MIAI DAYS 2022

MIAI
Multidisciplinary
Institute in
Artificial Intelligence

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Neural-Symbolic Integration of Knowledge Extraction and Reasoning on Graph Data

LIG Lab - INRIA - TyrexTeam
3rd year
Supervisors: Nabil Layaida, Pierre Genèves

Deep Learning led to breakthroughs in many different domains….

ImageNet Challenge: Advancement in deep learning and computer vision

Deep Learning In Health Care -A Ray of Hope in the Medical World

AlphaGo defeats world Go champion Ke Jie

AlphaGo, the AI created by Alphabet's DeepMind, has beaten world champion Ke Jie at the ancient game of Go

How NVIDIA enabled GPU-accelerated deep learning and revolutionized the AI field

200 languages within a single AI model: A breakthrough in high-quality machine

January 11, 2022

Big Growth Forecasted for Big Data

Before Deep Learning became so popular AI research was focused on Symbolic AI

Grenoble Alpes
Multidisciplinary Institute
In Artificial Intelligence

“In Knowledge lies the power” [1]

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High-level symbolic representations of problems

Based on tools such as Logic Programming, Production Rules, Semantic Nets

Example applications: Ontologies, Automated theorem provers, Expert systems

Symbolic AI vs. Sub-Symbolic AI

Language-like/logic representations ⟺ Numeric representations

Symbolic AI vs. Sub-Symbolic AI

Language-like/logic representations $\Longleftrightarrow$ Numeric representations

Data-efficient $\Longleftrightarrow$ Data-hungry

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Generalisation capacity	⟺	Risk of overfitting
Interpretability	⟺	Black-box models

How Do Humans Learn ?

Learning from Experience/Exercise ⟺ **Learning from Explanation**

How Do Humans Learn ?

Learning from Experience/Exercise		Learning from Explanation
iterative unconsciously		non-iterative consciously
eg. practicing a sport, learning an instrument, learning to walk		eg. learning vocabulary, learning how to read music

Most learning activities in humans involve both components!

Neural-Symbolic Integration - Bringing together the best of both worlds

Neural-Symbolic Integration is a field where classic symbolic knowledge mechanisms are combined with neural networks

Neural-Symbolic Integration -
Bringing together the best of both worlds

Goals of Neural-Symbolic Approaches

👍 Increased performance

👍 Data efficiency

👍 Interpretability

👍 Generalisation capacity

Knowledge in Neural-Symbolic Approaches - Symbolic vs. Numeric Knowledge

Symbolic Knowledge

First-Order Logic

$$\forall x, y : Horse(x) \wedge Stripes(x) \implies Zebra(x)$$

Numeric Knowledge

Vectors/Tensors in

in $\mathbb{R}^n$

Knowledge in Neural-Symbolic Approaches - Symbolic vs. Numeric Knowledge

Symbolic Knowledge

Representation

Numeric Knowledge

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Symbolic Knowledge

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Fuzzy Logic, T-conorm functions

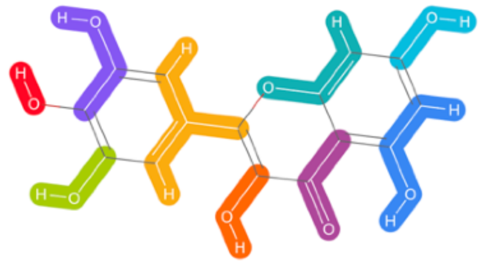
Neural functions for predicates

Formulas as constraints to the solution space

…

Neural-Symbolic Integration on Graph Data

Graphs are omnipresent!



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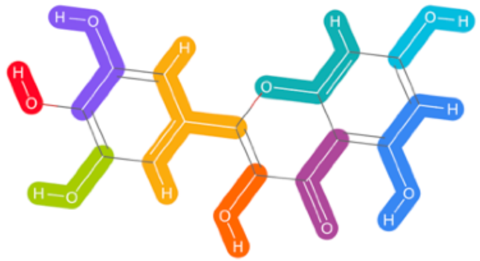

