Explaining Metaphors in the French Language by Solving Analogies using a Knowledge Graph

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Abstract. An analogy is a relation which operates between two pairs of terms representing two distant domains. It operates by transferring meaning from a concept that is known to another that one would like to clarify or define. In this report, we address analogy both from the aspect of modeling and by automatically explaining it. We will then propose a system of resolution of analogical equations in their notation in symbol chains. The model, based on the common sense knowledge base *JeuxDeMots* (a semantic network), operates by generating a list of potential candidates from which it chooses the most suitable solution. We conclude by evaluating our model on a collection of equations, and reflecting upon future work.

Keywords: Analogy · Metaphor · Figurative language · Natural language processing · Knowledge base.

1 Introduction and state of the art

From more or less complex ideas and reasoning, eloquent and persuasive expressions can emerge in a non-trivial way, carrying clear or nuanced meanings. Language production and understanding are accepted as faculties specific to humans, being capable of high-level semantic interpretation. A speaker seems to refer, subconsciously and effortlessly, to a complex and hierarchical apparatus built from his knowledge of the world. We seek here to "achieve [...] the formalization of an operation that everyone recognizes as being at work in language" [8] with the aim of automatizing it. Our main challenge is to carry out such refined semantic reasoning automatically.

We can describe analogy as a fundamental way of expression used in languages across the world [2]. Beyond this universality, the omnipresence of analogies and metaphors in written language justifies the interest of further research in the field. Manual annotation of metaphorical figures from the British National Corpus revealed that 241 out of 761 sentences contained this type of language [9]. The study, although marked by an idiomatic dimension specific to the English language, represents an indicator of the prevalence of analogies in natural language. However, these figures cannot *a priori* be generalized to other languages.

It is important to underline the central character of the operation of analogy in the human cognitive apparatus, whether in its fundamental natural operations, or in more complex and methodical demonstrations and reasoning (*system 1/system 2* of Kahneman [5]). We are used to approaching the resolution of a difficult or new problem by trying to reduce it to another for which the solution is known. Hofstadter [3] [4] believes that thought and analogy are inseparable, he argues that analogy is the core of the cognitive functioning of human beings, and that every problem we encounter is nothing other than an assembly of analogies that we navigate more or less fluidly through our reasoning. He thus bases his theories on this hypothesis of a close connection between reasoning and analogy.

In this perspective, the interpretation of analogies represents a crucial step forward in the development of work in Natural Language Processing (NLP). In the ambitious perspective of identifying and then analyzing this mechanism, it is crucial to scrutinize the subtleties of language, and to analyze their functioning from cognitive and linguistic points of view. A large part of the work in NLP still focuses on elementary, or first level, linguistic tasks (morpho-syntactic labeling, syntactic analysis, coreference resolution, recognition of named entities, etc.), while another part of the research aims to improve automatic inference mechanisms and the extraction of new knowledge from textual corpora. Ultimately, even less work focuses on bringing together the lessons and progress provided by each of these scientific directions, in order to get closer to human linguistic capacity and thus simulate high-level linguistic reasoning such as the understanding of expressions in all their creativity.

In this work, we present a prototype for interpreting analogies by exploiting a common sense knowledge base in the form of a graph, the *JeuxDeMots* network (*JDM*) [7]. We will formalize statements in analogical squares (see Section 2) and present methods for evaluating the quality of these analogies (see Section 3). For an analogy, it is a question of bringing out correspondences between terms which are provided to the system by the user. The demonstrator of a first proof of concept associated with this article is available at the following address: `https://analogie.demo.lirmm.fr`.

2 Analogy square

An analogy (when formalized in an analogy square) is a set of 4 terms linked by similarity relationships (see Fig. 1). The strength of an analogy comes from the similarity of the terms that compose it, its *explainability* is based on the multiple relationships between these terms.

