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Workshop on Automated Formal Reasoning for Trustworthy AI Systems



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Dynamic Epistemic Logic in Neural Layer Transparency

Towards a Formal Understanding of Knowledge Evolution in Neural Networks

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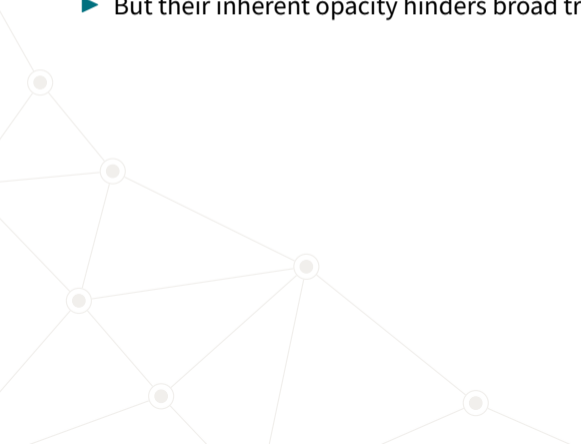
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- ▶ But their inherent opacity hinders broad trust and acceptance.
- ▶ The main hurdle is their intrinsic complexity; understanding their detailed internal processes remains elusive.
- ▶ Many attempts have been made to bring **interpretability** and **transparency** to ANN. For example:
 - ▶ XAI
 - ▶ Saliency maps
 - ▶ Attention mechanisms
 - ▶ Influence functions

But they are yet to gain widespread acceptance.

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- ▶ The ‘black box’ nature of neural networks raises concerns in ethical AI applications and decision-making processes.
- ▶ Addressing these challenges is crucial for advancing AI towards more **transparent**, **interpretable**, and **trustworthy** systems.

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- ▶ **Neuro-symbolic AI** seeks to fuse neural networks' empirical strength with classical AI's symbolic reasoning.
- ▶ One promising approach for Neuro-symbolic AI is the application of **Dynamic Epistemic Logic (DEL)** to understand neural behaviors.

Dynamic Epistemic Logic (DEL) Overview

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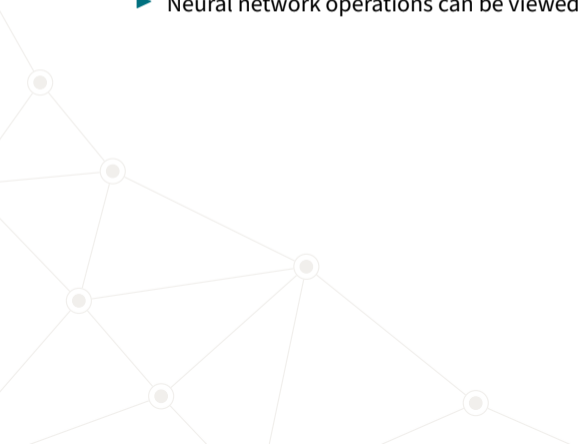
▶ DEL Formulas:

- ▶ Basic form: $[A]F$, meaning “after action A , formula F is true.”
- ▶ Actions update the Kripke model, reflecting the change in knowledge.

DEL and Neural Networks

▶ Applying DEL to Neural Networks:

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▶ Modeling Knowledge Flow:

- ▶ Knowledge flow through layers can be represented as transitions in the Kripke model: $[L_i \rightarrow L_{i+1}]F$, where F is a knowledge state.
- ▶ This reflects how information is processed and transformed across the network.

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▶ Modeling Knowledge Dynamics:

- ▶ Using DEL to express and analyze the flow of information between layers.
- ▶ For layers L_1, L_2, \dots, L_n , knowledge transition can be represented as $[L_1 \rightarrow L_2 \rightarrow \dots \rightarrow L_n]F$.

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▶ Visualization of Knowledge Evolution:

- ▶ Developing tools to visualize the changes in knowledge as interpreted by the DEL framework.
- ▶ Aimed at making the understanding of neural network processes more accessible.

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▶ Initial Logic Operators:

- ▶ Defining DEL operators to capture neural processing, e.g., $[L]P$ signifies knowledge after processing by layer L .
- ▶ These operators represent the transformation of knowledge states within the network.

Case Study Selection

Criteria for selecting case studies:

1. Neural networks with different complexities.
2. Tasks with different domains.
3. Examples of how our framework reveals knowledge dynamics in neural networks.

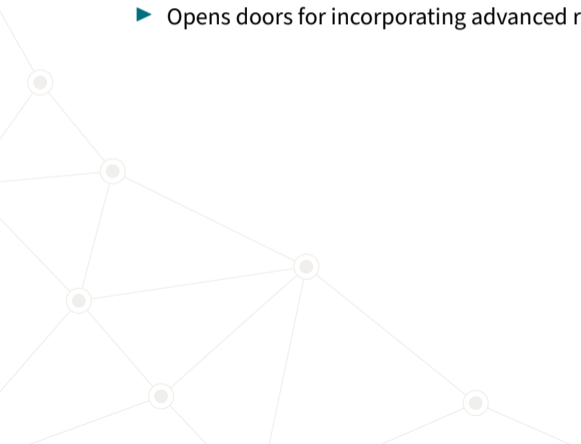
Visualization Tool Development

Planned features:

- ▶ Show how epistemic models and action models vary across layers and after forward or backward propagation.
- ▶ Let users modify inputs or parameters and see how knowledge dynamics are affected.
- ▶ Work with common neural network libraries, making it easy for researchers and practitioners to use it for their models.

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- ▶ Visualization Tool.
 - ▶ Develop an interactive visualization tool.
- ▶ Trustworthy AI Systems.
 - ▶ Better understand how neural networks acquire, transform, and use knowledge, and how they justify their outputs.

Challenges & Risks

- ▶ The complexity of modern neural networks.
- ▶ The ambiguity in epistemic mapping.
- ▶ The reception and integration of our approach within the wider AI community.
- ▶ Ethical risks associated with increased transparency of neural networks.

Thank You/Contact

Thank You for Your Attention!

Any further questions or discussions can be directed to:

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