Continual Reasoning:
Non-monotonic Reasoning in Neurosymbolic AI using Continual Learning

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PROBLEM

Deep learning models are good at **Parallel Reasoning**
But, not good at more complex forms of reasoning, such as **Common Sense reasoning** and **Non-Monotonic reasoning.**

Parallel Reasoning

- Reasoning by similarity
- Example: Chain of thought prompting

Non - Monotonic Reasoning

- Ability to jump to conclusion and retract it once new information is available.
- Example: Penguin Exception Task

Solutions to Non-Monotonic Logic

Autoepistemic Logic

Circumscription

Default Logic

Negation by Failure

However,

Computationally Expensive

Struggle with exception to the exception
ex. a super penguin

More Advanced Reasoning Models

Challenge

Balancing logical formalization (explicit rules and structured reasoning) with neural network efficiency (pattern recognition and scalability)

Existing Methods

Formalized logic

- Connectionist Inductive Learning and Logic Programming System (CILP)
- Differentiable Inductive Logic Programming (∂ILP)

Probabilistic approach

- DeepProbLog

Disadvantages

- Scalability
- Dynamic Adaption
- Simplicity

Proposed Method:
Continual Reasoning

Neuro Symbolic Model

Models that combine machine learning and symbolic reasoning

Able to:

- Reason
- Learn with increased explainability
- Data efficiency
- Generalization

Main Idea

Reasoning tasks, especially non-monotonic reasoning, should be approached by learning data and the knowledge base through a multi-stage training process.

Implemented using:

- Logic Tensor Network (LTN)
- Continues Learning

What are LTN and Continues Learning?

Logic Tensor Network (LTN)

Framework that combines logic and machine learning.

Variable ⟶ Vector Embedding

Predicate ⟶ Neural Network ⟶ [0,1]

ex. is_bird(penguin) = 0.8

Why LTN?

- Integrates symbolic logic to constrain loss and handle learning and reasoning tasks
- Highly modular
- Good for learning in continual mode

Satisfiability: Measure how well a set of logical rules align with the data. [0,1]

Continues Learning

A machine learning approach where models learn tasks incrementally and sequentially, retaining past knowledge while acquiring new information.

Catastrophic Forgetting

Rehearsals

Implementation: Continual Reasoning

Task Seperation	**Knowledge Completion**
Teaching a model by breaking learning into clear, separate tasks. Each task is learned one at a time, allowing the model to focus on one specific type of knowledge before moving on to the next. Usually separated by predicates.	Implemented by progressively building the model's understanding, starting with foundational facts and incrementally adding more complex rules and exceptions.
Ex. Learning math 1. Learn addition 2. Then learn subtraction 3. then concepts like multiplication and exceptions	Ex. Learn to Drive a Car 1. Learn accelerator, brake, string wheel 2. Obey traffic rules 3. Learn exceptions (drive slower in the snow)

Implementation: Continual Reasoning Example

Knowledge Base: Penguin Exception Task

1. $\forall_{Norm\_Birds}\ is\_bird(Norm\_Birds)$ (normal birds are birds)
2. $\forall_{Cows}\ \neg\ is\_bird(Cows)$ (cows are not birds)
3. $\forall_{Animals}\ is\_bird(Animals) \Rightarrow can\_fly(Animals)$ (birds can fly)
4. $\forall_{Animals}\ \neg\ is\_bird(Animals) \Rightarrow \neg\ can\_fly(Animals)$ (non-birds cannot fly)
5. $\forall_{Penguins}\ is\_penguin(Penguins)$ (penguins are penguins)
6. $\forall_{Non\_Penguins}\ \neg\ is\_penguin(Non\_Penguins)$ (non-penguins are not penguins)
7. $\forall_{Animals}\ is\_penguin(Animals) \Rightarrow is\_bird(Animals)$ (penguins are birds)
8. $\forall_{Animals}\ is\_penguin(Animals) \Rightarrow \neg\ can\_fly(Animals)$ (penguins do not fly)

