Efficient Rectification of Neuro-Symbolic Reasoning Inconsistencies by Abductive Reflection

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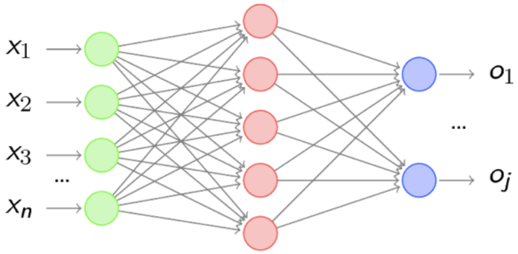
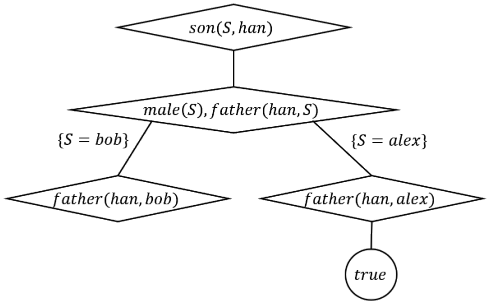
This paper has won the **Outstanding Paper Award** of AAAI 2025

Neural Network + Logical Reasoning

Effectively combining neural network and logical reasoning is the "**holy grail**" of AI.

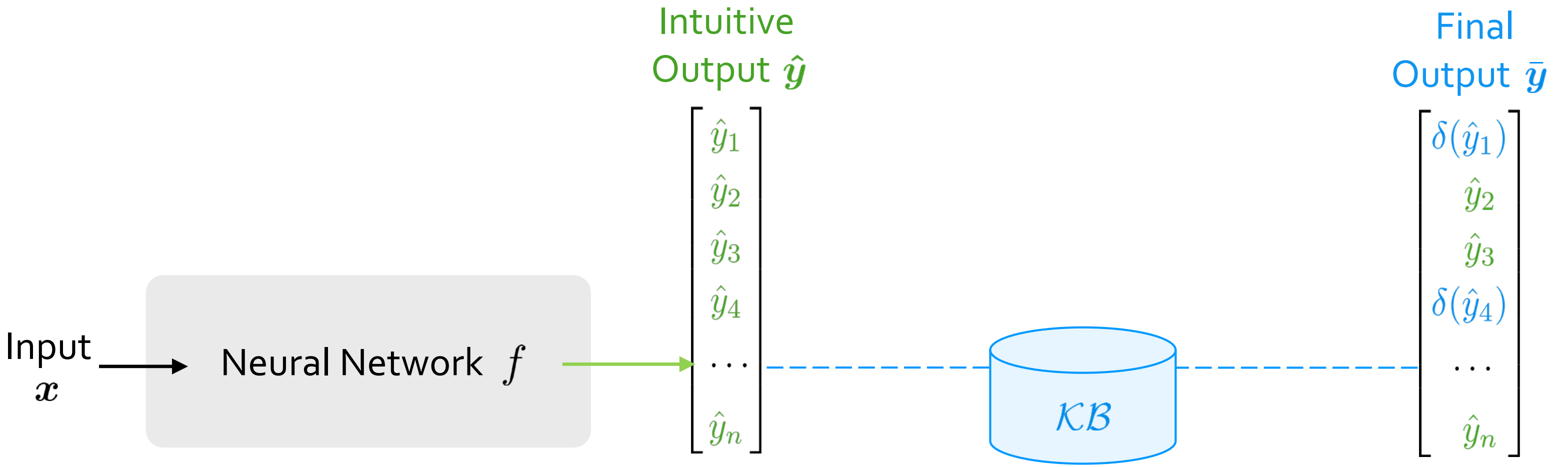




Neural network is adept at using **data**

Logical reasoning is adept at using **knowledge**

Abductive Learning

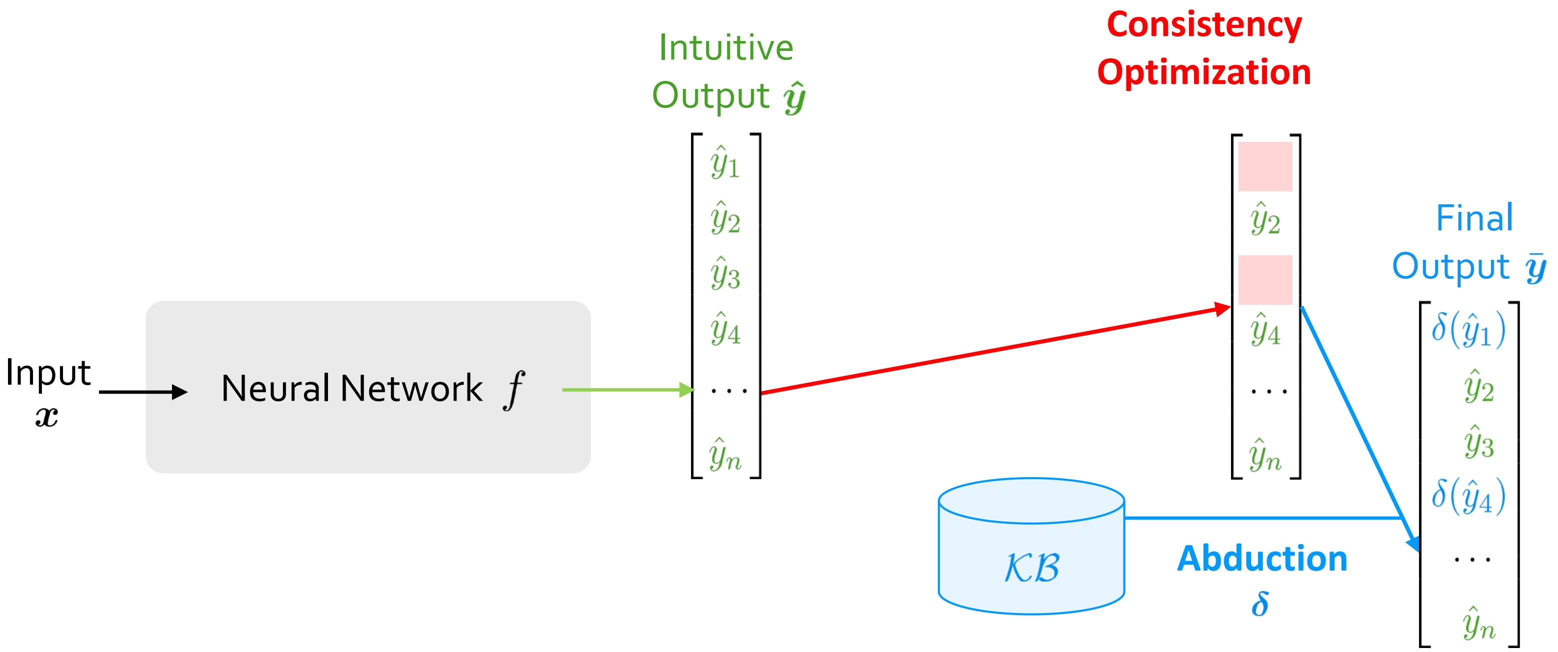


Neural network f maps input $\boldsymbol{x}$ into $\hat{\boldsymbol{y}} = [\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n]$.