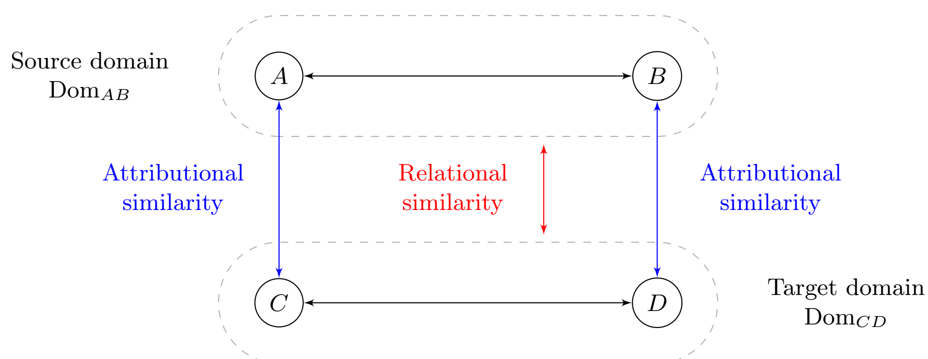


Fig. 1. Simplified diagram of the analogy square (example: A=eye, B=sight, C=hand, D=touch)

2.1 Analogy and similarity

Generally speaking, figurative speech aims to integrate, into the description of one concept, attributes of a second, chosen on the basis of its semantic similarity with the concept described. Here, we tackle the distinction between the two notions of similarity emanating from the work of Gentner [1], who argues that there are at least two types of similarities:

- **Relational similarity**, which consists of the correspondence between the relations of two pairs of concepts.
- **Attributional similarity**, which is the correspondence between the attributes of two concepts.

The notions of attribute and relation are accepted in the sense of first-order logic, where an attribute is a single variable predicate, while a relation is a predicate with two variables. We qualify two terms, each designating a concept, as synonyms, when their **attributional similarity** is sufficiently high, while we designate two pairs of terms as analogous if their **relational similarity** is high [10].

We can, following this relational similarity, argue that it would be possible to generate a correspondence (analogy) $A \to B$ transferring knowledge from a so-called source concept A to a target concept B. The source concept is generally abstract, uncertain or unknown, the one on which we wish to establish an easy to understand and concrete target. Here are examples of pairs of concepts constituting analogies:

$$(\textit{confidence} \text{ and } \textit{success}) \text{ with } (\textit{sun} \text{ and } \textit{flower}) \ \text{ abstract-concrete} \tag{1}$$

$$(\textit{electron} \text{ and } \textit{plasma}) \text{ with } (\textit{person} \text{ and } \textit{crowd}) \ \text{ unknown-known} \tag{2}$$

$$(\textit{carpenter} \text{ and } \textit{wood}) \text{ with } (\textit{mason} \text{ and } \textit{stone}) \tag{3}$$

The analogy (3) taken from the work of Turney and Pantel [11] could be formulated: "the *carpenter* is to *wood* what the *mason* is to *stone*". The meanings of the relationships between the concepts *mason* and *carpenter* respectively with *stone* and *wood* are indeed similar. On the one hand, these are professions, and on the other hand, materials very closely linked to these respective professions. The introduction of a characteristic specific to the distant concept (*source*) therefore makes available to the speaker all the contextual knowledge of the concept and operates, in the case of an explanatory speech or reasoning, as a familiar and edifying support, or, in the case of a poetic intention, as an evocative agent helping to color the language and offering a complementary lyrical richness.

2.2 Symbol strings and analogy equation

When it comes to the notion of equality of relationships (proportionality), between two pairs of terms (A, B) and (C, D), the statement (3) can be written more concisely with a symbol chain notation "$A : B :: C : D$". The notation illustrated by the example of the proportional analogy between the pairs (carpenter, wood) and (mason, stone) previously mentioned then becomes (4).

$$\textit{carpenter : wood :: mason : stone} \tag{4}$$

The operator ":" indicates the existence of relational relationships between its operands, in this case the terms *carpenter* and *wood*. The "::" operator then transfers this relationship **from the**

source* to the *target by asserting the existence of a relationship of the same semantic nature between the terms of the second pair (terms *mason* and *stone*). This notation is adopted for its clear separation between the *source* (*carpenter* and/or *wood*) and the *target* (*mason* and/or *stone*) in an analogy.

