Neurosymbolic Artificial Intelligence – some results regarding knowledge graphs

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• Two current trends:
  – Neuro-Symbolic Artificial Intelligence
  – Knowledge Graphs
• And their convergence:
  – Added Value for Deep Learning
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  – Added Value for Knowledge Graphs
    • Example: Deep Deductive Reasoning
Neuro-Symbolic Artificial Intelligence
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

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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)
- 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 / knowledge graphs are 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

• But how to do this best?
• 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

**Books:** Automated Theorem-proving in Non-classical Logics, Automated Deduction - Cade-13
Knowledge Graphs

Laura Kelly

hasBirthDate

01/24/1950

hasEducation

Indiana University

hasPresident

Michael McRobbie

hasEducation

University of Queensland

hasStudents

110,436

hasEducation

Indiana University

hasEducation

University of Queensland
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.
W3C Standards

RDF 1.1 Concepts and Abstract Syntax

W3C Recommendation 25 February 2014

This version:
http://www.w3.org/TR/2014/REC-rdf11-concepts-20140225/

Latest published version:
http://www.w3.org/TR/rdf11-concepts/

Previous version:
http://www.w3.org/TR/2014/PR-rdf11-concepts-20140109/

Previous Recommendation:
http://www.w3.org/TR/rdf-concepts

Editors:
Richard Cyganiak, DERI, NUI Galway
David Wood, 3 Round Stones
Markus Lanthaler, Graz University of Technology

Both established 2004 as versions 1.0.

OWL 2 Web Ontology Language Primer (Second Edition)

W3C Recommendation 11 December 2012

This version:
http://www.w3.org/TR/2012/REC-owl2-primer-20121211/

Latest version (series 2):
http://www.w3.org/TR/owl2-primer/

Latest Recommendation:
http://www.w3.org/TR/owl-primer

Previous version:
http://www.w3.org/TR/2012/PER-owl2-primer-20121018/

Editors:
Pascal Hitzler, Wright State University
Markus Krötzsch, University of Oxford
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Peter F. Patel-Schneider, Nuance Communications
Sebastian Rudolph, FZI Research Center for Information Technology
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.
Gartner, 2021

The diagram illustrates the evolution of technology trends over time, from innovation trigger to plateau of productivity. Key areas highlighted include:

- Knowledge Graphs
- Smart Robots
- Transformers
- Decision Intelligence
- Synthetic Data
- Neuromorphic Hardware
- Human-Centered AI
- Generative AI
- AI Governance
- Responsible AI
- ModelOps
- Machine Customers
- AI Orchestration and Automation Platform
- Composite AI
- AI TRI$M
- Physics-Informed AI
- Artificial General Intelligence
- Edge AI
- AI Maker and Teaching Kits
- Deep Neural Network ASICs
- Digital Ethics
- AI Cloud Services
- Deep Learning
- Data Labeling and Annotation Services
- Natural Language Processing
- Machine Learning
- Intelligent Applications
- Chatbots
- Autonomous Vehicles
- Computer Vision
- Semantic Search

The diagram also indicates the time frame for reaching the plateau of productivity, with symbols representing different timeframes:

- ○ < 2 yrs.
- ▲ 2-5 yrs.
- □ 5-10 yrs.
- ▲ >10 yrs.
- ⚫ Obsolete before plateau

As of July 2021
Gartner

Hype Cycle for Artificial Intelligence, 2022

Plateau will be reached:
- less than 2 years
- 2 to 5 years
- 5 to 10 years
- more than 10 years
- obsolete before plateau

As of July 2022

gartner.com

Source: Gartner
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KnowWhereGraph

