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Applicability of Emotion to Intelligent Systems

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Abstract: We propose to investigate the connection between emotions and cognition in intelligent systems through the dynamic concept of language, which links context to logic in both human and machine language. For this, our approach is inspired on aspects of the information theory of Abraham Moles. We analyze emotions under the semantic dimension, linked to a subjective context, which gives rise or not to decisions. We demonstrate that intelligent systems can, on the one hand, work with previously categorized emotions (say in a frozen context); or, on the other hand, process information under a dynamic aspect. This is possible when considering that the algorithm, as the core of the system's language, must be adapted to functions that reflect an updated context. Thus, adapting emotions to AI means working with time-dependent communication-interpretation, in an optimized way, uniting syntax and semantics in the intended behavior of the machine. We conclude that misinterpretations can be avoided by inserting a contextual appreciation together with a categorized appreciation of emotions at the heart of the system. This allows it to absorb pre-established values in a unified way with the fluid values of emotions, making the system more intuitive. It is believed that, in this way, Computational Linguistics is focused on the characteristics of Cognitive Computing, teaching the system to interpret the appropriate context of the emotion at stake.

Keywords: Computational Linguistics, emotion, intelligent systems, language,optimization.

1 Introduction

The third wave of Artificial Intelligence, AI, and Machine Learning, ML,[1] focuses, among other things, on AI interpretability and decision making. The representation of human reasoning aiming the interpretation task done by the systems is the basis of cognitive computing. An example of this is deep learning that integrates neural systems with symbolic systems [2] in search of solutions that explain symbolic representations for network models.

In this article we relate the human linguistic process to the linguistic process in AI to identify the main ingredients that must constitute the neuro-symbolic bases of the interpretive or decision-making process, which overlaps in human and machine language [3]. Based on the human cognitive-linguistic process - endowed with symbolic representation (representation of linguistic information through symbols and not measures) with the potential to be allied to semantics and emotions - it is possible to learn lessons about the representations used in computational linguistics and go beyond. The fact that we link symbolic information to emotions, for example, directs computational linguistics to cognitive computing, precisely because it explores the discursive layer of human language.

Aware that it is very difficult to explain reason processing in artificial neural networks and inspired by the work of Santos and colleagues [4,5,6] on the empirical study of emotions in Portuguese, we explore some principles of machine learning based on neural networks.

Neurolinguistic principles govern interpretation and decision making [3,7]; the semantic dimension to which they are subject derives not only from syntactic logic, but also from the context (which can encompass emotion among other elements), making information the product of a dynamic process of language [3,7,8], and not the portrait of a static substance (set of signs).

These principles provide the basis for improving intelligent systems by involving semantics (emotions included in some cases) and statistics in forming a meaning with universal consistency. In this paper, universal consistency is opposed to the concept of ideal consistency based on the evaluation of a set of previously established data or a manipulated context, which may give rise to biases in interpretation [7,9]. It is proposed to

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adapt to the machine the way emotions are processed by human language through representation, which makes ML consider some contexts beyond logical reasoning, acquiring specificities of the intuitiveness of the human mind. It is hoped that the insights provided here can shed new light on the increasingly prominent role of intelligent neuro-symbolic systems coupled with data enriched with contextual information (emotions included). We know, however, that there are still many challenges for AI research that address the diverse perspectives provided by neuro-symbolic systems.

This article discusses interpretation in the dynamics of human language, identifying the bases of the interpretive or decision-making process, be them processed by human or machine language. Human linguistic process teaches us that the semantic dimension does not derive only from syntactic logic, but also from context, which can encompass emotion among other elements.

