Knowledge Graphs and Neuro-Symbolic Artificial Intelligence

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http://www.daselab.org
DaSeLab

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  - Joshua Schwartz
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  - Patrick Stingley
  - Reihaneh Amini
  - Rushrukh Rayan
  - Sanaz Saki Norouzi
  - Sulogna Chowdhury

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  - Andrew Eells
  - Brayden Pankaskie
Contents

• Two current trends:
  – Neuro-Symbolic Artificial Intelligence
  – Knowledge Graphs

• And their convergence:
  – Added Value for Deep Learning
    • Example: Explainable AI
  – Added Value for Knowledge Graphs
    • Example: Deep Deductive Reasoning
Neuro-Symbolic Artificial Intelligence
Some Background


Barbara Hammer and Pascal Hitzler (eds), Perspectives of Neural-Symbolic Integration, Springer, 2007

Neural-Symbolic Learning and Reasoning: A Survey and Interpretation

Neuro-symbolic Artificial Intelligence: The State of the Art
Pascal Hitzler and Md Kamruzzaman Sarker, editors
Frontiers in AI and Applications Vol. 342, IOS Press, Amsterdam, 2022
https://www.iospress.com/catalog/books/neuro-symbolic-artificial-intelligence-the-state-of-the-art

Preface: The 3rd AI wave is coming, and it needs a theory
Frank van Harmelen

Introduction
Pascal Hitzler and Md Kamruzzaman Sarker

Chapter 1. Neural-Symbolic Learning and Reasoning: A Survey and Interpretation

Chapter 2. Symbolic Reasoning in Latent Space: Classical Planning as an Example
Masato Arai, Hiroshi Kajino, Alex Fukunaga and Christian Mui
t

Chapter 3. Logic Meets Learning: From Aristotle to Neural Networks
Vaishak Belle

Chapter 4. Graph Reasoning Networks and Applications
Qingxing Cao, Wentao Wan, Xiaodan Liang and Liang Lin

Chapter 5. Answering Natural-Language Questions with Neuro-Symbolic Knowledge Bases
Haitian Sun, Pat Verga and William W. Cohen

Chapter 6. Tractable Boolean and Arithmetic Circuits
Adnan Darwiche

Chapter 7. Neuro-Symbolic AI = Neural + Logical + Probabilistic AI
Robin Manhaeve, Giuseppe Marra, Thomas Demeester, Sebastijan Dumančić, Angelika Kimmig and Luc De Raedt

Chapter 8. A Constraint-Based Approach to Learning and Reasoning
Michelangelo Dilligenti, Francesco Giannini, Marco Gori, Marco Muggini and Giuseppe Marra

Chapter 9. Spike-Based Symbolic Computations on Bit Strings and Numbers
Ceca Krišniković, Wolfgang Maass and Robert Legenstein

Chapter 10. Explainable Neuro-Symbolic Hierarchical Reinforcement Learning
Daoming Lyu, Fangkai Yang, Hugh Kwon, Bo Liu, Wen Dong and Levent Yilmaz

Chapter 11. Neuro-Symbolic Semantic Reasoning
Bassem Makai, Monireh Ebrahimi, Dagmar Gromann and Aaron Eberhart

Chapter 12. Learning Reasoning Strategies in End-to-End Differentiable Proving
Pasquale Minervini, Sebastian Riedel, Pontus Stenetorp, Edward Gregorinette and Tim Rockclus

Chapter 13. Generalizable Neuro-Symbolic Systems for Commonsense Question Answering
Alessandro Oltramari, Jonathan Francis, Filip Ilievski, Kaixin Ma and Roshanak Mirzaee

Chapter 14. Combining Probabilistic Logic and Deep Learning for Self-Supervised Learning
Hofjung Poon, Hai Wang and Hunter Lang

Chapter 15. Human-Centered Concept Explanations for Neural Networks
Chih-Kwan Yeh, Been Kim and Pradeep Ravikumar

