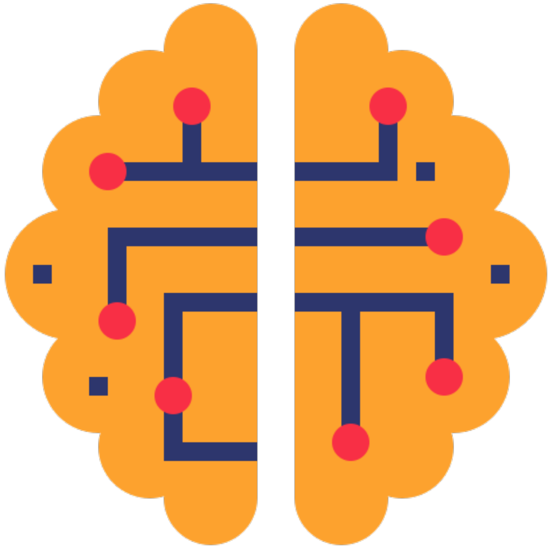
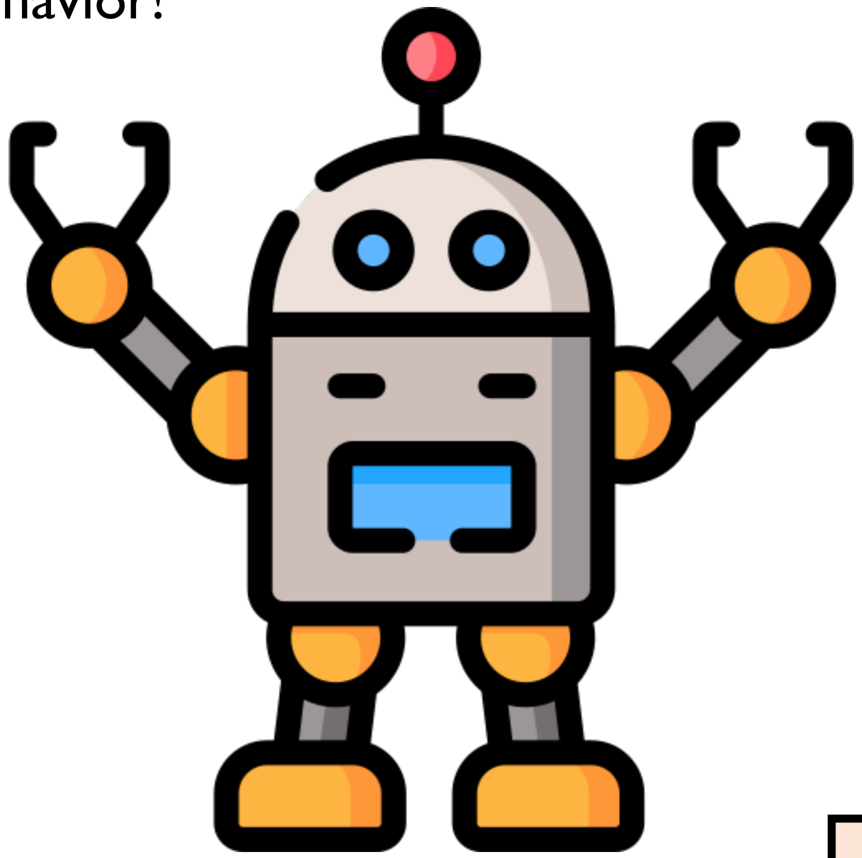
Towards the integration of symbolic and deep learning systems: the Neuro-Symbolic approach.



Pisa,
26/10/2022

What is AI?

- «A branch of computer science dealing with the simulation of intelligent behavior in machines» [1]
- The capability of a machine to emulate intelligent human behavior!



[1] *https://www.merriam-webster.com/dictionary/artificial%20intelligence*

Current status of AI

AI is still lacking:

- Adaptability
- Generalizability
- Robustness
- Explainability
- Abstraction
- Common sense
- Causal reasoning
- …

Narrow AI	Broad AI	General AI
Single task, single domain, superhuman accuracy and speed for certain tasks	Multi-task, multi-domain, multi-modal, distributed AI, explainable AI	Cross-domain learning and reasoning, broad autonomy

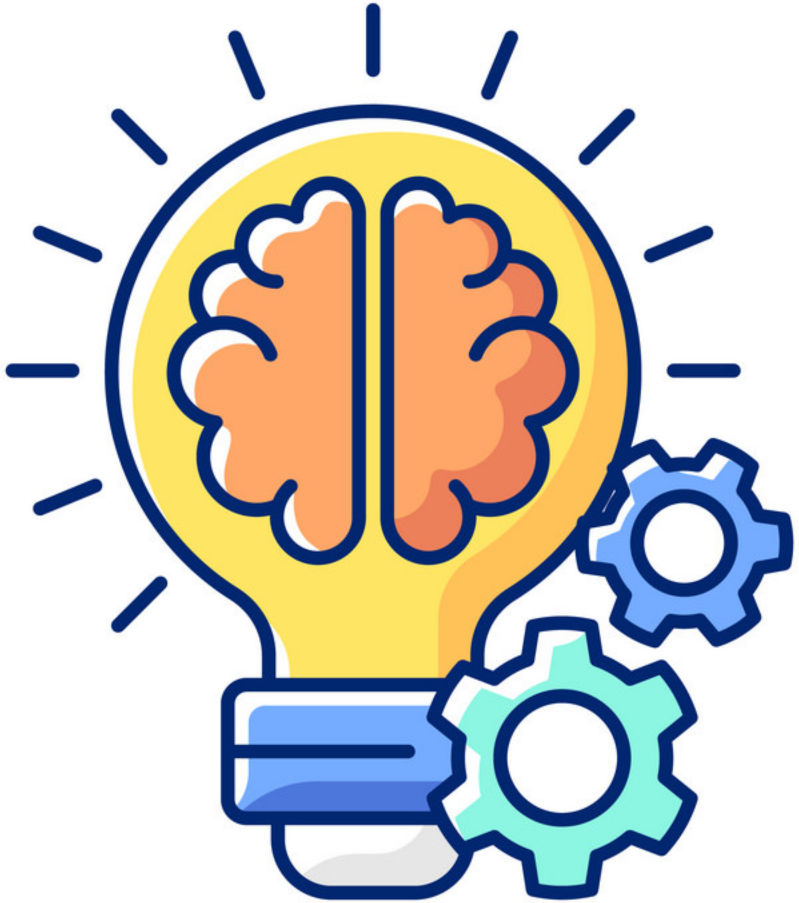
We are here

2050 and beyond..

