Interactions Between Knowledge Graph-Related Tasks and Analogical Reasoning

A Discussion

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Context & Motivation

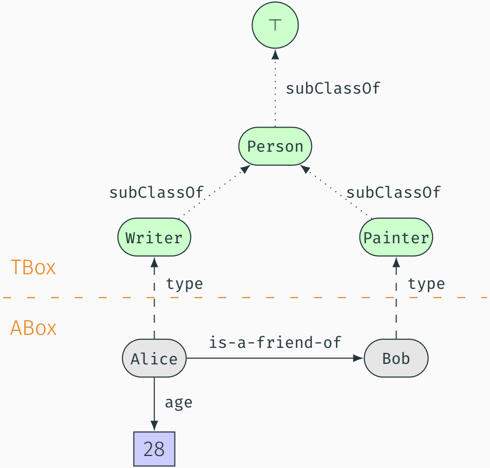
Knowledge graphs (KGs) in the Web of data

- Directed and labeled multigraphs
- Nodes

  Individuals Classes Literals
- Edges
  - Labeled by a predicate
  - Defined by triples

$$\langle \mathit{subject}, \mathit{predicate}, \mathit{object} \rangle$$

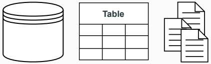
- Semantic Web standards
  RDF, URI, RDFS, OWL, SPARQL, ...
  (Berners-Lee et al. 2001)



From a general assessment about the Web of data...

- Increasing volume of available data in various formats
- Open Data portals, internal repositories of companies

→ Automatic knowledge extraction approaches to build KGs



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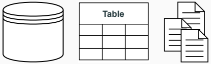
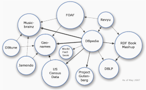
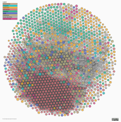


- Increasing size and number of available KGs
- Possible overlaps
- Interest in their conjoint use

→ Matching similar units within and across KGs



LOD Cloud in 2007



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from `lod-cloud.net` –

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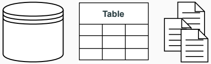

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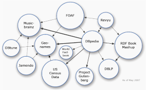

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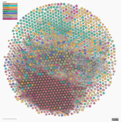

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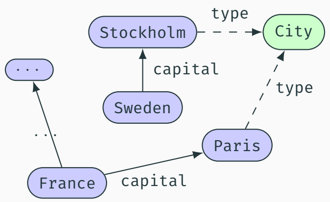
→ **KGs support various applications**

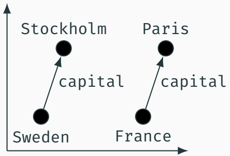
e.g., search, question-answering, recommendation

From a general assessment about the Web of data...

- Various methods for KG construction, matching, refinement, and usage
- Impressive performance of Knowledge Graph Embeddings



Graph structures
(*e.g.*, nodes)



d-dimensional space
preserving graph properties

(Cai et al. 2018; Chami et al. 2020; Ji et al. 2020; Nickel et al. 2016; Wang et al. 2017)

- Various types of models, *e.g.*, translational, convolutional

… to our research questions about analogies

- Analogies have been extensively studied in NLP (Alsaidi et al. 2021)
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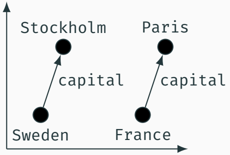

e.g., TransE (Bordes et al. 2013)

$$\overrightarrow{\texttt{France}} - \overrightarrow{\texttt{Paris}} = \overrightarrow{\texttt{Sweden}} - \overrightarrow{\texttt{Stockholm}} = \overrightarrow{\texttt{capitalOf}}$$

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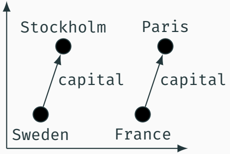

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- KG link prediction and data mining approaches for analogy solving (Portisch et al. 2022)

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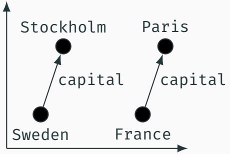

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Towards further interactions between analogical reasoning and KG-related tasks?