It is proposed to adapt the way emotions are processed by human language to the machine to acquire specificities of the intuitiveness of the human mind. The content of this article is organized into 8 sessions. Section 2 deals with emotions and their importance for intelligent systems, explaining that the human linguistic process captures stimuli (emotions included) through subsystems and carries them to the central cognitive system. If systems work with a frozen approach to emotion, they will not reflect the variety of expression of emotion in different cultures. It is proposed that, since emotions are cognitive responses or neurophysiological actions, this dynamic aspect of them cannot be ignored by AI, which must work with time-dependent communication-interpretation, that is, in an optimized way. Natural intelligence as a structural model to relate emotions with Artificial Intelligence is the subject of Section 3, which discards the studies of syntax separate from semantics, claiming that the latter underpins intelligence and must be replicated for AI, which must have a mechanism for understanding of abstract objects, events, and ideas, and to represent instincts and emotions. The content of Section 4 deals with the artificial language of intelligent systems, explaining that the challenge of these systems to process semantically valuable information depends not only on the algorithms, but also on principles that explain "how" the intended behavior of an algorithm happens. For this, the fundamentals of human language are unraveled, presenting axiomatic (contextual) and logical characteristics that overlap in the cognitive architecture of biological and intelligent systems. Section 5 relates machine language to human language, detailing rules and conditions for the dynamic functioning of language to produce intuitive and quick solutions: synchrony of the cognitive (biological) system with the structure of language as a convention (set of rules), giving rise to a specialized organization of brain connections to generate an increasing order of instances within a dynamic system. This reveals the existence of a structural core underlying the connectivity between neural networks, whose role is to integrate cognition into the linguistic process. The explanation that language is a form and not a substance in Section 6, considering thought (formalism) and society (context) synchronized under a single core of language, prepares Section 7, which details the reasons to apply emotion to intelligent systems. The central nervous system, CNS, receives and processes sensory information to create appropriate responses. CNS is the site of emotion, memory, cognition, and learning. Its functioning must be mimicked by AI to optimize information processing. Cultural differences put obstacles to a "common" categorization of the group leading the system to errors in interpretation. To circumvent this difficulty, we propose strategies on 'how' to search for the appropriate meaning for a given context by performing the interpretive task properly, instilling in the system a contextual appreciation along with a categorized appreciation of emotions. The adequacy of emotions to intelligent systems must be performed simultaneously in two perspectives: under categorizations (conventional language) and under relationships (dynamic linguistic process), making different computational approaches to effective linguistics. Section 8 supports the conclusion that the dynamic concept of language (as an axiomatic/contextual and logical linguistic process) is suitable for working with emotions in intelligent systems because it shelters categorizations and adapts the contextual varieties of emotions. The dynamic concept of language incorporates pre-established values and fluid values resulting from relationships, which increases the systems' interpretive capacity, making them intuitive and capable of absorbing values and contexts simultaneously. In this way, Computational Linguistics is directed towards the characteristics of Cognitive Computing, teaching the system to interpret the appropriate context of the emotion at stake.

2 Emotions and their importance for intelligent systems

Intelligence results from the linguistic process, which captures stimuli (emotions included) through subsystems and carries them to the central cognitive system, which organizes them [8,10,3] into information that can give rise to decision-making. Understood as a 'process' (which we conventionally call natural language or human language) and not as a 'substance' (which we conventionally call languages spoken around the world), language has a structure shared between humans and machines, which makes systems equipped with language and intelligence and capable of generating information or decision-making as humans do.

As they are part of the linguistic process [3], emotions are formalized in spoken language (conventional language) [5]. Santos and Maia [5] give examples of computational resources, presenting an overview of emotion processing and stating that the variety of languages and cultures makes a universal approach impossible. Monte-Serrat and Cattani [3] focus on the relationship between emotion and the linguistic process (language as a form and not a substance), explaining how emotion interferes with the processing of stimuli collected by subsystems until they are organized by the central nervous system, falling into a logical chain that generates meaning/information [3,7,8]. Schacter [11] state that emotion is understood as responses to significant internal and external events, understanding it, therefore, as the cognitive process consequence. According to Fox [12], emotions constitute a set of verbal, physiological, behavioral or neural responses. They may involve responding to a trigger, according to Doux [13]; they can constitute mental states triggered by neurophysiological action according to Panksepp, [**?**],Damasio [15], Ekman [16], Canabac [17]; or they may even be associated with creativity as stated by Averill [18].