From «Neurosymbolic AI» by David Cox

Symbolic AI systems

- **GOFAI** (**G**ood **O**ld **F**ashioned **A**rtificial **I**ntelligence)
- Founded on the principles of logic
- Exploiting background knowledge
- Not occurring naturally, produced by humans
- Using symbols to represent the world
- It is well-suited for representing explicit knowledge

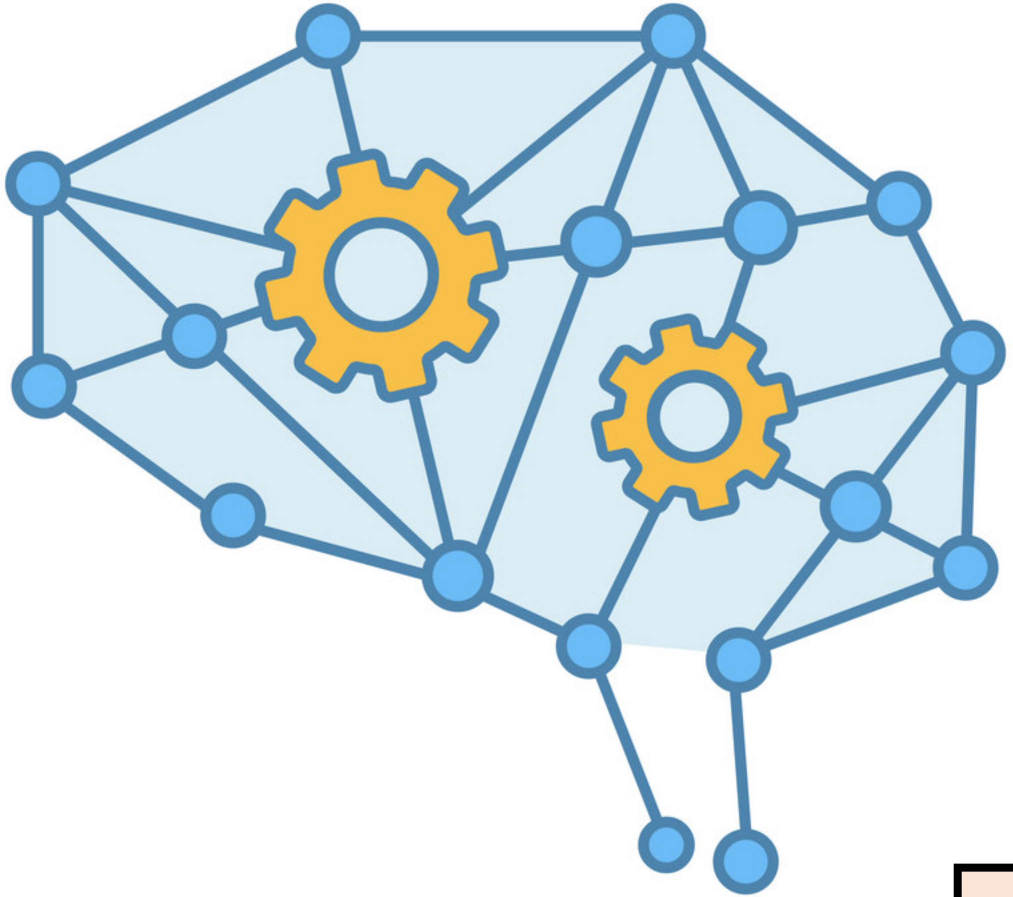


- Expressive
- Can generalize from few examples
- Human-understandable

- Inference is typically expensive
- A lot of human effort
- Difficult to deal with high-dimensional data

Deep Learning systems

- **<u>Neuro</u>**-Symbolic AI -> focused on neural network
- Long tradition (at least from 1950's), e.g. Hebb, Rosenblatt, Grossberg, McClelland, O'Reilly.
- Biologically inspired
- Nodes, links, activation, weights, learning algorithms



- Excellent function approximators
- Automatically learn pattern/features
- Efficient processing of high-dimensional data

- Data hungry
- Uninterpretable
- Lack of reasoning

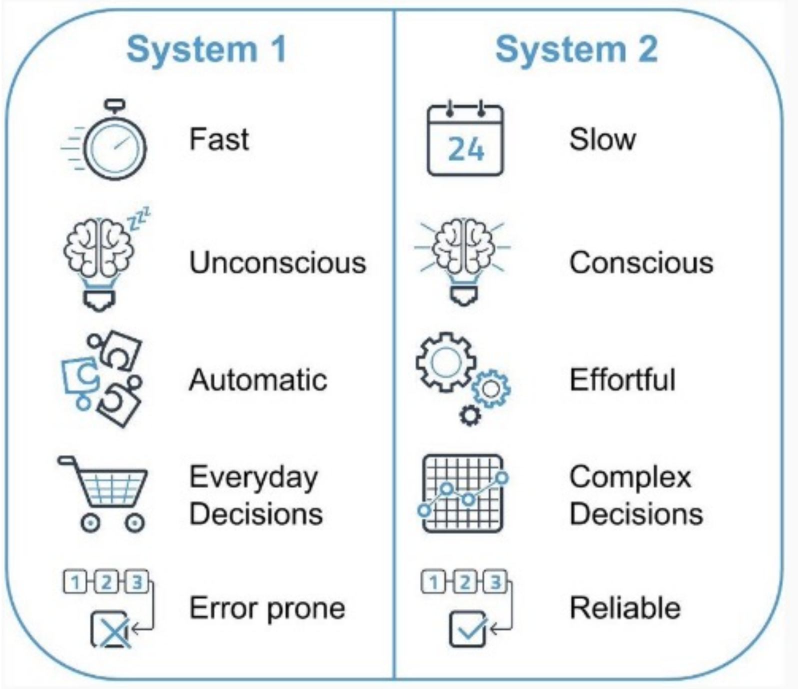
What is (still) difficult for DNN?

1. Deep learning thus far is data hungry
2. Deep learning thus far is shallow and has limited capacity for transfer knowledge
3. Deep learning thus far has no natural way to deal with hierarchical structure
4. Deep learning thus far is not sufficiently transparent
5. Deep learning thus far has not been well integrated with prior knowledge
6. Deep learning thus far cannot distinguish causation from correlation
7. Deep learning presumes a largely stable world, in ways that may be problematic!
8. Deep learning thus far works well as an approximation, but its answers often cannot be fully trusted

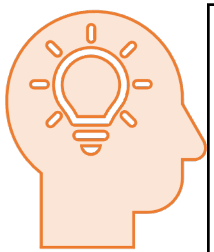
[Gary Marcus, Deep Learning: a critical appraisal, 2018]

Combination

- Learning + reasoning -> Data driven AI + Knowledge driven AI
- Deep Learning (System 1): concentrates on intuitive perceptual thinking
- Symbolic Approaches (System 2): focuses on conceptual, rule-based thinking



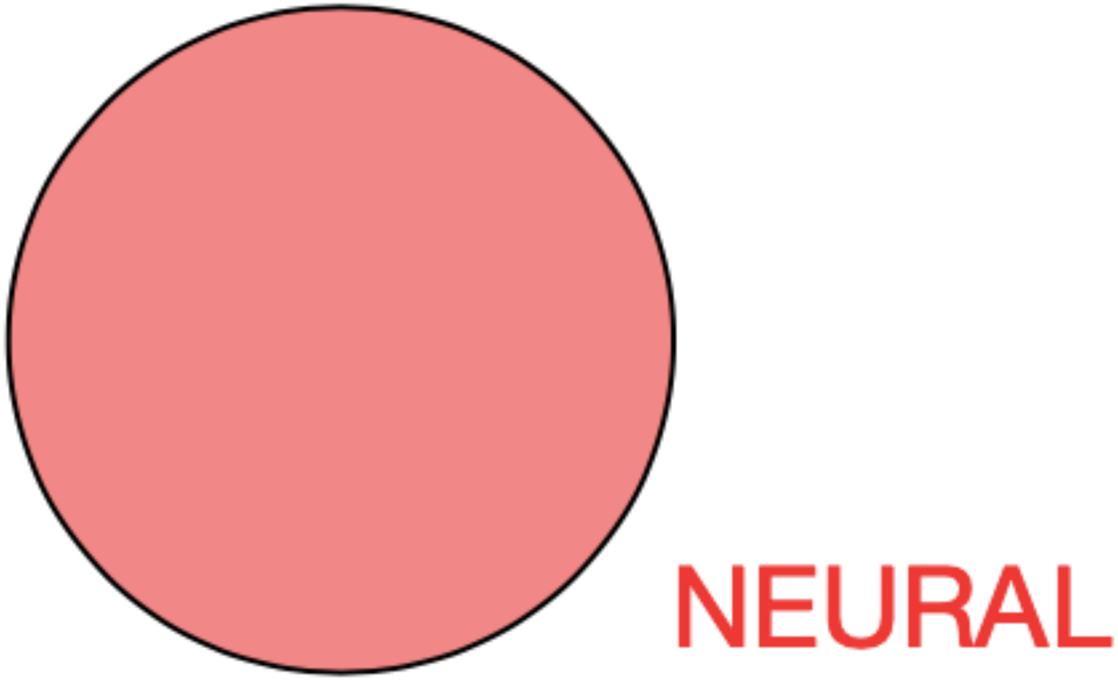
[Image by D. Vanderbyl]



