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The Path to Autonomous Learners

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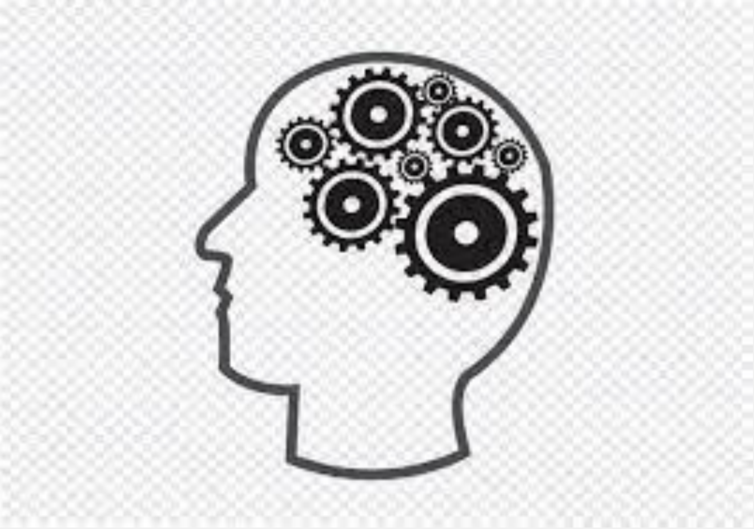
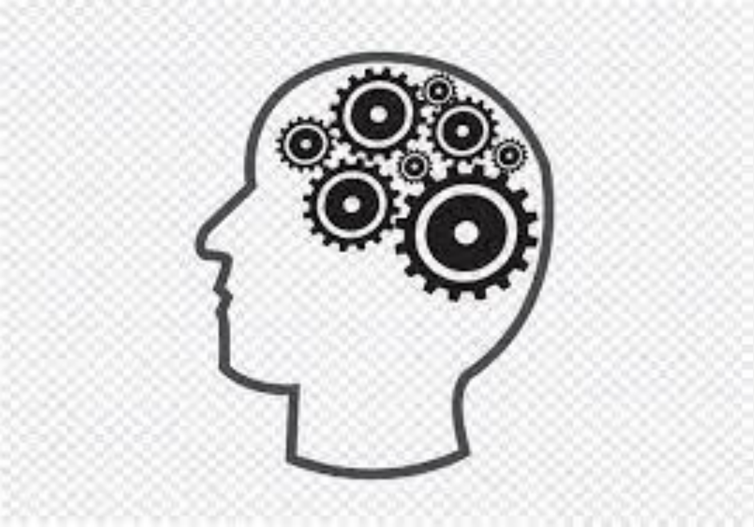
Research Questions



Is it possible to build a system that can learn with minimal input knowledge?



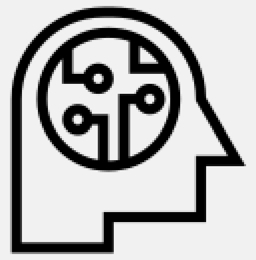
To what extent is such a system capable of reasoning on its own in an explainable and trustworthy manner?

Hypothesis

It is possible to build a framework that relies on an incremental learning mechanism based on higher-order concepts and accumulate new knowledge based on reasoning coupled with its existing data.