Since the approach of this paper is about the 'applicability' of emotions to intelligent systems, they are considered as a dynamic response to external stimuli. This is a form of human communication that cannot be neglected regarding Artificial Intelligence, as they reflect the interpretative skill that humans perform connected to external stimuli. When individuals are under stress due to love, fear, anger, these feelings are communicated to people through physiological-chemical signals from the body. This is the aspect of emotion linked to natural language (linguistic processing of emotion). Emotions establish complexity in conventional language (spoken languages), although they are a simple way for people to communicate by expressing them. The interpretation of emotions by the other, on the other hand, can be a difficult task. Example of that is the case of some people being more intuitive to understand emotions than others; or the case of emotions varying in different cultures [5]. Probably in a primitive society whose context of life experiences was equally simple, emotions could be more clearly shared and understood. Apparently, the primitive phonemes and short sounds were used to show anger or fear and that was enough. Even animals share some sounds with nearby individuals to communicate their emotions. The multiplicity of cultures has made language processing more complex. This increase in the social context is reflected even in the meanings of emotions:

> Other relevant issues are irony and sarcasm, especially prevalent in Twitter comments and blogs, phenomena which cannot, by definition, be identified literally. One has to know the overall feeling towards a particular event or personality, and/or interpret it together with the increasingly frequent emoticons that may signal a joke or irony. [5]

The processing of emotion by the human linguistic system (natural language) makes emotions acquire dynamic aspects when shared. Natural language is a dynamic process by which emotions and feelings are shared. This makes both a physical event (communication-interpretation) time-dependent, in the sense that it is used in such a way that interpretation by others would be done in the shortest possible time. From a logical-mathematical point of view, this can be thought of as a communication-interpretation optimization process in which the "objective function" is maximized in the minimum time (min-max process), that is, for people to understand the maximum they can (max) within a minimum time (min).

Adapting a system to understand human language (natural language) becomes a difficult task if we do not know 'how' this language works in its dynamics. An observation that must be considered initially is the difference between the concepts of language as a process and conventional languages spoken in the world. "Different languages (and cultures) embody different data, categories, and assumptions" [19] (p. 10). They originate from rules considered static if compared to the linguistic process, defined as follows:

> Natural language is a dynamic process in which an axiomatic-logical structure is related to reasoning (sign to sign within a closed system relationship); to the body (biological substrate linked to a symbolic system that distinguishes the body itself from externality); and to the social context (which has the role of building the self, a form of mental integration). The human cognitive system (natural intelligence) unites the biological system with the symbolic as any process that goes from the input of a stimulus taken as the starting point of a thought, a belief, and an output of perception resulting from it. Artificial intelligence and cognitive computing must take this union into account because the mind is relational, it works according to a functional hierarchy to build the process of understanding. [20] (abstract Ch 3,pp.17-70)

Working with emotion in Artificial Intelligence, AI, makes the task of adapting natural language to the machine even more complex while linked to cognition, imagination, wisdom, creativity, skills, cunning [19].

Since emotions involve cognition [13, 19] responses to events [11] and that these responses can be behavioral [12] and associated with creativity [18], it is necessary - based on the dynamic structure of natural language described above [3] -, to explain, albeit succinctly, that decision-making and cognitive processes can occur in different realities: virtual and real ones [23].

The foundations of the linguistic process (axiomatic/contextual and logical) [3] make it clear that the production of meaning can be, on the one hand, guided by (virtual) conditions previously placed (that is, under logical conditions that anticipate a truth "if P then Q") [21], which happens detached from their environment [22] (pp. 162-163). Or, on the other hand, the production of meaning may be unpredictable, not embracing the logical principle of bivalence (False versus True), interfering with the complex decision-making phenomenon, which may encompass intuitiveness [23, 24]. Summarization can be an example of opinion-gathering targeting where some facets of a product are previously assumed to be important (virtual reality). Public opinion is not about 'evaluating what is important', but 'evaluating what has already been considered important'. In this case, it can be said that there is an idealization of the context in which what is considered important is taken for granted, which in some cases can generate an interpretive bias.