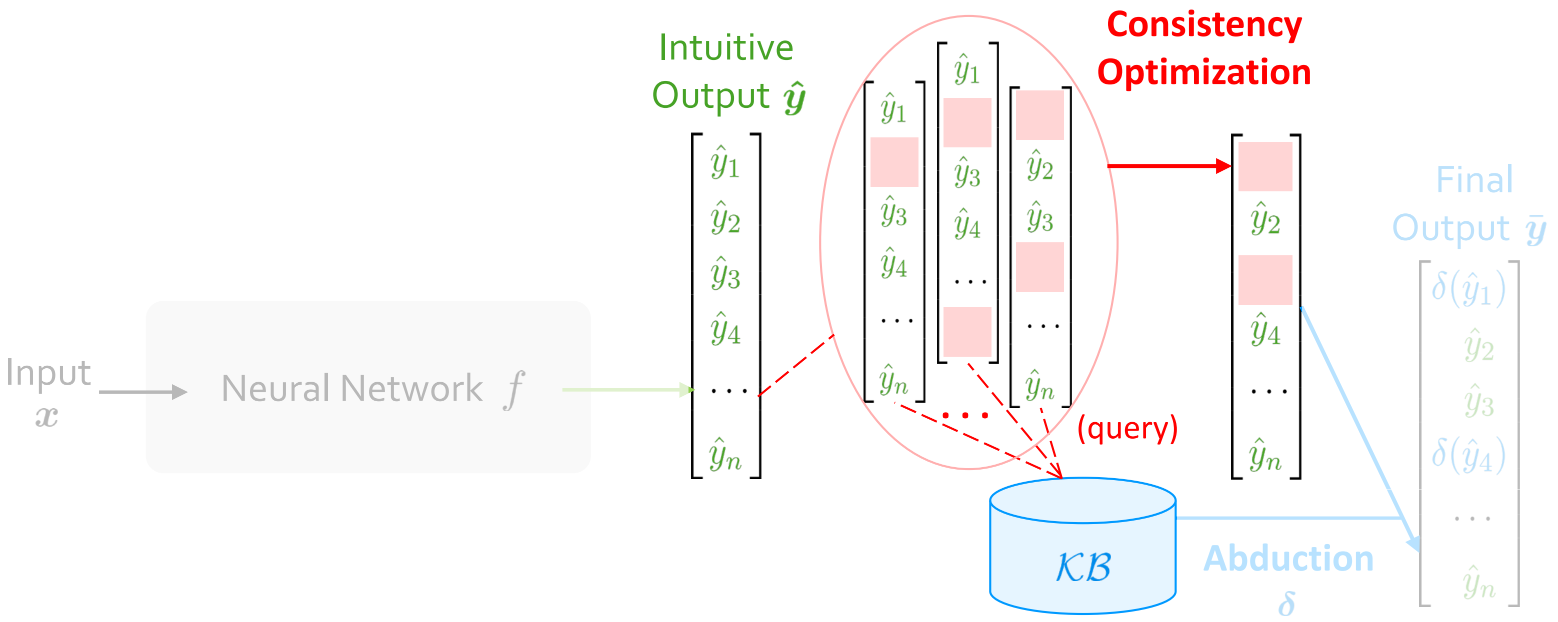
Knowledge base $\mathcal{KB}$ holds constraints on $\boldsymbol{y}$, and can perform reasoning.

Zhou, Z.-H. 2019. Abductive learning: towards bridging machine learning and logical reasoning. Science China Information Sciences, 62: 1–3.

Abductive Learning (cont.)

