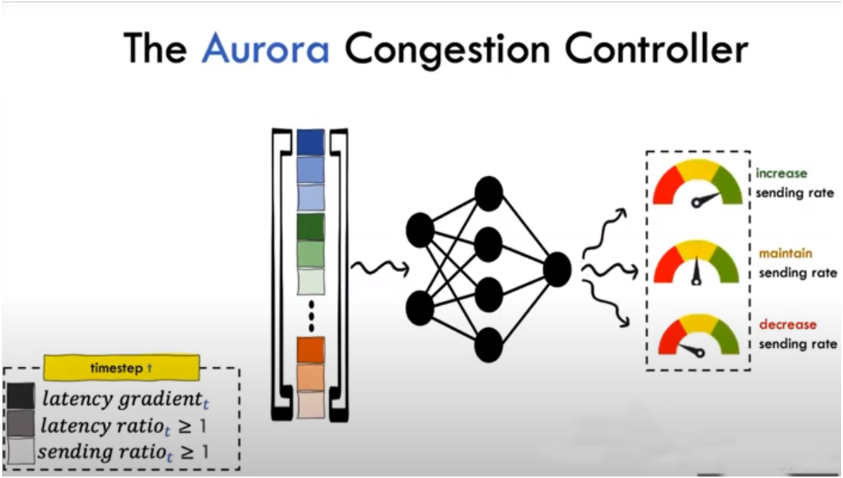
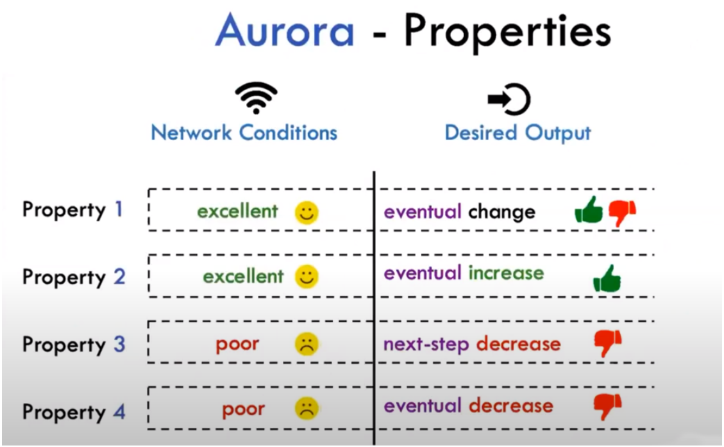
The DNN's single output provides a decision regarding the sending rate, which can be one of the following: Increase, Decrease or Maintain.

Aurora

Architecture Diagram



Properties for Aurora



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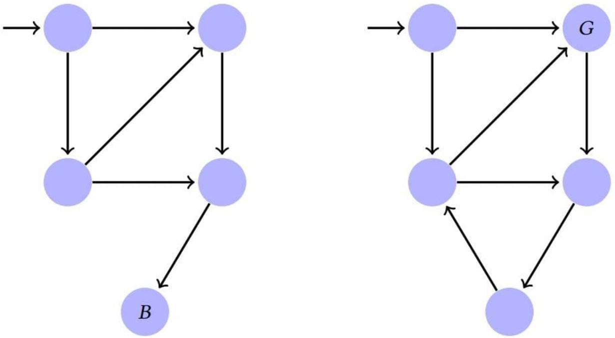
- Liveness properties relate to the occurrence of desirable events or the persistence of a certain behavior in a system.
- A violation of a liveness property is typically demonstrated by a lasso-shaped infinite trace, which indicates that the system gets stuck in a loop or fails to progress towards a desired outcome.

Safety vs Liveness
Visualisation

Safety concerns the prevention of reaching an undesirable state within a transition graph, starting from an initial state. In contrast, Liveness focuses on avoiding getting trapped in a repetitive loop without ever reaching a favorable state.

B denotes a bad state while G means a good state.