2.3 Metaphors and comparisons: gap analogies

#	A : B :: C : D				Sentence	Type (number of unknowns)
1	a	b	c	d	a is to b what c is to d	Analogy (0)
2	a		c		a is like c	Comparison (2)
3		b		d	b is like d	
4	a			d	a of d | d of a	Metaphor (2)
5		b	c		b of c | c of b	
6	a	b	c		c of b is a | c is like a : it has its b	Comparative metaphor (1) | Metaphorical comparison (1)
7	a	b		d	d of a is b | d is like b : it has its a	
8	a		c	d	a of d is c | a is like c : it has its d	
9		b	c	d	b of c is d | b is like d : it has its c	

Example

a = carpenter, b = wood, c = mason, d = stone

1.	The **carpenter** is to the **wood** what the **mason** is to the **stone**.	(analogy)
2.	The **carpenter** is like the **mason**.	(comparison)
3.	The **wood** is like the **stone**.	(comparison)
4.1.	The **carpenter** of the **stone**.	(metaphor)
4.2.	The **stone** of the **carpenter**.	(metaphor)
5.1.	The **wood** of the **mason**.	(metaphor)
5.2.	The **mason** of the **wood**.	(metaphor)
6.1	The **mason** of the **wood** is the **carpenter**.	(comparative metaphor)
6.2	The **mason** is like the **carpenter** : he has its **wood**.	(metaphorical comparison)
7.1	The **stone** of the **carpenter** is the **wood**.	(comparative metaphor)
7.2	The **stone** is like the **wood** : it has its **carpenter**.	(metaphorical comparison)
8.1	The **carpenter** of the **stone** is the **mason**.	(comparative metaphor)
8.2	The **carpenter** is like the **mason** : he has its **stone**.	(metaphorical comparison)
9.1	The **wood** of the **mason** is the **stone**.	(comparative metaphor)
9.2	The **wood** is like the **stone** : it has its **mason**.	(metaphorical comparison)

Fig. 2. Behavior observed depending on the positioning of unknowns in an analogy

In the context of Aristotelian analogies, we find the case where one (or more) of the four symbols is missing, raising what is called an analogical equation of the form "$A : B :: C :?$". The interpretation of the analogy comes down to solving this equation and consists of deducing the possible values of the missing term(s). In a desire for formalism, similar to King and Gentner [6], we start from the postulate that metaphors and comparisons can be formalized as manifestations of gap analogies (analogical equations with 1 or 2 unknowns). Fig. 2 illustrates the different cases observed.

3 Strength of an analogy and election of candidates

Let us now see the methods proposed for the evaluation of similarities with a view to electing the best candidate term(s) for resolving a gap analogy.

3.1 Relationships between words

We denote "$a\ r\_t\ b$", the relation r of type t from a to b and its weight "$p(a, r\_t, b)$". In our knowledge base, we have information about a term (or node in the context of a knowledge graph): its relationships with other words. We exploit the types of relationships present in JDM[1] and we limit ourselves to those mainly relating to semantics: *r_associated*, *r_domain*, *r_isa*, *r_anto*, *r_hypo*, *r_has_part*, *r_holo*, *r_agent*, *r_patient*, *r_lieu*, *r_instr*, *r_carac*[2].

We can group the relationships between terms/nodes A, B, as presented in Fig. 3, depending on whether they are direct or indirect (with iAB nodes) as well as oriented in one direction or the other. For a given relationship, it is possible to calculate a normalized weight p_{norm}: the ratio of the weight of the relationship $a\ r\_t\ b$ by the maximum weight of all relationships of type t from node a. The p_{norm} value makes it possible to classify the relationships of a node and to select those considered to be the most strongly associated, i.e. the first[3] n relationships with the best normalized weights with regard to the type t of the relationship. This allows us to control the combinational cost when calculating the strength of similarities (see Section 3.2). The detailed formula for the normalized weight for fixed a, r_t and b is defined in (5).