Chapter 16. Abductive Learning
Zhi-Hua Zhou and Yu-Xuan Huang

Chapter 17. Logic Tensor Networks: Theory and Applications
Luciano Serafini, Artur d’Avila Garcez, Sunny Badreddine, Ivan Donadello, Michael Spranger and Federico Bianchi
Neuro-symbolic AI

Publications on neuro-symbolic AI in major conferences (research papers only):

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See
Md Kamruzzaman Sarker, Lu Zhou, Aaron Eberhart, Pascal Hitzler
Neuro-Symbolic Artificial Integration: Current Trends
New Book for 2023

Compendium of Neuro-Symbolic Artificial Intelligence (tentative)

approx. 30 chapters and 700 pages

Each chapter based on 2 or more related published papers.

Book will provide an even more comprehensive overview of the state of the art.

[We can still add a few chapters – see https://daselab.cs.ksu.edu/content/call-book-chapter-proposals-compendium-neuro-symbolic-artificial-intelligence and send your chapter proposal very quickly.]
Neural

- Refers to computational abstractions of (natural) neural network systems.
- Prominently includes Artificial Neural Networks and Deep Learning as machine learning paradigms.
- More generally sometimes referred to as connectionist systems.

- Prominent applications come from the machine learning world.
- And of course, there is the current deep learning hype.
Symbolic

- Refers to (computational) symbol manipulations of all kind.
- Graphs and trees, traversal, data structure operations.
- Knowledge representation in explicit symbolic form (data base, ontology, knowledge graph)
- Inductive and statistical inference.
- Formal logical (deductive or abductive) reasoning.
- Prominent applications all over computer science, including expert systems (and their modern versions), information systems, data management, added value of data annotation, etc.
- Semantic Web data is inherently symbolic.
Neuro-Symbolic

Computer Science perspective:

• Let’s try to get the best of both worlds:
  – very powerful machine learning paradigm
  – robust to data noise
  – easy to understand and assess by humans
  – good at symbol manipulation
  – work seamlessly with background (domain) knowledge

• How to do that?
  – Endow connectionist systems with symbolic components?
  – Add connectionist learning to symbolic reasoners?
  – ... ?
Example Themes

- Learning of knowledge bases
- Improving symbolic algorithms
- Improving deep learning systems
- Commonsense reasoning
- NLP
- Question Answering
- Explaining deep learning systems (XAI)
- Solving complex AI problems
• Two current trends:
  – Neuro-Symbolic Artificial Intelligence
  – Knowledge Graphs
• And their convergence:
  – Added Value for Deep Learning
    • Example: Explainable AI
  – Added Value for Knowledge Graphs
    • Example: Deep Deductive Reasoning
Knowledge Graphs
Laura Kelly is an American politician serving as the 48th governor of Kansas since 2019. A member of the Democratic Party, she represented the 18th district in the Kansas Senate from 2005 to 2019. Kelly ran for governor in the 2018 election and defeated the Republican nominee, Kansas Secretary of State Kris Kobach. Wikipedia

Born: January 24, 1950 (age 69 years), New York, NY
Spouse: Ted Daughety
Party: Democratic Party
Office: Governor of Kansas since 2019
Education: Indiana University, Bradley University, Indiana University Bloomington
Children: Kathleen Daughety, Molly Daughety

Indiana University is a multi-campus public university system in the state of Indiana, United States. Indiana University has a combined student body of more than 110,000 students, which includes approximately 46,000 students enrolled at the Indiana University Bloomington campus. Wikipedia

Mascot: Referred to as "The Hoosiers"
Endowment: 1.986 billion USD
Students: 110,436 university-wide
President: Michael McRobbie
Academic staff: 8,733 university-wide
Subsidiaries: Indiana University Bloomington, MORE

Michael Alexander McRobbie AO is an Australian-American computer scientist, educator and academic administrator. He became the eighteenth president of Indiana University on July 1, 2007. Wikipedia

Born: October 11, 1950 (age 69 years), Melbourne, Australia
Spouse: Laurie Burns (m. 2005)
Education: The Australian National University, The University of Queensland
Knowledge Graphs

Laura Kelly

hasEducation

Indiana University

hasPresident

Michael McRobbie

hasStudents

110,436

hasEducation

University of Queensland

hasBirthDate

01/24/1950
A good schema is critical for ease of reuse. This is only a diagram. A full schema (an ontology) consists of axioms in a formal logic.
Both established 2004 as versions 1.0.
Knowledge graphs are critical to many enterprises today. They provide the structured data and factual knowledge that drive many products and make them more intelligent and "magical."