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Validity is ensured by taking the Negation and looking for an UNSAT result.

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- **Under-Approximation Efficiency:** Optimize by setting $T(s, s')$ to false for some reachable states, reducing computational complexity.
- **Avoiding Vacuity:** Carefully prevent setting $T(s, s')$ to false for all states, preventing vacuous system results.

Negation of Safety Encoding

$$\exists x_1, \ldots, x_k \in S \mid I(x_1) \wedge \left(\bigwedge_{i=1}^{k-1} T(x_i, x_{i+1}) \right) \wedge \left(\bigvee_{i=1}^{k} B(x_i) \right)$$

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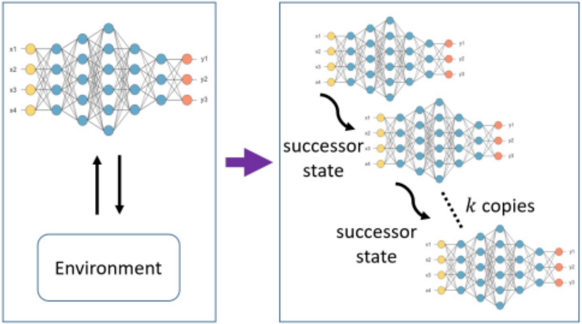
Negation of Liveness Encoding

$$\exists x_1, \ldots, x_k \in S \,|\, I(x_1) \wedge \left(\bigwedge_{i=1}^{k-1} T(x_i, x_{i+1}) \right) \wedge \left(\bigwedge_{i=1}^{k} \neg G(x_i) \right) \wedge \left(\bigvee_{i=1}^{k-1} x_k = x_i \right)$$

Employing BMC in a DRL

To evaluate the safety or liveness of a system, a technique involves replicating the original input DNN N, k times, creating a larger network, N'. This expansion also extends to the input layer, effectively encoding k successive states.



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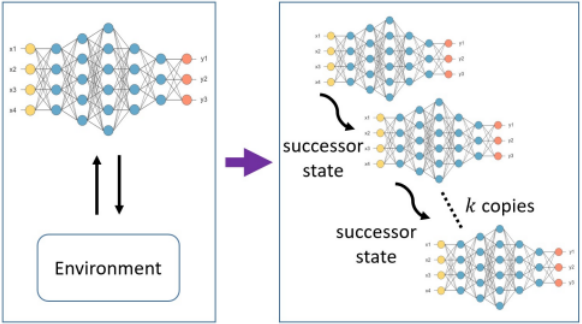
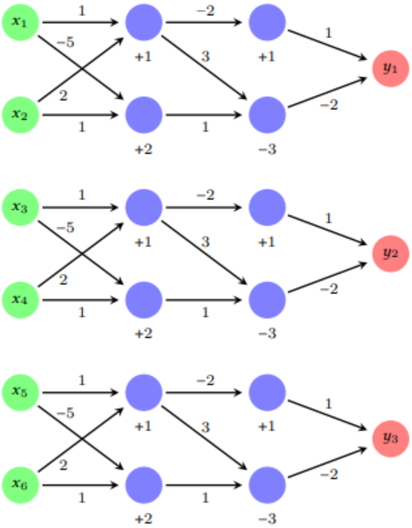


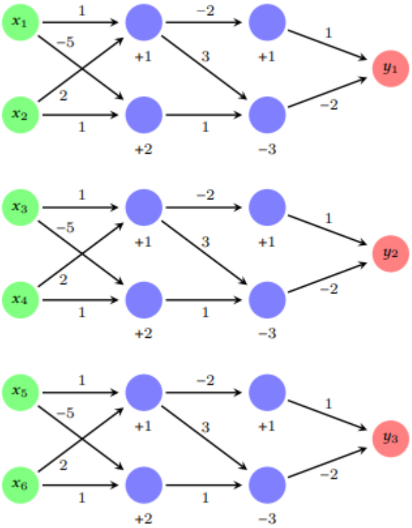
Then use this N' along with Pre and Post conditions P and Q.