Solution: KD-LNN

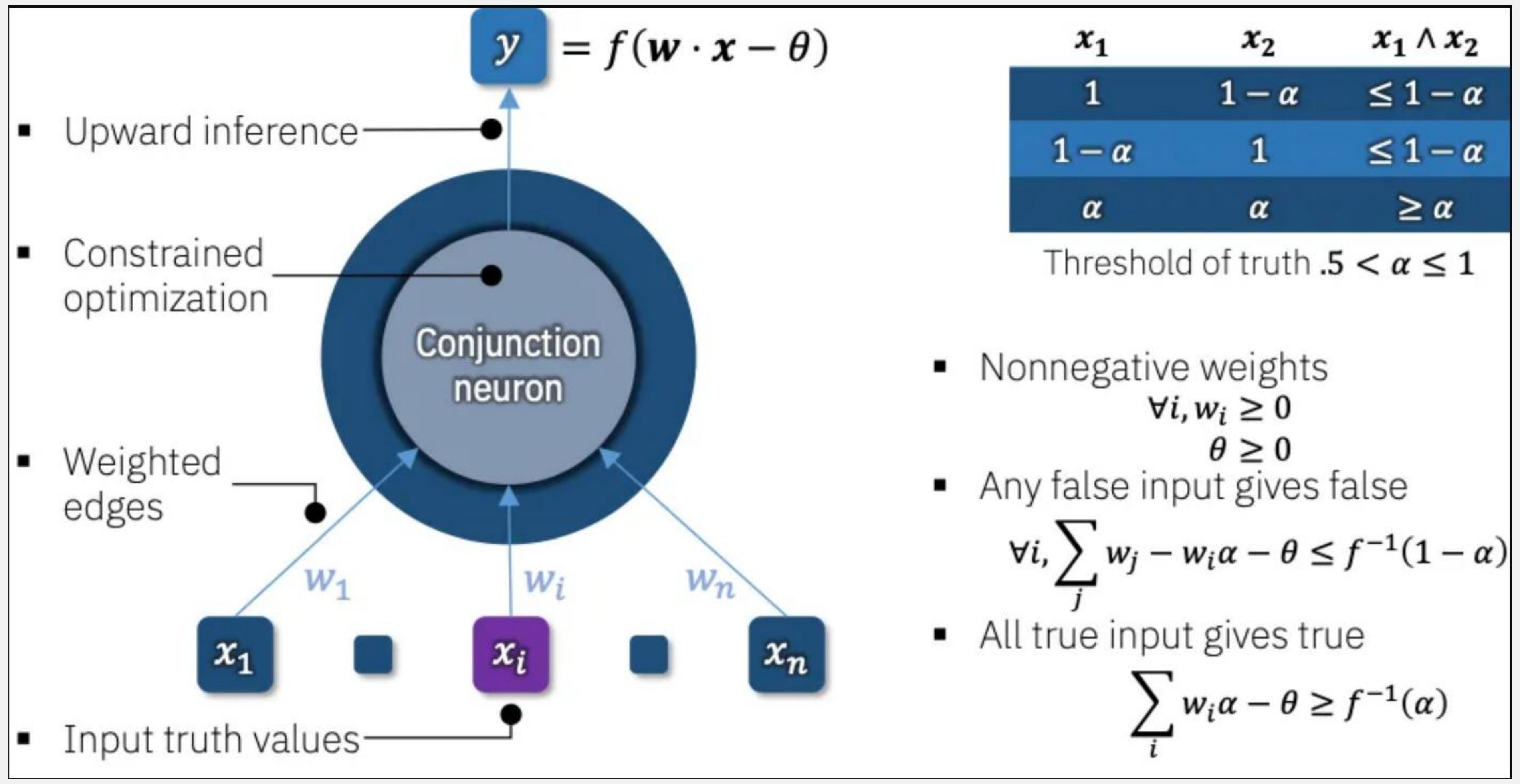
Knowledge-Driven Logical Neural Network is a theoretical framework based on:



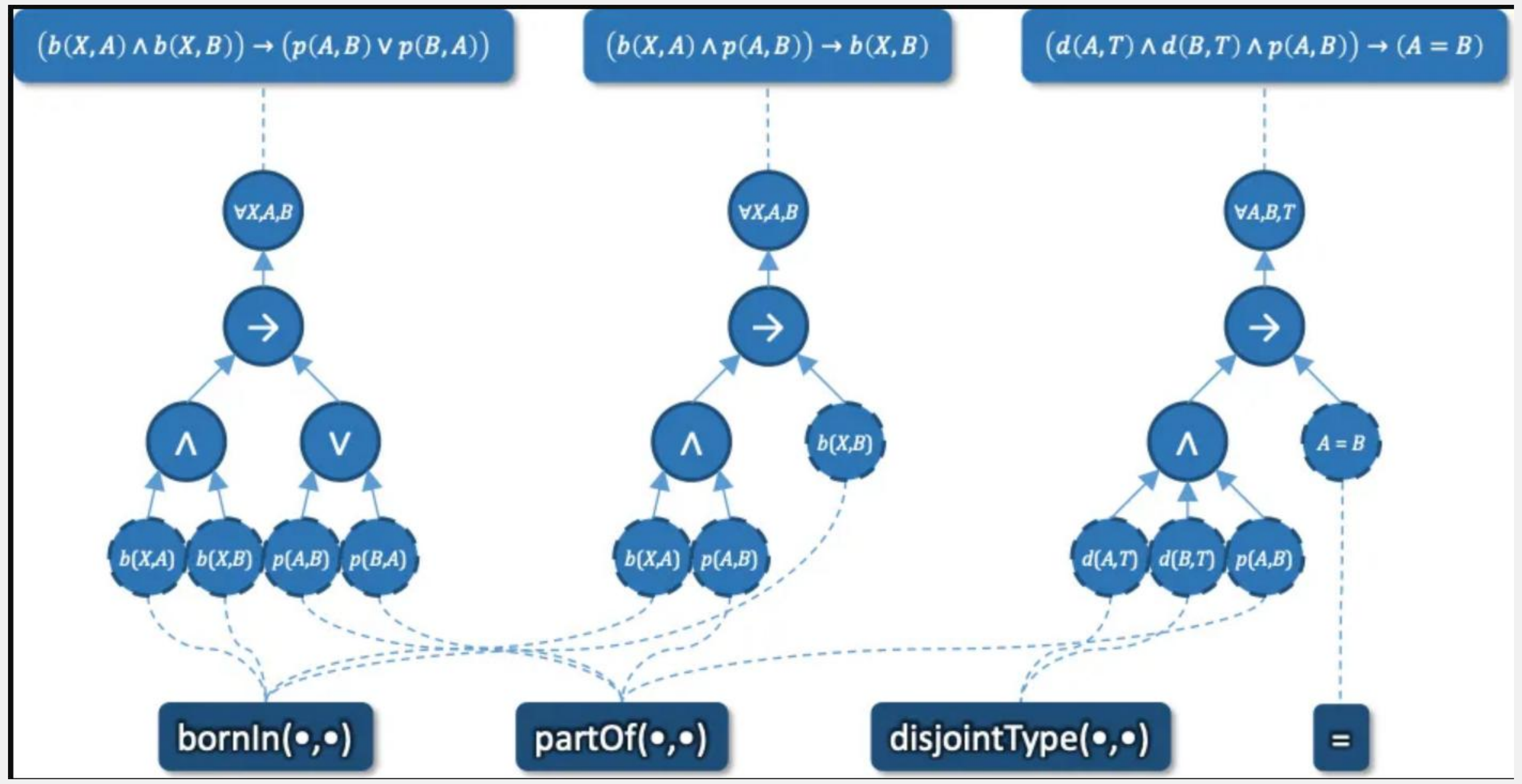
A model: A LNN base module for reasoning and learning

A knowledge base: A graph of concepts and their relations

A minimal input knowledge source: A starting set of concepts that serves as its initial data



A weighted, real-valued logical neuron and its associated constraints.



An example logical neural network structure modelling three rules.

