A Post-Modern Approach to Automatic Metaphor Identification

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Abstract
This paper provides the theoretical bases for a symbolic approach to text classification, particularly metaphor identification, that generalizes the existing ones and is inspired by similar generalizations of symbolic approaches to learning models for non-text-related tasks.

Keywords
Automatic metaphor detection and interpretation, Symbolic learning, NLP, Modal logic

1. Introduction

Metaphors involve talking and, potentially, thinking of one thing in terms of another; the two things are different, but we can perceive sets of correspondences between them. In other words, a metaphor corresponds to using a word or phrase from the context in which it is expected to occur to another context, where it is not expected to occur [1]. Metaphors are ubiquitous in language [2]: they cannot only be considered a pure artistic ornament that exclusively pertains to literary discourse, but they are essential for the development of language and culture [3, 4, 5].

Much work has been devoted to discussing the metaphor identification and interpretation process, as in [6]. In this sense, a qualitative approach represents the safest methodology since metaphors regard an aspect of language that occasionally can be ambiguous. For example, two speakers from the same linguistic and cultural context can interpret the same metaphor differently. However, this approach is time-consuming and requires at least more than two human coders to be effectively reliable. Despite this phenomenon, it remains a computationally hard task given the many structural problems that make automatic identification not quickly effective [7]. Scholars between digital humanities and computational linguistics have developed different approaches to support automatic identification. Indeed, the recent improvements regarding artificial intelligence and machine learning might consistently impact metaphor research regarding the time and quantity of analyzed text [8].

From a computational point of view, metaphor identification is a particular case of text classification. The recent literature on general text classification, particularly metaphor identification, is quite broad and includes both *top-down* approaches [9] and *bottom-up* ones. Top-down approaches start from a human-designed theory of the phenomenon, which is later digitalized to provide automatic identification. Bottom-up, or *data-driven* ones, on the other hand, aim to perform identification starting from a dataset of examples. Bottom-up strategies can be, in turn, separated into *symbolic* and *sub-symbolic* approaches. Sub-symbolic approaches, commonly realized via several types of neural networks, produce black-box models which in some cases can be very accurate [10]. Along with the application of pre-trained and large language models they currently are a de-facto standard for text-related learning tasks, and quite a lot of results exist even in the narrow field of metaphor identification (see, among many others, [11, 10, 12, 13, 14]). Conversely, the purpose of a symbolic approach is to provide an identification model *and* a statistically validated theory of the phenomenon, written in a suitable logical language. While symbolic systems are sometimes used for text-related tasks in general, their application to the case of metaphor identification needs to be addressed.

In this paper, we provide the theoretical bases for a symbolic approach to text classification, particularly metaphor identification, that generalizes the existing ones and is inspired by similar generalizations of symbolic approaches to learning models for non-text-related tasks.

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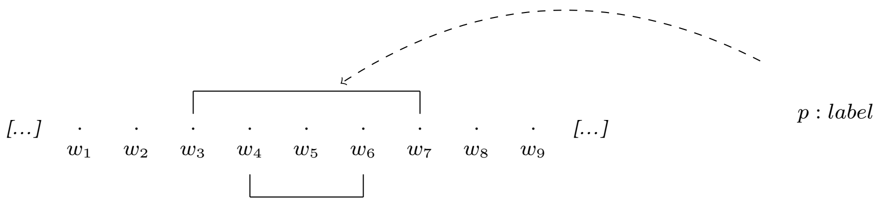

Figure 1: Example of generalized 2-gram.

2. A Logic-Based Post-Modern Approach

Symbolic and sub-symbolic approaches to text-related tasks are different in spirit. In both cases, the key idea is to provide a representation of the text later used for learning. However, in the case of sub-symbolic strategies, such a representation, usually referred to as *embedding*, is numerical. The most famous examples of sub-symbolic representations are (all variants of) *vectorizations* of tokens (i.e., words, sentences, or paragraphs). Each token is mapped to a point of a high-dimensional space so that mathematical tools can be used to reason about texts, and a learned model, for example, for metaphor identification, takes the form of a mathematical function.