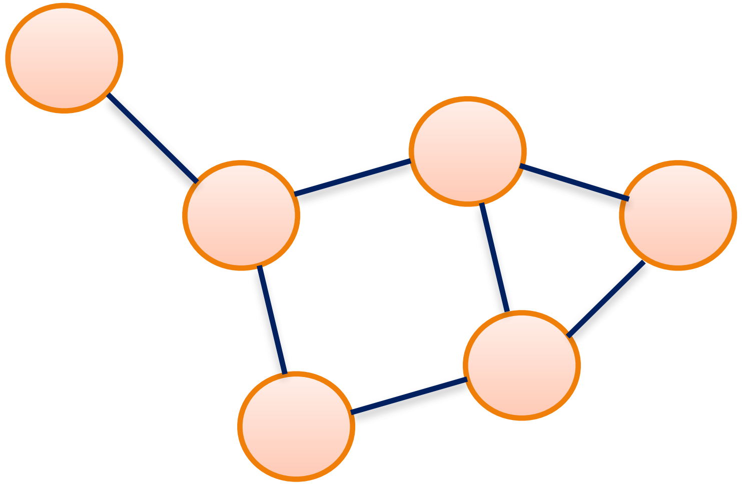

Graph: Set of related objects

Beyond grid-structured data

What is special about Graph Data ?

☝️Arbitrary Size

☝️Complex topological structure

☝️No fixed ordering or reference point

☝️Often dynamic

☝️Heterogeneous node and edge features

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Learning on Graphs requires algorithms that…

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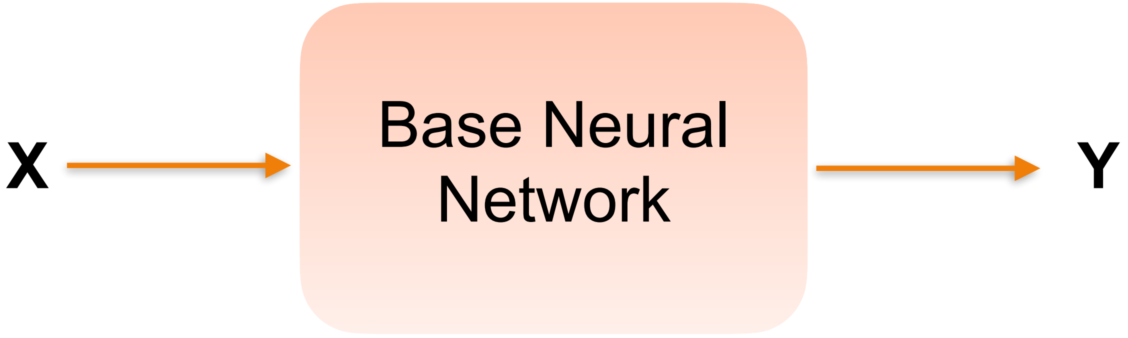
Scalable Graph Neural Networks

Neural-Symbolic Approaches on Graphs - Knowledge Enhanced Neural Networks (KENN) [2]