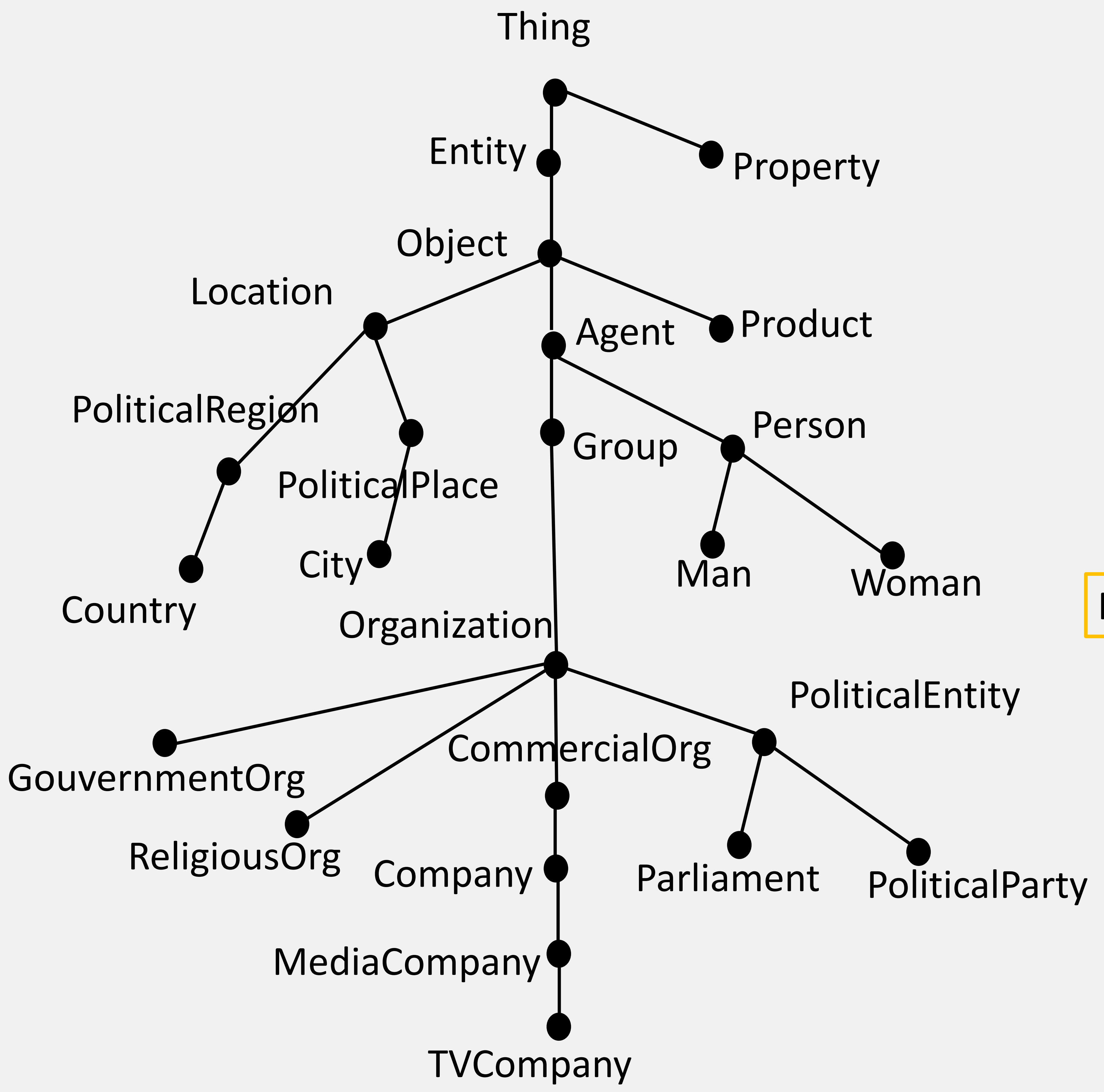
KD-LNN Architecture

Data Ingestion

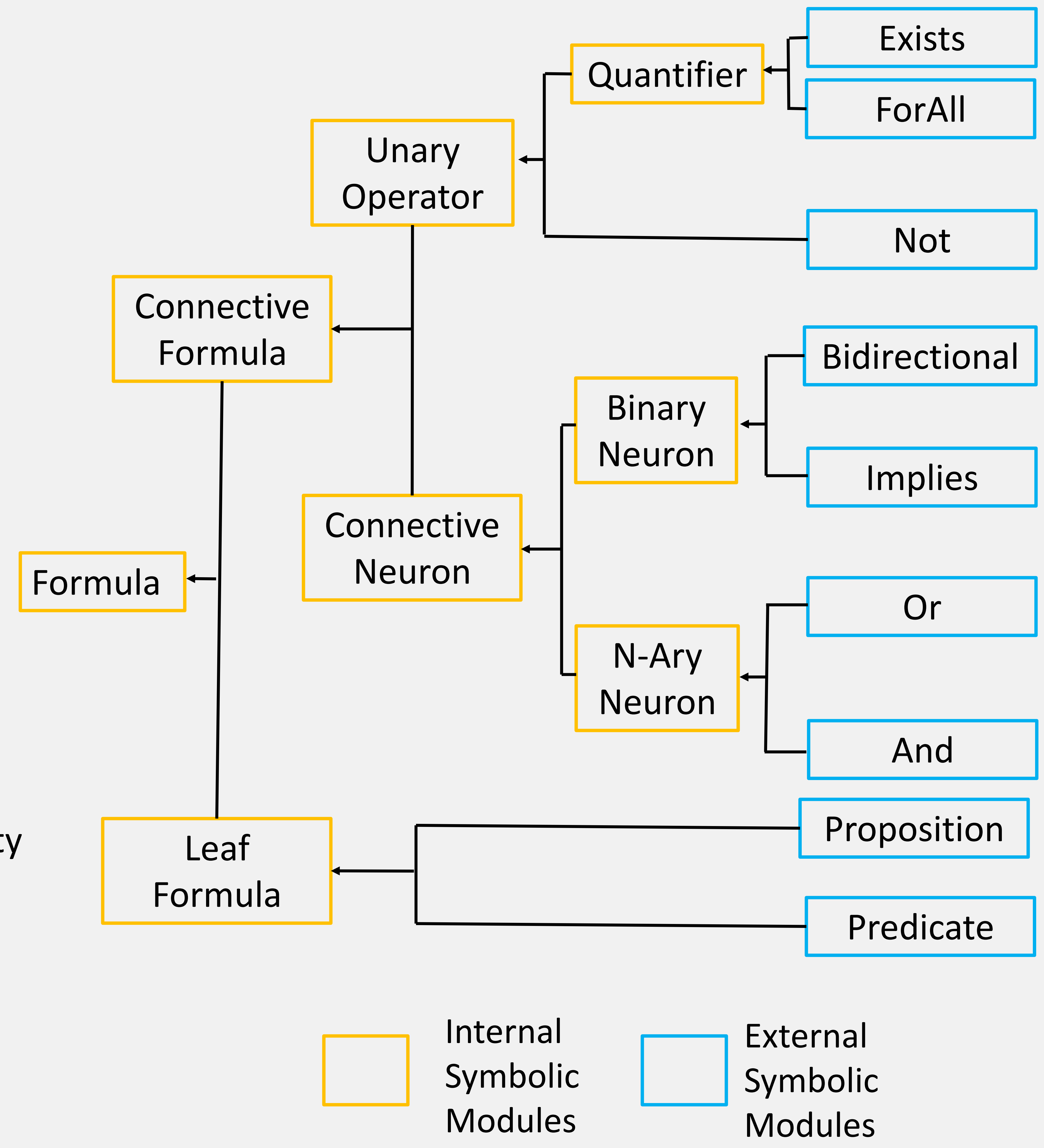
Top Module

Abstract
ContactInformation
Document
Event
GeneralTerm
Group
Happening
InformationResource
Job Position
Language
Location
Number
Object
Organization
Person
ProductModel
Rôle
Service
Situation
SocialPosition
Statement