$$p\_norm(a, r, b) = \frac{p(a, r\_t, b)}{max\_val\_for\_type(a, t)} \tag{5}$$

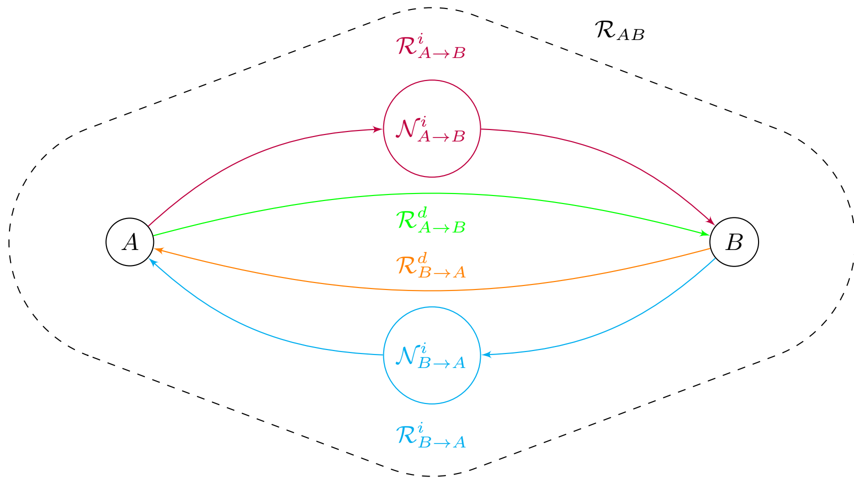
3.2 Relational similarity

When analyzing an analogy $A : B :: C : D$, we want to recover all the direct and indirect relationships between A and B (in both directions) as well as between C and D (in both directions). The goal is then to perform an intersection between these types of relationships between A and B on the one hand and C and D on the other hand in order to evaluate the strength of the relational similarity.

[1] `https://www.jeuxdemots.org/jdm-about-detail-relations.php`

[2] Some relations are conversive, that is to say that $a\ r\_t\ b \Leftrightarrow b\ r\_t_{-1}\ a$ has with r_t_{-1} the conversive relation to r_t (example: *r_isa* and *r_hypo*).

[3] We have arbitrarily chosen in our demonstrator the 2 most relevant relationships (if there are any) for reasons of simplification. Note that the intermediate node may be the same for these 2 relationships.



$$\mathcal{R}_{AB} = \mathcal{R}_{A\to B} \cap \mathcal{R}_{B\to A} \tag{6}$$
$$= \mathcal{R}^d_{A\to B} \cap \mathcal{R}^i_{A\to B} \cap \mathcal{R}^d_{B\to A} \cap \mathcal{R}^i_{B\to A} \tag{7}$$

Fig. 3. Notation of sets of direct and indirect relationships between A and B

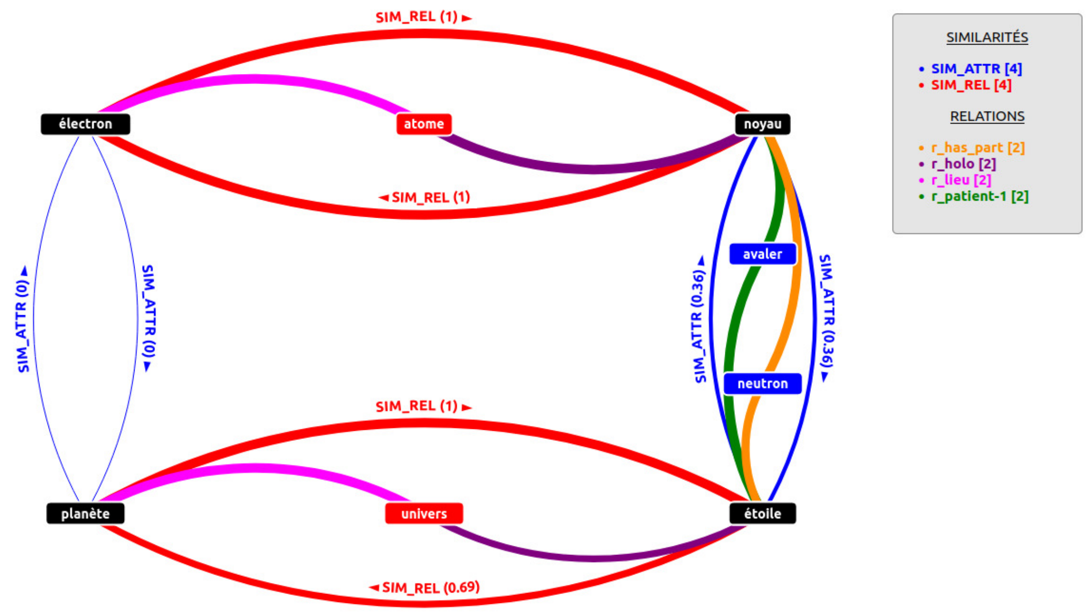
In the example presented in Fig. 4, we see that we have the same types of relationships between *electron* and *nucleus/stone*[4] as between *planet* and *star*. In this case, the relationships are indirect, because no direct relations of the same type were found. We establish the strength of the relational similarity observed when exploring from A to B[5] by averaging the normalized weights of the relations from A to B combined with those from A to the intermediate nodes iAB. For the relations from B to A, we operate the same way. In practice, the results are satisfactory in the sense that the values obtained correspond to intuition, with the values approaching 1 for a similarity considered strong. Similarly, the similarity is considered weak when the calculated value approaches 0. It is equal to 0 when no relationship (direct or indirect) is observed. Note that this measurement is taken as a baseline and can be refined to improve precision.