BMC for DRL

Example

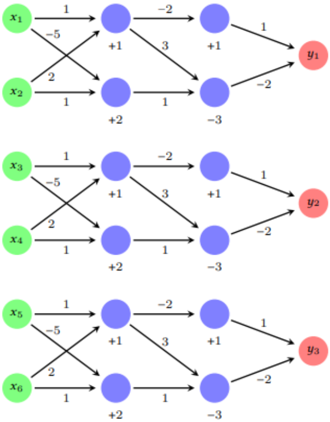


The top-most DNN is our original DNN, suppose for $k = 3$ we want to verify some property.

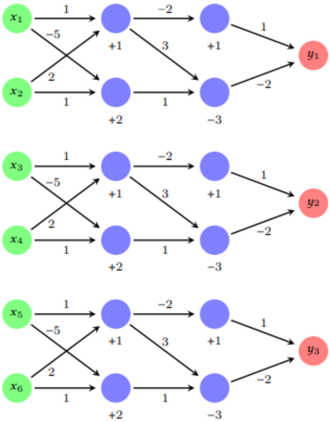


The top-most DNN is our original DNN, suppose for $k = 3$ we want to verify some property.

We copy the DNN thrice and this expanded network has 6 input neurons and 3 output neurons (tripled from the original 2 inputs and 1 output).



Let s_1 be (x_1, x_2) the first state, and s_2 be the state (x_3, x_4). Here, the DNN N, gives us an action $y_1 = N(s_1)$



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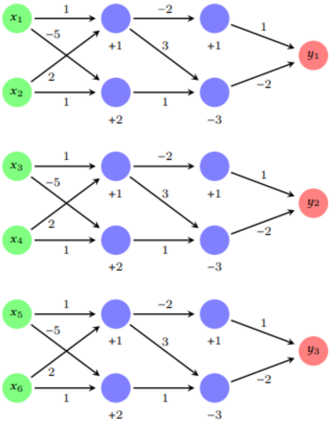

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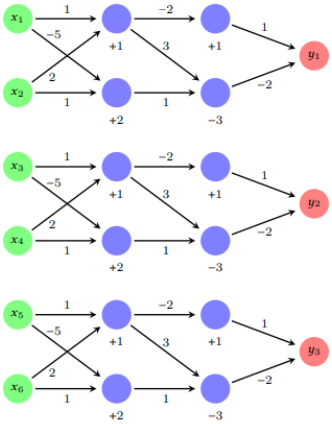
Let T_{BMC} be the transition relation here. $T_{BMC}(s, s')$ is False, if s' is not reachable from s.

BMC for DRL

Example Cont.



T_{BMC} here is the transition relation for the unwinded DNN, and through N, $N(s_1) = y_1$ and using y_1 gives us a new state s_2, so we set $T_{BMC}(s_1, s_2) = \text{True}$

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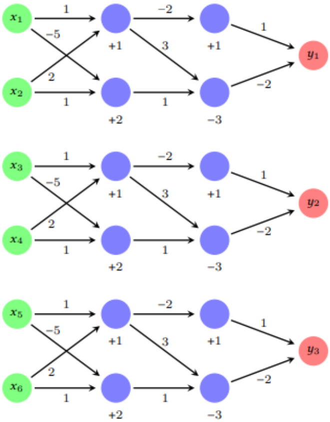

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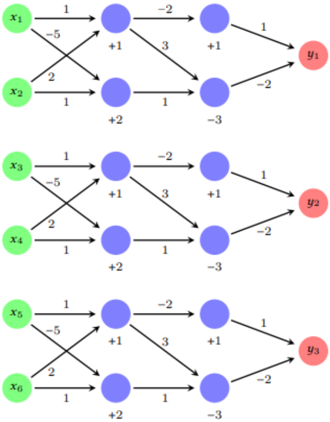