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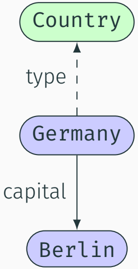
The examples of

- Semantic Table Interpretation
- Knowledge Matching
- KG-based Recommendation

Semantic Table Interpretation

Semantic Table Interpretation: definition & tasks

Understanding the semantic content of tables by annotating with KG elements



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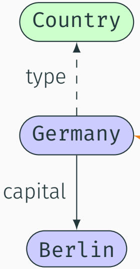

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Cell-Entity Annotation (CEA) associates cells with entities;

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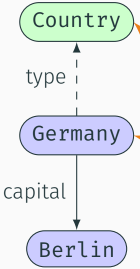

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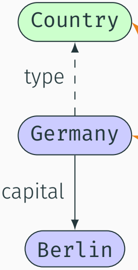

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capital

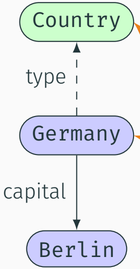
Cell-Entity Annotation (CEA) associates cells with entities;

Column-Type Annotation (CTA) associates columns with types;

Columns-Property Annotation (CPA) associates pairs of columns with properties.

Semantic Table Interpretation: (some) applications

Understanding the semantic content of tables by annotating with KG elements



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- **KG completion** with table content
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- Data set search services

Semantic Table Interpretation: issues

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- Different encoding charsets
- Misaligned cells, missing values
- Little context to disambiguate candidate entities, *e.g.*, from Wikidata
  - Q142 (`Germany`, the European country)
  - Q13505654 (`Germany`, the constituency of the European Parliament)

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- **Useful property: semantic coherence of columns**

Analogies to support Semantic Table Interpretation

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→ **Allows to see a table through the lens of analogies**

e.g., from pairs of columns, `France` : `Paris` :: `Germany` : `Berlin`

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- Filling missing values → analogy solving

Retrieval (entity in KG) or generation (entity not in KG)

- Disambiguation → choose the entity that maximizes analogy detection

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- Scalability issue: from “Country” and “Capital” $\rightarrow$ 12 analogies
- Are all analogies necessary? Restricting to the most *useful*?

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- **Alternative view** (Prade et al. 2010; Hug et al. 2016)
  - Rows r_i vectors $\overrightarrow{r_i} = (r_{i1}, r_{i2}, \ldots, r_{in})$
  - Analogies holding b/w some components $J \subset [1, n]$
  - Analogies should hold b/w remaining components

$$\frac{\forall j \in J, r_{1j} : r_{2j} :: r_{3j} : r_{4j}}{\forall k \in [1, n] \setminus J, r_{1k} : r_{2k} :: r_{3k} : r_{4k}}$$

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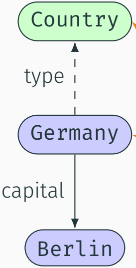
- **Scalability?**
- **(Dis)advantages of each view?**

Analogies to support Semantic Table Interpretation: opportunities & challenges



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- **Interactions between analogies and STI**

  → Analogy tasks could rely on graph or table embeddings
- **Challenges**

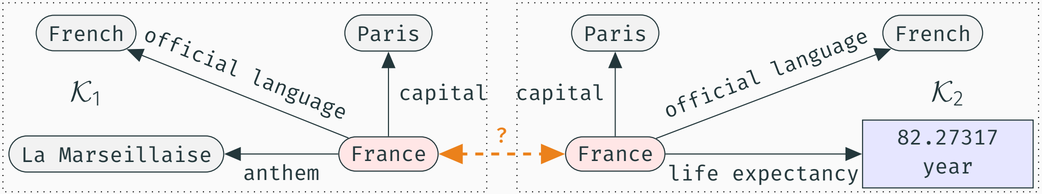
  → Cells with multiple entities, mix of entities and literals, other forms of tables, …

Knowledge Matching

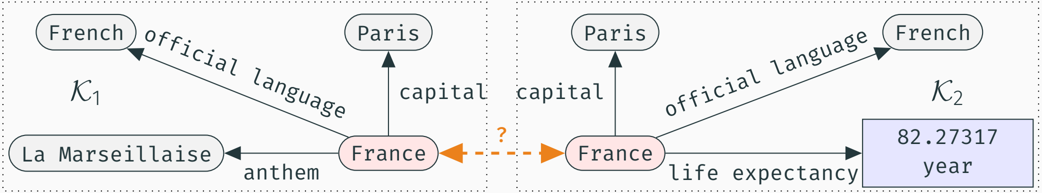
Knowledge Matching: definition

- KGs are concurrently published and edited → possible overlaps

→ **Key task in matching their content** (Euzenat et al. 2013)



Identifying, within aggregated KGs or across KGs,
equivalent, more specific, weakly related, or contradictory elements
(*e.g.*, nodes, predicates)