We also implement some weighting according to the type of relationship, which allows, for example, to consider a relationship of the type *r_isa*, *r_lieu* or *r_has_part* as more important with regard to its semantic contribution, relative to an *r_associated* relationship which is more vague [6]. We hypothesize that establishing a precise link between electron and nucleus then finding this same link on the other side of the analogy between planet and star (with other intermediate nodes) makes it possible to ensure the strength of this **relational similarity** more than if it were a simple relation of association of ideas or even if one did not exist.

[4] The word 'noyau' in French has a translation of 'stone' as in the hard core of stone fruits.

[5] Note that the strength of relational similarity from A to B is not necessarily the same as that from B to A since there are relationships oriented in both directions and of different weights.

[6] In the future, we will be able to use a *TF-IDF* type approach which consists of seeing how an ArB is as specific as possible to A, such an approach would however be computationally intensive.



Node type	A	B	C	D	iAB	iCD	iBD	
French	électron	noyau	planète	étoile	atome	univers	avaler	neutron
English translation	electron	nucleus/stone	planet	star	atom	universe	swallow	neutron

Fig. 4. Execution of our demonstrator (`https://analogie.demo.lirmm.fr`) on the analogy square *electron : nucleus :: planet : star*

3.3 Attributional similarity

We now analyze the relationships of the same types between each of the terms A, B and a certain intermediate node iAB. The desired pattern therefore corresponds to $A\ r\_t\ iAB$ and $B\ r\_t\ iAB$. We proceed in the same way and independently with C and D. In Fig. 4, we see that there is no such intermediate node between electron and planet in *JDM*, the **attributional similarity** is therefore equal to 0. This is not enough to assert that electron and planet have nothing to do with each other, this rather means an absence of attributional similarity from the point of view of the knowledge base in its current state. On the other hand, we note between *nucleus*/*stone* and *star* the presence of the *swallow* node via a relationship $r\_patient_{-1}$, undoubtedly because a star can for example "be swallowed by a black hole" and the *stone* of a fruit can "be swallowed by a child" (*stone* and *nucleus* in french (*noyau*) being homonyms). A human speaker will immediately notice that two different meanings of the word *noyau* are involved. It will therefore be necessary to carry out semantic refinements by distinguishing the different meanings of each word to obtain better results; *JDM* is equipped to handle this type of word sense disambiguation.

3.4 Overall strength and election of candidates in the case of metaphor

An analogy is considered more meaningful when the relational and attributional similarities it contains are sufficient, or from a statistical point of view if their score is high. By taking an average[7] between all of these similarities we obtain a value which we will consider as a strength of association in the form of a probability. This score takes on its meaning when it comes to classifying different candidates in the case of a gap analogy[8]. We can therefore evaluate the relevance of these candidates by calculating the score for each of them with the known nodes of the analogy with which they have sufficiently high similarity ratios. Take for example the hole analogy *leg : knee :: arm : ?*, the proposed candidate is *elbow* which corresponds to a response that comes naturally. In our implementation, the relations $a\ r\_t\ b$ displayed and currently used for calculating the weight are the first 2 in order of decreasing weight for each pair (a, b); this makes the calculation times reasonable and gives satisfactory results for a proof of concept.