Knowledge Completion

Task Seperation

Curriculum	Stage 1	Stage 2	Stage 3
PET-KC	normal birds are Birds cows are not Birds penguins are Penguins non-penguins aren't Penguins	birds can Fly non-birds cannot Fly penguins are Birds	penguins cannot Fly
PET-TS	normal birds are Birds cows are not Birds penguins are Penguins non-penguins aren't Penguins penguins are Birds	birds can Fly non-birds cannot Fly	penguins cannot Fly

Evaluation of Continual Reasoning

Penguin Exception Task

	Curr	Rules	Stage 1	Stage 2	Stage 3
Single shot	Baseline	is_bird(Norm_Birds)	-	-	97.1% ± 0.11%
		is_bird(Penguins)			61.8% ± 0.00%
		can_fly(Birds)			**96.2% ± 0.33%**
		¬ can_fly(Penguins)			62.8% ± 0.00%
Random Splitting of the KB	Random	is_bird(Norm_Birds)	61.8% ± 47.8%	88.2% ± 33.0%	97.7% ± 0.02%
		is_bird(Penguins)	54.5% ± 45.9%	58.2% ± 48.3%	67.1% ± 21.7%
		can_fly(Birds)	28.5% ± 43.9%	65.7% ± 49.1%	90.5% ± 7.06%
		¬ can_fly(Penguins)	71.2% ± 43.7%	44.0% ± 48.4%	79.7% ± 16.8%
Knowledge Completion	KC	is_bird(Norm_Birds)	99.9% ± 0.01%	99.9% ± 0.01%	99.9% ± 0.01%
		is_bird(Penguins)	22.5% ± 24.3%	98.9% ± 2.22%	99.1% ± 1.16%
		can_fly(Birds)	57.6% ± 6.21%	99.1% ± 1.94%	91.9% ± 7.29%
		¬ can_fly(Penguins)	41.4% ± 4.81%	2.64% ± 5.74%	78.7% ± 43.5%
Task Seperation	TS	is_bird(Norm_Birds)	99.9% ± 0.00%	99.9% ± 0.00%	**99.9% ± 0.01%**
		is_bird(Penguins)	99.8% ± 0.02%	99.9% ± 0.01%	**99.5% ± 0.32%**
		can_fly(Birds)	53.9% ± 5.53%	99.9% ± 0.00%	84.7% ± 2.21%
		¬ can_fly(Penguins)	53.1% ± 5.25%	0.01% ± 0.01%	**99.7% ± 0.25%**