- Neural Network to assist Symbolic systems:
  - Explore combinatorial spaces more efficiently.
- Symbolic systems to assist Neural Networks:
  - Better performance
  - Less data
  - More generizability

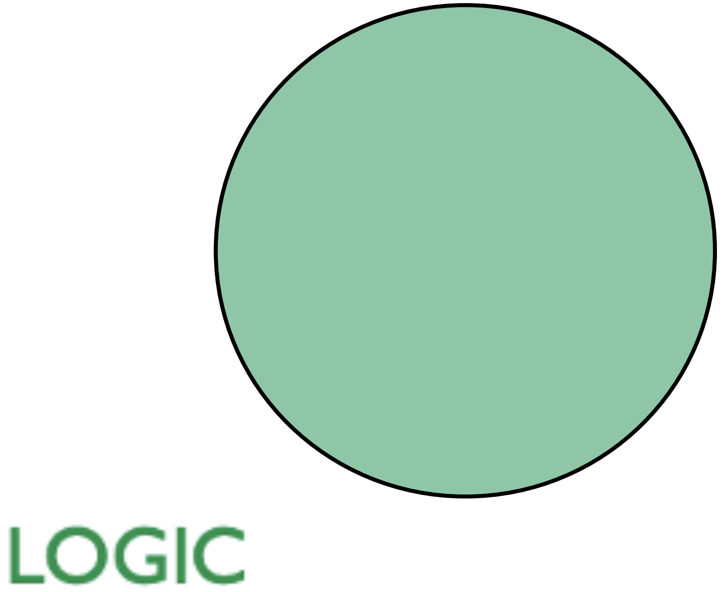
Thinking fast

MAIN PARADIGM in AI
Focus on Learning

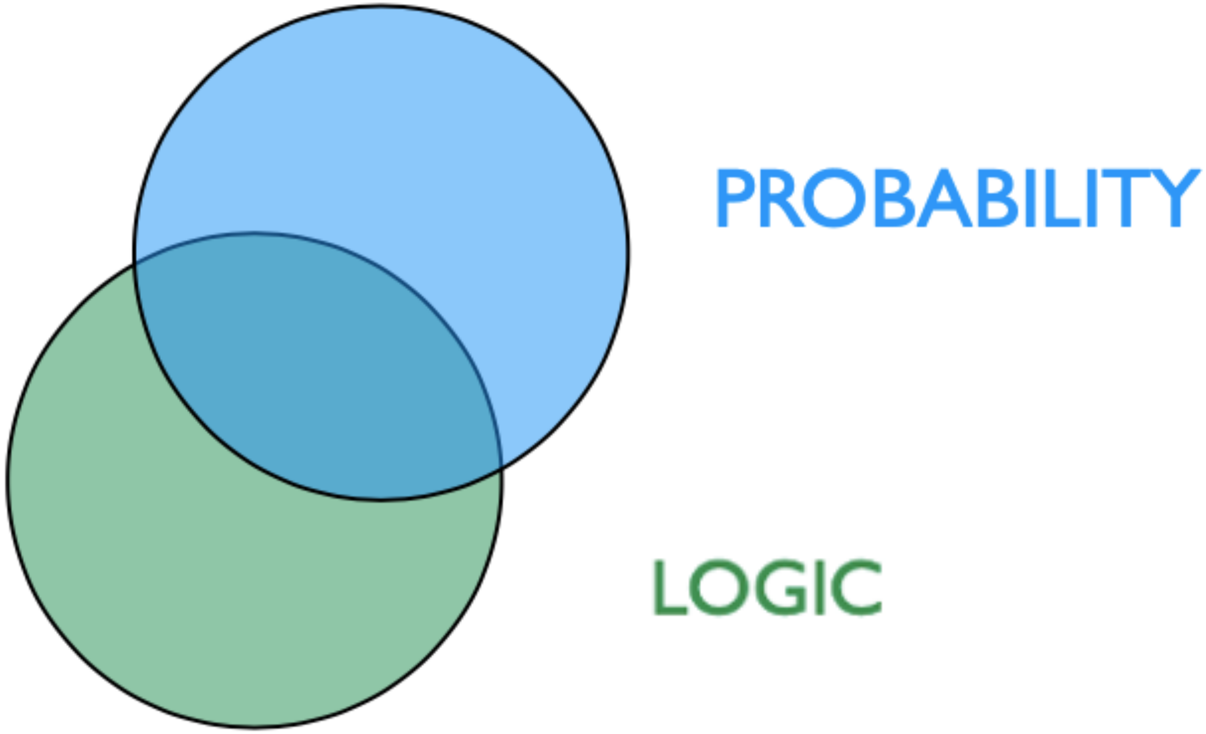


Thinking slow

Symbolic AI



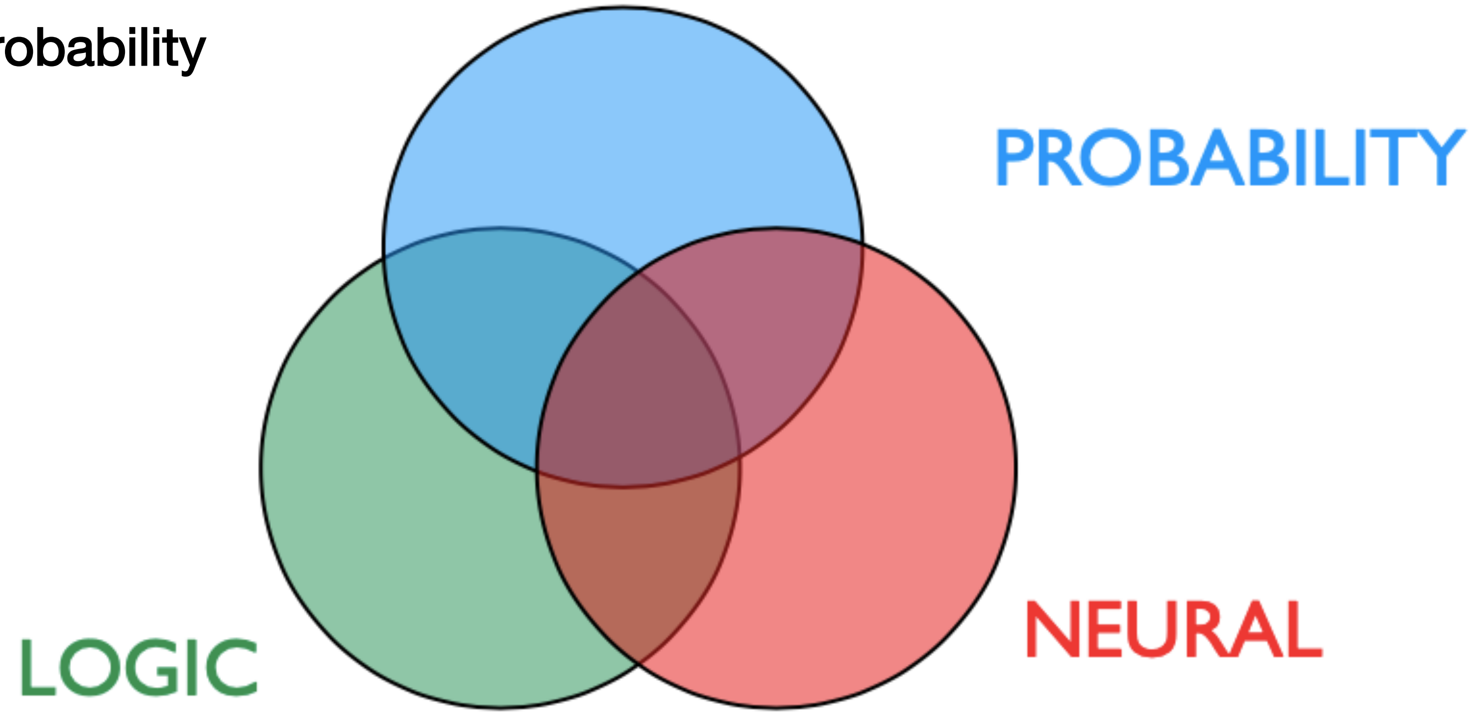
Statistical Relational AI (StarAI)



["From Statistical Relational AI to Neural Symbolic Computation", Luc De Raedt et.al.]

Neuro-Symbolic AI

- Logic + Neural
- Logic + Neural + Probability



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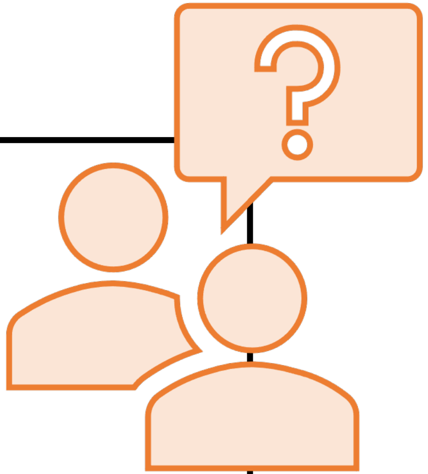
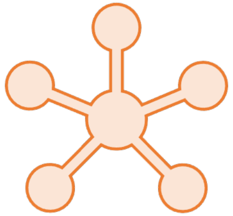
Neuro-Symbolic AI dimensions



1. **Knowledge representation**