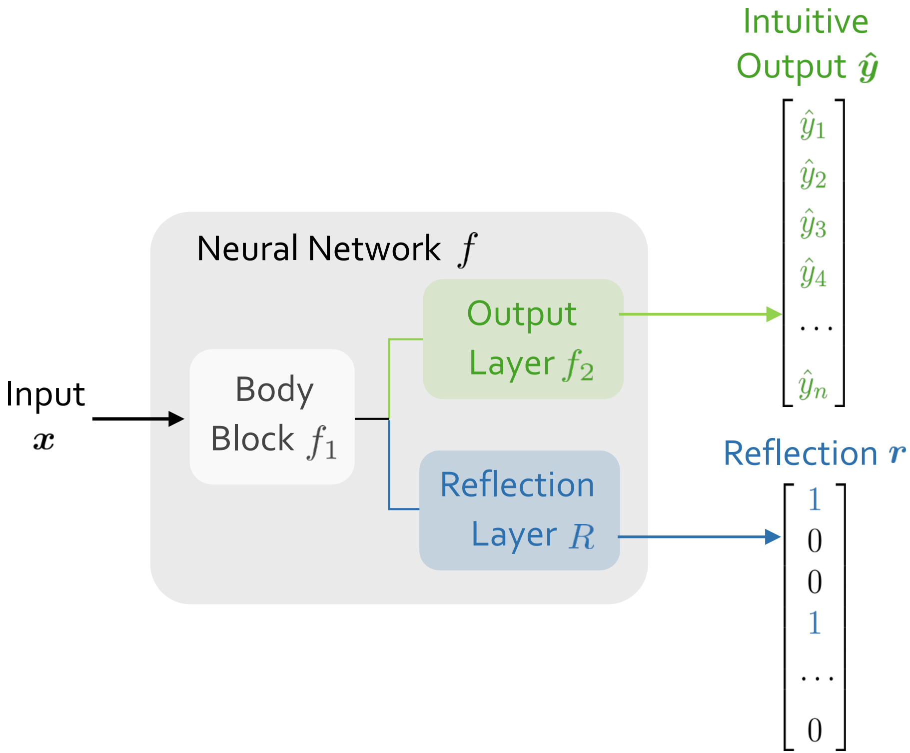


Consistency Optimization an Efficiency Bottleneck of ABL

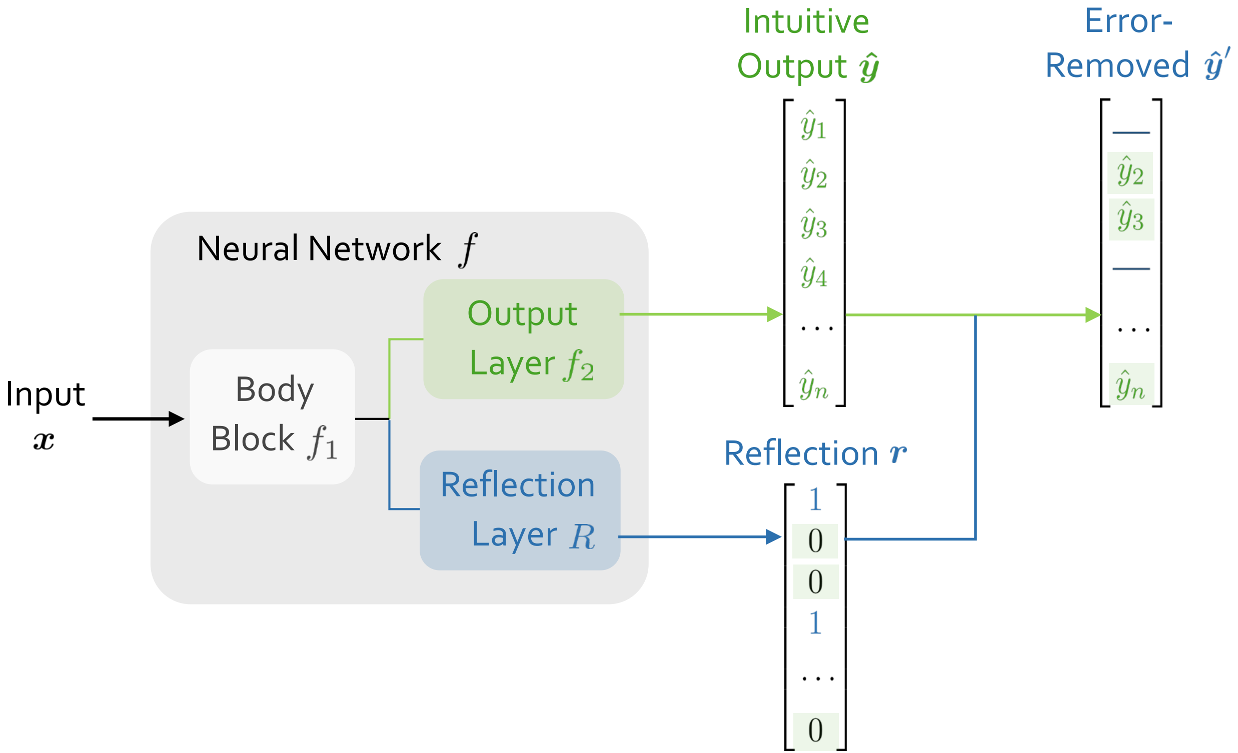


⚠ Too many possible solutions to query, too much time spent on consistency evaluation