- 3 years, $5.6M. 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
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/
<table>
<thead>
<tr>
<th>Dataset Name/Theme</th>
<th>Source Agency</th>
<th>Key Attributes</th>
<th>Spatial Coverage</th>
<th>Temporal Coverage</th>
<th>Place-Centric Dataset</th>
<th>Defining Authority</th>
<th>Spatial Coverage</th>
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</thead>
<tbody>
<tr>
<td>Soil Properties</td>
<td>USDA</td>
<td>soil type, farmland class</td>
<td>Targeted regions in US</td>
<td>Current</td>
<td>S2 Cells</td>
<td>Google</td>
<td>Lvl 9 (Global), Lvl 13 (US),</td>
</tr>
<tr>
<td>Wildfires</td>
<td>USGS, USDA, USFS, NIFC</td>
<td>wildfire type, burn severity, num. acres burned, contained date</td>
<td>US</td>
<td>1984–current</td>
<td>Global Administrative Regions</td>
<td>University of Berkeley, Museum of Vertebrate Zoology and the International Rice Research Institute</td>
<td>Global</td>
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<tr>
<td>Climate Hazards</td>
<td>NOAA</td>
<td>injuries, deaths, property damages</td>
<td>US</td>
<td>1950–2022</td>
<td></td>
<td></td>
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<td>Expert - General</td>
<td>KWG, UC System, DR, Semantic Scholar</td>
<td>name, affiliation, expertise with spatiotemporal scopes</td>
<td>Global</td>
<td>unlimited</td>
<td>National Weather Zones</td>
<td>NOAA</td>
<td>US</td>
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<td>Cropland Types</td>
<td>USDA</td>
<td>crop types (raster data)</td>
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<td>2008-2021</td>
<td>FIPS Codes</td>
<td>NRCS</td>
<td>US</td>
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<td>Smoke Plumes</td>
<td>NOAA</td>
<td>daily smoke plumes extent</td>
<td>US</td>
<td>2010-2022</td>
<td>ZIP</td>
<td>ZCTA</td>
<td>US</td>
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<td>Climate Observations</td>
<td>NOAA</td>
<td>temperature, precipitation, PDSI, PHSI</td>
<td>US</td>
<td>1950 - 2022</td>
<td>Climate Division</td>
<td>NOAA</td>
<td>US</td>
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<tr>
<td>Disaster Declaration</td>
<td>FEMA</td>
<td>designated area, program, amount approved, program designated date</td>
<td>US</td>
<td>1953 - 2022</td>
<td>Census Metropolitan Area</td>
<td>US Census</td>
<td>US</td>
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<td>Smoke Plume Extents</td>
<td>NOAA</td>
<td>Smoke extent</td>
<td>US</td>
<td>2017 - 2022</td>
<td>Drought Zone</td>
<td>NDMC, USDA, NOAA</td>
<td>US</td>
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<tr>
<td>BlueSky Forecasts</td>
<td>Bluesky</td>
<td>PM10, PM5</td>
<td>US</td>
<td>2022-03-07</td>
<td></td>
<td>Geographic Name Information System</td>
<td>US</td>
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<tr>
<td>Transportation (highway network)</td>
<td>DOT</td>
<td>road type, road length, road sign</td>
<td>US</td>
<td>2014</td>
<td></td>
<td></td>
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<tr>
<td>Public Health</td>
<td>CDC, US Census</td>
<td>below poverty level percent, diabetes age adjusted 20 plus percent, obesity age adjusted 20 plus percent</td>
<td>US</td>
<td>2017</td>
<td></td>
<td></td>
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<td>Social Vulnerability</td>
<td>CDC/ATSDR</td>
<td>social vulnerability index</td>
<td>US</td>
<td>2018</td>
<td></td>
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<tr>
<td>Hurricane Tracks</td>
<td>NOAA</td>
<td>max wind speed, min pressure</td>
<td>US</td>
<td>1851-2020</td>
<td></td>
<td></td>
<td></td>
</tr>
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Contents

• Two current trends:
  – Neuro-Symbolic Artificial Intelligence
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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


Concept

Training images → hasMapping → Knowledge Graph

- Snow subclass of BodyOfWater
  - And some others

CNN to classify images

Positive images

Negative images

Concept Induction

$\exists \text{contains.}(\text{HighLand} \cap \text{BodyOfWater})$
DL-Learner [Lehmann, Hitzler]

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

Positive examples:                               negative examples:

1. ![Positive example 1](image1)
2. ![Positive example 2](image2)
3. ![Positive example 3](image3)
4. ![Positive example 4](image4)
5. ![Positive example 5](image5)

1. ![Negative example 1](image6)
2. ![Negative example 2](image7)
3. ![Negative example 3](image8)
4. ![Negative example 4](image9)
5. ![Negative example 5](image10)

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

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

DL-Learner result: \( \exists \text{hasCar.}(\text{Closed} \cap \text{Short}) \)

In FOL:

\[ \{ x \mid \exists y (\text{hasCar}(x, y) \land \text{Closed}(y) \land \text{Short}(y)) \} \]
For scalability, we developed ECII (Efficient Concept Induction from Instances) which trades some correctness for speed. [Sarker, Hitzler, AAAI-19]

**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 Background Knowledge

- Wikipedia category hierarchy (curated)
- approx. 2M concepts
- For each known object in image, create an individual for the ontology which is in the appropriate class.