In general, a knowledge graph describes objects of interest and connections between them. For example, a knowledge graph may have nodes for a movie, the actors in this movie, the director, and so on. Each node may have properties such as an actor's name and age. There may be nodes for multiple movies involving a particular actor. The user can then traverse the knowledge graph to collect information on all the movies in which the actor appeared or, if applicable, directed.

Many practical implementations impose constraints on the links in knowledge graphs by defining a schema or ontology. For example, a link from a movie to its director must connect an object of type Movie to an object of type Person. In some cases the links themselves might have their own properties: a link connecting an actor and a movie might have the name of the specific role the actor played.
Welcome to Wikidata

the free knowledge base with 97,501,043 data items that anyone can edit.

Introduction • Project Chat • Community Portal • Help

Want to help translate? Translate the missing messages.

Welcome!

Wikidata is a free and open knowledge base that can be read and edited by both humans and machines.

Wikidata acts as central storage for the structured data of its Wikimedia sister projects including Wikipedia, Wikivoyage, Wiktionary, Wikisource, and others.

Wikidata also provides support to many other sites and services beyond just Wikimedia projects! The content of Wikidata is available under a free license, exported using standard formats, and can be interlinked to other open data sets on the linked data web.

Learn about data

New to the wonderful world of data? Develop and improve your data literacy through content designed to get you up to speed and feeling comfortable with the fundamentals in no time.
Enslaved
Peoples of the Historic Slave Trade

Building a Linked Open Data Platform for the study and exploration of the historical slave trade.

Learn More
enslaved.org process

1. Quality Graph Design.
2. Realization in Wikibase.
   (Engine for Wikidata)
3. Knowledge graph construction and interaction through Wikibase as.
4. Additional front-end (simplified view)

(4) https://enslaved.org/
(3) https://lod.enslaved.org/

>53M RDF triples from Wikibase export
KnowWhereGraph

- 2 years, $5M. Follows a $1M, 1-year pilot.
- NSF “Open Knowledge Networks” (OKN) program.
  21 phase 1 projects; 5 phase 2 projects.

Team and Partnership

PI: Krzysztof Janowicz, UCSB
Co-PIs: Mark Schildhauer, Wenwen Li,
  Dean Rehberger, Pascal Hitzler
(some) project goals

• pushing the state of the art in spatiotemporal Knowledge Graph (KG) engineering
• transfer of KG technology towards adoptable practice
• application showcases

Addressing the bottleneck in data science:

80% is data processing
20% is deriving insights

http://KnowWhereGraph.org/
Public release

- Knowledge Graph with about >12B triples
  - One of the currently largest public knowledge graphs.
  - Focus on spatial data related to environment and natural disasters
- (forthcoming)
  - open source software for access and management

http://knowwheregraph.org/
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<tr>
<th>Thematic Datasets</th>
<th>Place-Centric Datasets</th>
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<td><strong>Source Agency</strong></td>
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<td>Soil Properties</td>
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<tr>
<td>Wildfires</td>
<td>USGS, USDA, USFS, NIFC</td>
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<tr>
<td>Earthquakes</td>
<td>USGS</td>
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<tr>
<td>Climate Hazards</td>
<td>NOAA</td>
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<td>Expert - General</td>
<td>KWG, UC System, DR, Semantic Scholar</td>
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<td>Cropland Types</td>
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<td>Climate Observations</td>
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<td>Disaster Declaration</td>
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<td>Smoke Plume Extents</td>
<td>NOAA</td>
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<tr>
<td>BlueSky Forecasts</td>
<td>Bluesky</td>
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<tr>
<td>Transportation (highway network)</td>
<td>DOT</td>
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<tr>
<td>Public Health</td>
<td>CDC, US Census</td>
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<td>Social Vulnerability</td>
<td>CDC/ATSDR</td>
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<td>Hurricane Tracks</td>
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Two current trends:
  – Neuro-Symbolic Artificial Intelligence
  – Knowledge Graphs