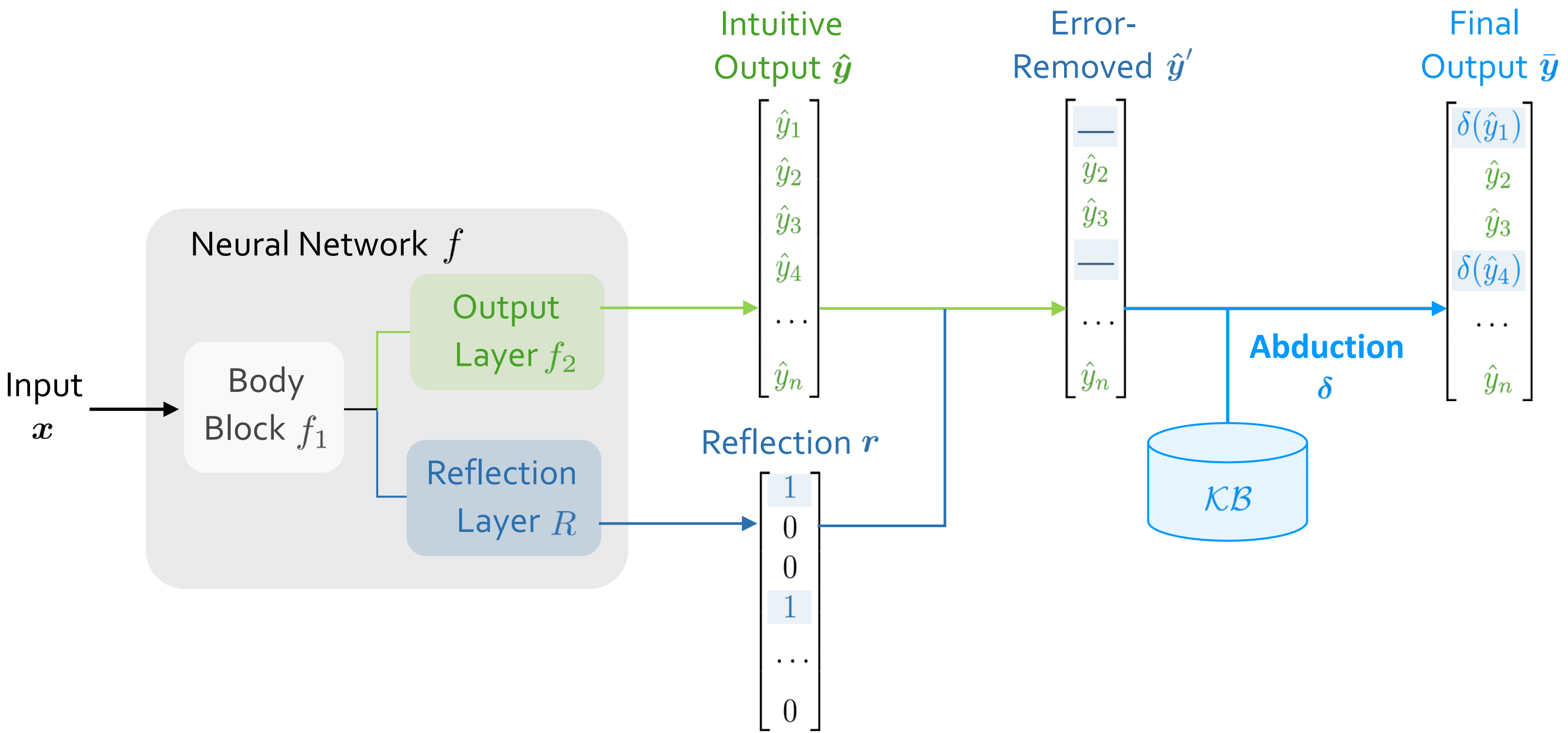
Our Method: **Abductive Learning** with **Reflection**