contains road1
contains window1
contains door1
contains wheel1
contains sidewalk1
contains truck1
contains box1
contains building1
Idea Recap

- Generate explanation of the whole model
- Global explanation

CNN to classify images

Training data

hasMapping

Knowledge Graph

Mountain subclassof UpLandArea

Concept Induction

Explanations

UpLandArea \cap LandForm

Positive instances

Negative instances
Understanding hidden layer activations Through Concept Induction
Results

Neuron number 04 (dense layer, i.e. before output layer):

- Total number of images that got activated = 612/1370 (1370= test_dataset)
- Highest activation = 12.627778
- Total number of positives = 149 (images that has value >= 6)
- Total number of negatives = 150 (images that has value < 6)

Solution given by ECII analysis for neuron 04

solution 1: (:Bed)
solution 2: (:WN_Bed)
solution 3: (:WN_Table)
solution 4: (:WN_Lamp)
solution 5: ((:WN_Table) ∩ (:Bed))
solution 6: (:Night_table)
solution 7: (:Cushion)
solution 8: ((:Cushion) ∩ (:WN_Cushion))
solution 9: (:WN_Shade)
solution 10: ((:Pillow) ∩ (:WN_Bed))
solution 14: (:WN_Pillow)
solution 17: ((:WN_Cushion) ∩ (:WN_Lamp))
solution 19: (:WN_Headboard)
solution 24: ((:WN_Lamp) ∩ (:Pillow))
solution 25: (:WN_Table)

Distinct Concepts from the solution

Bed
Table
Night Table
Lamp
Pillow
Cushion
Headboard
Results

Google analysis for Neuron number 04:

- Take each concept from distinct concept list for e.g: Bed, Table and collect images from Google.
- First set analysis, all images activate (853 images)
- Second set analysis, all images activate (900 images)
Results

Neuron number 05:

- Total number of images that got activated = 787/1370 (1370 = test_dataset)
- Highest activation = 10.196102
- Total number of positives = 116 (images that have value >= 5)
- Total number of negatives = 150 (images that have value < 5)

Solution given by ECII analysis for neuron 04:
- solution 1: (:WN_Table)
- solution 2: (:Floor)
- solution 4: (:WN_Flooring)
- solution 5: (:Window)
- solution 7: ((:WN_Flooring) ∩ (:Window))
- solution 10: ((:Ceiling) ∩ (:WN_Table))
- solution 15: (:Picture)
- solution 17: (:WN_Picture)
- solution 22: (:Chair)
- solution 24: (:WN_Lamp)
- solution 26: ((:WN_Windowpane) ∩ (:WN_Painting))

Distinct Concepts from the solution:
- Table
- Floor
- Window
- Ceiling
- Picture
- Chair
- Lamp
- Painting
Results

Google analysis for Neuron number 05:

- Take each concept from distinct concept list for eg: Window, Chair, Picture and collect images from google.
- First set analysis, all images activate (1500 images)
- Second set analysis, all images activate (508 images)
Results

Neuron number 11:

- Total number of images that got activated = 794/1370
- Highest activation = 17.6951
- Total number of positives = 262 (images that has value >= 9)
- Total number of negatives = 250 (images that has value < 9)

Solution given by ECII analysis for neuron 11:

solution 1: (:WN_Edifice)
solution 2: (:WN_Building)
solution 3: (:Building)
solution 4: (:WN_Sky)
solution 5: (:Sky)
solution 6: (:WN_Road)
solution 7: (:WN_Route)
solution 8: (:Road)
solution 9: (:WN_Tree)
solution 10: (:WN_Motorcar) ∩ (:WN_Machine)
solution 14: (:WN_Automobile)
solution 17: (:WN_Route) ∩ (:WN_Building)
solution 19: (:WN_Automobile) ∩ (:WN_Route)
solution 24: (:Sidewalk)
solution 25: (:WN_Pavement)

Distinct Concepts from the solution:

- Edifice(Building)
- Building
- Sky
- Road
- Route
- Tree
- Motorcar
- Machine
- Automobile
- Sidewalk
- Pavement
Results

Google analysis for Neuron number 11:

- Take each concept from distinct concept list for eg: Building, Sky and collect images from google.
- First set analysis, all images activate (183 images)
- Second set analysis, all images activate (454 images)
Are Concept Induction explanations meaningful to humans?
Are the results human-compatible? Part I

**Hypothesis:**
- ECII explanations are better than semi-random explanations, but worse than human-generated explanations.