3 Natural intelligence as a structural model to relate emotions to Artificial Intelligence

Ellis [25] states that since the time when [26] Chomsky published on syntactic structures, research in linguistics has turned to the studies of syntax. Chomsky's generative grammar teaches that to understand language it is necessary to study syntax in addition to semantics. Ellis [25] criticizes Chomsky for arguing that the theory of language goes beyond a theory of syntax, which disregards semantic content, making research on language counterproductive. According to Ellis [25] grammar and lexicon represent a continuum of meaning and that language and philosophy have been seriously restricted by inadequate theories. This author [25] relies on philosophy to state that the fundamental aspect of language is not communication, but categorization, which gives clues to understanding the purpose of language.

This article, instead of considering philosophy or categorizations as criteria to conceptualize language, seeks, in the functioning of natural language [3], tips and ways to think about language as a dynamic process linked to cognition, which makes the construction of understanding complex. The dynamic concept of language can be abstracted into an ethereal algorithm [3] that describes "how" natural language operates the interpretation: complex biological systems, that absorb the stimuli to which the human body is exposed, take these stimuli to a central system that 'translates' them so that the individual understands them.

It is a complex living system whose parts interact to generate a new quality of behavior, such as emotions, actions, understanding. Once this ethereal algorithm is understood, it can be replicated for Artificial Intelligence, as natural and artificial intelligence share the language universal structure [3]. Developing our understanding on machine learning involves unraveling the principles that underlie intelligence [27]. When the constitutional characteristics of intelligence are present in the machine's algorithm, the latter will present an intuitive or optimized performance.

Natural intelligence performs higher-level and lower-level bidirectional functional interactions [28]. Sometimes a higher-level model unifies lower-level models to create a more abstract and general concept, characterizing natural intelligence as: i) The mechanism for understanding abstract objects, events, and ideas; ii) instincts, as a mechanism for measuring important vital parameters; iii) emotions, which communicate instinctual needs to the mechanisms of understanding of conceptual recognition [3] (p. 40). There is a hierarchical structure that governs cognition and behavior (decision making), [3, 29].

4 Natural language of intelligent systems

Artificial Intelligence, AI, and intelligent systems are taken synonyms in this paper. Santos [19] notes that machines and humans considered intelligent can fail if the understanding of the principles is based on mistaken ideas or facts, as is the case with the visual identification of cancerous tissue: previously requiring specific training of medical staff, this activity was partially assumed by image recognition systems built on machine learning over large amounts of data. However, the system can err when evaluating images produced by a different vendor, something that would not deceive a human, as stated by Santos [19]. Machine learning, in this example [19], did not work with the real environment (axiomatic feature of natural language) that relates the exam to a person with cancer, instead it was exposed to statistical analysis (detached from the real context) to analyze the images under a virtual appreciation of quantity. In other words, the axiomatic (contextual) aspect was not inserted in the algorithm design, giving the analysis a virtual aspect based on quantities of images detached from their context, leaving the intuitiveness of the intelligence impaired [7] [7] by neglecting the operating language value structures [29].

The challenge for intelligent systems to process semantically valuable information depends not only on the algorithms, but also on the principles that explain 'how' the intended behavior of the algorithm should occur. For this, Monte-Serrat and Cattani [3, 7] explain the foundations of human language to clarify that the combination between algorithms and natural language principles can be adapted to artificial intelligence. The authors [3, 7] identified a structure with axiomatic (contextual) and logical characteristics that overlap in the cognitive architecture of biological and intelligent systems. From this structure it is possible to understand which is the most suitable choice for an algorithm to offer optimized performance analysis.

