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Interactions Between Knowledge Graph-Related Tasks and Analogical Reasoning: A Discussion

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Abstract

Analogical reasoning has been extensively studied and relies on statements of the form "A is to B as C is to D" that are called analogical proportions. The motivation of our work is based on the following twofold observation. On the one hand, recent analogy-based settings relying on character or word embeddings have achieved state-of-the-art performance on Natural Language Processing tasks. On the other hand, graph embedding approaches are now mainstream for knowledge graph-related tasks, *e.g.*, knowledge discovery, knowledge graph refinement, or recommendation. Inspired by these works, we advocate for the further study of interactions between knowledge graph-related tasks and analogical reasoning. In particular, we outline how knowledge graph embeddings combined with analogical reasoning could support semantic table interpretation, knowledge matching, and recommendation.

Keywords

Analogical reasoning, Graph Embedding, Semantic Table Interpretation, Knowledge Matching, Recommendation

1. Introduction

Analogical reasoning is a remarkable capability of the human mind [1]. *Analogical proportions* or, simply, *analogies*, are statements of the form "A is to B as C is to D"' which are often written as $A : B :: C : D$. A typical example of an analogy would be "Paris is to France as Stockholm is to Sweden". Most of the recent works on analogy use the formalization proposed in Lepage [2], and that subsumes common intuition on analogies viewed as a geometric proportion (Equation (1)), an arithmetic proportion (Equation (2)), or as a parallelogram in a vector space (Equation (3)):

$$\frac{A}{B} = \frac{C}{D} \quad (1) \qquad A - B = C - D \quad (2) \qquad \overrightarrow{A} - \overrightarrow{B} = \overrightarrow{C} - \overrightarrow{D} \quad (3)$$

Traditional tasks related to analogical reasoning include analogy detection (*i.e.*, classifying a quadruple as a valid or invalid analogy) and analogy solving (*i.e.*, finding an x such that

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$A : B :: C : x$ constitutes a valid analogy). Analogies have been extensively studied in Natural Language Processing settings with applications in word morphology [3, 4], machine translation [5] and semantic tasks [6, 7, 8].

Also, knowledge graphs (KGs) have gained a significant interest from both academic and industrial actors. A KG can be seen defined as "a *graph of data intended to accumulate and convey knowledge of the real world, whose nodes represent entities of interest and whose edges represent relations between these entities*" [9]. Atomic elements of KGs are *triples* $\langle s, p, o \rangle$ where s is the subject, p the predicate, and o the object of the triple respectively. An example of a triple could be $\langle \texttt{Paris}, \texttt{capitalOf}, \texttt{France} \rangle$, where the predicate (also called property) `capitalOf` qualifies the relation holding between `Paris` and `France`. KGs support several downstream applications including offering a consolidated view of knowledge scattered across sources, fact-checking, search engines, e-commerce, question answering, or recommendation [10, 11, 12, 13, 14]. Various techniques have been developed to build, refine, and use KGs, including Knowledge Graph Embedding (KGE) techniques which have shown impressive performance [12, 15]. Interestingly, the parallelogram view of an analogy (Equation (3)) can be related to the translational view adopted by some KGE models. For example, TransE [16] models a triple $\langle \texttt{Paris}, \texttt{capitalOf}, \texttt{France} \rangle$ as a translation $\overrightarrow{\texttt{Paris}} + \overrightarrow{\texttt{capitalOf}} = \overrightarrow{\texttt{France}}$. Hence, we would have:

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

It is noteworthy that some embedding techniques already consider analogical properties. For example, Liu et al. [17] argue that analogical inference is desirable for knowledge graph completion and include analogical structures in their learning objective. Alternatively, Portisch et al. [18] evaluate link prediction and data mining approaches developed for knowledge graphs on an analogy inference task with the goal of retrieving the last element (D) of a quadruple given the three first elements (A, B, and C). Inspired by such previous work, we advocate in this article for a further study of interactions between analogical reasoning and knowledge graph-related tasks.

This paper is organized as follows. In Section 2, we discuss possible interactions between analogical reasoning and Semantic Table Interpretation (STI) as STI can be supported by knowledge graph embeddings. In Section 3 we reformulate knowledge matching in terms of analogical proportions, and we further explore this discussion for knowledge graph-based recommendation (Section 4). We then conclude by briefly outlining some noteworthy perspectives in Section 5.

2. Analogies for Semantic Table Interpretation

Semantic Table Interpretation (STI) aims at understanding the semantic content of tabular data such as Excel or CSV files, or Web tables. This process is carried out by annotating elements of tables with constituents of a knowledge graph through the three following tasks:

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.