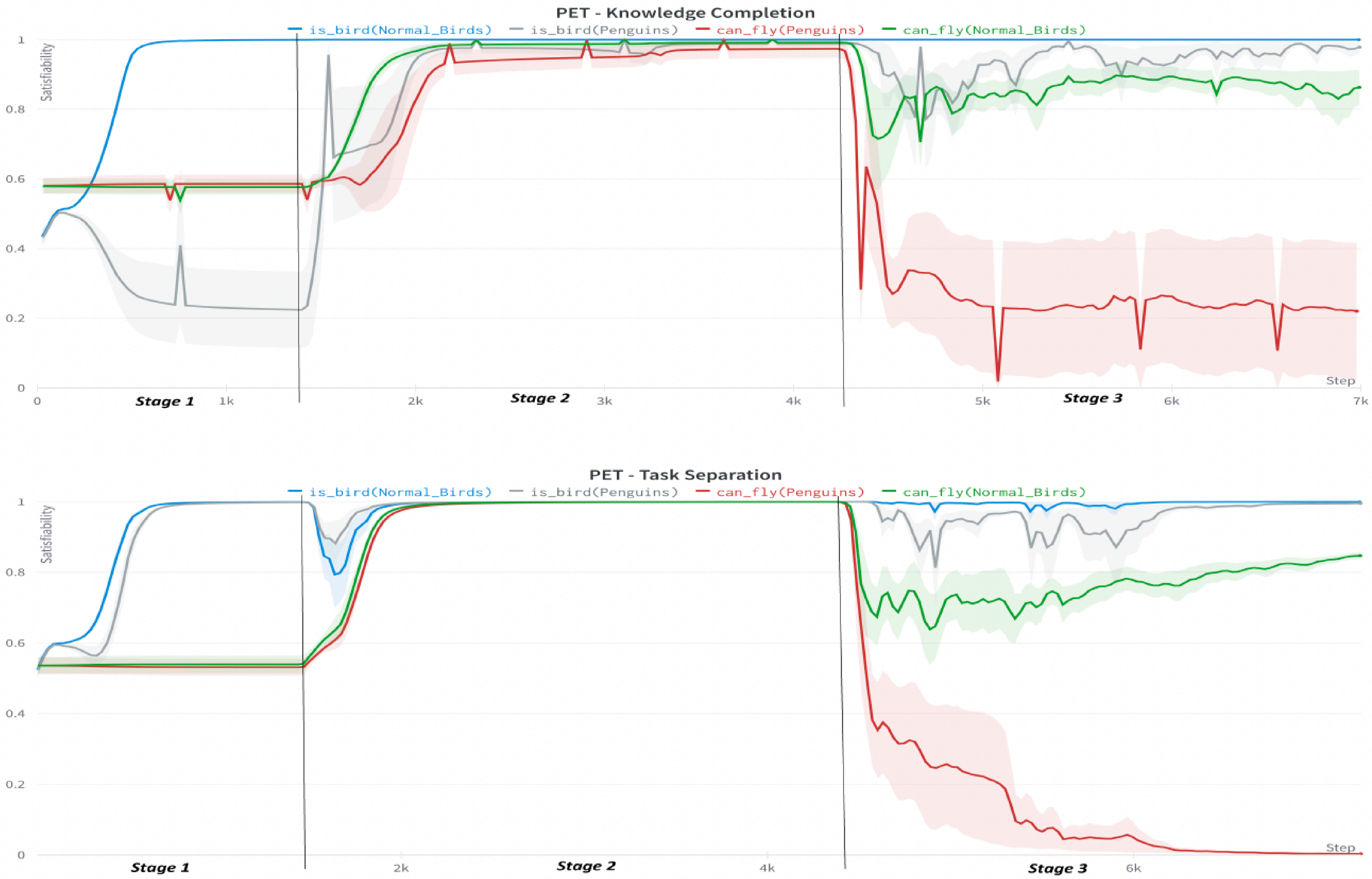
Evaluation of Continual Reasoning

is_bird(Normal_Bird)

is_bird(Penguins)

can_fly(Penguins)

can_fly(Normal_Birds)



Other Evaluation of Continual Reasoning

Smokers and Friends Task

- Setup: Models how smoking spreads among friends and leads to cancer.
- Rules: "Smokers influence friends to smoke" and "Smoking causes cancer."
- Chaining: Links social influence to health impacts.
- Goal: Tests reasoning about interconnected rules and exceptions.

Knowledge Completion outperformed Task Seperation and One Shot learning in identifying smoking causes cancer

bAbI - Task 1

- List of storylines given as facts and questions
- Ex. Mary went to the office. Jack travelled to the garden. **->** Where is Mary?

- Convert to FOL using GPT-3.
- Train using Continual Reasoning.

- 96.6% accuracy

Conclusion

This paper shows that the specific sequence in which the rules are learned and the facts are recalled can affect the model's outcome and accuracy.

In reasoning tasks, especially Non Monotonic Reasoning, the order in which the knowledge is learned matters.

Continual Reasoning methods can improve the accuracy of the Deep learning models in Non-Monotonic Reasoning.

Limitations

- Mostly failing to learn the exception to the exception (super penguin)
- A Neural Network for each predicate can be computationally expensive for a large KB with many predicates.

Open Questions

- How Continual Reasoning handles complex, evolving tasks in lifelong learning, where rules and contradictions must be updated and integrated over time?
- Would the results hold with a larger KB?
- When to use each Continual Reasoning method?

Future Work

- Using more advanced Neural Network architecture
- More sophisticated methods recall methods, i.e. active learning
- Work with larger KB
  - Catastrophic forgetting

Thank You!

Any Questions?