2. **Knowledge reasoning**
3. **Knowledge combination/integration**

Knowledge Representation

Logical formulae



Knowledge Graphs

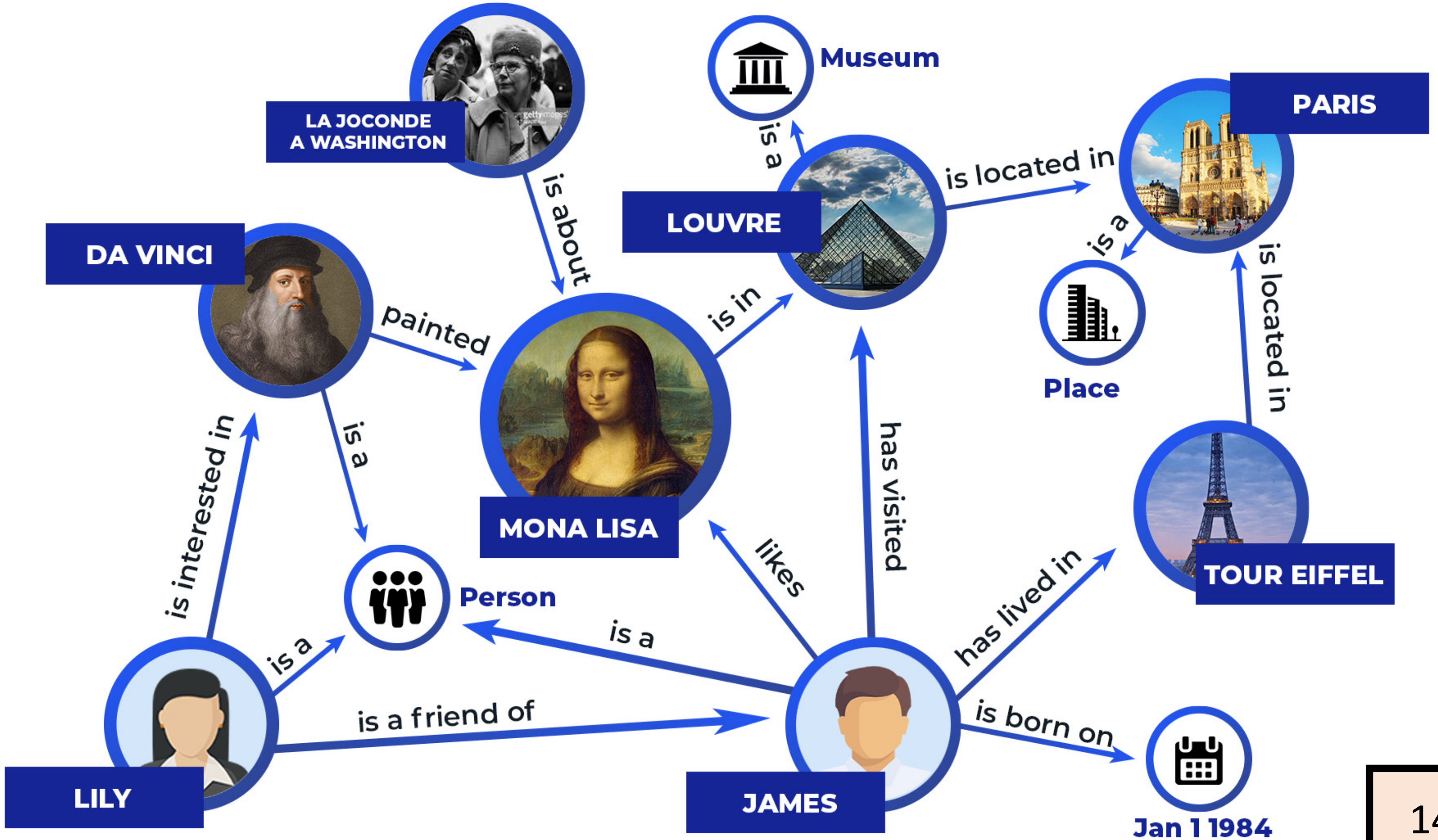
Logical Formulae

- Different types of logic exist
- Different types of logic enable different functionalities
- Logic uses logical connectives: $\wedge$ (conjunction), $\vee$ (disjunction), $\neg$ (negation)

- **Propositional Logic**
  - It is based on propositions: declaritive sentences that are True or False
  - It works on 0 and 1 thus it is also known as 'Boolean Logic'.
- **First Order Logic**
  - It is based on predicates (a.k.a 'Predicate Logic'): sentences whose value depends on parameters.
  - It uses quantifiers : universal, and existential, e.g $\forall x{:}\, Person(x) \ni y : (Mother(y))$.