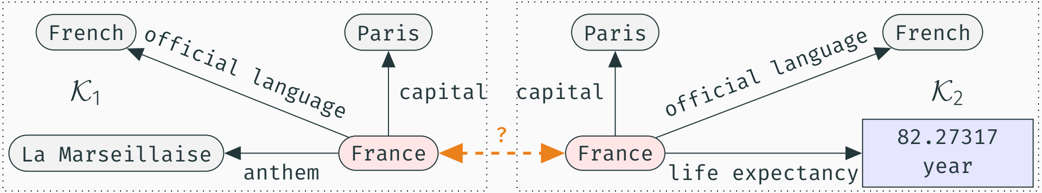


Analogy-based node matching

- Nodes can be seen in analogies with their neighbors

  e.g., based on the `capital` predicate, $\texttt{France}_{\mathcal{K}_1} : \texttt{Paris}_{\mathcal{K}_1} :: \texttt{France}_{\mathcal{K}_2} : \texttt{Paris}_{\mathcal{K}_2}$

Analogies to support Knowledge Matching



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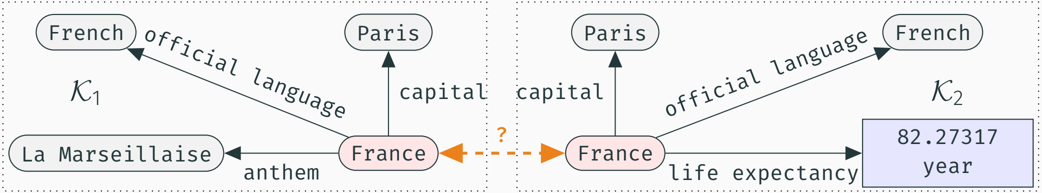

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- Other analogies for other alignments (*e.g.*, equivalences, contradictions)

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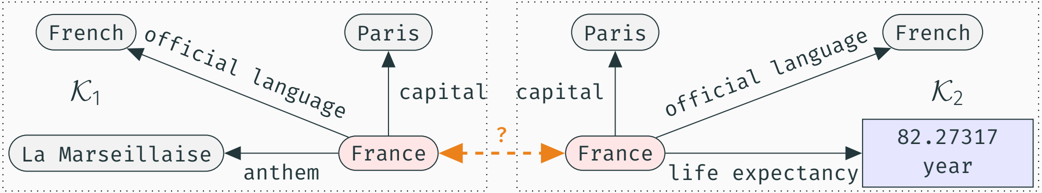

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- Scalability? Sufficient overlaps?

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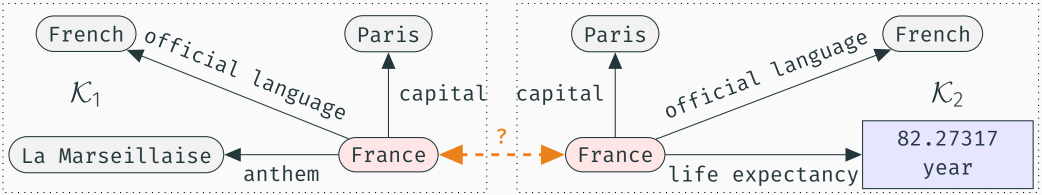

Analogy-based node matching (alternate view – analogy solving)

- Based on alignments: predicting x such that

$$\texttt{Paris}_{\mathcal{K}_1} : \texttt{Paris}_{\mathcal{K}_2} :: \texttt{France}_{\mathcal{K}_1} : x$$

$$\texttt{French}_{\mathcal{K}_1} : \texttt{French}_{\mathcal{K}_2} :: \texttt{France}_{\mathcal{K}_1} : x$$

Choose the mostly output x

- Based on existing edges: predicting x such that

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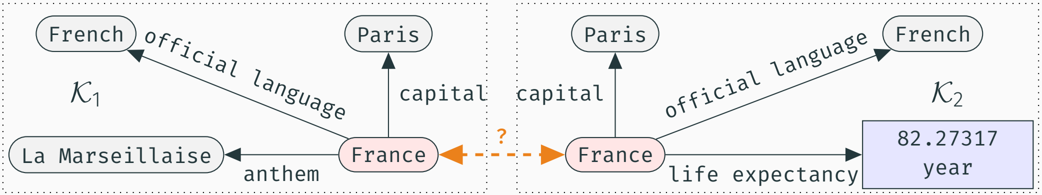

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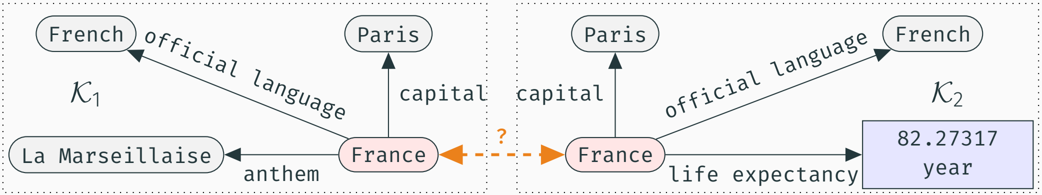
Scalability? Completness?

