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Theoretical Linguistic Structures for Dealing with Treebanks in the Syntactic Context

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Abstract: The linguistic process involves symbols and interpretation, which are fundamental elements both in human language and machine language (be it supervised or unsupervised learning). Axiomatic and logical elements form the basis of language and give clues as to why syntactic parsing distorts rules of language. In this paper we discuss the possibility that syntax and semantics are side by side in the parsing, and the semantics must be in accordance with the dynamic structure of the language, and not decontextualized into label categories, which make the language static. It is also shown that the axiomatic-logical structure is the most adequate to avoid ambiguity in syntactic parsing in any conventional language.

Keywords: Language. Syntax. Semantics. Parsing. Ambiguity.

1 Introduction

Language is a phenomenon resulting from a symbolic process [1, 2], it consists of a structure that intermediates contextual reality and the human mind [3]. It involves symbols and interpretation and these elements are common to the human linguistic process and, also, to language from a computational perspective; it can be deduced, then, that there is something common to both languages: a universal structure . In their theoretical model, [4–7] the Authors have shown that the structure of language, either biological or computational, it is axiomatic-logical. It is not surprising that some authors [8–10] when writing about artificial intelligence are between choosing the symbolic paradigm based on logic or the connectionist paradigm. The logical characteristic of the linguistic structure is able to generalize logical representations [8, 11], whereas its axiomatic characteristic is based on inputs [12, 13]. According to [14, p. 330], memories potentially increase a system's adaptability, increasing its complexity and, therefore, the potential proximity of 'correspondence' between the system's environment model and the environment itself (infinitely complex). According to [8, p. 854] language is fault tolerant and exhibits the ability to learn from experience. Then, the ideal way to combine logical and axiomatic characteristics in hybrid systems [8–10] is sought in order to achieve the state of the art in artificial intelligence research, artificial intelligence (AI). The main purpose of this article is to outline theoretical structures of linguistics and neurolinguistics that help to deal with treebanks in the syntactic context of any spoken language. For this, it is assumed that language is a process [6, 15], that reflects elements of thought and intelligence [6, 13, 16]. The content of this article describes linguistic bases for dealing with treebanks in syntactic contexts, presented in the following order: Section 2 explains the existence of a language structure common to man and machine, which should serve as a strategy to include semantic and contextual aspects in the analysis of text collections. Then, section 3 shows Language as a dynamic connected and invariant process, which is well represented by neural networks. Syntactic parsing is explored in section 4 to show that researchers carry out analyzes based on statistical training associated with analysis techniques based on the rules of spoken languages. This produces changes in the logical relationship between words and distortion of the traditional formal grammar. The conclusion is given in section 5, by showing that exploring the semantics (for syntactic parsing) through the description of fixed context categories freezes the

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semantics, distancing the analysis of the language dynamic behavior. It is also suggested that semantics and syntax should be evaluated at the same time under a dynamic concept, suitable for neural networks.

2 Natural language dimension for AI

Natural language processing in the field of computing is conceived as something distinct from human language [17]. We intend to show in this article that language is not a substance, but it is a form [15], showing that language, whether biological or computational, has a common structure to both [7], either considering the language used by humans to communicate or by the elements of computer systems that try to emulate humans by understanding or generating it. The contrast that researchers find in biological or computational language is due to the fact that a limited starting point is used in computer programming, that is, experts in machine learning take for granted that biological language is reduced to a set of grammatical rules that standardize speech and writing, forgetting that human language is a special dynamic system [5–7, 18], where dynamic should be intended as the characteristic feature of a process (substance evolving in time). When artificial intelligence deals with a set formed by varieties of conventional languages taking them as natural language, many obstacles happen in the computational processing of these languages during the search for a pattern for the different regulations to which they are subject. If the objective of artificial intelligence is to correlate biological and dynamic language to something corresponding in machine learning, a common, universal structure [5–7, 18] should be sought, which establishes a dialogue between both like e.g. what we call the axiomatic-logical structure.