Knowledge Graphs

- A set of facts represented as triplets : (head entity, relation, tail entity)
- Knowledge Graph as KB
- KGC
- KGQA



Knowledge Reasoning

- Manipulation of symbols in such a way as to construct representations of new propositions.

Induction

- Bottom-up process: from the specific to the general

- Effective for world building

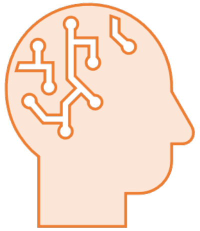
- Typical in ML

Deduction

- Top-down process: from the general to the specific

- Effective to reach certain conclusions

- Typical in Symbolic AI



Abduction

- It reveals most plausible premises given certain conclusions

- Effective in medical and investigation domains

- Best guess reasoning

Knowledge Reasoning

Major premise:
Mary uses left-handed scissors.

Minor premise:
Mary is left-handed.

Conclusion:
Each left-handed person uses left-handed scissors.

Major premise:
All plants perform photosynthesis.

Minor premise:
A cactus is a plant.

Conclusion:
A cactus performs photosynthesis.

Major premise:
Shoes are wet.

Minor premise:
Shoes are wet if it rained.

Conclusion:
It rained.

Neuro-Symbolic approaches

Combination

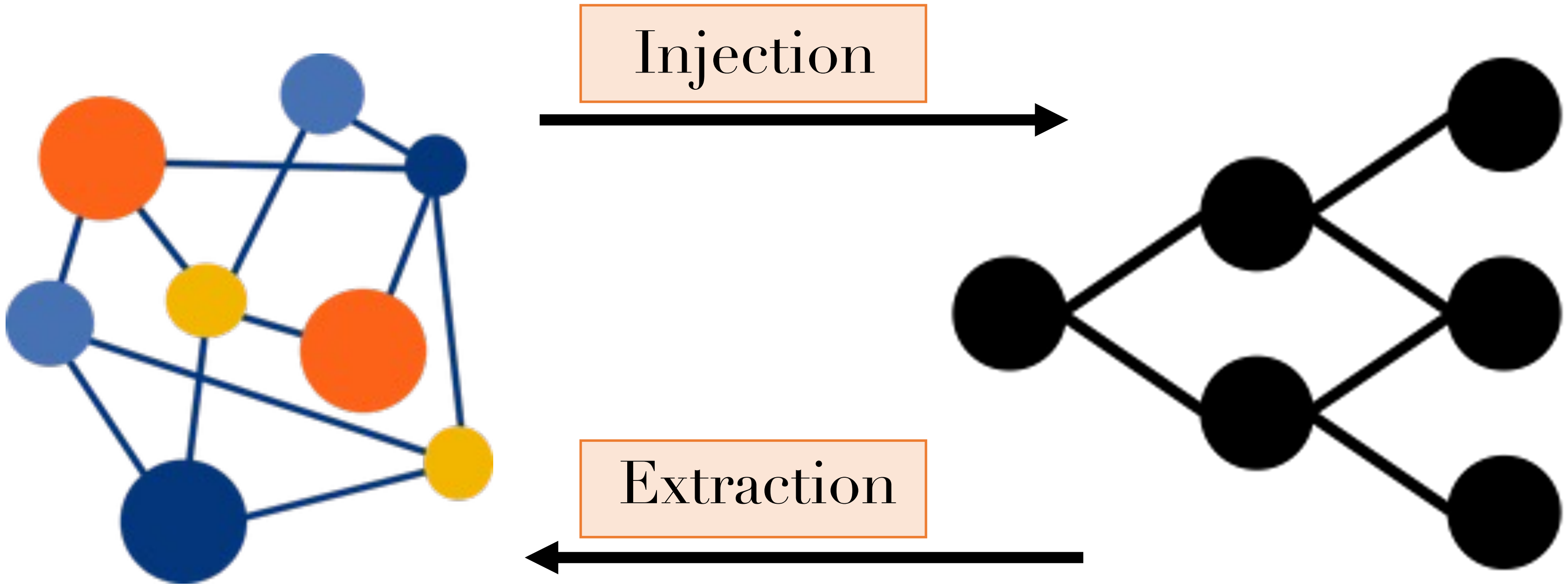
- Symbolic and sub-symbolic techniques still work as distinct blocks which are jointly exploited

Integration

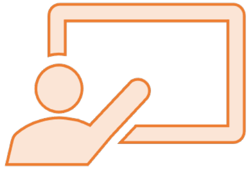
- Symbolic and sub-symbolic techniques are blended together in a single model

Calegari Roberta, Ciatto Giovanni, and Omicini Andrea. ‘On the Integration of Symbolic and Sub-symbolic Techniques for XAI: A Survey’.

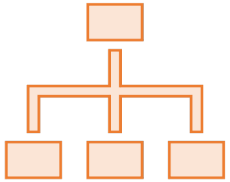
Knowledge Injection and Extraction



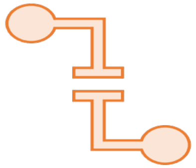
Knowledge Injection



Guided Learning



Predictor structuring



Knowledge embedding

Why?

1. Provide additional knowledge to the system, e.g reduce amount of training data
2. Possibly reduce the complexity of the system
3. Provide the system with reasoning capabilities

Guided learning

- i.e loss constraining
- Altering the learning process of the system
- Penalising inconsistent behaviours
- Incentivising consistent behaviours
- Logic is usually translated into **fuzzy logic**

- Boolean variables relaxed into real variables in [0, 1].
- Conjunction relaxed using t-norm
- Disjunction relaxed using t-conorm
- Existential quantifier relaxed as maximum (over dataset)
- Universal quantifier relaxed as minimum (over dataset, usually replaced by average)