3.5 Evaluation of analogy equation resolution

We have a list of analogies with a distribution of responses provided by *JDM* players (control)[9]. We check if the top 4 predicted candidates include the best control term (see Fig. 5). This preliminary work results in an accuracy of around 37%. A perspective for improvement consists, firstly, of taking into account a more covering set of semantic relationships, and then calibrating the methods for calculating similarities and their aggregations. It will be necessary to put in place more in-depth procedures for exploring the knowledge base such as inference and reasoning mechanisms. It is also possible to carry out data preparation, such as morpho-syntactic normalization[10] or even semantic disambiguation.

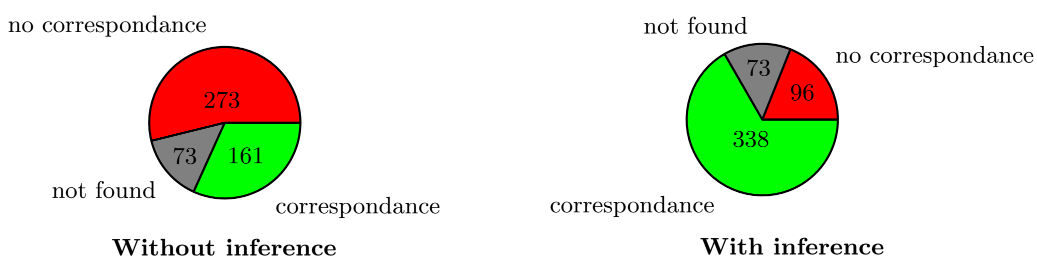


Fig. 5. Evaluation of the relevance of the candidates (first 4) compared with the most played control in *JDM* for the same metaphor (on a corpus of 507 metaphors) with and without inference

[7] Arithmetic and geometric means produce similar results.

[8] We have only discussed metaphors so far, comparisons being a broader subject given that their two unknowns in the context of the analogical square constitute a combinatorial challenge.

[9] By simulating the intersections for a list of just over 2000 metaphors played in JDM (`http://jeuxdemots.org/analogies.php` → “exporter données”), we note that around 87% of failure cases are due to missing relationships. Deductive inference processes can overcome this problem in 65% of cases. Example of inference: *child r_has_part leg* → *child r_isa human r_has_part leg.*

[10] Passage through lemmatization by observing all the relationships of close words such as *petit, petite, petits, petites* (which means *small* in feminine and masculine and in singular and plural in french) when one of them is concerned.

4 Synthesis

We consider the Aristotelian analogy in its symbol chain notation **A : B :: C : D**, which means "A **is to** B **what** C **is to** D" and we say that there is (see Fig. 6):

- **relational similarity** (correspondence between the relations of 2 pairs of concepts):
  - $R_{AB} = A : B$ (with A and $B \in$ *source* domain denoted Dom_{AB})
  - $R_{CD} = C : D$ (with C and $D \in$ *target* domain denoted Dom_{CD})
  - $\mathrm{SimRel} = R_{AB} \cup R_{CD}$
  - It is possible to have a correspondence $A \to B$ (respectively $C \to D$) transferring knowledge from a generally familiar and concrete *source* concept A (respectively C) to a generally unknown and abstract *target* concept B (respectively D)
- **attributional similarity** (correspondence between the attributes of 2 concepts):
  - $\mathrm{SimAttr}_{AC}$ between A and C (co-P)[11]
  - $\mathrm{SimAttr}_{BD}$ between B and D (co-P)
- **analogy** when there is a non-empty intersection of the relations of R_{AB} and R_{CD}, its understanding is improved with the presence of attributional similarities