2.1 The axiomatic-logical structure of language

> *The will is infinite and the execution confined, The desire is boundless and the act a slave to limit.* (Cesàro, 1905)

Among the various arguments in favor of the axiomatic-logical structure of language, we recall Joseph Weizenbaum's ELIZA program [19, p. 2016], designed to imitate a psychiatrist. Human language presents, as ELIZA, a logical aspect, a pre-programmed functioning, based on the methodologies and principles that govern the branches of science [7]. However, it is not limited to this logical characteristic, human language can unfold in unpredictable situations and responses [20]. As long as the focus of machine translation is on combining user inputs with stored patterns, patterns will return between input and output, such as ELIZA [21] that achieved stereotyped results, and, also, the failed version that intelligence artificial made from the book Harry Potter [22]:

> "What about Ron magic?" Offered Ron. To Harry, Ron was a loud, slow, and soft bird. Harry did not like to think about birds. "Death Eaters are on top of the castle!" Ron bleated, quivering. Ron was going to be spiders. He just was. He wasn't proud of that, but it was going to be hard to not have spiders all over his body after all is said and done. [22, Chp. 13]

Many researchers have bet on some aspects of linguistic processing to disambiguate the word [23–25]. Much was invested, among others, in the associative processes of the brain that made nouns correspond to a network of concepts [26]; in 'semantic memory' [27]; in the inferential answer to questions [28] dependent on a stock of prototypical forms of complex events. Recent research moves away from traditional text representation approaches, in search of strategies that include semantic and contextual aspects of the analyzed text collections [29], or in seeking for neural network models, like the coreference resolution [30] aiming to find in a text all the mentions that identify the same entity in the real world, under an end-to-end neural reference model to consider all excerpts of text in a document as potential mentions and learns to link a background to each possible mention. Research [31] has also been found in which the sequences of supervised learning from recurrent neural networks were highlighted. The sequence-to-sequence structure seeks to efficiently represent the joint sequence probability. Problems were found in inputs and / or outputs of variable size, not classified as sequences, making the task of organizing the results corresponding to random variables difficult. What we seek to argue with the random citation of these researches is the utility of knowledge of the axiomatic-logical concept of language [5–7], that is, for better analysis results in computing tasks, the strategy would be to combine models based on logic (conventional language as a set of rules) to models based on the axiomatic (biological) aspect of human language, as a dynamic system, being better represented by neural networks.

2.2 Human linguistic process model

Language is not taken as a substance, but as a process that goes from the input of stimuli in the human body until the latter are translated into information in the central cognitive system [7]. This path that the stimulus takes until it is transformed into intelligible information needs to be the source of inspiration for artificial intelligence in its search for the state of the art. In this way, it is proposed that computational processing strategies are based on hybrid models articulating axiomatic and logical aspects of language. What is proposed in this topic is not 'the' algorithm that will solve all challenges, but the structural (universal) relationship of language (understood as a process and not as a substance) to be considered in the construction of algorithms for machine learning. The language understood as a process comes from Saussure (1916) and although he dealt only with writing, in this article, we extend this concept to the entire human linguistic process. For this reason, logical (set of rules), biological (axiomatic; dynamic system) and social (social context) elements must be considered together in the study of language to design their treebanks in the syntactic context. The first thing, to be observed, is the scientific context from which the data will be taken, since the context is related to the value of the word used [32–35]. Although the structure is common, the language differs in values according to the branch of science: the methodology used in each of these branches directly interferes in the construction of meaning [32–36]. Therefore, the database should be built with elements from the same scientific branch [7], harmonizing interpretation with the methodology that guides this same branch of science. The value criteria are embedded in the axiomatic-logical structure of language, to organize ideas and words in terms of relationships and functions when building meaning (Monte-Serrat & Cattani, 2021). This mode of operation presents a narrative characteristic of a given field of science, which implies legitimacy [32, 37]. Language is a process in which symbols (gestures, letters, numbers) are manipulated so that there is intermediation between the real world and the human mind, which means that there is a human being manipulating interpretation. The theory of the Abstract Meaning Representation, (AMR) [38], suggests abstraction, the absence of manipulation of symbols for the formation of meanings through computer programming. What this AMR theory suggests is not in line with human linguistic functioning, which, when forming meaning, contextualizes it [7, 36]. If the context is detached from the formation of meaning, or if there is a list of possible labels [38, p. 178] previously established for syntactic treebanks, the construction of meaning will be slave to limit, will have its execution confined [39], giving occasion to ambiguity. How to apply this knowledge to the encoding and decoding of information? In this case, the symbolic structure of AI must imitate the cognitive process whose layers are connected and invariable to the input transformations. Therefore, research in language that deals with neural networks reaches a score closer to the state of the art. We emphasize that only neural networks are not enough, because the universal structure of language is axiomatic (dynamic) and logical (static). The linguistic process is developed by interlinking axiomatic, biological and logical elements to, in the end, build meaning