The semantic dimension of human linguistics and computational linguistics need to be alert to the fact that language is established as a 'form' (dynamic/axiomatic process) and not just as a substance (a set of logically linked signs) [3, 7]. This understanding offers a basis for improving systems by providing them with consistency and bias reduction in the interpretation of data. An example of bias caused by statistical analysis is the ”wisdom of the crowd”, as Santos [19] (p. 6) points out: the incorporation of words based on co-occurrence (the words stand out from the context that gave rise to their meaning, to adapt to a context of co-occurrence), which gives them an unstable meaning, dependent on the people group.

While statistics offer an idealized consistency (whose logic is based on the manipulated amount of data detached from their context), contextual semantics (axiomatic aspect of the language structure) analyzes data as they are presented in relation to their environment, giving rise to a good information classifier with acceptable performance that avoids semantic distortions [7].

5 Relating machine language to human language: foundation of rules and conditions for the dynamic functioning of the language

Information about the structure of human language transmitted to the design of intelligent systems is the essence of the concept of artificial intelligence, according to Goodfellow [27]. Inspired by natural language, the machine can produce intuitive and fast solutions in which an algorithm repeats patterns in new data. It is known that the human cognitive process is formed by several layers of biological subsystems densely connected and invariant to many input transformations [8]. This invariant is much sought after by cognitive computing in its attempts to reproduce strategies applied repeatedly to the various neural layers [27] (p. 365-366). So that these strategies can be understood and reproduced by computer technicians, it is suggested to start from the principle that language and cognition (both man and machine) share their foundations (axiomatic and logical at the same time) linked to a property of representation with the ability to specify a generalized function (model representation capability), serving as a framework to be applied in a specific circumstance [7,20] [20] (Ch 3).

Cognition connects neural network activity, cognitive science, and behavior with a focus on ’mental action’ or the ’process of acquiring knowledge and understanding’ [30] [30].

There is, therefore, a synergy that results from a single structure that triggers intellectual processes, such as attention, memory, judgment, emotion, evaluation, and decision-making. Monte-Serrat and Cattani [3] understand that cognition is not limited to mental processes but extends to the linguistic process (stimuli collected from the subsystems auditory, tactile, olfactory, visual, etc. as axiomatic characteristics of language integrating and building meanings) that transports stimuli to the central cognitive system, which organizes them (logical feature of language organizing meanings in a sequence).

Lenneberg [31] corroborates this idea by observing that there is a latent structure of cognition determined by the biological properties of the human being. This framework works on categorization based on operational characteristics of the brain’s data processing mechanism [31]: there is an underlying symbolic and structural mechanism in human beings (natural intelligence) linked to the development of spoken language and, in the absence of conditions to develop the latter, other capacities take their place, as in the case of the deaf and blind who develop language capacities in configurations of physical perception and stimuli.

Cognition, for Chardin [32] (p. 39) involves the perception of the world and its symbolization, corresponding to these two external and internal faces of the world to replace ’mechanical interaction’ with ’consciousness’.

Monte-Serrat and Cattani [3] describe this structure that mediates between external reality and the individual’s mind as having axiomatic-logical features. To describe it, the authors (op. cit.) relied on the information theory of Abraham Moles [33] : The symbolization mechanism carries different operators helping the brain to translate aspects of the physical world into information intelligible to the biological body. In this way, the axiomatic-logical structure of natural language provides two faces for natural intelligence: the process of construction of meaning by the cognitive (biological) system and, on the other hand, the information previously provided by the structure of language as a convention (set of rules), enabling a specialized organization of the brain’s connections to generate an increasing order of instances within a dynamic system, which becomes integrated into persuasion, information, understanding and so on. It is through this structure that human language performs the functions of a dynamic system, collecting stimuli from the environment through subsystems (tactile, auditory, visual, etc.) taking them to the central nervous system, which organizes them [10] (pp. 202-203). It is possible to infer the existence of a structural core underlying the connectivity between neural networks, which integrates the brain to the linguistic process: the axiomatic-logical architecture (natural language core) that acts in the formation of cognition and that goes beyond the general brain network.