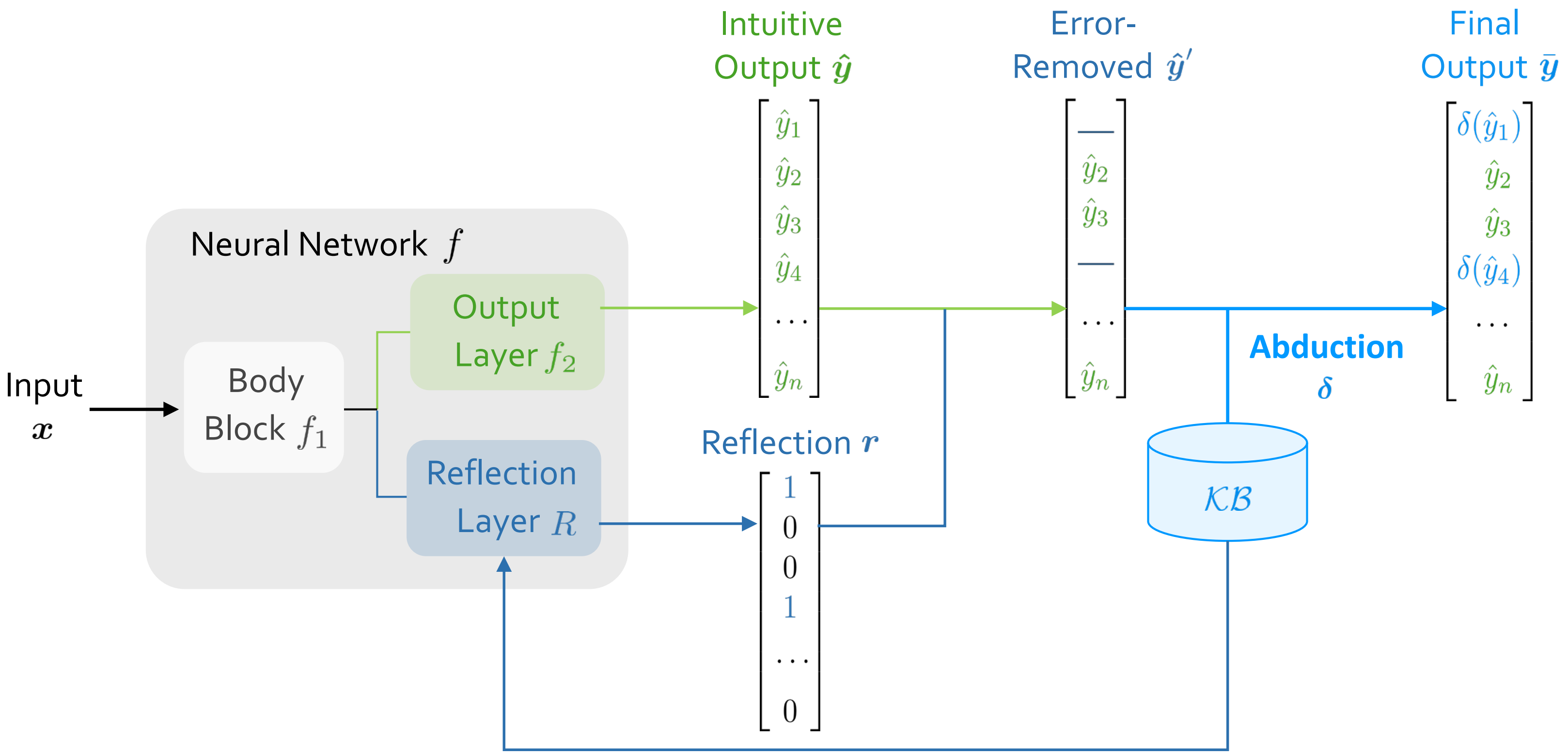
Our Method: **Abductive Learning** with **Reflection** (cont.)