In symbolic approaches, on the other hand, we encode a token (typically, an entire sentence or paragraph) as a logical model. In the most uncomplicated cases, following the so-called *bag-of-words* methodology, a text is encoded starting from a fixed (arbitrarily long) dictionary; it is translated into a binary vector of length N, being N the size of the dictionary, where the i-th component takes the value 1 if and only if the i-th word of the dictionary occurs in the text. Text-based encodings are easily generalized along two directions: bag-of-words become *bag-of-n-grams*, and vector components become counters so that the i-th component takes value m if and only if the i-th n-gram of the fixed n-grams vocabulary occurs exactly m times in the text (in this context, n-grams are not used in their canonical, probabilistic version, that is, to predict the n-th element from the previous $n-1$ ones, but, instead, in their crisp one, that is, a straightforward generalization of single words). In most cases, the experiments show that using 2-grams attain the best compromise between the computational complexity of the tasks and the performances of the learned models. The logical interpretation of symbolic encoding emerges by introducing propositional letters to represent the text by the presence of relevant n-grams. Simplifying, a symbolic encoding classification model can be described by (sets of) rule(s) of the type:

If 'flood of immigrants' occurs then metaphor.

In the above example, *'flood of immigrants'* is a 2-gram (before tokenization, stemming, and stop words elimination), and the rule that has been learned checks whether or not that particular 2-gram occurs. Towards an abstract representation, 2-grams can be encoded into propositional letters, which can represent not only their occurrence but also other interesting properties, such as the number of times that they occur. In the end, a text is represented as a model of propositional logic, and a (set of) propositional rule(s) can be statistically learned from a dataset of texts.

A further generalization of symbolic text-based encodings requires two steps: generalizing the concepts of n-gram and increasing the expressive power of the logic that we use to describe texts. Both ideas are simple. Focusing on 2-grams, specifically, the most natural generalization consists of eliminating the constraint of two words being one next to the other to form a 2-gram. So a *generalized* 2*-gram* can be defined as any pair of successive, non-consecutive words. Such a generalization has two main consequences: first, the label of a generalized 2-gram may be much richer than the label of a standard one, and second, the encoding of a text using generalized 2-grams can be much more expressive than the encoding of the same text using standard ones.

Let us focus on labeling. As explained above, a standard 2-gram is logically labeled using (the number of times) that it *occurs*. A generalized 2-gram, on the other hand, can be labeled using the occurrences of the words in between. In Fig. 1, we see the abstract idea of a generalized 2-gram: the pair of words w_3, w_7 form a generalized 2-gram (they are two, possibly non-consecutive, words) and, in the encoding, they are represented by a propositional letter (in the example, p). The meaning of such a propositional letter is no longer limited to depend on the occurrence of w_3, w_7, either separately or together. On the contrary, one can use the entire sentence between w_3 and w_7 to build p; examples may range from the topic of the sentence, to its length, the semantic category of any word between the extremes of the generalizes 2-gram, and so on.

Concerning the expressive power of the encoding, *These people. They arrive forming a continuous wave, an endless flow that changes societies at all levels, swirling together different and irreconcilable cultures. These are the migrants, often considered a problem.*

$$\langle L\rangle(\text{topic 'migrants'} \wedge \langle D\rangle\text{topic 'fluid'})$$
$$\Downarrow$$
metaphor

These people, the migrants, arrive on dilapidated boats at the mercy of the waves and flows. They risk their lives and when they arrive they are often rejected, because, it is believed, they risk changing societies at all levels, including cultural ones.

$$\langle L\rangle(\text{topic 'migrants'} \wedge \neg[D]\text{topic 'fluid'})$$
$$\Downarrow$$
not a metaphor

Figure 2: Example of generalized 2-grams in text, and of metaphor identification via their qualitative relationship.

