I-Tensors
Trends in AI and the ENEXA Project

Foundations of Neuro-Symbolic AI

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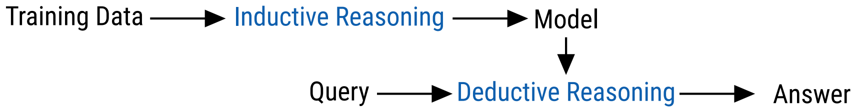
How to approach Artificial Intelligence?

Learning: Inductive Reasoning

Use training data to identify models representing the knowledge about a system.



Inference: Deductive Reasoning

Retrieve specific parts of the knowledge based on a query containing evidence.

How to mechanize Reasoning?

Modelling assumptions

- **Ontological**: What properties does a system have?
  $\rightarrow$ We assume fixed sets of categorical properties.
- **Epistemological**: What can we tell about these properties?
  $\rightarrow$ We associate possibilities or probabilities with states.

Two main frameworks differing in the empistemological assumptions:

- Logics (Possibilities): The traditional mathematical model of intelligence.
- Probability Theory (Probabilities): Handling uncertainties about the systems state.

In both cases, we encode our knowledge in an arrangement of numbers: Tensors with efficient representations by Tensor Networks.

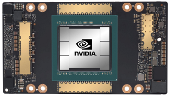
A computational interface: Tensors in Artificial Intelligence

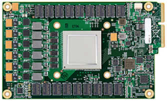
On the software side:

- Parallel computing based on tensor algebra
- Standard ML libraries: TensorFlow, Pytorch

On the hardware side:

- Dedicated for graphic processing: Graphic Processing Units (GPUs)
- AI-dedicated hardware: Tensor Processing Units (TPUs)





Do Large Language Models (LLM) suffice for reasoning?

Approach to

- Inductive Reasoning: LLMs are trained on massive amount of data and store knowledge in their weights
- Deductive Reasoning: LLMs answer prompts to retrieve knowledge in a specific context

LLMs make use of tensors:

- Organize computations in tensor contractions (layers of neural nets)
- Draw on AI-dedicated hardware for scaling

Two major concerns about LLMs

Besides having astonishing knowledge representation capabilities, LLMs lack in

- **Explainability:** Problems with Halluzinations
- **Efficiency:** Massive power consumptions during reasoning

Outlook: The Neuro-Symbolic AI Initiative

Neural Paradigm: Bringing efficiency

- Computations (gradients/inference) organized in layers (sets of neurons with tensor weights)
- Deep layers providing effective representation of data (task-dedicated neurons)

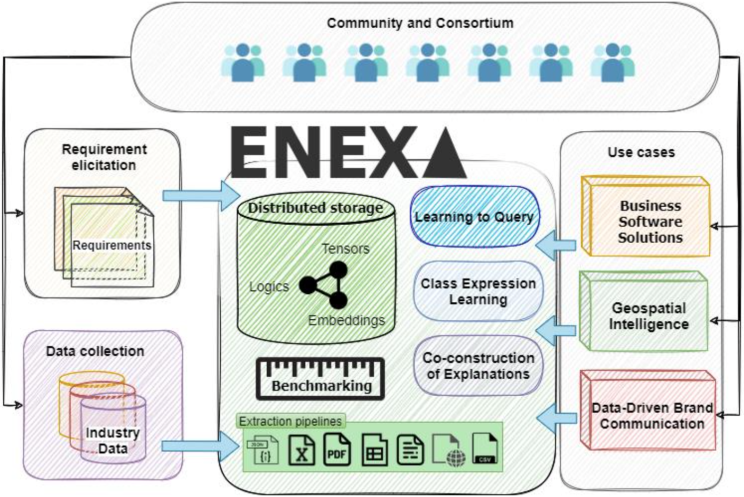
Symbolic AI: Bringing ante-hoc explainability

- Based on human interpretable logic
- Traditional approach to AI

How to bring both paradigm together?

Design neural architectures representing symbolic reasoning.

The ENEXA project: Efficient and Explainable Learning on Knowledge Graphs



Organizational Overview of ENEXA

Scientific Methods:

- Knowledge Extraction based on Large Language Models: University of Amsterdam (Prof. Paul Groth)
- Knowledge Representation and Reasoning in Knowledge Graphs: University of Paderborn (Prof. Axel Ngonga)
- Reasoning under Inconsistencies and Uncertainties: NCSR Demokritos Athens (Prof. Alexander Artikis)

Targeted Use Cases:

- Geospatial Intelligence: SatCen (Madrid)
- Brand Communication: webLyzard (Vienna)
- Business Software: DATEV (Nuremberg)

ENEXA for Explainable AI

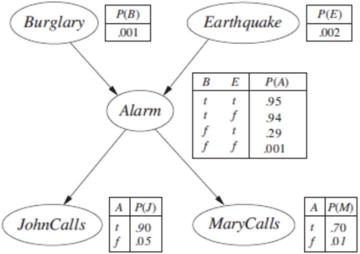
ENEXA provides **intrinsic and ante-hoc** explainable models.

- Logic as an interface between human and machine reasoning
- Humans can interpret and manipulate learned models
- Interpretations are globally valid, that is for all possible inputs to the model
- Guarantees on the behavior of the model can be derived

This is in contrast with typical **post-hoc** approaches to open black-box models at single datapoints.

ENEXA for Causal AI

Bayesian Networks are defined on directed graphs, which model causes and effects:



In ENEXA we go one step beyond and represent cause and effect relationships in terms of probabilistic logics.

Challenge

Since causality requires intervention with data or expert knowledge, how can we certify the causality of our models?

Downsides of the rich architecture

Expressivity:

- Small sets of logical sentences have limited expressivity
- Model training and interpretation as an interactive process

Efficiency:

- Reasoning algorithms come with worst-case infeasibilities
- Tradeoff between exactness and efficiency

Requirements for Use Cases

- Small number of discrete random variables (when requiring exact reasoning)
- Larger numbers can only be handled with approximative algorithms
- Intuition about their logical interdependence for training and human interpretation