6 Language as a form

‘Without language, there is no access to reality. Without language, there is no thought” [34] (p. 9). At the foundation of the science of Linguistics, Ferdinand de Saussure [35] abandoned speech and dedicated himself to studying writing. He had stated that ‘language is a form and not a substance’ [35] (p. 141).Understanding natural language as a form means, in this paper, considering thought (formalism) and society (context) synchronized under a single core of language that encompasses both a psychic and a social path [3].

Saussure [35] (p. 92) preferred to give attention to conventional language (set of necessary conventions) to preserve the scientific character of the linguistics. Other linguists followed this line, disregarding the semantics tied to the environment, although they themselves were aware that human language works under a universal framework in which our brain uses categories of representation when processing information [36,37,38,39] connecting the natural order of thoughts to the order of words, that is, they agree that there is an organizing process of communication [40].

7 Reasons to apply emotion to intelligent systems

Emotions and human language are part of a single system [3] (p. 44) that captures (inputs) stimuli outside the body and takes them to the central cognitive system (natural intelligence) enabling the human being to represent mentally those stimuli generating (output) an action, for example.

Copstead and Banasik [41] explain how natural intelligence works:

> The nervous system is traditionally divided into three principal anatomic units: the central nervous system (CNS), the peripheral nervous system (PNS), and the autonomic nervous system (ANS). These systems are not automatically or functionally distinct, and they work together as an integrated whole. Therefore, when function [...] the nervous system is more conveniently divided into sensory, motor, and higher brain functions.
> [...] The CNS includes the brain and the spinal cord. Its primary functions are receiving and processing sensory information and creating appropriate responses to be relayed to muscles and glands. It is the site of emotion, memory, cognition, and learning. The CNS is bathed in cerebrospinal fluid (CSF) [and] interacts with the neurons of PNS through synapses in the spinal cord and cranial nerve glia. The cranial and spinal nerves constitute the PNS. [41] (p. 858)

Emotions communicate through language when they are organized by the central nervous system, which gives humans a higher-level language compared to emotions expressed by animals. As social beings, individuals exchange information among themselves through conventions (logical aspect of human language), which makes language (conventional language/spoken languages) a clearer and faster means of communication. Sharing these linguistic conventions and rules optimizes the exchange of information in the sense of ”speeding up” communication. Emotions are categorized so that individuals share them more effectively within their social group. These categorizations of human experiences regularized for a given frozen context are informed to the systems that operate them satisfactorily.

However, when it comes to emotions, there is a very large variation of nuances and there are cultural differences that put obstacles to a common categorization of the group [5], leading the system to errors in interpretation. In this paper we offer suggestions for circumventing these interpretive impediments that cannot be resolved by logical categorizations of emotions. For this, we [29,3] present the dynamic concept of language in a synchronized combination between contextual/axiomatic and logical/categorization aspects, which makes systems more ‘intuitive’, leading them to learn ’how’ to search for the appropriate meaning for a given context. To give the machine intuitiveness is to give it optimization in the task of interpreting data that process emotions, for example.

> Operating values in the linguistic process is specially linked to cognition, since the meaning (that is a result of this operation) is an immediate and fundamental data of man’s experience with languages [42,43]. Identical linguistic (or sign) forms can have different meanings; different forms (signs) can refer to equivalent meanings [42,43]. This statement demonstrates that the linguistic process reveals partial autonomy in establishing correlations through its structures. A mathematical model can then limit the meaning to be designed on preestablished patterns (logical pattern) or it can be conditioned to the evaluation of the contextual pattern to construct the meaning. The semantics resulting from the human cognitive process is characterized, then, not only by logic, but also by principles that guide the transformation of the senses linked to biological stimuli [44,?]. This explains different semantic values for data collected out of context, conflicting with the values provided by the latter. [29] (p. 35)

Understood as a form, the language to be endowed to the machine is a dynamic language that carries characteristics of the environment rather than a language that aggregates meanings detached from their context (abstract meaning defined in dictionaries for example, which is frozen in a definition). Informing the context for the system involves linguistic-cognitive activity of that dynamic language core. As emotions and subjectivity are part of the context, its information or stimuli must be collected by the machine.