And their convergence:
  – Added Value for Deep Learning
    • Example: Explainable AI
  – Added Value for Knowledge Graphs
    • Example: Deep Deductive Reasoning
Added Value for Deep Learning
Prospects

- KGs are a rich source of structured training data
- KGs are a rich source of background knowledge
- Improved performance and trainability of DL systems
- Interpreting and explaining DL systems via background knowledge
Explaining Deep Learning via Symbolic Background Knowledge


Explainable AI

- Explain behavior of trained (deep) NNs.

- Idea:
  - Use background knowledge in the form of linked data and ontologies to help explain.
  - Link inputs and outputs to background knowledge.
  - Use a symbolic learning system to generate an explanatory theory.

- We have key components for this now, but it’s still early stages.
Concept

Training images → CNN to classify images → Concept Induction

Knowledge Graph
- Snow subclass of BodyOfWater
- And some others

Positive images
- Contains ((HighLand \( \cap \) BodyOfWater))

Negative images

hasMapping
DL-Learner [Lehmann, Hitzler]

Approach similar to inductive logic programming, but using Description Logics (the logic underlying OWL).

Positive examples:

1. 
2. 
3. 
4. 
5. 

negative examples:

1. 
2. 
3. 
4. 
5. 

Task: find a class description (logical formula) which separates positive and negative examples.
DL-Learner

Positive examples:                               negative examples:

1. ![Image 1]
2. ![Image 2]
3. ![Image 3]
4. ![Image 4]
5. ![Image 5]

DL-Learner result:  

\[ \exists \text{hasCar.}(\text{Closed} \cap \text{Short}) \]

In FOL:  

\[ \{ x \mid \exists y (\text{hasCar}(x, y) \land \text{Closed}(y) \land \text{Short}(y)) \} \]
Scalability Issues with DL-Learner

• For large-scale experiments, DL-Learner took 2 hours or more for one run.
• We knew we needed at least thousands of runs.

• So we needed a more scalable solution.
• The provably correct algorithms have very high complexity.

• Hence we had to develop a heuristic which trades (some) correctness for speed.

• It is also currently restricted to using a class hierarchy as underlying knowledge base.
ECII algorithm and system

• We thus implemented our own system, ECII (Efficient Concept Induction from Instances) which trades some correctness for speed. [Sarker, Hitzler, AAAI-19]
ECII vs. DL-Learner

Figure 1: Runtime comparison between DL-Learner and ECII. The vertical scale is logarithmic in hundredths of seconds, and note that DL-Learner runtime has been capped at 4,500 seconds for ADE20k III and IV. For ADE20k I it was capped at each run at 600 seconds.

Figure 2: Accuracy ($\alpha_3$) comparison between DL-Learner and ECII. For ADE20k IV it was not possible to compute an accuracy score within 3 hours for ECII as the input ontology was too large.
Proof of Concept Experiment

Positive:

Negative:
Images

Come from the MIT ADE20k dataset
http://groups.csail.mit.edu/vision/datasets/ADE20K/
They come with annotations of objects in the picture:

001 # 0 # 0 # sky # sky # ""
002 # 0 # 0 # road, route # road # ""
005 # 0 # 0 # sidewalk, pavement # sidewalk # ""
006 # 0 # 0 # building, edifice # building # ""
007 # 0 # 0 # truck, motortruck # truck # ""
008 # 0 # 0 # hovel, hut, hutch, shack, shanty # hut # ""
009 # 0 # 0 # pallet # pallet # ""
011 # 0 # 0 # box # boxes # ""
001 # 1 # 0 # door # door # ""
002 # 1 # 0 # window # window # ""
009 # 1 # 0 # wheel # wheel # ""
Mapping to SUMO