Table 1
Example of a table listing countries, their capitals, their official language(s), and their GDP. This table is inspired from the Wikipedia pages "List of countries and dependencies and their capitals in native languages"[1] and "List of countries by GDP (nominal)".[2]

Country	Capital	Official language(s)	GDP (US$ million)
Finland	*(empty)*	Finnish, Swedish	297,617
France	Paris	French	2,936,702
Germany	Berlin	German	4,256,540
Sweden	Stockholm	Swedish	621,241
Switzerland	Bern (de facto)	German, French, Italian, Romansh	841,969

STI has seen a growing research interest over the past few years, for example with the SemTab challenge [19]. Indeed, large parts of company knowledge or knowledge available on the Web are encoded as tabular data. Consequently, understanding the content of tables paves the way for several downstream tasks such as table completion with KG content, KG completion with table content, or data set search services [20].

When interpreting tabular data, several issues arise, *e.g.*, different encoding charsets, misaligned cells, or missing values (for example, the capital of Finland in Table 1). Tables alone also provide little context to help disambiguate candidate entities for cell annotation [21]. For example, consider Table 1 and its annotation with Wikidata, an encyclopedic knowledge graph [22]. Based solely on entity labels and string matching, annotation candidates for cell "Germany" are entity Q142[3] (Germany, the European country) and entity Q1350565[4] (Germany, the constituency of the European Parliament). To cope with such issues, current STI approaches rely on syntactic lookups and majority voting [23, 24], or graph embedding-based disambiguation [25]. In the latter case, Chabot et al. [25] rely on the assumption that columns of tables are semantically coherent. Thus, when applying a clustering algorithm on the embeddings of candidate entities for a whole column, valid entities should be grouped in the same cluster. In our example, Q142 should be grouped in the same cluster as the entities representing the other countries appearing in the table.

Interestingly, the semantic coherence of columns also allows to see a table through the lens of analogies. A first view consists in considering cells in pairs of columns as taking part in analogical proportions. For example, Table 1 can be seen as sets of analogies of the form `France : Paris :: Germany : Berlin` or `France : French :: Germany : German`. In such a setting, the task of filling missing table values can be thought of as an analogy solving task, *e.g.*, we would like to find x such that `France : Paris :: Finland : x` is a valid analogy. In STI, such as task could be carried out both by retrieval (in case the correct entity is in the knowledge graph) and generation (in case the correct entity is absent from the target knowledge graph). Regarding disambiguation between candidate entities, this could be achieved by choosing the entity that satisfies the highest number of analogies generated from the table. However, it is

[2]https://en.wikipedia.org/wiki/List_of_countries_and_dependencies_and_their_capitals_in_native_languages
[2]https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal)
[3]https://www.wikidata.org/wiki/Q183
[4]https://www.wikidata.org/wiki/Q1350565

noteworthy that tables can lead to a high number of analogies. For example, only considering columns "Country" and "Capital" of Table 1 already produces 12 analogies. One could thus wonder about the computational complexity of such an approach. Future work could investigate the need for generating all possible analogies or, on the contrary, for restricting to the most useful analogies to the task at hand. Such a notion of usefulness may be task- or domain-dependent and remains to be defined and discussed. A first approach to generating all analogies or pruning redundant analogies can be achieved by taking into account properties such as the symmetry of analogical proportions (*i.e.*, $A : B :: C : D \rightarrow C : D :: A : B$).

Alternatively to generating analogies from pairs of columns independently, tables could be considered as whole in an analogical setting that follows the work of Prade and Richard [26] and Hug et al. [27]. Rows r_1, r_2, r_3, and r_4 could be seen as vectors $\overrightarrow{r_i} = (r_{i1}, r_{i2}, \ldots, r_{in})$ such that analogical proportions hold on some of their components $J \subset [1, n]$. Then, from the analogical inference principle, it follows that analogical proportions should also hold on the remaining components:

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

This more holistic view may guide the STI process by focusing on analogical proportions that are valid on a high number of columns. However, in both views, analogical validity may not be possible over the entire table, *i.e.*, all generated analogies may not be detected as valid. In such case, analogical validity ratios may be interesting metrics to guide and evaluate the quality of the STI process.

Inspired by recent approaches [3, 17, 18], we assume that analogical reasoning for Semantic Table Interpretation could be supported by graph or table embeddings [12, 28]. However, some challenges inherent to tabular data must be integrated into analogical formalizations. For example, tables can contain cells with multiple entities (*e.g.* "Finnish, Swedish" in Table 1) and columns can involve a mix of entities and literals (*e.g.*, column "GDP (US$ million)"). This leads to consider multi-modal embeddings. In a table-graph multi-modal embedding space, one could also envision the CEA task as detecting or solving analogies of the form $r_{i1} : e_{i1} :: r_{i2} : e_{i2}$ where r_{ij} are cells of a table and e_{ij} are their matching entities in the knowledge graph.