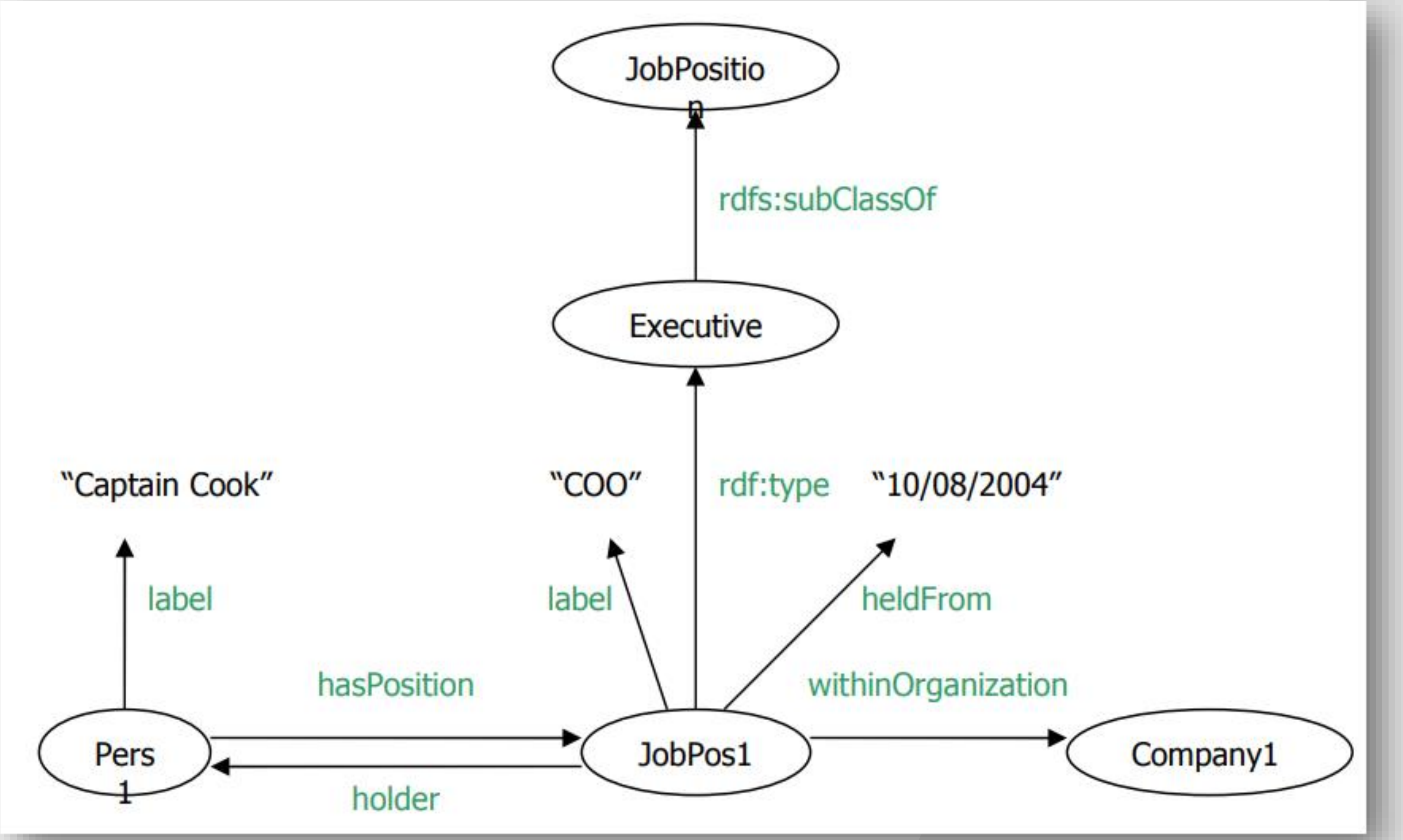
Data Modelling



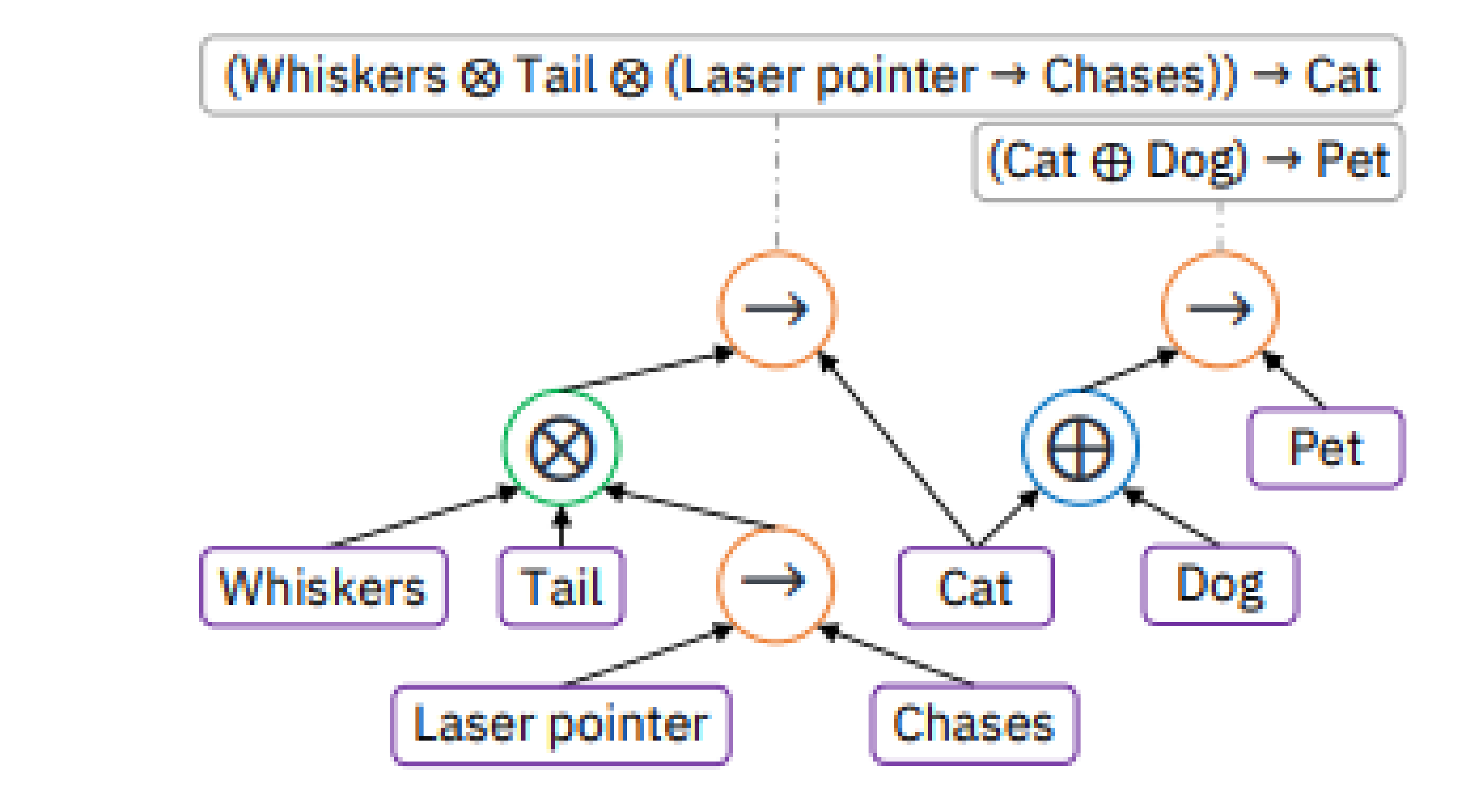
Learning & Reasoning