Simple approach: for each known object in image, create an individual for the ontology which is in the appropriate SUMO class:

- contains road1
- contains window1
- contains door1
- contains wheel1
- contains sidewalk1
- contains truck1
- contains box1
- contains building1
SUMO

• Suggested Merged Upper Ontology
  http://www.adampease.org/OP/

• Approx. 25,000 common terms
  covering a wide range of domains

• Centrally, a relatively naïve class hierarchy.

• Objects in image annotations became individuals (constants),
  which were then typed using SUMO classes.
DL-Learner input

Positive:

img1: road, window, door, wheel, sidewalk, truck, box, building
img2: tree, road, window, timber, building, lumber
img3: hand, sidewalk, clock, steps, door, face, building, window, road

Negative:

img4: shelf, ceiling, floor
img5: box, floor, wall, ceiling, product
img6: ceiling, wall, shelf, floor, product

DL-Learner results include: ∃contains.Transitway
∃contains.LandArea
Proof of Concept Experiment

Positive:

Negative:

∃contains.Transitway

∃contains.LandArea
Experiment 2

Positive (selection):

Negative (selection):

∃contains.SentientAgent

AIKP, July 2022
Experiment 5

Positive:

Negative (selection):

\exists \text{contains}. \text{BodyOfWater}
Idea Recap

- Generate explanation of the whole model
- Global explanation

Training data

hasMapping

Knowledge Graph
Mountain subclassof UpLandArea

Concept Induction

CNN to classify images

Positive instances

Negative instances

Explanations
UpLandArea ∩ LandForm
Wikipedia CH (curated) produces better coverage score. The reason behind this is the large number of concepts it has. Approximately 2M concepts.

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<th>#Images</th>
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Work in Progress

• Value of Explanations (end-to-end) to
  – humans
  – detect bias
  – improve deep learning accuracy

• Explaining hidden neuron activation patterns
  – scalability challenges
  – background knowledge challenges
Contents

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Added Value for Knowledge Graphs
Prospects

DL systems to assist with

- schema (ontology) modeling
- KG construction based on schema
- schema alignment
- co-reference resolution
- data quality assurance
- KG reasoning
Deep Deductive Reasoners

Monireh Ebrahimi, Aaron Eberhart, Federico Bianchi, Pascal Hitzler,
Towards Bridging the Neuro-Symbolic Gap: Deep Deductive Reasoners.
Applied Intelligence 51 (9), 6326-6348, 2021.

Pascal Hitzler, Frank van Harmelen
A reasonable Semantic Web.
Deep Deductive Reasoners

• We trained deep learning systems to do deductive reasoning.

• Why is this interesting?
  – For dealing with noisy data (where symbolic reasoners do very poorly).
  – For speed, as symbolic algorithms are of very high complexity.
  – Out of principle because we want to learn about the capabilities of deep learning for complicated cognitive tasks.
  – To perhaps begin to understand how our (neural) brains can learn to do highly symbolic tasks like formal logical reasoning, or in more generality, mathematics. A fundamental quest in Cognitive Science.
Reasoning as Classification

• Given a set of logical formulas (a theory).

• Any formula expressible over the same language is either
  – a logical consequence or
  – not a logical consequence.

• This can be understood as a classification problem for machine learning.

• It turns out to be a really hard machine learning problem.
Knowledge Materialization

• Given a set of logical formulas (a theory).

• Produce all logical consequences **under certain constraints**.

• Without **the qualifier** this is in general not possible as the set of all logical consequences is infinite.