3. Analogies for Knowledge Matching

Knowledge graphs are freely aggregated, published, and edited in the Web of data, and may thus overlap. Hence, a key task resides in matching (or aligning) their content [29]. This task encompasses the identification, within an aggregated knowledge graph or across knowledge graphs, of nodes that are equivalent, more specific, weakly related, or that represent contradictory knowledge units. Matching allows to obtain a consolidated view of scattered elements of knowledge which is beneficial to many applications, such as fact-checking or query answering. The task of matching elements of knowledge graphs has been extensively studied in the literature. We refer the interested reader to the book of Euzenat and Shvaiko [29] for a comprehensive review of existing work.

A knowledge matching task can be approached as an analogical setting. Indeed, nodes of knowledge graphs can be seen in analogical proportions with their neighbors. For ex-

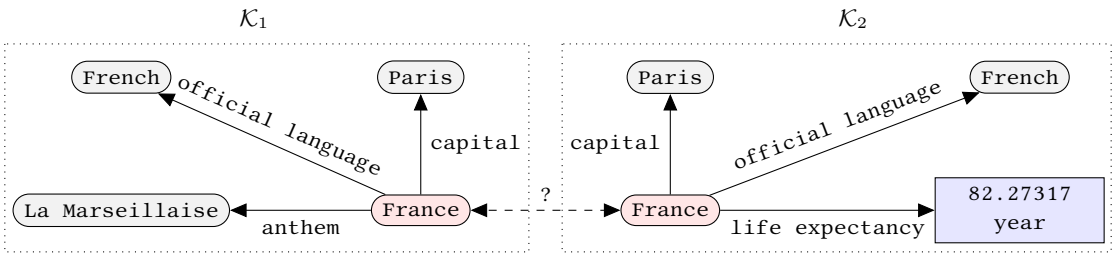

Figure 1: Example of a knowledge matching setting between two knowledge graphs $\mathcal{K}_1$ and $\mathcal{K}_2$ inspired from Wikidata.

ample, from the two knowledge graphs represented in Figure 1, it is possible to generate the analogy $\texttt{France}_{\mathcal{K}_1} : \texttt{Paris}_{\mathcal{K}_1} :: \texttt{France}_{\mathcal{K}_2} : \texttt{Paris}_{\mathcal{K}_2}$. The matching task then comes down to aligning nodes that maximize the validity of such analogical proportions between their respective neighbors with an analogy detection task. This corresponds to a structure-based matching [29]. This analogy-based matching process could be strengthen by considering existing alignments between neighbors (*e.g.*, $\texttt{Paris}_{\mathcal{K}_1}$ and $\texttt{Paris}_{\mathcal{K}_2}$) that could result from different matching methods (*e.g.*, string matching). For example, from the reflexivity property of analogical proportions (*i.e.*, $A : B :: A : B$), the inner symmetry (*i.e.*, $A : B :: C : D \implies B : A :: D : C$), the uniqueness postulate (*i.e.*, given A, B, and C, there exists only one D such that $A : B :: C : D$), the alignment $\texttt{Paris}_{\mathcal{K}_1} = \texttt{Paris}_{\mathcal{K}_2}$, and the analogical proportion $\texttt{Paris} : \texttt{France}_{\mathcal{K}_1} :: \texttt{Paris} : \texttt{France}_{\mathcal{K}_2}$, it follows that $\texttt{France}_{\mathcal{K}_1} = \texttt{France}_{\mathcal{K}_2}$. Such an analogical matching process could also produce valid results without preexisting alignments by only taking into account structural similarities. Thus, it could be used to start a matching pipeline. Note that the previous analogical proportion relies on similarities between identical nodes to match. By generating analogies based on granularity differences or contradictions between nodes, we could output such different alignment types. From the previous observations, a challenge thus resides in having a set of preexisting alignments of different types that could guide the analogy-based matching towards specific types of alignments.

It should be noted that other analogy-based views to match nodes can be considered. For example, given a set of preexisting alignments, matching a node $\texttt{France}_{\mathcal{K}_1}$ can be seen as solving a set of analogical equations of the form

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

and chosing the entity that is mostly output as x. Analogies could also serve as a basis to align predicates (*e.g.*, $\texttt{capital}_{\mathcal{K}_1}$ and $\texttt{capital}_{\mathcal{K}_2}$). Indeed, if two predicate are identical, then analogical proportions should hold between the entities they link, *e.g.*,

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

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

Hence, the alignment of predicates could be carried out by matching predicates that have a high number of valid analogical proportions between the entities they respectively connect.

