Neural-Symbolic Integration of Knowledge Extraction and Reasoning

Luisa Werner

LIG Laboratory - Tyrex - INRIA - Université Grenoble Alpes

luisa.werner@inria.fr

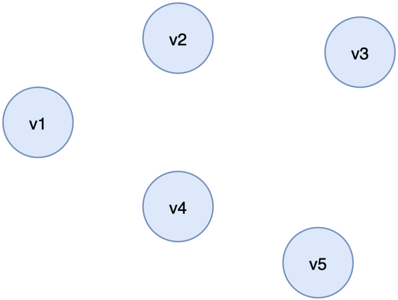
29/09/22

Graph-structured Data

- Graph data is omnipresent in many fields e.g. World Wide Web, bioinformatics, social networks, ...
- Graphs can capture dependencies
- Challenges: Graphs are often large, heterogeneous and noisy

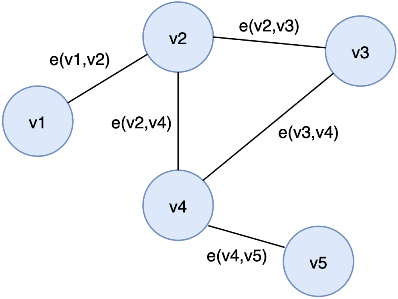
Example: Citeseer Citation Graph [6]

- Nodes represent scientific papers in different categories



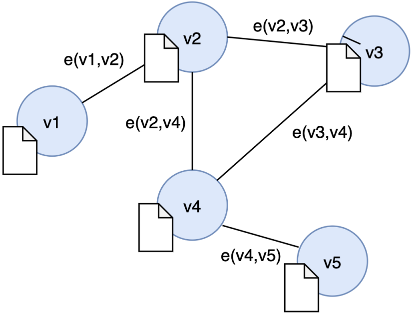
Example: Citeseer Citation Graph

- Edges represent citations between two documents



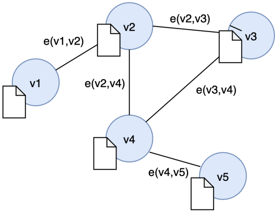
Example: Citeseer Citation Graph

- Node features encode the text in the papers as word2vec vectors



Example: Citeseer Citation Graph

- **Task: Node Classification**
- Assign one out of six subject categories to each paper



Graph Neural Networks [7]

- **Graph Neural Networks** are neural networks adapted to the structure of graph data
- **Graph Convolution:** Iterative aggregation over the neighborhood of a node
- **Goal:** Obtain meaningful representations to solve downstream prediction tasks

Advances in Deep Learning

- Remarkable results in several research domains (NLP, Computer Vision, Game Playing...)
- Ability to discover features in high dimensional data without human intervention

BUT

- All knowledge is represented in network weights
- "Black-box" models
- Data-intensive
- Poor generalisation capacity
- Concerns about reliability

Zero-shot learning

Recognising objects from classes not previously seen at training stage.

Neural-Symbolic Integration - Motivation

Example

- If a child knows what a horse is and what a horn is, by explaining that a unicorn is a horse with a horn it will be able to recognize a unicorn without having seen one before

Learning from experience vs. learning from explanation

Symbolic AI

- Carrying out a series of logic-like reasoning step over language-like representations
- Transfer learning and generalization capacity
- Data efficiency
- Understandability
- BUT: not learning from data and not robust to exceptions/errors/noise

Neural-Symbolic Integration

- The strengths of Symbolic AI align with the shortcomings of deep learning
- Bring together the best of both worlds

Neural-Symbolic Integration - Definition

Figure 1. Conflict between theoretical extremes.

Source: https://www.youtube.com/watch?v=KhkCjCmK8m0

Neural-Symbolic Integration - Definition

Definition

Neural Symbolic Integration is a field in which classical symbolic knowledge mechanisms are combined with neural networks.