• So we have to **constrain** to consequences of, e.g., a certain syntactic form. For relatively simple logics, this is often reasonably possible.
## Published deep deductive reasoning work

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<td>low</td>
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<td>[6]</td>
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<td>very low</td>
<td>high</td>
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<td>yes</td>
<td>moderate</td>
<td>high?</td>
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<td>(new)</td>
<td>$\mathcal{EL}^+$</td>
<td>yes</td>
<td>yes</td>
<td>moderate</td>
<td>high?</td>
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[12]: Ebrahimi, Sarker, Bianchi, Xie, Eberhart, Doran, Kim, Hitzler, AAAI-MAKE 2021

[25]: Makni, Hendler, SWJ 2019


[20]: Hohenecker, Lukasiewicz, JAIR 2020

[6]: Bianchi, Hitzler, AAAI-MAKE 2019

(new): Ebrahimi, Eberhart, Hitzler (preliminary report)
RDFS Reasoning using Memory Networks


additional analysis by Sulogna Chowdhury, Aaron Eberhart and Brayden Pankaskie
Memory Network based on MemN2N
# Experiments: Performance

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<td>506</td>
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<td>0</td>
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<td>52</td>
<td>0</td>
<td>1</td>
<td>0.07</td>
<td>700</td>
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</tbody>
</table>

Table 2: Statistics of various datasets used in experiments

Baseline: non-normalized embeddings, same architecture

<table>
<thead>
<tr>
<th>Training Dataset</th>
<th>Test Dataset</th>
<th>Valid Triples Class</th>
<th>Invalid Triples Class</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Precision</td>
<td>Recall /Sensitivity</td>
<td>F-measure</td>
</tr>
<tr>
<td>OWL-Centric Dataset</td>
<td>Linked Data</td>
<td>93</td>
<td>98</td>
<td>96</td>
</tr>
<tr>
<td>OWL-Centric Dataset (90%)</td>
<td>OWL-Centric Dataset (10%)</td>
<td>99</td>
<td>91</td>
<td>89</td>
</tr>
<tr>
<td>OWL-Centric Dataset</td>
<td>OWL-Centric Test Set b</td>
<td>79</td>
<td>62</td>
<td>68</td>
</tr>
<tr>
<td>OWL-Centric Dataset</td>
<td>Synthetic Data</td>
<td>65</td>
<td>49</td>
<td>40</td>
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<tr>
<td>OWL-Centric Dataset a</td>
<td>Linked Data a</td>
<td>54</td>
<td>98</td>
<td>70</td>
</tr>
<tr>
<td>OWL-Centric Dataset</td>
<td>Linked Data a</td>
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<td>72</td>
<td>67</td>
</tr>
<tr>
<td>OWL-Centric Dataset (90%)</td>
<td>OWL-Centric Dataset (10%) a</td>
<td>79</td>
<td>72</td>
<td>75</td>
</tr>
<tr>
<td>OWL-Centric Dataset</td>
<td>OWL-Centric Test Set ab</td>
<td>58</td>
<td>68</td>
<td>62</td>
</tr>
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<td>Synthetic Data a</td>
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<td>57</td>
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</tr>
<tr>
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<td>Synthetic Data a</td>
<td>67</td>
<td>23</td>
<td>25</td>
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<tr>
<td></td>
<td><strong>Baseline</strong></td>
<td>73</td>
<td>98</td>
<td>83</td>
</tr>
</tbody>
</table>

Table 3: Experimental results of proposed model

*a* More Tricky Nos & Balanced Dataset

*b* Completely Different Domain.
## Experiments: Reasoning Depth

<table>
<thead>
<tr>
<th>Test Dataset</th>
<th>Hop 0</th>
<th>Hop 1</th>
<th>Hop 2</th>
<th>Hop 3</th>
<th>Hop 4</th>
<th>Hop 5</th>
<th>Hop 6</th>
<th>Hop 7</th>
<th>Hop 8</th>
<th>Hop 9</th>
<th>Hop 10</th>
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</thead>
<tbody>
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<td>93</td>
<td>77</td>
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<tr>
<td>Linked Data</td>
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<td>0</td>
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<td>19</td>
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<td>78</td>
<td>48</td>
<td>47</td>
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<tr>
<td>Synthetic</td>
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<td>46</td>
<td>33</td>
<td>31</td>
<td>87</td>
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<td>66</td>
<td>55</td>
<td>44</td>
<td>25</td>
<td>45</td>
</tr>
</tbody>
</table>