KD-LNN Advantages



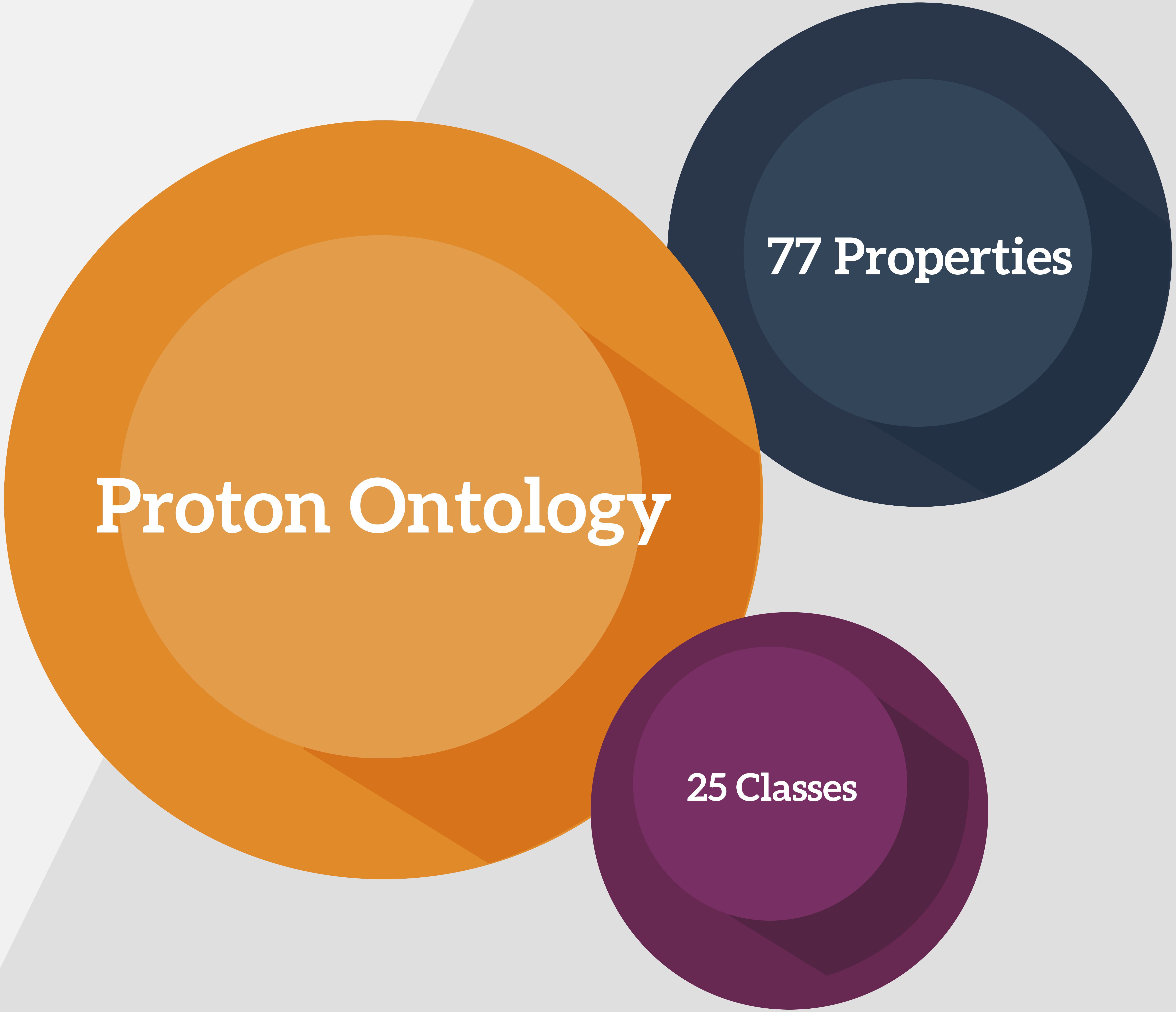
Knowledge graph representation
preserves entities and relationships



