

BEARS Make Neuro-Symbolic Models Aware of their Reasoning Shortcuts





Emanuele Marconato 1,2 Antonio Vergari³

Emile van Krieken³ Samuele Bortolotti ¹ Andrea Passerini ¹

Stefano Teso ¹

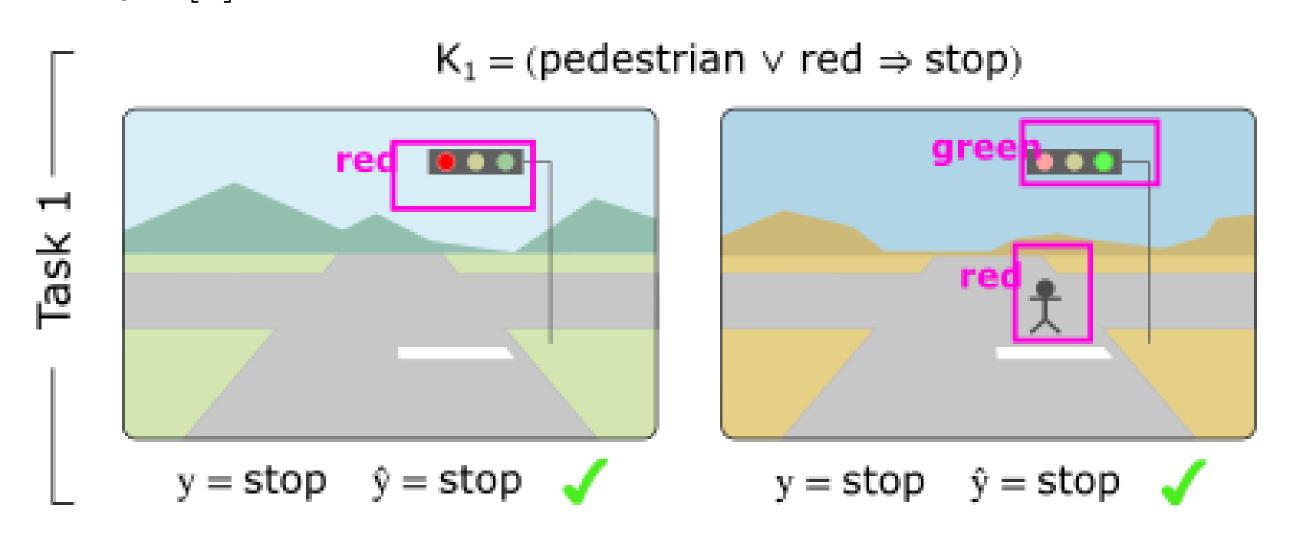
¹University of Trento ²University of Pisa ³University of Edinburgh