Recent matching approaches rely on graph embeddings [30, 31, 32, 33]. Hence, it could be of interest to use such graph embeddings in an analogical setting for matching. This could correspond to aligning the embedding spaces of the KGs to match [34]. Enforcing analogical properties in the training procedure similarly to Liu et al. [17] could also be tested to learn specific graph embeddings tailored for analogical reasoning. However, it should be noted that analogy-based approaches to knowledge matching need to cope with issues similar to those described in Section 2. Indeed, KGs mix entities and literals (*e.g.*, the life expectancy in $\mathcal{K}_2$), which may require the use of multi-modal embeddings. Additionally, KGs may be incomplete and two equivalent nodes may not be entirely comparable based on their neigbhors. For example, in Figure 1, $\texttt{France}_{\mathcal{K}_1}$ is associated with its anthem `La Marseillaise` which is absent from $\mathcal{K}_2$. Additionally, not all nodes from a KG may found their counterpart in another KG. Hence, an analogy-based matching approach should try to maximize analogical validity without reaching full coverage. Due to the increasing size of KGs, the computational complexity of such an analogy-based matching approach and the need for generating all possible analogies or only the most useful should also be taken into account.

4. Analogies for Knowledge Graph-Based Recommendation

In this section, we consider the task of recommending items to users. Traditional approaches rely on similarity between users and/or items. Indeed, collaborative filtering-based recommender systems simultaneously consider similarities between users, items, and users and items based on their interactions. Alternatively, content based-recommender systems consider features of items to find and recommend items similar to the ones liked by the users.

As such, recommendation is a natural setting for analogical reasoning since it is also based on similarities. That is why, analogies have already been applied to recommendation with the objective of predicting the rating of an item by a user based on ratings of other similar users [27, 35]. Precisely, consider four users a, b, c, and d such that for each item j commonly rated, the analogical proportion $r_{aj} : r_{bj} :: r_{cj} : r_{dj}$ holds, with r_{aj} the rating of user a for item j. From the analogical inference principle, it is possible to predict the rating r_{di} for an item i that has only been rated by a, b, and c by solving the analogical proportion $r_{ai} : r_{bi} :: r_{ci} : x$. This analogy-based setting has also been adapted to preference learning with the objective of learning to rank a set of objects [36, 37], and considered in case-based reasoning [38, 39].

Recently, KGs have been introduced in recommender systems as sources of side information [11, 13]. Indeed, KGs allow to represent relations between items and their attributes, between users and items, and any additional user information. Hence, KGs better capture mutual relations between these different entities. Such rich KGs and their advantages motivated the use of knowledge graph embeddings for recommendation [11, 13]. However, these embeddings models do not take into account potential analogical constraints holding between users and items. Hence, we propose to study how knowledge graph embeddings could be combined with analogical proportions for recommendation. Such proportions could involve

users and items to directly support the recommendation, *e.g.*, $\texttt{user}_1 : \texttt{item}_1 :: \texttt{user}_2 : \texttt{item}_2$. We could also envision user-only analogies $\texttt{user}_1 : \texttt{user}_2 :: \texttt{user}_3 : \texttt{user}_4$ allowing to find similar users that could then support the recommendation of an item. Item-attribute analogies $\texttt{item}_1 : \texttt{attribute}_2 :: \texttt{item}_3 : \texttt{attribute}_4$ could highlight similarities between items whereas user-attribute analogies $\texttt{user}_1 : \texttt{attribute}_2 :: \texttt{user}_3 : \texttt{attribute}_4$ could emphasize the importance of some attributes to users. Such analogical proportions could be used to enrich training data or to check outputs of models by ensuring a minimum level of valid analogies with the recommended item(s). Alternatively, such analogies could be directly integrated in the learning procedure of the graph embeddings, similarly to the work of Liu et al. [17].

5. Conclusion & Perspectives

In this article, we advocated for the deeper study of the interactions between analogical reasoning and knowledge graph-related tasks. On the one hand, one can profit from recent analogy-based settings with state-of-the-art results on various tasks such as in Natural Language Processing and decision making, that make use of suitable data representations (embeddings). On the other hand, approaches based on knowledge graph embeddings are now mainstream and achieve competitive results for several tasks associated with knowledge graphs.

Motivated by these developments, we illustrated how analogy-based settings emerge naturally in semantic table interpretation, knowledge matching, and recommendation. While they could be suitably supported by available table or graph embeddings, such settings pose several challenges and open questions that need to be addressed. In particular, it remains to assess whether analogical views of such tasks actually improve performance. Interestingly, aside performance, such an integration of analogical reasoning could pave the way towards additional interpretability and explainability of approaches as discussed by Hüllermeier [40]. This could, in turn, strengthen the line of research studying knowledge graphs as tools for explainable AI [41].

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