Efficient Rectification of Neuro-Symbolic Reasoning Inconsistencies by Abductive Reflection

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LAMDA Learning And Mining from DatA

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NeSy AI

Neuro-Symbolic AI models human dual-process cognition,

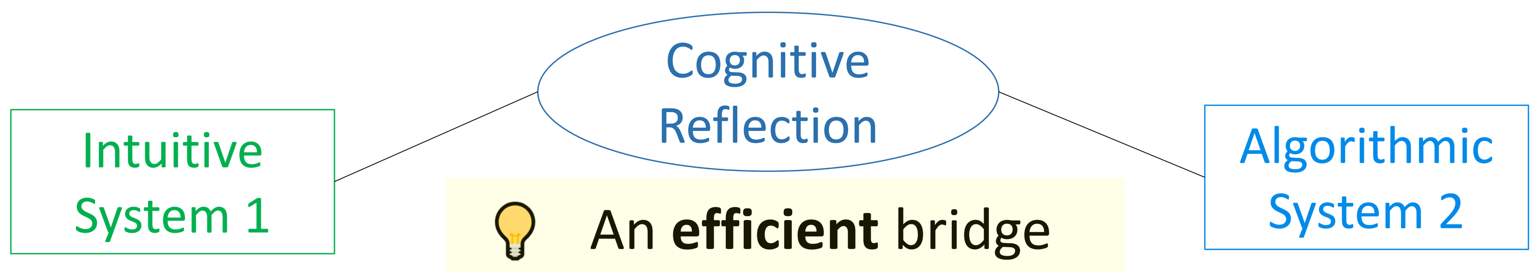
Neural Networks <-> System 1 (Intuitive)
Fast, yet often incorrect

Symbolic Reasoning <-> System 2 (Algorithmic)
Slow, leverage domain knowledge

⚠ Humans can easily use System 2 to rectify System 1 errors, but this is challenging for AI systems.