3 Language as a connected and invariant process

We propose as a dimension of natural language for AI, that axiomatic elements be related to logical elements. The logical characteristic of language has the principle "if P then Q" [4, 40]; it is a static concept of language. This front of human language establishes a correspondence (or association) relationship between the elements of an initial set and a final set. This correspondence (of elements with other elements), when defined, is denoted by an ordered pair. Once the logical elements of language are matched, a structure overlaps those sets that will restrict this relationship. A class of these structures is the function class, whose application is necessary based on the dynamic concept of language, suitable for tree structures. In the latter case, the function establishes the relationship of a set with another set, establishing the domain, being well represented by the kernel method [41–43]. Decision trees applied to machine learning [44] bring the advantage of invariability in dimensioning and other transformations of resource values. We argue that the accuracy of these trees will be increased when they are based on the dynamic characteristic of language (axiomatic-logical) and not only in conventional language (static set of language rules). In machine learning, it is suggested that the kernel establish the connection between random forests and the kernel methods [41]. The link between the forest and the kernel favors the estimate of adaptation to the nearest neighbor [42]. In [43] the Authors show that the Random Forest Kernel has consistency rates that take it to the state of the art.

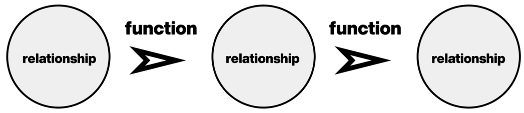

Fig. 1: *The correspondence between elements is established (logical relations of the rules of language). Overlapping these formed sets is another structure (functions) that will restrict the relationship of a set with another set, establishing the domain. This structure combining relationship and function is adapted to the difficulty found in increasing the scale, as it is understood that the referred structure circumvents the problem of 'knowledge acquisition bottleneck'.*

Emerging structures that focus on computational treatability of syntactic analysis together with the mapping of syntax to semantics are similar to the axiomatic-logical structure of language. According to the axiomatic-logical conception of language, the relationship between functions would be established in layers, looking like neural networks. Neural information processing has been gaining ground in natural language processing. In [45] the Authors extract the incorporation of an interpretable phrase by introducing self-attention to produce a significant performance gain compared to other phrase incorporation methods. They work with sequential data processing through language or translation models based on n- grams. The language or translation model based on n-grams [46, p.463] has the set of symbol strings partitioned according to a tree structure so that the later sharing corresponds to the previous one. In [46, p. 565-568] the Authors explain a model in which the direction is represented in the drawing with an arrow. One direction of the arrow indicates the probability of distribution of the sense, defined in terms of context (of the other).

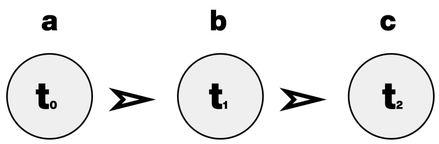

Fig. 2: *The language model by Goodfellow [46, p. 463] in which the later sharing corresponds to the previous one. The direction of the arrow indicates distribution of meaning so that the meaning in 'b' depends on the meaning value of 'a' and so on.*

The arrow drawn from 'a' to 'b' means the probability of building meaning in 'b' by means of a conditional distribution, with 'a' being one of the conditioning variables that build meaning. In other words, the distribution of meaning in 'b' depends on the meaning value of 'a'. This certainly reduces the number of parameters used, reducing the occurrence of ambiguities, determining the starting point of meaning and defining which variables are allowed as arguments. In [47] the Authors suggest dominant sequence transduction based on complex conventional or recurrent neural networks, connecting the encoder and decoder through attention mechanisms. [48] use two-layered superficial neural networks trained to reconstruct linguistic contexts of words, Word2vec, whose vector space houses each unique word in close proximity to other words that share common contexts in the corpus, measuring syntactic and semantic word similarities. In [8] the Authors propose a hybrid symbolic-connectionist system that combines symbolic approaches to connectionism, in which words within a sentence are represented by means of semantic resources encoded in network inputs.