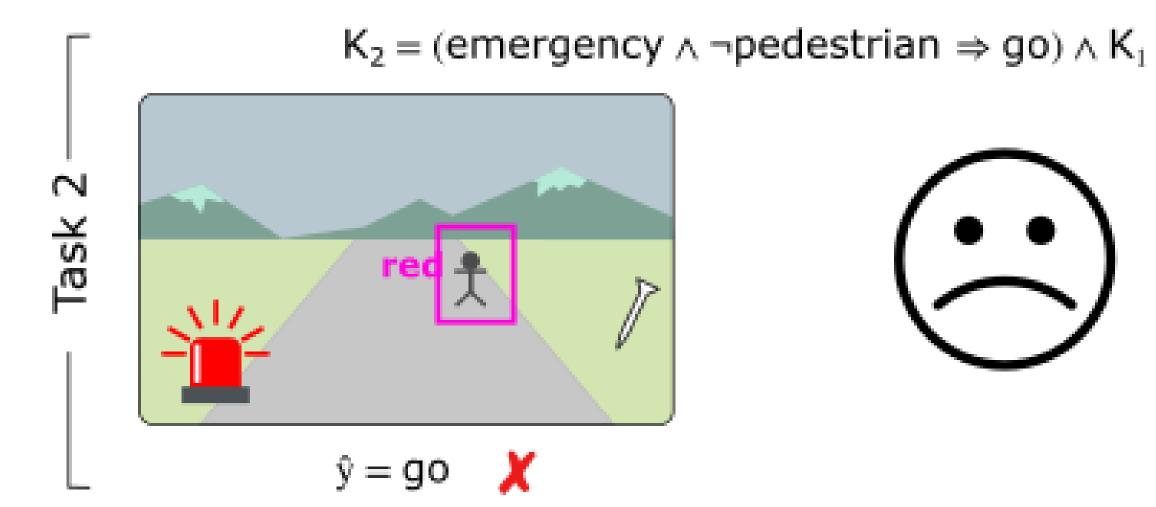


REASONING SHORTCUTS

NeSy predictors such as $\mathbf{DeepProbLog}[1]$, and \mathbf{Logic} \mathbf{Tensor} **Networks**[2], acquire concepts that comply with the knowledge.

Are learned concepts interpretable and is the model trustworthy? Not always![3]







Reasoning Shortcuts (RSs) like this might affect any NeSy predictor!

MITIGATION STRATEGIES

DESIDERATA

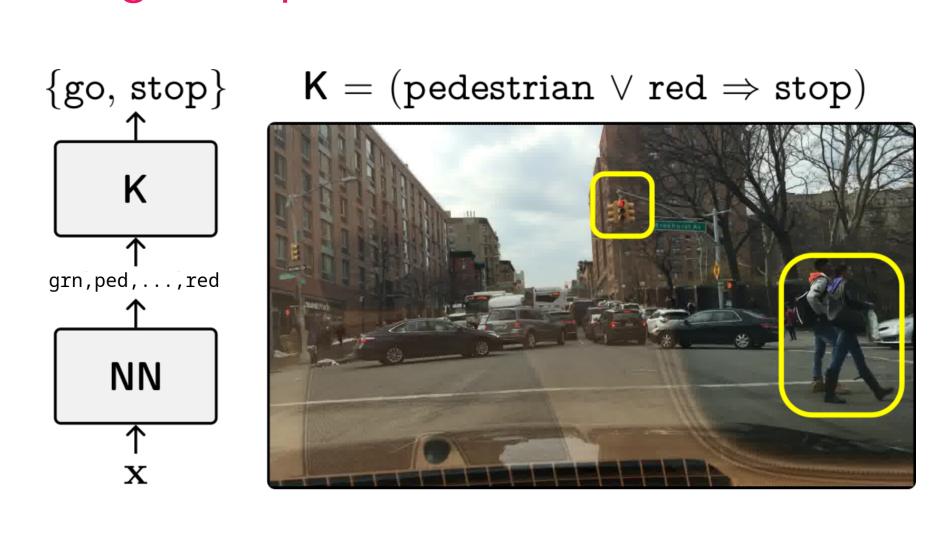
STRATEGY	REQUIRES
Multi-Task	tasks
Concept Sup.	concepts
Reconstruction	(decoder)
Disentanglement	structure

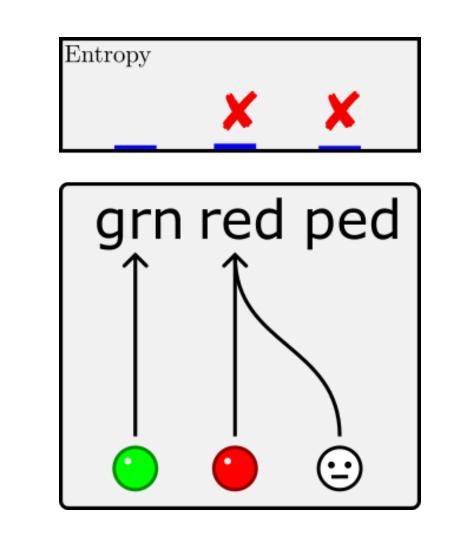
- Concept calibration
- Performance
- Cost effectiveness

MAIN PROBLEM

Effective mitigation strategies for RSs, like concept supervision, are often impractical. If the model learns a RS what concepts can we trust?