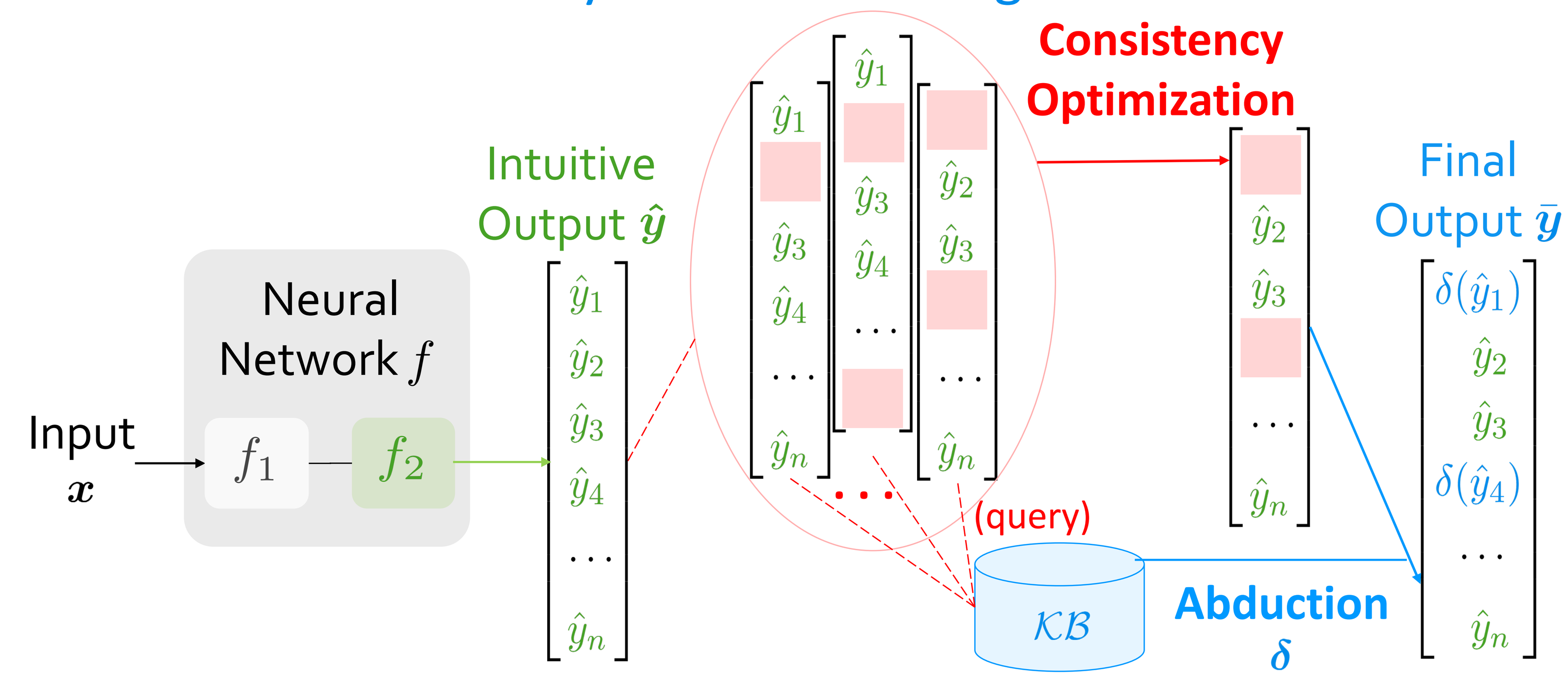
Inspiration from Human Cognition

Key in human cognition: **Cognitive Reflection**, promptly forms upon System 1 response, detects which part may contain errors and invokes System 2 to focus on.



Abductive Learning

A framework that preserves full expressive power in both neural networks and symbolic reasoning.



f: directly maps x into output $\hat{\boldsymbol{y}}$;

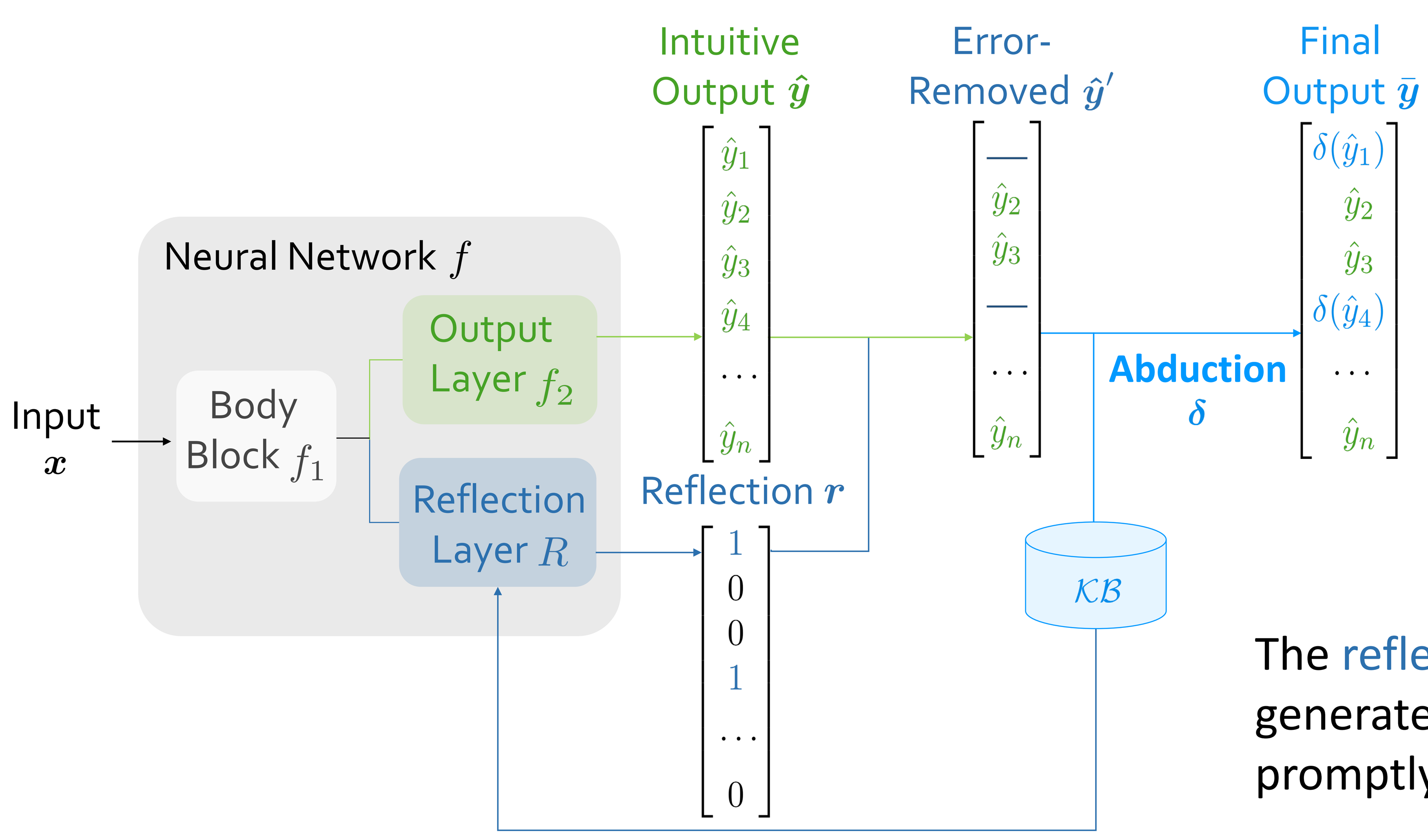
$\mathcal{KB}$: holds constraints between symbols in $\boldsymbol{y}$, and can perform reasoning (e.g., abduction) with a symbolic solver.