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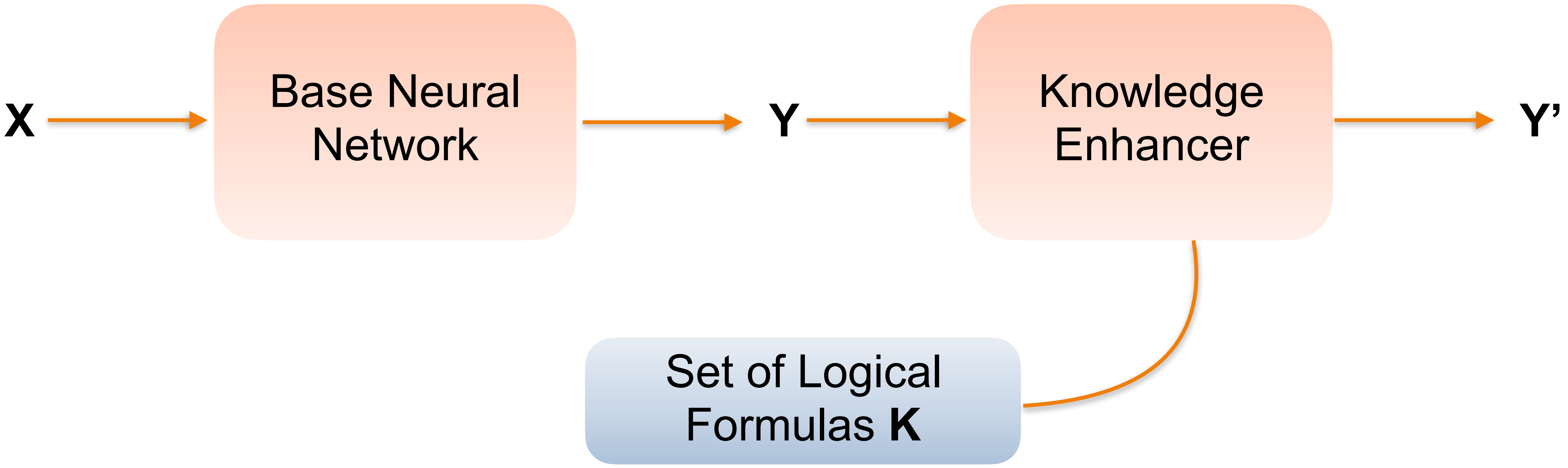
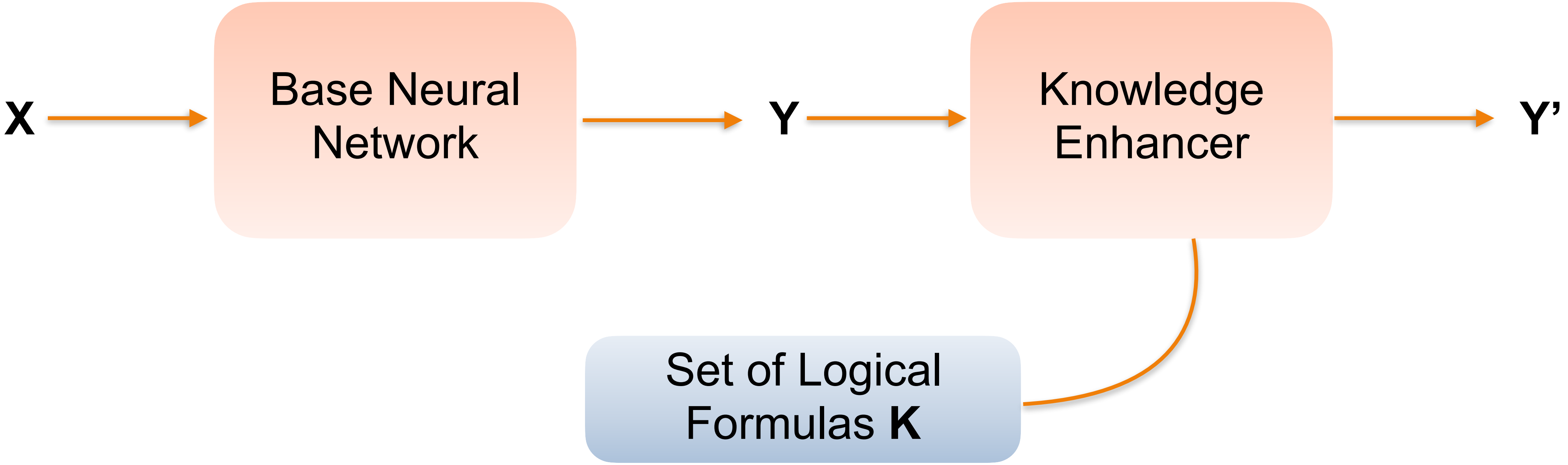


Relational KENN [2]



Binary predicates P(x,y) to encode relations

Relational KENN [2]

Use Case: Citeseer Citation Graph

Task Classify scientific publications in categories

Background Knowledge
"Documents that cite each other have the same category"

$$\forall x, y : Class(x) \land Cite(x, y) \implies Class(y)$$

Results

👍 Performance improvement through Knowledge Enhancers

👍 Particularly helpful when training data is scarce

Research Gaps in Neural-Symbolic Integration on Graphs

(1) Relational KENN is not implemented in a graph-oriented framework

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Apply KENN to Datasets from Open Graph Benchmark [4]

(Paper in submitted and in review)