The reason for applying emotion to intelligent systems is not that the latter express emotions like humans do, but that they at least understand emotions by performing the interpretive task properly. As explained in the introduction to this article, emotion is part of cognition, and this makes decision-making systems more intuitive. Human intuitiveness is linked to system optimization. In other words, the emotion inserted into the algorithm provides cognitive resources to the machine, making it smarter. In this way the system's ability to integrate elements will operate at or above user expectations.

While the language processing logic feature works with categorized information sets, the optimization insertion demands the understanding of modeling issues in which technicians work by maximizing or minimizing some function in relation to a range of available choices for a given meaning. Thus comparing the different choices in order to find the best.

Setting up an optimization problem can help in the processing of emotions because they refer not only to the annotated corpora, but also to other devices existing in the language, that is, we will be working with the conventional language (languages spoken in the world) and with the processing linguistic (axiomatic feature of human language) at the same time. Speech devices, communicative patterns and gestures influence the transmission and excitement of emotions [5]. Santos and Maia [5] cite some strategies that aim to articulate emotional state to systems: Picard [45] deals with other inputs such as computer-enabled heightened perception; Schröder [**?**] (apud [5], p. 9) attempts around a framework that can handle manual annotation, automatic discovery, and generating emotional behavior.

Santos and Maia [5] (pp. 9-10) mention, for example, conventionalized body postures, ways of saying and colors associated with feelings as specificities that make the machine's task to express emotions more complex. The authors [5] (pp. 9-10) teach that decision-making such as "smiling, laughing, crying, screaming or frowning" are linked to emotions, evidencing the existence of disagreement between the meaning of these words in the lexicon (frozen sense) and their meaning assigned separately in labels that refer to particular affective states. Another important mention made by Santos and Maia [5] (p. 10) is that there are words that directly refer to emotions (happy, angry, sad) and others that, although not loaded with emotion, provoke emotions in the interlocutors (cancer, malignancy).

In view of the difficulties presented by applying emotions to the intelligent systems, it is proposed in this paper to work on language processing, simultaneously articulating the language dynamic front (which considers optimization techniques in the modeling), with the front of existing techniques (which deal with meanings linked to categorizations previously established by the computational linguistics). This synchronized articulation is based on the axiomatic-logical core of the human linguistic process [3].

The configuration of optimization in modeling is subject to questions such as: What emotional characteristics are advantageous or disadvantageous in a given context? What tools are available? How can emotion interpretation problems be usefully categorized? How can solutions be recognized and characterized? What ways of simplifying the concept of emotion are appropriate? How can different contextualized emotion assessment techniques be compared and evaluated? These and other questions that put in a hard spot the application of emotions to intelligent systems direct the work perspective to the dynamic core of human language that simultaneously articulates context with reasoning, inserting cognition in computational linguistics.

It is proposed, instead of 'special tools', 'structural strategies' that account for the combination of elements that develop optimization for the system. Thus, some ideas that will be dealt with here are suggestions for optimization areas. A first recommendation would be that the values of certain parameters could be collected already under some conditions that would determine the scope and interrelationships of the worked emotion. This choice then determines the values of other variables on which the final interpretation depends. We could bring the example of the word 'surprise' in opinion mining, which can be classified as 'pleasant' or 'unpleasant' by the computer system [5]. In this case, the word 'surprise' could be accompanied by the criterion of the meaning that would be 'better' in the context of the analysis.

Determining the value of the parameters depends on human intelligence. Therefore, supervised, and unsupervised systems are subject to some human interference, whether direct or indirect [27,3] (p. 84).