⚠ Involves consistency optimization before abduction, requiring large number of queries to $\mathcal{KB}$ that increases exponentially with data scale, largely hindering efficiency.

Our Method: Abductive Learning with Reflection Mechanism (ABL-Refl)

Replaces the time-consuming ~~consistency optimization~~ in ABL with an efficient **reflection mechanism**:

Incorporating a reflection layer R after the body block f_1, generating a reflection vector $\boldsymbol{r}$, each element, r_i, acts as a classifier to indicate whether the corresponding intuitive output $\hat{y}_i$ is an error leading to inconsistencies with $\mathcal{KB}$ (flagged as 1) or not (0) .



Key features

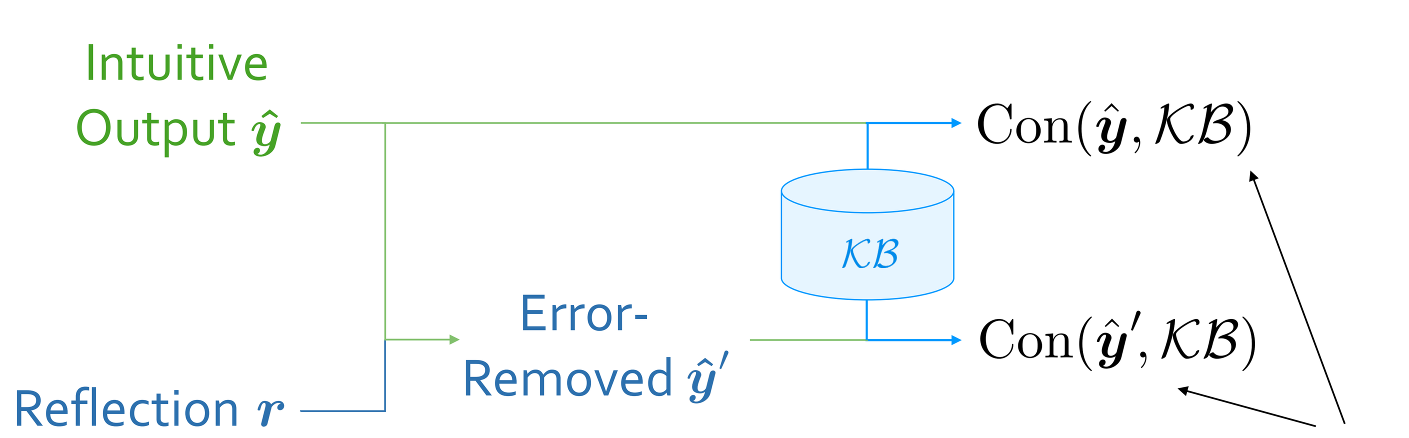
- Reflection vector is generated **simultaneously** with intuitive output;
- During each time of inference, $\mathcal{KB}$ is only invoked only **once**, regardless of data scale;
- Reflection mechanism is trained using information **directly from** $\mathcal{KB}$.