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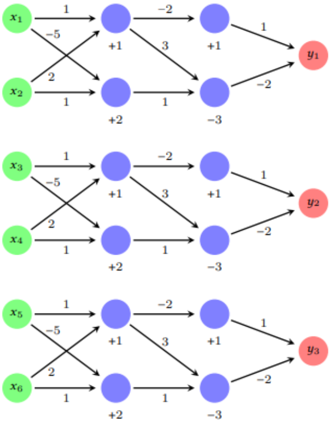
Set T_{BMC} accordingly to complete the transitional relation.



The intial state here is defined as:

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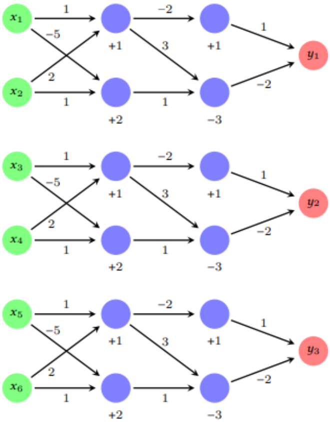

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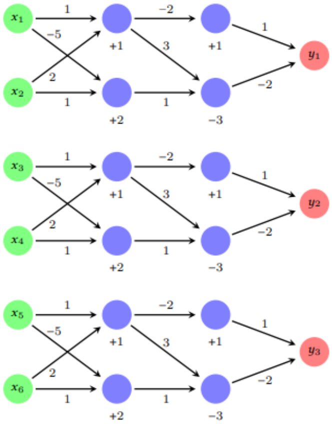

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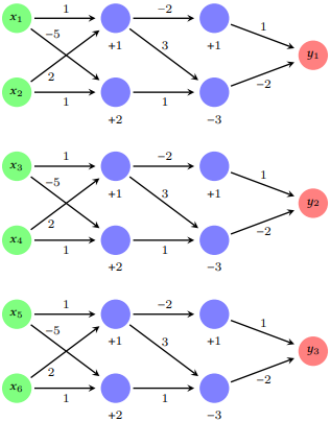

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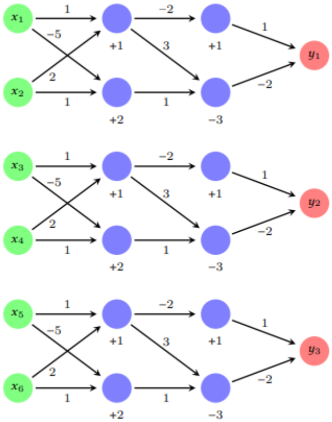

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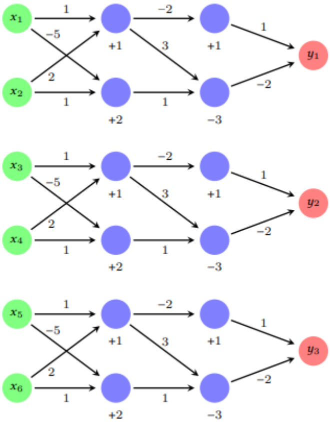
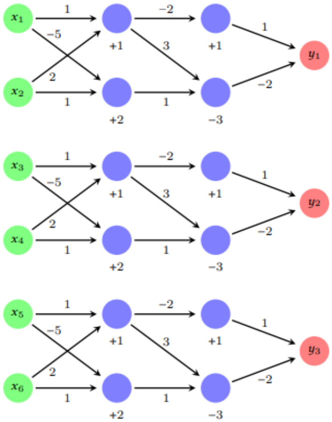
- Input's increase is limited to at most 1/2 if the previous output was positive
- Input's decrease is restricted to at most 1/2 if the previous output was non-positive



Let $z_i = (x_{2 \cdot i-1}, x_{2 \cdot i})$ a vector for the same DNN input, then:



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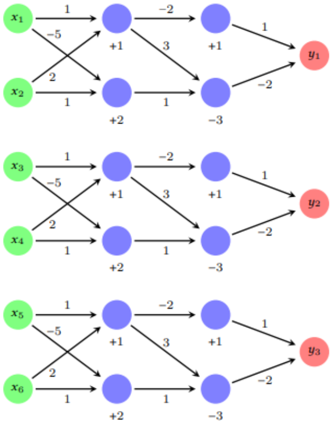

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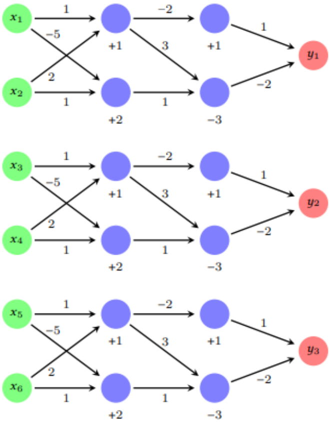

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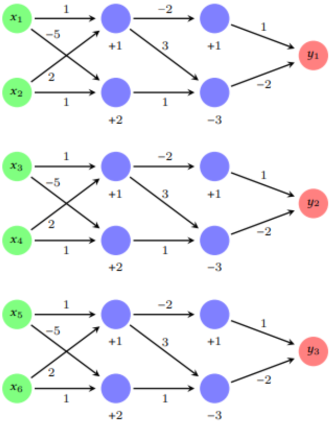
And the transition relation is given by:

$$T_{BMC}(z_i, z_{i+1}) =$$

$$(y_i > 0 \rightarrow z_{i+1} \geq z_i + \frac{1}{2} \geq z_i)$$

$$\vee$$

$$(y_i \leq 0 \rightarrow z_{i+1} \leq z_i - \frac{1}{2} \leq z_i)$$



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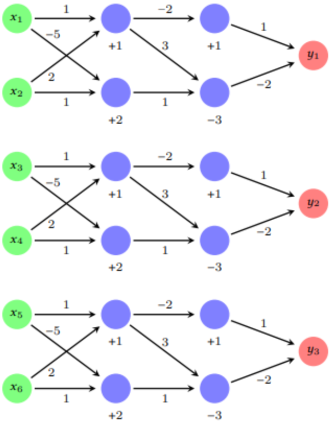
$$\bigwedge y_i < 10$$



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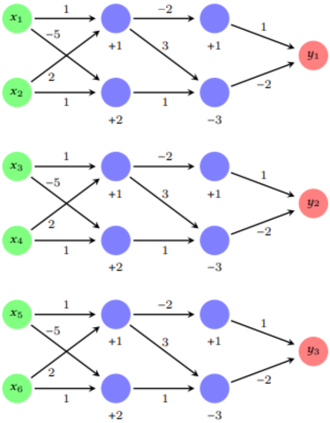

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Pass Init, T_{BMC}, B to a SAT-Solver to look if our safety property is verified or if we find a counterexample

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For a safety verification, whiRL takes these inputs, and copies the DNN k times and constructs the BMC query accordingly, then we get UNSAT if system is safe, SAT otherwise.

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Both results took just a few seconds.

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Further examining which properties are verified could aid in reasoning the sufficiency of training.

Limitations of whiRL

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- **Incomplete Proofs:** The model uses BMC, so we can only check up to a bound depending on our resources and not prove unbounded properties.

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- whiRL2.0 uses this technique and finds Inductive Invariants automatically, so it works with unbounded models to show complete proofs and gets to those proofs faster.

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- **New Training Metric:** The study introduces a novel metric that assesses the sufficiency of training, providing a valuable tool for determining readiness.
- **Future Research:** This research lays the groundwork for further exploration in DRL verification and training assessment, with a focus on ongoing improvement and innovation.

Acknowledgment

- Verifying Learning-Augmented Systems
- Images taken from: SIGCOMM'21 Technical Session

Thank You!