Goals of Neural-Symbolic Integrated Approaches

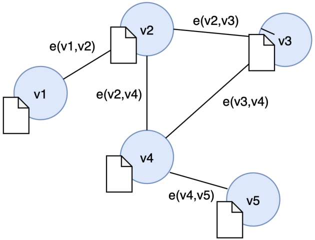
- Generalization capacity
- Data efficiency
- Zero-shot learning
- Human Interpretability

Knowledge Enhanced Neural Networks [1]

[Alessandro Daniele, Luciano Serafini, 2020]

Node Classification on Citeseer

Input: Graph Data and Background Knowledge
Goal: Predict node labels (1 of 6 document classes)

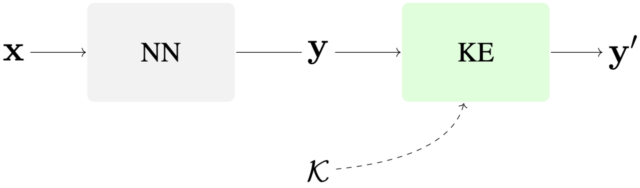


- $AG(x) \wedge Cite(x,y) \rightarrow AG(y)$
- $AI(x) \wedge Cite(x,y) \rightarrow AI(y)$
- $DB(x) \wedge Cite(x,y) \rightarrow DB(y)$
- $IR(x) \wedge Cite(x,y) \rightarrow IR(y)$
- $ML(x) \wedge Cite(x,y) \rightarrow ML\ (y)$
- $HCI(x) \wedge Cite(x,y) \rightarrow HCI(y)$

Knowledge Enhanced Neural Networks

The Idea:

- The Base Neural Network makes predictions **y**
- The Knowledge Enhancer updates **y** to **y'** as additional layer to increase the truth values of the clauses in the knowledge
- Both components are end-to-end differentiable



Neural-Symbolic Integration - Definition

How do we measure the satisfaction of a clause?

Symbolic knowledge

Terms, Facts, General Formulas, Constants,... in **First-Order Logic**

Numeric knowledge

Vector/Points in $\mathbb{R}^n$

Knowledge Enhanced Neural Networks

How do we measure the satisfaction of a clause?

- **Fuzzy Semantics**
- **T-conorm** functions are used to assign numerical truth values to logical clauses
- The **Knowledge Enhancer** aims to increase the t-conorm function for each clause
- **Clause weights** are the learnable parameters of the Knowledge Enhancer

Node Classification on Citeseer

The Experiments in [1]

- Multi-Layer Perceptron as Base Neural Network
- Six clauses as background knowledge
- The Knowledge Enhanced Neural Network outperforms a simple Multi-Layer Perceptron
- Superior performance in comparison to Relational Neural Machines [8]
- Improvement is larger when the training data set is small

Node Classification on Citeseer

Remarks on the Experiments

- Citeseer is the only data set to which KENN is applied
- The Citeseer data set does not correspond to real-world graph data sets (only 4732 nodes and 6 classes, homogeneous)
- The Multi-Layer Perceptron does not consider node edges at Base Neural Network level

Extensions of Knowledge Enhanced Neural Networks

1. Application to the **Cora** data set [4]
2. Application to the **OGB Benchmark** data set [2] (realistic, large-scale benchmarking datasets for machine learning on graphs)
3. Replacing the Base Neural Network by a Graph Neural Network to consider edges as part of the model

Conclusion

- **Graph Neural Networks** can be used to find meaningful embeddings for graph-structured data
- **Neural-Symbolic approaches** aim to integrate the advantages of symbolic and subsymbolic learning and lead to more data efficiency, flexibility and understandability
- **Knowledge Enhanced Neural Networks** use an additional layer on top of a Base Neural Network to modify predictions and increase the satisfaction of background knowledge
- **In my work** the experiments are extended to other larger and more complex data sets and the Base Neural Network is replaced by a Graph Neural Network

Questions?

References

1 Alessandro Daniele and Luciano Serafini. Neural Networks enhancement through prior logical knowledge

2 Hu et al. Open Graph Benchmark: Datasets for Machine Learning on Graphs (2020)

3 Prithviraj Sen. Collective Classification in Network Data (2008)

4 Marta Garnelo and Murray Shanahan. Reconciling deep learning with symbolic artificial intelligence: representing objects and relations (2019)

5 Artur d'Avila Garcez et al. Neural-Symbolic Computing: An Effective Methodology for Principled Integration of Machine Learning and Reasoning (2019)

6 Ryan A. Rossi and Nesreen K. Ahmed. The Network Data Repository with Interactive Graph Analytics and Visualization (2015)

7 Zhou et al. Graph Neural Networks: A Review of Methods and Applications. AI Open (2020)

8 Marra et al. Relational Neural Machines (2020)

Questions?