The reflection can be seen as an efficient **attention mechanism**, generated from neural network, and abduced from $\mathcal{KB}$, promptly directing the focus for symbolic search on a reduced space.

Training Paradigm

For the reflection, we want to achieve two goals:

1. Leverage training information directly from $\mathcal{KB}$:



The difference,

$$\mathrm{Con}(\hat{\boldsymbol{y}}' \mid \mathcal{KB}) - \mathrm{Con}(\hat{\boldsymbol{y}} \mid \mathcal{KB})$$

indicates how well $\boldsymbol{r}$ identifies errors in $\hat{\boldsymbol{y}}$, use REINFORCE to maximize it —> $L_{con}(\boldsymbol{x})$.

2. Constrain the size of reasoning, invoking it judiciously:

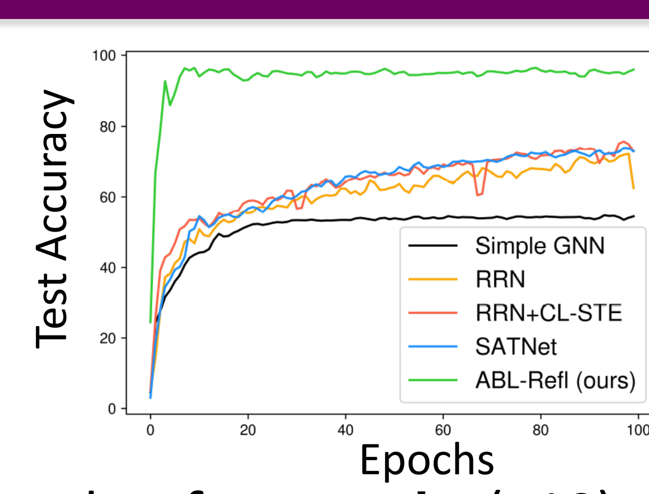
$$L_{size}(\boldsymbol{x}) = \max\left(0,\ C - \frac{1}{n}\sum_{i=1}^{n}(1 - R(f_1(\boldsymbol{x}))_i)\right)^2$$

Overall loss function:

$$\mathcal{L} = \frac{1}{|D_l|}\sum_{(\boldsymbol{x},\boldsymbol{y})\in D_l} L_{label}(\boldsymbol{x},\boldsymbol{y}) + \underbrace{\frac{1}{|D_l \cup D_u|}\sum_{\boldsymbol{x}\in D_l\cup D_u}(\alpha L_{con}(\boldsymbol{x}) + \beta L_{size}(\boldsymbol{x}))}_{\text{Reflection, do not need information from data label}}$$

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



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

$\mathcal{KB}$ Form	Solver	Method	Inference Accuracy	Inference Time (s)		
				NN Time	Abduction Time	Overall Time
Propositional logic	MiniSAT	Solver only	100±0	-	0.227±0.024	0.227±0.024
		ABL-Refl	97.4±0.3	0.021±0.004	**0.196**±0.015	**0.217**±0.019
First-order logic	Prolog with CLP(FD)	Solver only	100±0	-	105.81±5.62	105.81±5.62
		ABL-Refl	97.4±0.3	0.021±0.004	**31.86**±1.88	**31.88**±1.89

Enhances the **efficiency of symbolic solvers**, applicable for both propositional logic (MiniSAT) and first-order logic (Prolog).

Conclusion

ABL-Refl efficiently integrates neural networks with symbolic reasoning while preserving their integrity, enabling broad uses requiring rigorous reasoning.

Full paper

Contact me

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