Ontology provides domain-specific knowledge

Neuro-symbolic network models neurons as formulae
built as logical (first-order) rulesets

Experiment 1



Learning

- Ingest the Proton ontology
- Model classes as entities and properties as relationships in knowledge graph
- Build logical ruleset to capture nodes and edges
- Query LNN module to validate learned data

Experiment 2

Reasoning

- Ingest the BFO ontology
- Generate BFO knowledge graph
- Apply previous ruleset to deduce similarities
- Query LNN module to validate correct reasoning over common concepts and properties

Results

Axiom 1: propagate-class-instance-to-superclass (Axiom 1): $\forall x \forall y \forall z (isinstanceOf(x, y) \wedge subClassOf(y, z) \implies (isinstanceOf(x, z)))$

Axiom 2: propagate-class-property-to-instance (Axiom 2): $\forall x \forall y \forall z (isinstanceOf(x, y) \wedge propertyOf(z, y) \implies (propertyOf(z, x)))$

Axiom 3: propagate-subproperty-to-class (Axiom 3): $\forall x \forall y \forall z (subPropertyOf(x, y) \wedge propertyOf(y, z) \implies (propertyOf(x, z)))$

Axiom 4: propagate-inverse-to-class (Axiom 4): $\forall x \forall y \forall z (inverseOf(x, y) \wedge propertyOf(y, z) \implies (propertyOf(x, z)))$

First-Order Logical Experimental Ruleset

Element	Type	Initial	Created	Extended	Retained	Score
Class	Node	57	0	0	57	100%
Property	Node	75	0	0	75	100%
Instance	Node	0	3	0	3	100%
propertyOf	Relation	60	0	3	63	100%
subPropertyOf	Relation	30	0	0	30	100%
inverseOf	Relation	7	0	0	7	100%
subClassOf	Relation	57	0	0	57	100%
instanceOf	Relation	0	3	6	9	100%

KD-LNN learning and reasoning results

Conclusion

- KD-LNN leverages the power of Neural Networks to handle large-scale and complex data
- KD-LNN uses a rule-based framework to provide transparent, explainable and transferable learning
- KD-LNN is domain-agnostic
- KD-LNN overcomes the “Big Data” and compute constraints

Research Directions

- Domain-specific autonomous learners
- Consolidated Upper-Level Universal Ontology
- Multi-language conversational agents

Thank You