> [...] to assign value is something absolutely human: good and bad do not exist in nature or reality. In order to evaluate, you have to compare with something else. Usually, human judgement. But – and this is a highly relevant detail – not all judgements are consensual. All of us are aware of ethical paradoxes, different legal opinions, etc. In fact, and even in a more general sense, cultures have been defined [...] as different rankings of values. The bottom line is that human language always includes values, and these values are inherently human. [19] (p. 6)

When formulating the mathematical model for the algorithm, there is an implementation of values in the core of the system [29]. The technician becomes aware of the data through experiment or observation and decides/specifies which parameters best fit the data for a given situation. In this case, the "best" parameter is related to a criterion that will lead to optimization of the system. Optimization methods can describe the evolution of a process in time (discrete or continuous), involving parameters for which values can be chosen as a function of time. Thus, under various assumptions, there will be a mapping that assigns each choice a control function to a time interval. Having restrictions on these functions, one can search for the choice that is optimal according to some criterion.

This is a technical task, a mathematical construction that must adapt to the contextual conditions in which the tool will be used, for this reason it cannot be said that one tool is better than the other [47]. This statement fits with the fundamentals of modelling, which

> deals with 'relationship' to generate interpretation. Consistent meanings result from the 'processing' of this 'relationship', which must occur in a unified way, imitating human cognition when operating values through axiomatic (contextual) and logical characteristics in the construction of unique meanings. [29] (p. 31)

System deficiencies and errors in system analysis direct scholars to consider analyzing language from a perspective capable of also encompassing dynamic aspects of it, especially regarding emotions and their nuances. The dynamics in emotion analysis leads to interpretive results that are more appropriate to the context. Contemplating optimization methods means instilling in the system a contextual appreciation along with a categorized appreciation of emotions, enabling the machine to adapt to very special cases of interpretation. Machine decisions may concern not only the values of continuous variables (encompassing the dynamics of the linguistic process), but also of discrete variables (encompassing meanings frozen by the conventions of the various spoken languages). The adequacy of emotions to intelligent systems can be performed from two perspectives: under categorizations (conventional language) and under relationships (dynamic linguistic process). Different views of language processing are integrated under strategies (such as the use of optimization methods) that make different approaches to computational linguistics effective.

8 Conclusion

The dynamic concept of language (as an axiomatic/contextual and logical linguistic process) is suitable for working with emotions in intelligent systems.

This duplicity in the core is in line with what Cleeremand [48] (p. 193) teaches about the two forms of learning: one occurs through specialized algorithms whose operation follows certain logical or rational principles (that is, based on categorizations); the other takes place through nonspecific and predominantly associative (i.e., relationship-based) mechanisms.

The same can be observed in Tamba and Tamba and Mecz [42,49,50] who consider that there is an organization in the semantic structure to form distinct units. For this organization to occur, these authors (op. cit.) mention some general principles of structuring the senses:

> i) synonymy (to ensure referential equivalence; ensure interchangeability without changing the meaning) [42,49] (p. 92).
> ii) antonymy (which links an element of the same category to its opposite or negative under the binary character 'or'; dichotomized which can be contradictory: front/back; polar: long/short; reverse: up/down; reciprocal: purchase sale) [42, 49] (pp. 97-103).
> iii) hyperonymy (process of subdivision to form a complex meaning from hierarchical structures in language) [42,49] (p. 103).

Tamba [50] (pp. 98-99), [29] (p. 39) conceive hyperonymy as a foundation of the category that corresponds to the maximum degree of schematic generalization in the order of perception (contextual / axiomatic in the case of this article), dissociating it from structures dependent on logical classifications, such as synonymy and antonymy.

The double aspect of the linguistic dynamic core shelters categorizations and adapts the contextual varieties of emotions, incorporating pre-established values and fluid values resulting from relationships, increasing the interpretive capacity of the systems, and making them intuitive according to human cognition. In this way, Artificial Intelligence absorbs values and contexts simultaneously. It is believed that the strategies and methods proposed in this article direct Computational Linguistics towards Cognitive Computing characteristics, teaching the system to interpret the appropriate context of the emotion at stake. Santos [19] (p. 5) states that languages are much more complex entities than mere functional behavior or stylized syntax, encompassing community and shared values beyond values that are returned from a function call.

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