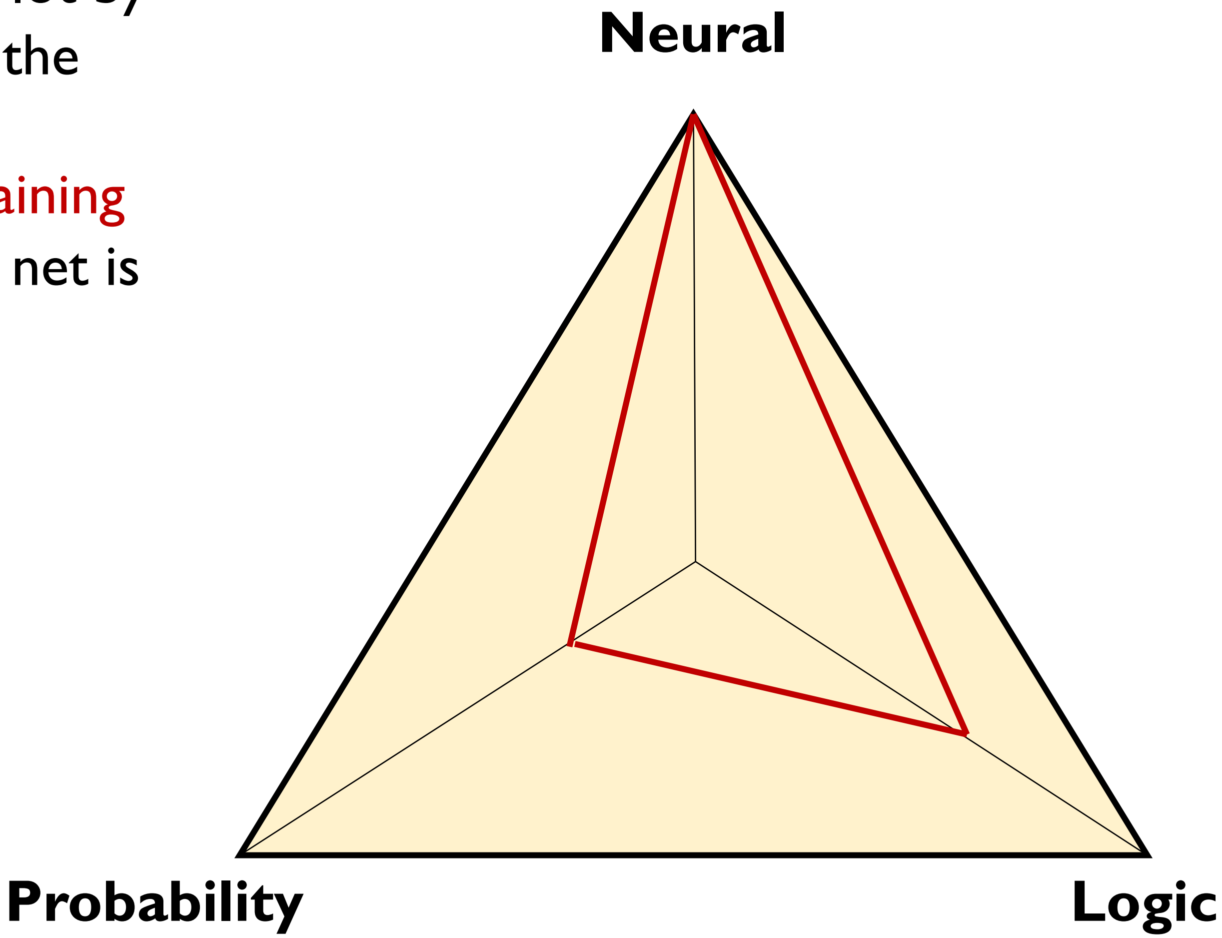
Semantic Loss

$$\mathcal{L}_s(\phi, \mathbf{p}) \propto -\log \sum_{\mathbf{y} \models \phi} \prod_{\mathbf{y} \models Y_i} p_i \prod_{\mathbf{y} \models \neg Y_i} (1 - p_i)$$

$$\mathcal{L}_{reg} = traning\_loss + \lambda \; semantic\_loss$$

[Xu et al., ICML 18]

- They sacrifice the logic and probability a lot by pushing everything inside the weights of the neural network.
- Logic and probability are used only at training time. At inference time, only the neural net is used.



SBR (Diligenti et al, AI 2017)
LTN (Donatello et al, IJCAI 2017)
SL (Xu et al, ICML 2018)

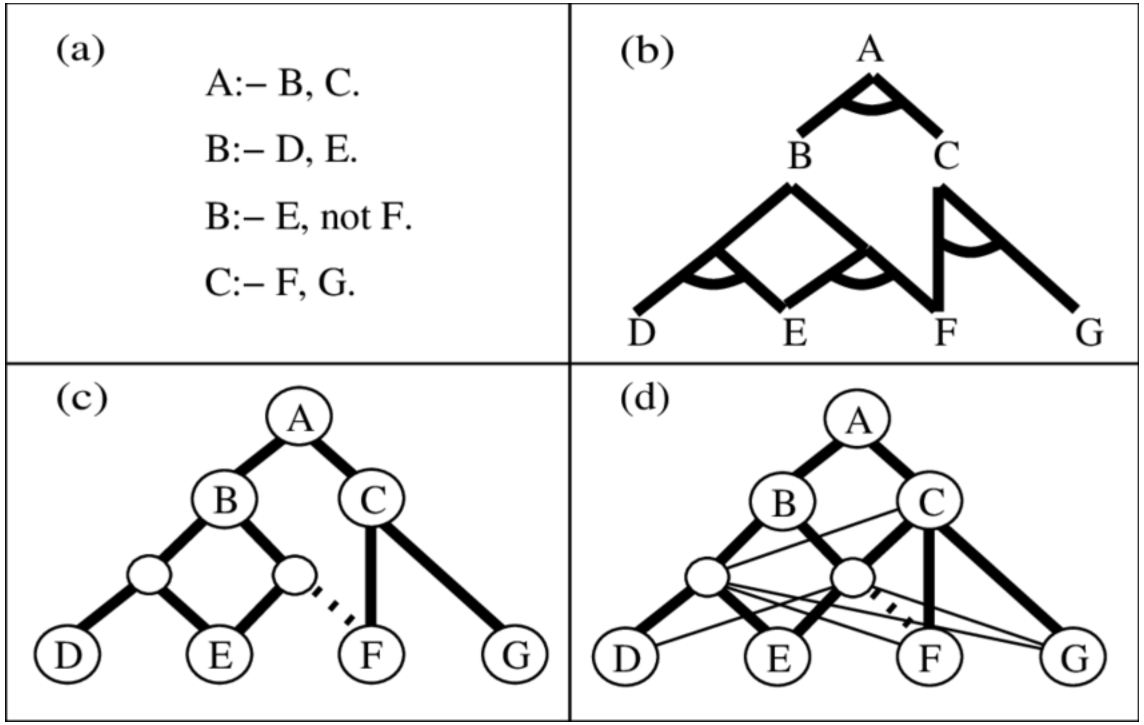
[From Statistical Relational AI to Neural Symbolic Computation, Luc De Raedt et. al]

Predictor structuring

- i.e structural constraining
- Altering the system structure to reflect the symbolic knowledge
- Setting connections, hidden layers, weights, or bias values.

