

Concept Learning in Description Logics

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Section 1

Motivation



Motivation

Data Web



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Charles III / Age

74 vears

November 14, 1948

People also search for









Princess

72 years

illiam. Prince of 41 vears





Charles III (ing of the United Kingdom

Charles III is King of the United Kingdom and 14 other Commonwealth realms. Charles was born in Buckingham Palace during the reign of his maternal grandfather. George VI, and was three years old when his mother, Elizabeth II, acceded to the throne in 1952, making him the heir apparent, Wikipedia

Born: November 14, 1948 (age 74 years), Buckingham Palace, London, United Kingdom

Full name: Charles Philip Arthur George Height: 1.78 m

- Most popular application of knowledge graphs (KGs) is Web search
- Approx. 30% of search gueries at Google answered by the Google Knowledge Graph
- Further applications in finance, health, e-commerce, and Industry 4.0
- Predominant portion of open KGs are in RDF



Motivation Data Web



Domains with Triples URLs with Triples embedded-jsonld : 8,596,990 embedded-jsonld : 877,812,654 icrodata : 7,471,628 nicrodata : 801,909,298 mf-hcard : 3.880.98 -mf-hcard : 318.625.913 rdfa : 594.018 rdfa: 91,100.238 -mf-xfn - 349 876 mf-hcalendar : 20.810 mf-hcalendar : 1.319.116 -mf-hreview : 17.303 -mf-hreview : 1.279.142 others : 219,488 2,500,000 5 000 000 7 500 000 10 000 000 1 000 000 000 250 000 000 750.000.000

- RDF knowledge bases are now first-class citizens of the Web
- Approx. 50% of websites contain RDF¹
- 2+ billion URLs contain RDF statements
- Ca. 100 billion statements in Linked Open Data

¹See http://webdatacommons.org/structureddata/#results-2022-1



Motivation



Description Logics



- Terminology of RDF datasets in description logics
- Popular DLs include *ELH* (e.g., for biomedical domain), *ALC* (e.g., for ML-driven applications), and *SROIQ* (e.g., on the Web)





Section 2

Basic Setting



Learning Problem





- ► Given
 - ► Knowledge base G (often called background knowledge)



Learning Problem





- ► Given
 - Knowledge base G (often called background knowledge)
 - ► Set of positive examples, e.g., $E^+ = \{Louvre, TourEiffel\}$

²Source: https://bit.ly/3sxCj6e



Learning Problem





- Given
 - Knowledge base G (often called background knowledge)
 - Set of positive examples, e.g., $E^+ = \{Louvre, TourEiffel\}$
 - Set of negative examples, e.g., $E^- = \{Lily, James\}$

²Source: https://bit.ly/3sxCj6e



Learning Problem





- Given
 - ► Knowledge base G (often called background knowledge)
 - ► Set of positive examples, e.g., $E^+ = \{Louvre, TourEiffel\}$
 - Set of negative examples, e.g., $E^- = \{Lily, James\}$
- Goal: Find concept H that "describes" E⁺ and "does not describe" E⁻, e.g., H = ∃ isLocatedIn.Place

²Source: https://bit.ly/3sxCj6e



Symbolic Approaches





Often based on refinement operators

³Source: https://bit.ly/3sxCj6e









- Often based on refinement operators
- + Explainable, exploits background knowledge
- Slow :-(

³Source: https://bit.ly/3sxCj6e



Neural Approaches





• Deep Learning:
$$e(v_i) := \varphi \left(\bigoplus_{(v_i, p_k, v_j) \in G} e(p_k, v_j), e(v_i) \right)$$

⁴Source: https://bit.ly/3sxCj6e



Neural Approaches





• Deep Learning:
$$e(v_i) := \varphi \left(\bigoplus_{(v_i, p_k, v_j) \in G} e(p_k, v_j), e(v_i) \right)$$

+ Time-efficient

Unintelligible, does not exploits background knowledge

⁴Source: https://bit.ly/3sxCj6e





Neuro-Symbolic Approaches



+ Exploit time efficiency of neural approaches

Keep explainability of symbolic approaches

⁵Source: https://bit.ly/3sxCj6e