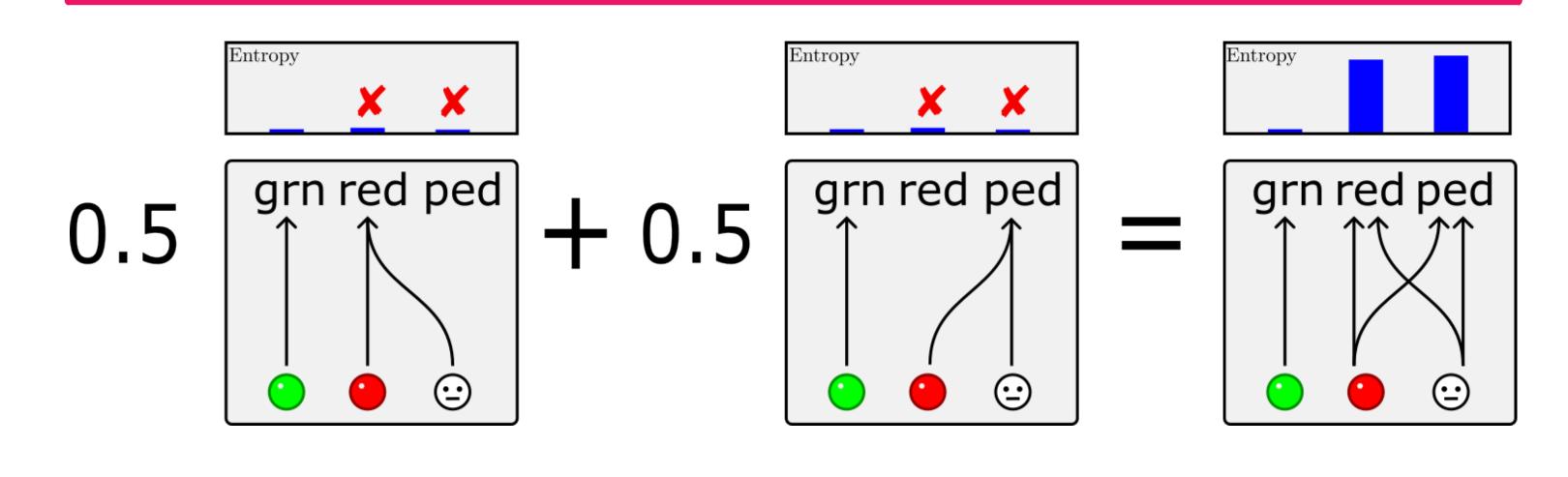
Over-confident solutions are dangerous: impossible to be aware of wrong concepts!





We propose bears to estimate concept uncertainty!

BEARS: BE AWARE OF REASONING SHORTCUTS!



bears combines Deep Ensembles + diversification

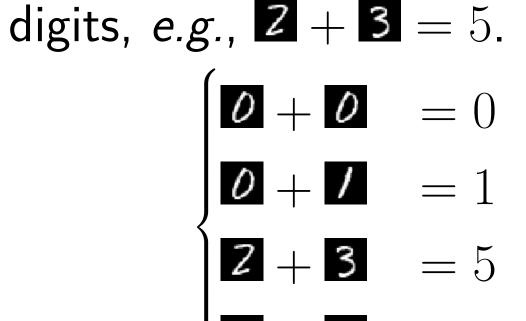
(\sim Bayesian NeSy) and provably optimizes for all desiderata:

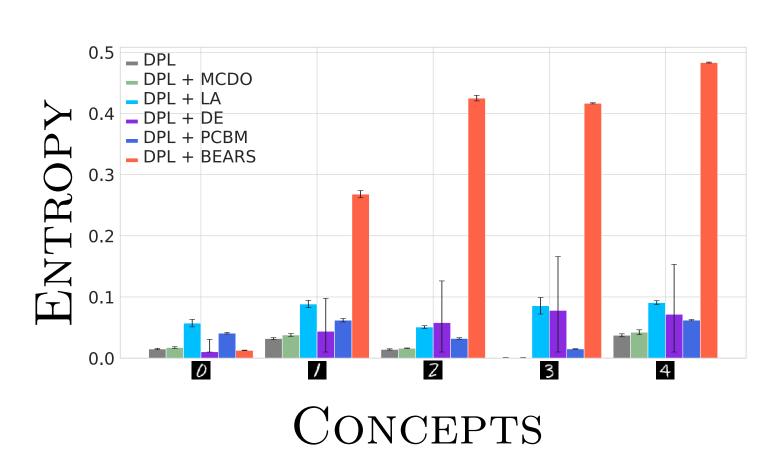
$$\begin{split} \mathcal{L}_{\text{bears}} &= \mathcal{L}(\mathbf{x}, \mathbf{y}; \mathbf{K}, \theta_t) \\ &+ \gamma_1 \cdot \mathsf{KL} \big(p_{\theta_t}(\mathbf{C} \mid \mathbf{x}) \mid\mid \frac{1}{t} \sum_{j=1}^t p_{\theta_j}(\mathbf{C} \mid \mathbf{x}) \big) \\ &+ \gamma_2 \cdot H(p_{\theta_t}(\mathbf{C} \mid \mathbf{x})) \end{split}$$