4 Syntax and parsing

After seeing the structure of natural language (under a dynamic concept) and which computational treatment is most appropriate for this axiomatic-logical structure, we outline what syntax is before delving into the parsing and analysis of a conventional language. Traditional formal grammars focus on the logical structure of language, drawing clear limits for the formation of meaning. Occurs that the axiomatic element of language also interferes with the building of signification. Contextual interferences (such as regional variations, dialects, sloppy language with incorrect spelling and punctuation, hesitation in speech) act on that idealized grammar, distorting it, causing malformation of meaning or ambiguous phrases. Consequently, syntactic parsing must predict the variation provided by the axiomatic aspect of language to form the basic phrasal tree structure (see suggestions that work with neural networks in the previous topic). Statistical training associated with analysis techniques leads to results that modify the logical relationship between words, distorting the traditional formal grammar [16], even though the latter was developed with systematic and treatable variants by computationally oriented linguists. Chomsky's definition of context-free grammars [49, 50] provided simpler analysis. It was later proved [16, 51], however, that decontextualized Chomsky's transformational grammars resulted in computationally intractable languages. According to [16] traditional formal grammars are limited and rigid in the grammatical criteria to provide a basis of robust coverage of natural languages. In [16] the Author suggests, as a solution to the decontextualized text, the context-free and probabilistic grammars such as Penn Treebank, which provide a structural and also distributive model of language, predicting the ocurrence frequency of several phrases sequences. Even so, the analysis precision is not reached (regarding the probabilities of expansion for a certain type of phrase) due to disregarding the surrounding phrasal context and, also, the detailed properties (such as header words) of the generated constituents. In [16] the Author claims that the language distributive modeling needs to take into account the semantic content, (structure of speech, intentions in communication) and not just the structure of sentences. Goldberg asserts [51] that the conceptual basis for the construction of language statistical models must couple language patterns (common sentence structure, clichés and idioms) with their meanings and function in speech. Connectionist models that perform syntactic analysis using layered (artificial) neural networks (RNAs, NNs) [52] implement cooperation or competition between alternatives in a temporal sequence, which requires the retention of information about recently processed parts. Simple recurrent networks (SRNs) use one-to-one feedback connections from the hidden layer for special context units aligned with the previous layer, in effect storing their current outputs in those context units so that in the next cycle the hidden units use their outputs with new layers of inputs [16]. Connectionist models offer the challenge of an active entity not being linked to other activated entities [53]. The grammatical language taken as the basis of AI is structurally equivocal, leading to ambiguity at all structural levels, as pointed out by [16] when dealing with coping with syntactic ambiguity:

> at the level of speech sounds ('recognize speech' vs. 'wreck a nice beach'); morphology ('un-wrapped' vs. 'unwrap-ped'); word category (round as an adjective, noun, verb or adverb); compound word structure (wild goose chase); phrase category (nominal that-clause vs. relative clause in 'the idea that he is entertaining'); and modifier (or complement) attachment ('He hit the man with the baguette').

Understanding natural language comprehensively [7], in its complex dynamics, and not only accounting for its grammatical aspects, is a strategy that helps to analyze its requirements as raw data that will be transformed into resources. When one learns to define the typical pattern of natural language, it will be the basis that will guide the interpretability performed by the machine, reducing the possibilities of ambiguity. According to [5–7] the language structure is axiomatic-logical. Considered this way, the context is accounted for the meaning formation. This solution would lessen the ambiguity pointed out by Schubert [16] in the previous paragraph.

5 Conclusion

The construction of meaning is the goal of language [6, 54], which involves symbols and linguistic processes as elements that structure and design signification, better saying, that structure the idea transmitted or intended to be conveyed to the mind by language. As the syntax portrays only part of the signification process [16], specialists in machine learning also seek support in semantics, to give rise to the unequivocal generation of language. One of the theories that offer a solution to include semantic representation in data analysis is Abstract Meaning Representation, AMR [38], describing fixed categories of contexts. Banarescu [38] put labels for real situations, freezing the contexts and limiting the semantics. This solution is opposed to the dynamic functioning of language (axiomatic-logical), harming the result of the analyzes, which may present ambiguity or meaningless phrases. However, language should be considered in its complex dynamics, bringing advantages over the theory of AMR [38]. This broad and dynamic concept of language makes it possible for the analysis of language requirements to be done with raw data instead of based on static labels. It is under the dynamic pattern typical of human language that the transformation into resources must be defined, this procedure should serve as a guiding basis for the interpretability performed by the machine.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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