Analogies to support Knowledge Matching



Analogy-based predicate matching (analogy detection)

Analogical proportions hold between linked entities → identical predicates

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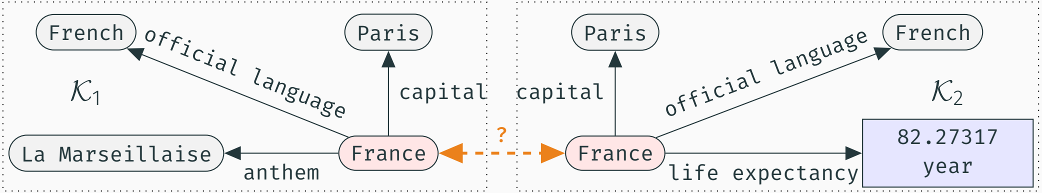
$$\texttt{Germany}_{\mathcal{K}_1} : \texttt{Berlin}_{\mathcal{K}_1} :: \texttt{Germany}_{\mathcal{K}_2} : \texttt{Berlin}_{\mathcal{K}_2}$$

$$\texttt{France}_{\mathcal{K}_1} : \texttt{Paris}_{\mathcal{K}_1} :: \texttt{Germany}_{\mathcal{K}_2} : \texttt{Berlin}_{\mathcal{K}_2}$$

$$\rightarrow \texttt{capital}_{\mathcal{K}_1} = \texttt{capital}_{\mathcal{K}_2}$$

Analogies to support Knowledge Matching



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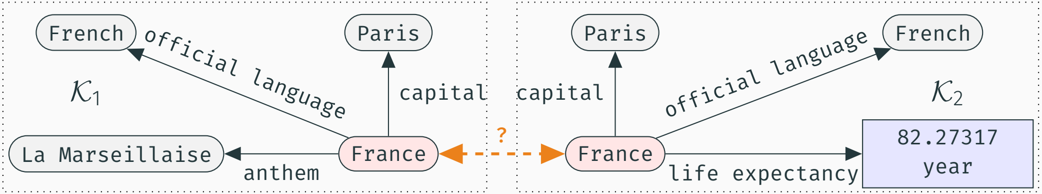
Scalability?

Analogies to support Knowledge Matching: opportunities & challenges



- Integrate analogical inference in knowledge matching matching
  $\rightarrow$ Analogical inference in symbolic or graph embedding-based approaches
- Challenges
  $\rightarrow$ Mix of entities and literals, completeness / sufficient overlaps, …

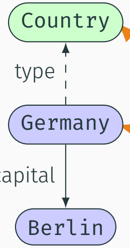
Conclusion & Perspectives

Conclusion & Perspectives

- **Analogies naturally appear in KG-related tasks**
  - Semantic Table Interpretation
  - Knowledge Matching
- Similarly to NLP, one could leverage Knowledge Graph Embedding
- **Open questions**
  - Actual improvement in performance?
  - Analogical setting to choose?
  - Scalability?
- Other interactions to study?

  e.g., analogies and KGs to support eXplainable AI (Hüllermeier 2020; Tiddi et al. 2022)

Thank you for your attention!



Country	Capital
Finland	*(empty)*
France	Paris
Germany	Berlin
Sweden	Stockholm
Switzerland	Bern (de facto)

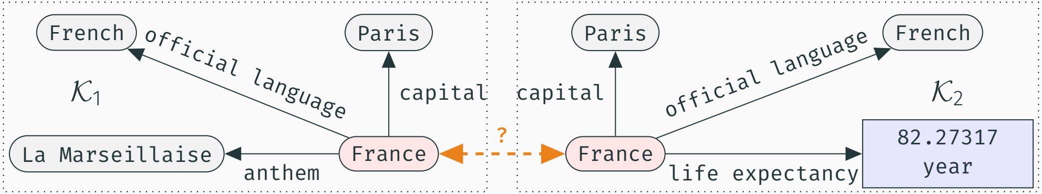
capital

Analogy for STI

$\texttt{France} : \texttt{Paris} :: \texttt{Finland} : ?$

Analogy for Knowledge Matching

$\texttt{Paris}_{\mathcal{K}_1} : \texttt{Paris}_{\mathcal{K}_2} :: \texttt{France}_{\mathcal{K}_1} : x$



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