**Experimental setting as before.**
- 300 Amazon Mechanical Turk participants
- Seven concepts taken from top ECII results.
- 45 image set pairs, each set corresponding to a category.
Are the results human-compatible? Part I

Which of these better represents what the images in group A have that the images in group B do not?

A: Bake, Bakery, Bread, Indoor, Product, Store, Woman

B: Basket, Bread, Cake, Ceiling, Floor, Person, Wall
Are the results human-compatible? Part I

<table>
<thead>
<tr>
<th></th>
<th>87-13</th>
<th>97-3</th>
<th>87-12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human v ECII</td>
<td>3856</td>
<td>4287</td>
<td>3862</td>
</tr>
<tr>
<td>Human v Random</td>
<td>580</td>
<td>153</td>
<td>578</td>
</tr>
<tr>
<td>ECII v Random</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Times Chosen

- Human
- ECII
- Random
Are the results human-compatible? Part II

- Hypothesis:
  - ECII explanations matched to correct images better than chance, but not as frequently as human generated explanations

- Experimental setting as before.
- 100 Amazon Mechanical Turk participants
- 16 image sets, from ML decision errors (logistic regression classifier)
Are the results human-compatible? Part II

A

B

Explanation: Home, Manufacturing, Clothing, Clothing Manufacturers, People, Chairs, Tableware

Which group of images do you think this explanation refers to?

Image Group A

Image Group B
Are the results human-compatible? Part II

- Bayesian hierarchical signal-detection model (SDT)
  - yields discriminability measure
Improving Deep Learning through Concept Induction
Improving deep learning

Experimental set-up

• Dataset: Twitter Dataset for toxicity analysis
  – Classes like “Lie, Dangerous, Insult”

• Language Model Used: Bert Base Model
  – 12 layers
  – 768 hidden layer neurons
  – 110M parameters

Data examples – “insult” class

• "Fiore, an occupation sympathizer..." This article makes me feel sick. An insult to Oregonians who have tolerated 41 days and more from this unwanted intrusion. An insult to the LE that put their lives and reputations at risk to resolve this. The mutual admiration between her and Bundy's counsel is to be expected.

• I'm not sure what you're trying to say, or what the source is of you're information you've implied is somehow not relevant to this article. Forget about mainstream media and the tired and over used commentary that dismiss all mainstream media and politicians making up canned rhetoric repeating it so often that easily manipulated people actually believe them. We all need to worry about individuals that have an ax to grind and make statements out of thin air, try to shock and change the subject on issues. There is racism in our country and it has been passed down from one generation to another but all good people with moral compasses will continue to work within the process by joining together for the rights of all human beings, we will all benefit and it has nothing to do with political sides blather or insults directed at media. We have options, as a society, our sources for information from credible research is unlimited. You may be looking for truth in all the wrong places.

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I'm not sure what you're trying to say, or what the source is of your information you've implied is somehow not relevant to this article. Forget about mainstream media and the tired and overused commentary that dismiss all mainstream media and politicians making up canned rhetoric repeating it so often that easily manipulated people actually believe them. We all need to worry about individuals that have an ax to grind and make statements out of thin air, try to shock and change the subject on issues. There is racism in our country and it has been passed down from one generation to another but all good people with moral compasses will continue to work within the process by joining together for the rights of all human beings, we will all benefit and it has nothing to do with political sides blather or insults directed at media. We have options, as a society, our sources for information from credible research is unlimited. You may be looking for truth in all the wrong places.
Concept Induction Analysis

- Run ECII on false positives vs. true positives
- Take first 20 results from ECII
- Get new examples that fall under all of the ECII classes
- Retrain with the additional examples
  - initial training set size: 10,000
  - retraining set size: 11,800
  - i.e. 18% added