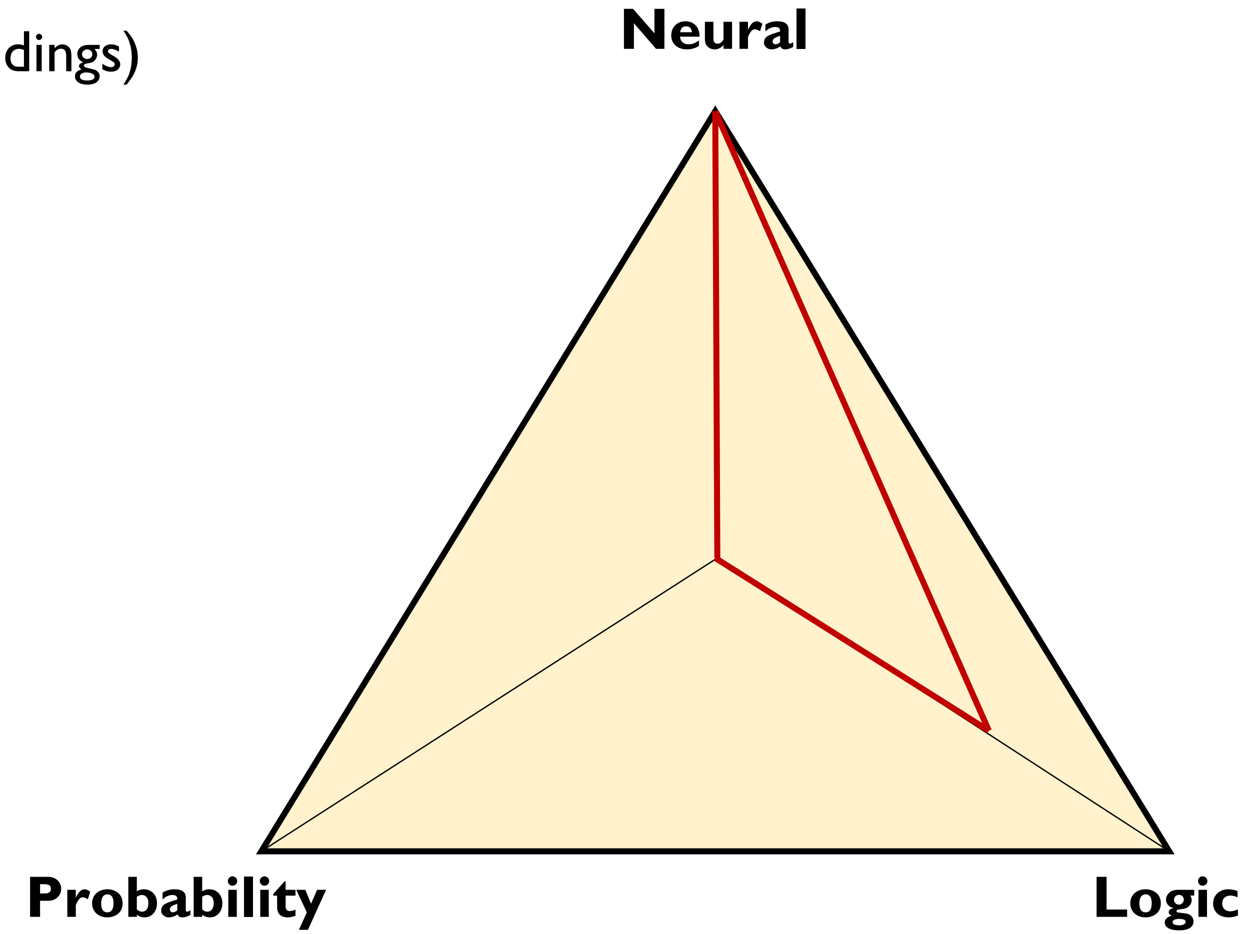
KBANN

- Given a set of training examples and a domain theory **(a)**
- The knowledge base is translated into a NN **(b)**
- Mandatory antecedent w, prohibitory –w **(c)**
- Add units and links not specified by translation **(d)**
- Perturb the network with a random noise (near 0)



[Towell et al., 1990]

- They sacrifice a bit of logic to obtain neural capabilities (weighted reasoning, embeddings)



KBANN (Towell 1994)
LRNN (Sourek, 2017)
NTPs (Rocktäschel, 2017)
DiffLog (Si et al., 2018)

[From Statistical Relational AI to Neural Symbolic Computation, Luc De Raedt et. al]

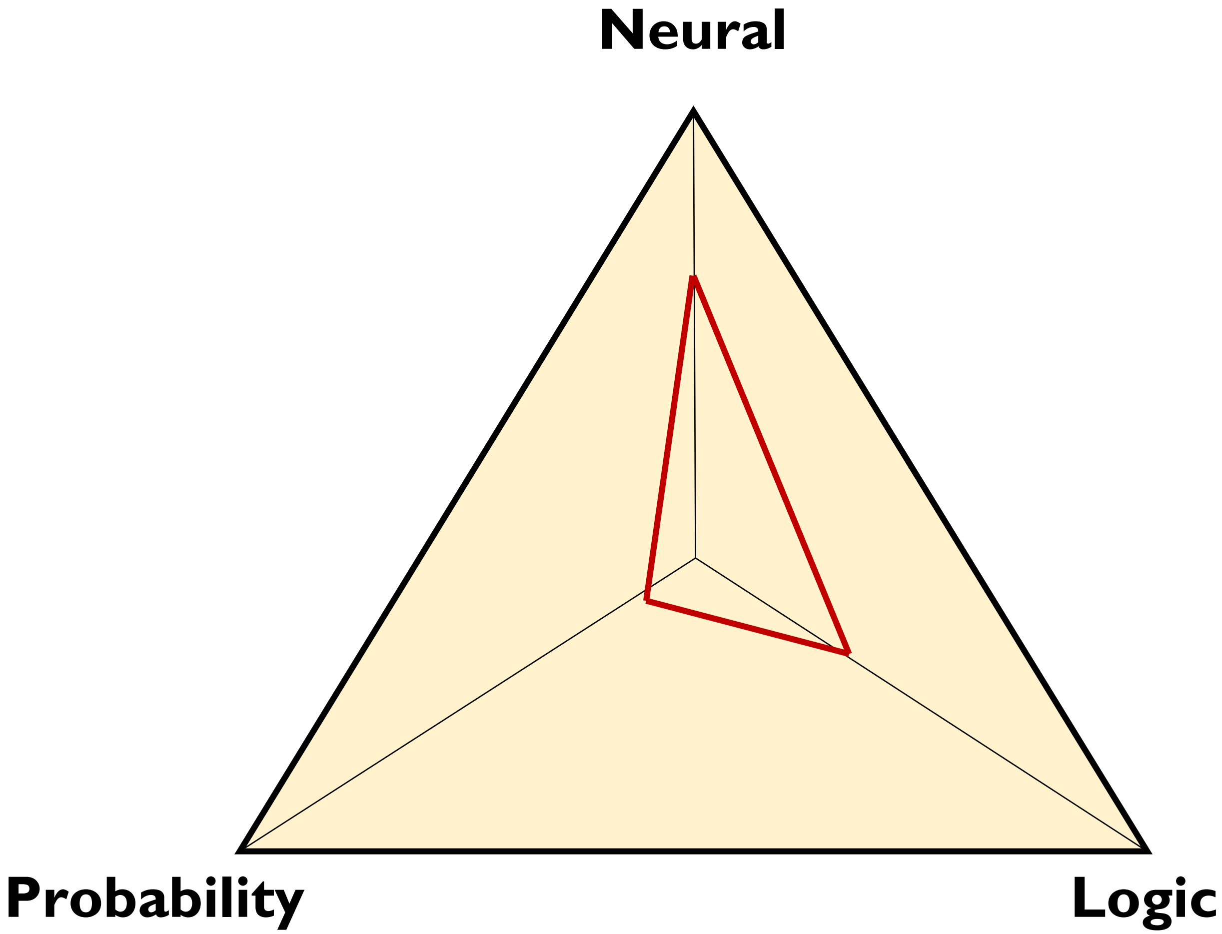
Knowledge embedding

- i.e. projections of entities and relations into a continuous low-dimensional space
- Mainly based on score function: measures how distant two nodes relative to its relation type.

- **Translation-based :**
  - Geometric transformation between the head and tail of the triple.
  - Score function is based on distance measure.
- **Bilinear-based:**
  - Use a linear equation to embed the connection between the entities through a relation.
  - The embedded representation of the relations is a bidimensional matrix.

- Most scalable solution!