Research Gaps in Neural-Symbolic Integration on Graphs

(3) Relational KENN is not applicable to arbitrary large graphs

Research Gaps in Neural-Symbolic Integration on Graphs

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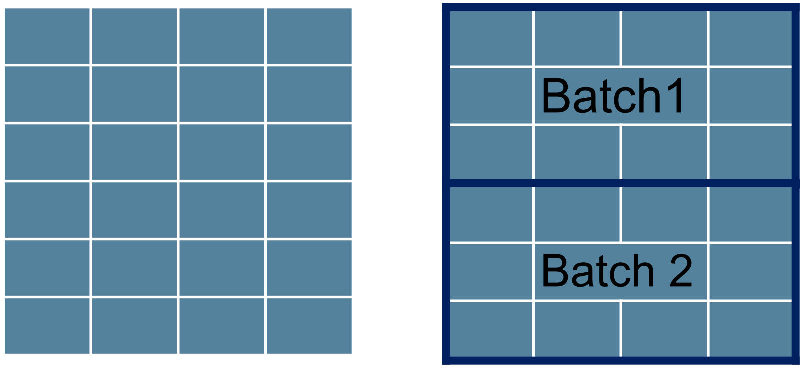
Mini-batching on
non-relational data



Mini-batching on
relational data

Objects are not independent: Tradeoff
Feasibility vs. Information Loss

Apply graph-specific batching algorithms[5] to Relational KENN

Research Gaps in Neural-Symbolic Integration on Graphs

(4) Relational KENN is only tested in conjunction with a simple Base NN

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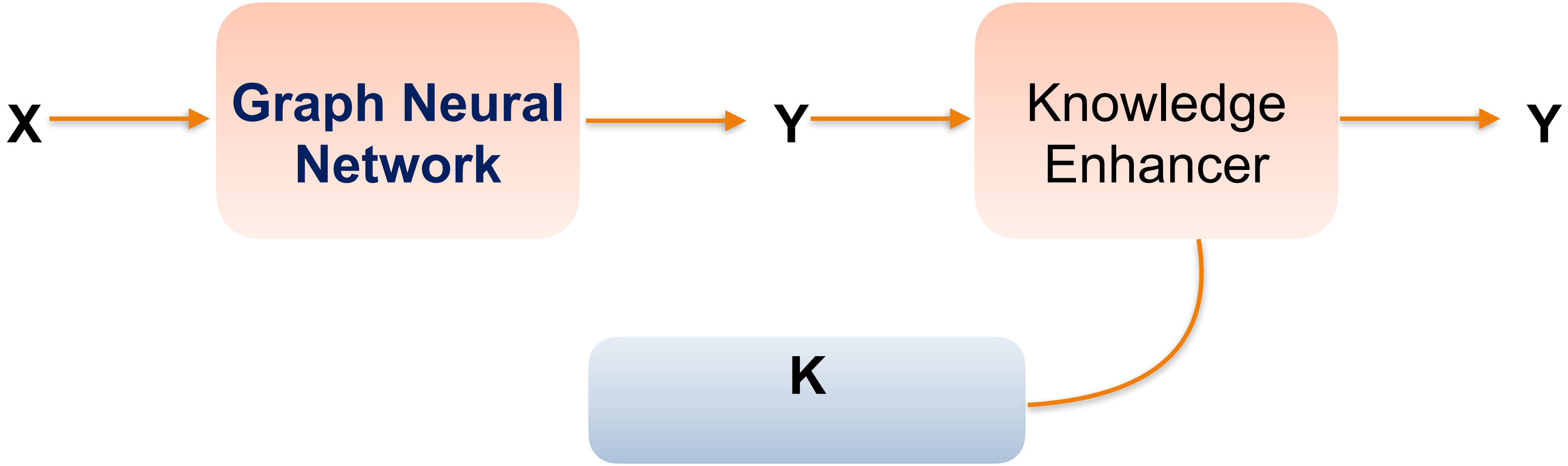

Use State-of-the-Art Graph Neural Networks [5] as Base Neural Networks and test them on multiple Node classification benchmark datasets

Future Work -
Neural Symbolic Learning on Knowledge Graphs

Knowledge Graphs

📌Knowledge base that uses graph-structured data

📌Collection of various heterogeneous data sources AND underlying semantics (ontologies)

📌**Examples:** YAGO, DBPedia, Freebase

📌**Applications:** search engines, question-answering systems

📌**Tasks to solve with Neural-Symbolic approaches:** KG completion, KG verification

Thanks for your Attention! 😊

Questions?

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[4] Hu et al. Open Graph Benchmark: Datasets for Machine Learning on Graphs. 2021. https://arxiv.org/abs/2005.00687.

[5] Duan et al. A Comprehensive Study on Large-Scale Graph Training: Benchmarking and Rethinking. 2022. https://arxiv.org/pdf/2210.07494.pdf

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