Does retraining improve classification?
### Results before and after training

<table>
<thead>
<tr>
<th>Class</th>
<th>Accuracy (before)</th>
<th>Accuracy (after)</th>
<th>Precision (before)</th>
<th>Precision (after)</th>
<th>F-Measure (before)</th>
<th>F-Measure (after)</th>
<th>Recall (before)</th>
<th>Recall (after)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lie</td>
<td>0.9483</td>
<td><strong>0.9721</strong></td>
<td>0.9333</td>
<td><strong>0.9464</strong></td>
<td>0.9589</td>
<td><strong>0.9789</strong></td>
<td>0.9859</td>
<td><strong>0.9897</strong></td>
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<tr>
<td>Dangerous</td>
<td>0.8731</td>
<td><strong>0.8947</strong></td>
<td>0.8485</td>
<td><strong>0.8711</strong></td>
<td>0.8682</td>
<td><strong>0.8890</strong></td>
<td>0.8889</td>
<td><strong>0.9120</strong></td>
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<tr>
<td>Crazy</td>
<td>0.8911</td>
<td><strong>0.9105</strong></td>
<td>0.8511</td>
<td><strong>0.8784</strong></td>
<td>0.8791</td>
<td><strong>0.8962</strong></td>
<td>0.9090</td>
<td><strong>0.9465</strong></td>
</tr>
<tr>
<td>Corruption</td>
<td>0.9455</td>
<td><strong>0.9788</strong></td>
<td>0.9167</td>
<td><strong>0.9533</strong></td>
<td>0.8800</td>
<td><strong>0.9125</strong></td>
<td>0.8462</td>
<td><strong>0.8782</strong></td>
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<tr>
<td>Fool</td>
<td>0.8983</td>
<td><strong>0.9427</strong></td>
<td>0.9483</td>
<td><strong>0.9788</strong></td>
<td>0.9016</td>
<td><strong>0.9433</strong></td>
<td>0.8594</td>
<td><strong>0.9652</strong></td>
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<tr>
<td>Insult</td>
<td>0.7813</td>
<td><strong>0.8333</strong></td>
<td>0.7885</td>
<td><strong>0.8123</strong></td>
<td>0.7961</td>
<td><strong>0.8211</strong></td>
<td>0.8039</td>
<td><strong>0.8349</strong></td>
</tr>
</tbody>
</table>
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
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.

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.
RDFS Reasoning using Memory Networks


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

<table>
<thead>
<tr>
<th>Training</th>
<th>Test</th>
<th>Valid Triples Class</th>
<th></th>
<th>Invalid Triples Class</th>
<th></th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Prec (%)</td>
<td>Rec</td>
<td>F-Measure</td>
<td>Prec</td>
<td>Rec</td>
</tr>
<tr>
<td>A</td>
<td>LD 1</td>
<td>93</td>
<td>98</td>
<td>96</td>
<td>98</td>
<td>93</td>
</tr>
<tr>
<td>A (90%)</td>
<td>A (10%)</td>
<td>88</td>
<td>91</td>
<td>89</td>
<td>90</td>
<td>88</td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>79</td>
<td>62</td>
<td>68</td>
<td>70</td>
<td>84</td>
</tr>
<tr>
<td>A</td>
<td>Synth 1</td>
<td>65</td>
<td>49</td>
<td>40</td>
<td>52</td>
<td>54</td>
</tr>
<tr>
<td>A</td>
<td>LD 2</td>
<td>54</td>
<td>98</td>
<td>70</td>
<td>91</td>
<td>16</td>
</tr>
<tr>
<td>C</td>
<td>LD 2</td>
<td>62</td>
<td>72</td>
<td>67</td>
<td>67</td>
<td>56</td>
</tr>
<tr>
<td>C (90%)</td>
<td>C (10%)</td>
<td>79</td>
<td>72</td>
<td>75</td>
<td>74</td>
<td>81</td>
</tr>
<tr>
<td>A</td>
<td>D</td>
<td>58</td>
<td>68</td>
<td>62</td>
<td>62</td>
<td>50</td>
</tr>
<tr>
<td>C</td>
<td>D</td>
<td>77</td>
<td>57</td>
<td>65</td>
<td>66</td>
<td>82</td>
</tr>
<tr>
<td>A</td>
<td>Synth 2</td>
<td>70</td>
<td>51</td>
<td>40</td>
<td>47</td>
<td>52</td>
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<tr>
<td>C</td>
<td>Synth 2</td>
<td>67</td>
<td>23</td>
<td>25</td>
<td>52</td>
<td>80</td>
</tr>
</tbody>
</table>

Baseline: non-normalized embeddings, same architecture
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>
</tr>
</thead>
<tbody>
<tr>
<td>[12]</td>
<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>
</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
Conclusions
Conclusions

• Two current trends:
  – Knowledge Graphs
  – Neurosymbolic AI

• Plenty of opportunities
  – Improving DL systems with KG-based background knowledge
    • Explainable AI by Concept Induction
  – Solving key KG problems using DL approaches.
    • Deep Deductive Knowledge Graph Reasoning
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


References


Thanks!