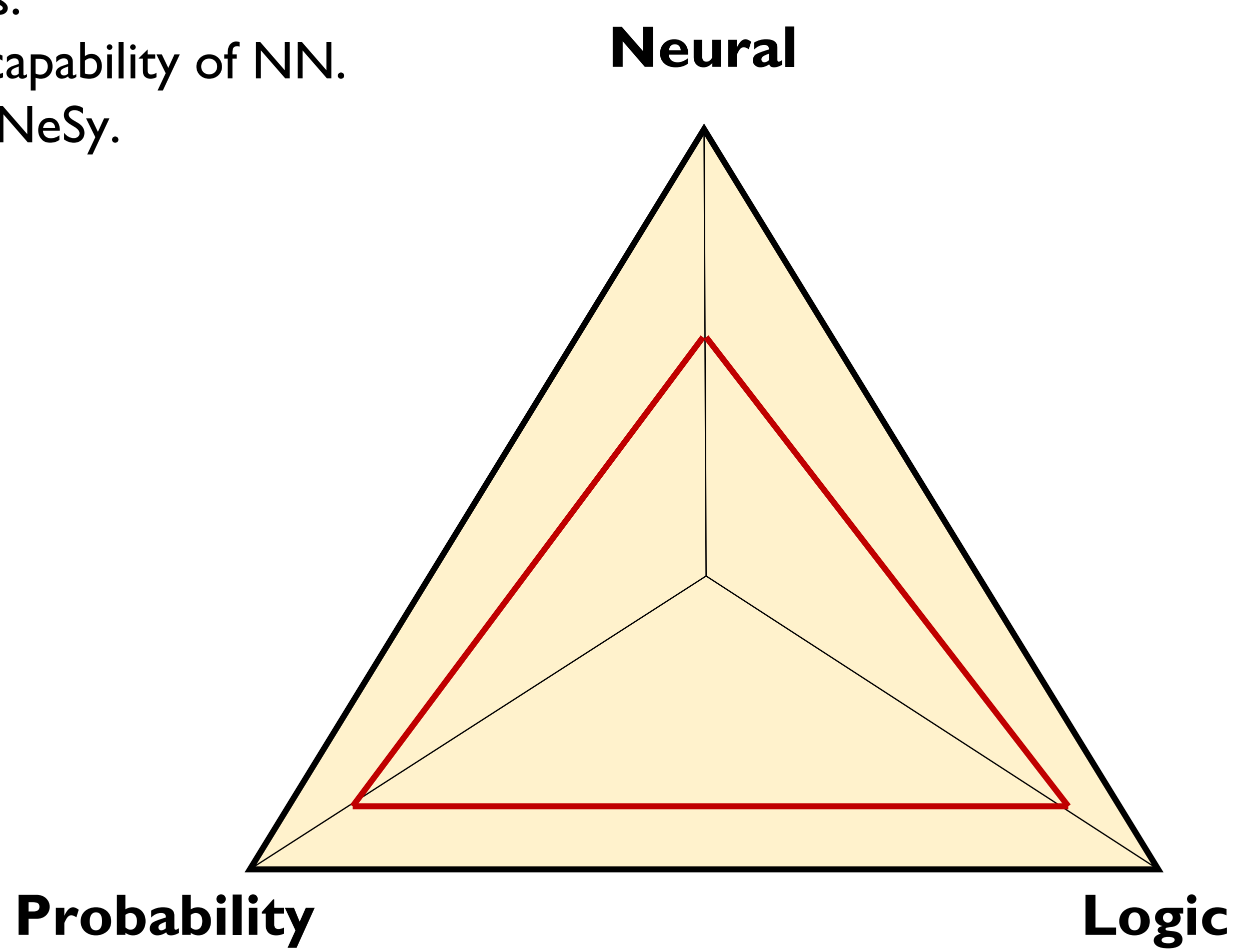
TransE (Bordes 2013)
DistMult (Yang, 2014)
ComplEx (Trouillon, 2016)
NTN (Socher, 2013)



[From Statistical Relational AI to Neural Symbolic Computation, Luc De Raedt et. al]

Other ways to do NeSy

- Extend StarAI with perception capabilities.
- They are not capable of using the entire capability of NN.
- One of the most promising direction for NeSy.



DeepProbLog (Manhaeve, 2018)

[From Statistical Relational AI to Neural Symbolic Computation, Luc De Raedt et. al]

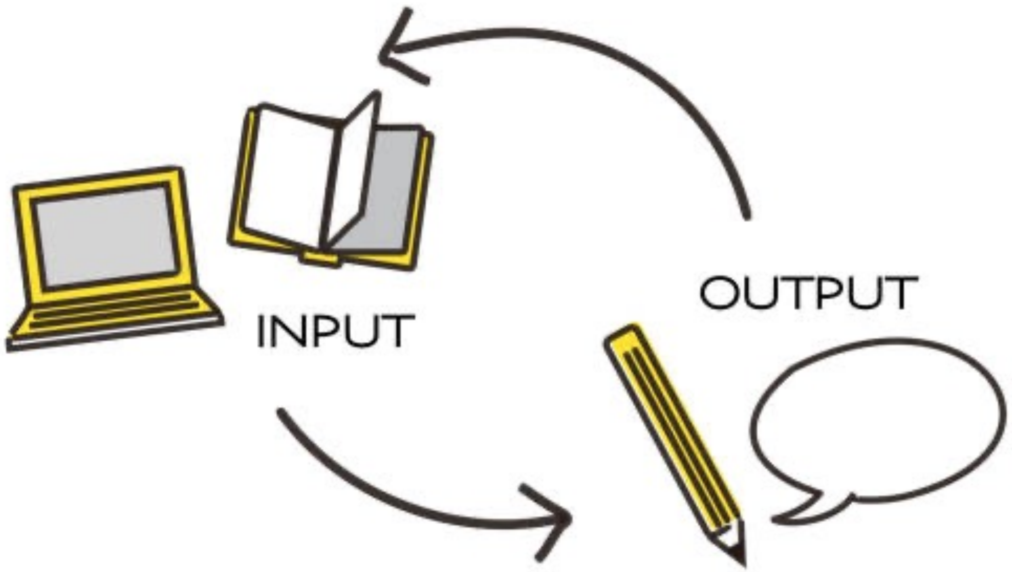
Knowledge extraction

Input

- Binary: $X \equiv \{0, 1\}^n$
- Discrete: $X \in \{x_1,...,x_n\}^n$
- Continuous: $X \subseteq R^n$

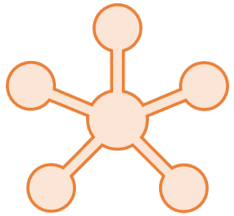
Output

- Rules
- Decision tree
- Knowledge Graph



Knowledge extraction

Decompositional



Pedagogical

Why?

1. From black-box to white-box: post-hoc explanations
2. To inspect possible attacks or malfunctions
3. To put neural information into a reasoner

Decompositional KE

- Model-specific: needs to inspect (even partially) the internal parameters of the black-box predictor.
- Provide a possible explanation for the features that have the greatest impact on the model’s prediction.

Pedagogical KE

- Model-agnostic: not need to take into account any internal parameter
- Can extract symbolic knowledge by only relying on the predictor's outputs.
- Provide a broader explanation!

Summary

- **Why?**
  - Collaboration btw symbolic and neural network systems
  - More transparency, interpretability, sustainability
- **How?**
  - Three main paradigms in NeSy: Logic, Probability, Neural
  - A lot of attempts of integrations
  - Many techniques and frameworks
- **Challenges**
  - Effective combination: robust learning and reasoning
    - What is the best way to use symbolic knowledge during the learning phase?
    - How does the neural network perceive symbolic knowledge?
  - Scalability
  - A more established theory of Neuro-Symbolic models