now observe that in the standard text-based approaches, the relative ordering of the original sentences is lost, while only the order of constituents of each n-words is preserved. Generalized 2-words, instead, are naturally linked to a qualitative, more-than-propositional logic that allows one to preserve the ordering in a very expressive way. The key idea is that a sentence can be seen as a *linearly ordered* sequence of words, which entails, in turn, a *temporal order*, as also proposed in other models, such as BiLSTMs [15, 16]. Thus, a generalized 2-words is an *interval* in such a order, and any two intervals on a linear order can be qualitatively related to each other in exactly one of thirteen ways. The family of logics that allow one to describe propositional properties of intervals on a linear order is called *interval temporal logics*, and they belong to the more general category of *modal logics*. Originally studied by Allen in the early 80s, interval temporal logic have been formalizes a few years later, and the most representative language for expressing propositional properties of intervals is the *modal logic of time intervals*, or HS [17]. In HS, each of the possible binary relations that may exist between two intervals becomes an accessibility relation; it can be immediately verified that they are, in fact, thirteen: *after* (capturing an interval that starts at the end of the current one, usually denoted by $\langle A\rangle$), *later* (capturing an interval that starts past the end of the current one, $\langle L\rangle$), *overlaps* (capturing an interval that starts during the current one and ending after it, $\langle D\rangle$), *during* (capturing an interval that starts and ends within the current one, $\langle D\rangle$), *begins* (capturing an interval that starts at the start of the current one and ends before it, $\langle B\rangle$), and *ends* (capturing an interval that starts within the current one and ends with it, $\langle E\rangle$). Working with the relations/operators as they were originally introduced may not be always suitable; interval temporal logics such as HS have been simplified for specific tasks in several ways. Among them, the most relevant proposals include the so-called *topological* versions of interval temporal logic, in which the relations are, in fact, disjunctions of Allen's relations. So, for example, in the case of HS_3 [18], two intervals can just *have at least one point in common* or can be *completely separated*; languages such as this one may in fact be designed, and its expressive power be modulated, depending on the task. Symbolic learning algorithms for interval temporal logic have been recently studied [19] and used for learning interval temporal properties in very different contexts, mostly, but not exclusively, in the medical sciences (see [20, 21], among others); in those cases, the object being encoded are multi-variate temporal series, via a process that eventually produces interval temporal models from which rules are ultimately learned. It is of notice how such diverse contexts, including text-related tasks, can in fact be approached with the same methodology. Continuing with the example in Fig. 1, the generalized 2-gram w_4, w_6 is *during* the generalized 2-gram w_3, w_7

In Fig. 2, we show how, in a text, relevant generalized 2-grams are identified; in both texts, two generalized 2-grams are identified. Focusing on the top paragraph, the first generalized 2-gram, in red color, is captured by the words *people* and *migrants*; the entire text in between (even ignoring the full stop, thus ignoring that they belong to two different sentences) is categorized as *topic 'migrants'*, thus imitating a human reader who, reading the complete text, can identify when the writer starts referring to some category of persons, when he/she stops doing that, and which one this category is. The second generalized 2-gram, in blue color, is captured by the words *wave* and *swirling*, and the entire text in between is categorized as *topic 'fluid'* (observe the frequencies of words that refer to fluids, and water in particular, that occur in the blue-highlighted text). The bottom paragraph shows similar words in a similar but identical order. Both topics are still present and identified in the same way. However, the two topics are in a different topological order. On the right-hand side, we propose a possible rule linking the topics' topological order to distinguish between metaphoric and non-metaphoric text written in propositional HS. Most interestingly, ChatGPT (version 3.5, consulted on the prompt in September 2023) classifies both texts as metaphoric, probably because metaphors linking fluids and migrants are statistically common.

3. Conclusions

This work represents an initial attempt to approach symbolic learning for text-related tasks like metaphor detection. A symbolic approach can extract a theory from a specific linguistic phenomenon, which raises at least three problems: first, determining whether a theory of a phenomenon should exist and in what terms; second, finding the appropriate logic for the extraction process; and third, ensuring the existence of an automatic method for extracting the theory in that logic. In this work, we have attempted to address the first and second points, and we did so using a logical formalism for which a solution to the third one already exists. Should this approach be successful, it can be used to address other text-related challenges, such as all variants of text classification. Additionally, our generalized 2-gram encoding can be further generalized to partially benefit from well-known word-to-vec approaches without compromising its symbolic essence.

We will further verify our hypotheses by conducting some tests on an annotated newspaper corpus, which was human-labeled as *metaphor* or *non-metaphor*, consisting of 13,000 tokens and 2,000 different words. The label pertains to the entire text, and the task will regard recognizing its metaphoric expressions.

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