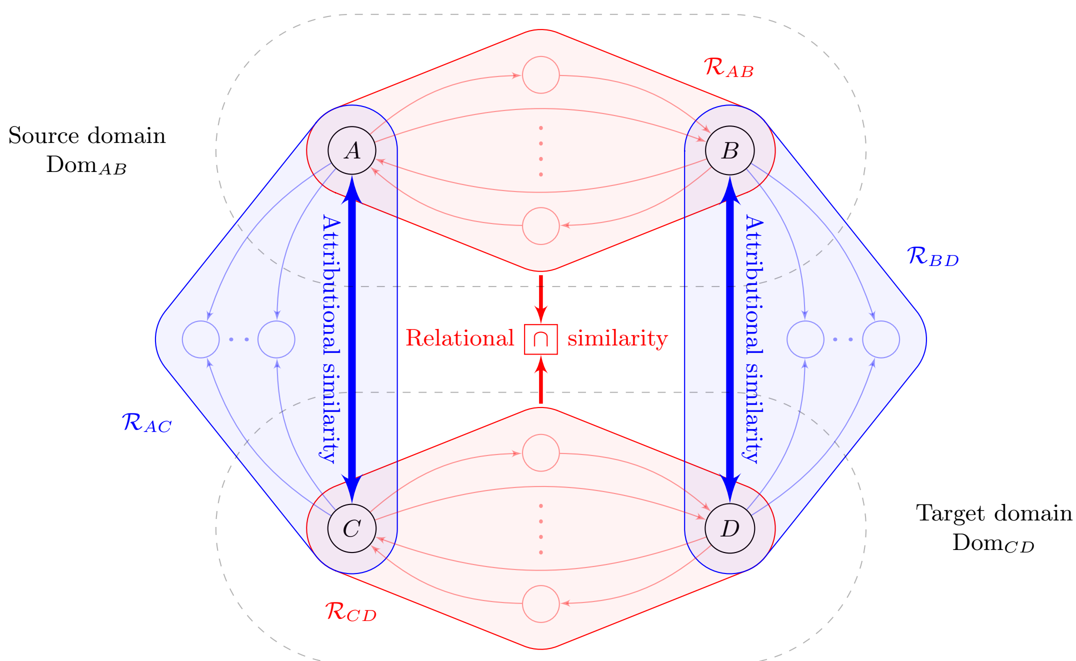


Fig. 6. Detailed diagram of the analogy square

[11] P being the semantic relation seen as a unary predicate of the same value

We believe that the strength of an analogy is defined through several aspects. First of all, it should be noted that the approach does not take place, with regard to the knowledge base, in a closed world context, in the sense that a missing relation *ar_tb* does not mean that it's not possible. Gaps in the knowledge base can result in mistakes in the system's analysis of the analogy. These gaps, highlighted by mistakes, need to be identified and corrected. The ongoing improvements of this proof of concept include, among other things, more efficient reasoning mechanisms, and approaches to resolving the polysemy of input terms.

In an analogical square, the relationships between words in the *source* domain are of the same type (one could say analogous) to those in the *target* domain establishing the strength of the relational similarity. Equivalent terms from opposite domains must have a relationship of the same type to an intermediate node (attribute). This configuration is referred to as *attributional similarity*, which is key to a better explanation of the analogy.

In any case, the more semantically precise the relation type, the more useful that type is in explaining the analogy as a whole. The overall strength of the analogy could correspond to the average of all the relational and attributional similarities weights. This currently makes it possible to elect the candidate(s) proving to be the most appropriate for a given metaphor (a hole analogy with a single unknown) in 37% of cases with a simple algorithm (constituting our baseline). However, a more precise aggregation of the different similarity scores would make it possible to take into account the nuances carried by each type of relationship; reason why the definition of this aggregation method represents one of the central aspects of our research. By definition, figurative language is subject to interpretation; the same analogy or its explanation can turn out to be more or less telling depending on the angle from which the explanation is approached. The goal of an automatic analyzer is to highlight what can most be considered a convincing or satisfactory interpretation (subjective concepts) for a given analogy. In the state of the art, it should be noted that the subject is often treated through theoretical and linguistic points of view rather than in computational and applied work.

This work aims to produce a resolution model but will also serve as a tool for identifying anomalies in the knowledge base (imperfect and incomplete by nature). Any shortcomings will be highlighted by cases of algorithm failure and will make it possible to consolidate the appropriate types of relationships. One avenue for future research could then be to design a game (with a purpose) on the intersections of associations to broaden the knowledge base in this regard.

5 Conclusions and future work

We have presented our work on the automated treatment of metaphors and analogies in natural language, using the knowledge graph of JeuxDeMots to generate plausible solution, and providing a prototype solver. We have also presented some promising preliminary results of our approach.

In the future, we will first extend our approach to incorporate word sense disambiguation, then look at different methods for detecting and resolving metaphors in their linguistic context.

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