EXPERIMENTS

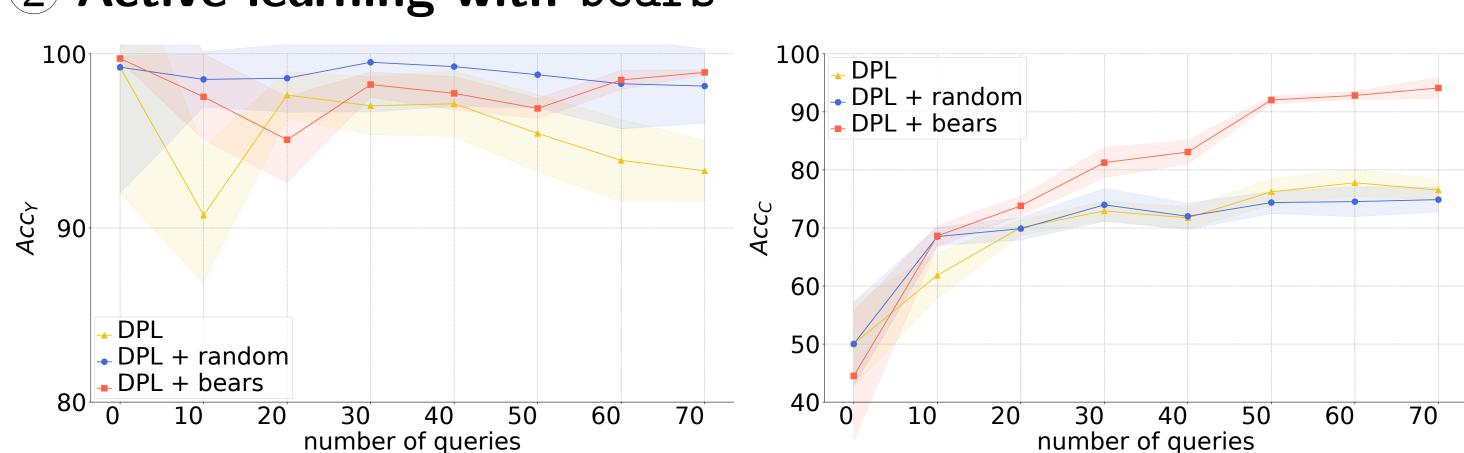
1) An example from MNIST-Addition

Solve the sum between two





2 Active learning with bears



3 bears in real-world: BDD-OIA [4]

	mECE_C	$ECE_C(F,S)$	$\mathrm{ECE}_C(R)$	$\mathrm{ECE}_C(L)$
DPL	0.84 ± 0.01	0.75 ± 0.17	0.79 ± 0.05	0.59 ± 0.32
+ MCDO	0.83 ± 0.01	0.72 ± 0.19	0.76 ± 0.08	0.55 ± 0.33
+ LA	0.85 ± 0.01	0.84 ± 0.10	0.87 ± 0.04	0.67 ± 0.19
+ PCBM	0.68 ± 0.01	0.26 ± 0.01	0.26 ± 0.02	0.11 ± 0.02
+ DE	0.79 ± 0.01	0.62 ± 0.03	0.71 ± 0.10	0.37 ± 0.12
+ bears	$\boldsymbol{0.58 \pm 0.01}$	0.14 ± 0.01	0.10 ± 0.01	$\boldsymbol{0.02 \pm 0.01}$

REFERENCES

- [1] Manhaeve et al., DeepProbLog, NeurlPS (2018)
- [2] Donadello et al., Logic Tensor Networks, IEEE (2018)
- [3] Marconato et al., Not All Neuro-Symbolic Concepts are Created Equal: Analysis and Mitigation of

Reasoning Shortcuts, NeurIPS (2023)

[4] Xu et al., BDD-OIA dataset, CVPR (2020).