* a LemonUby Ontology  
* b Agrovoc Ontology   
* c Completely Different Domain

Table 4: Experimental results over each reasoning hop

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Hop 1</th>
<th>Hop 2</th>
<th>Hop 3</th>
<th>Hop 4</th>
<th>Hop 5</th>
<th>Hop 6</th>
<th>Hop 7</th>
<th>Hop 8</th>
<th>Hop 9</th>
<th>Hop 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>OWL-Centric</td>
<td>8%</td>
<td>67%</td>
<td>24%</td>
<td>0.01%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Linked Data</td>
<td>31%</td>
<td>50%</td>
<td>19%</td>
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<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Linked Data</td>
<td>34%</td>
<td>46%</td>
<td>20%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
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<tr>
<td>OWL-Centric</td>
<td>5%</td>
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<td>30%</td>
<td>1%</td>
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</tr>
<tr>
<td>Synthetic Data</td>
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<td>1.42%</td>
<td>1%</td>
<td>1.56%</td>
<td>3.09%</td>
<td>6.03%</td>
<td>11.46%</td>
<td>20.48%</td>
<td>31.25%</td>
<td>23.65%</td>
</tr>
</tbody>
</table>

* a Training Set     
* b LemonUby Ontology  
* c Agrovoc Ontology   
* d Completely Different Domain

Table 5: Data distribution per knowledge graph over each reasoning hop

Training time: just over a full day
Published deep deductive reasoning work

<table>
<thead>
<tr>
<th>paper</th>
<th>logic</th>
<th>transfer</th>
<th>generative</th>
<th>scale</th>
<th>performance</th>
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</thead>
<tbody>
<tr>
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<td>RDFS</td>
<td>yes</td>
<td>no</td>
<td>moderate</td>
<td>high</td>
</tr>
<tr>
<td>[25]</td>
<td>RDFS</td>
<td>no</td>
<td>yes</td>
<td>low</td>
<td>high</td>
</tr>
<tr>
<td>[10]</td>
<td>$\mathcal{EL}^+$</td>
<td>no</td>
<td>yes</td>
<td>moderate</td>
<td>low</td>
</tr>
<tr>
<td>[20]</td>
<td>OWL RL</td>
<td>no*</td>
<td>no</td>
<td>low</td>
<td>high</td>
</tr>
<tr>
<td>[6]</td>
<td>FOL</td>
<td>no</td>
<td>yes</td>
<td>very low</td>
<td>high</td>
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<tr>
<td>(new)</td>
<td>RDFS</td>
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<td>yes</td>
<td>moderate</td>
<td>high?</td>
</tr>
<tr>
<td>(new)</td>
<td>$\mathcal{EL}^+$</td>
<td>yes</td>
<td>yes</td>
<td>moderate</td>
<td>high?</td>
</tr>
</tbody>
</table>

[12]: Ebrahimi, Sarker, Bianchi, Xie, Eberhart, Doran, Kim, Hitzler, AAAI-MAKE 2021
[25]: Makni, Hendler, SWJ 2019
[20]: Hohenecker, Lukasiewicz, JAIR 2020
[6]: Bianchi, Hitzler, AAAI-MAKE 2019
(new): Ebrahimi, Eberhart, Hitzler (preliminary report)
Conclusions
Conclusions

• Two current trends:
  – Knowledge Graphs
  – Neuro-Symbolic AI

• Plenty of opportunities
  – Improving DL systems with KG-based background knowledge
  – Solving key KG problems using DL approaches.
Thanks!
References


Barbara Hammer and Pascal Hitzler (eds), Perspectives on Neural-Symbolic Integration. Springer, 2007


Md Kamruzzaman Sarker, Lu Zhou, Aaron Eberhart, Pascal Hitzler
Neuro-Symbolic Artificial Integration: Current Trends
References


References


Thanks!