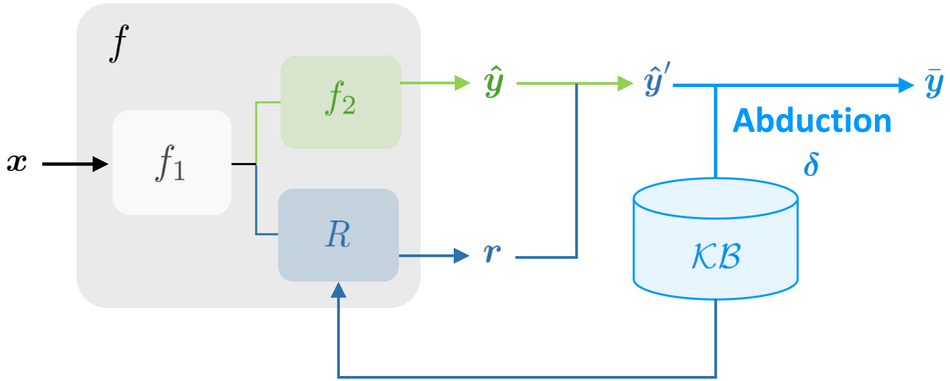
Our Method: **Abductive Learning** with **Reflection** (cont.)



Our Method: **Abductive Learning** with **Reflection** (cont.)



Method Recap



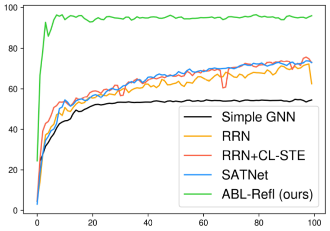
Neural network provides a fast, overall approximate solution, and

Reflection promptly directs the focus for **Symbolic reasoning** on a much reduced space.

- Reflection vector is generated **simultaneously** with intuitive output;
- During each inference, $\mathcal{KB}$ is only invoked **once**, regardless of data scale;
- Reflection is trained using information **directly from** $\mathcal{KB}$.

Experiments

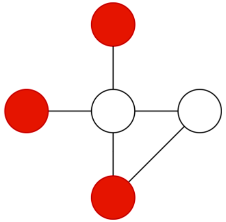
Method	Training Time (min)	Inference Time (s)	Inference Accuracy
RRN	114.8±7.8	0.19±0.01	73.1±1.2
CL-STE	173.6±9.9	0.19±0.02	76.5±1.8
SATNet	140.3±6.8	0.11±0.01	74.1±0.4
ABL-Refl	**109.8**±10.8	0.22±0.02	**97.4**±0.3



Solver	Method	Inference Time (s)		
		NN Time	Abduction Time	Overall Time
MiniSAT	Solver only	-	0.227±0.024	0.227±0.024
	ABL-Refl	0.021±0.004	**0.196**±0.015	**0.217**±0.019
Prolog with CLP(FD)	Solver only	-	105.81±5.62	105.81±5.62
	ABL-Refl	0.021±0.004	**31.86**±1.88	**31.88**±1.89

Achieves far better **accuracy** in only **a few epochs** (<10).

Enhances the **efficiency** of symbolic solvers.



Method	Dataset (Graph nums./Avg. nodes per graph/Avg. edges per graph)			
	ENZYMES (600/33/62)	PROTEINS (1113/39/73)	IMDB-Binary (1000/19/97)	COLLAB (5000/74/2457)
Erdos	0.883±0.156	0.905±0.133	0.936±0.175	0.852±0.212
Neural SFE	0.933±0.148	0.926±0.165	0.961±0.143	0.781±0.316
ABL-Refl	**0.991**±0.017	**0.985**±0.020	**0.979**±0.029	**0.982**±0.015

Capable of handling **scalable** data scenarios, and a **wide range of** domain knowledge.

Thanks!

Read the paper

Contact me

Presented by **Wen-Chao Hu**