A Review of Ontology-Based Approaches for Sentiment Analysis: Possible Improvements on the Brazilian Affective Computing Scenario

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Abstract

With machine learning (ML) advances, many statistical solutions were developed to solve Sentiment Analysis (SA) and Natural Language Processing (NLP) issues. However, no statistical classification process was yet capable of solving simple semantic and linguistic relations in the same way as the human brain. This work presents a brief review of ontologies for SA. The paper aims to raise discussions about possible expansion strategies for the SA field and reflections on taking a deeper look at digital humanities and its hybrid approaches, including ontologies, in the Brazilian-Portuguese scenario.

Keywords

Natural Language Processing, Sentiment Analysis, Ontology, Semantics

1. Introduction

With the rise of Web 2.0, social networks and the empowerment of users on the Internet, the number of User-Generated Content (UGC) became an ever-expanding hoard of information far exceeding human processing capabilities. The sharing of opinions has become frequent; therefore, UGC data highlights which topics are more relevant to the public, helping organizations understand consumers' impressions about their products [1]. This problem has motivated affective computing scientists to seek methods and tools to automate information retrieval and knowledge extraction from Web repositories.

Despite the variety of resources and techniques for Sentiment Analysis (SA), most applications are developed for English *corpus* [2]. Recently, new contributions have appeared in other languages [2], but research with Portuguese *corpora* is still scarce in Brazil [2]. With a population greater than 211 million, Brazil has one of the most present online communities and the second most active on Twitter [3], generating a large amount of textual data that justifies deeper looks at its linguistic scenario.

Motivated by the studies of da Silva Conrado et al. [4] and Cambria et al. [5], our research revealed that there is an important gap in the improvement of theories, methodologies, and even in the state-of-the-art of linguistics and affective computing: the absence of studies focusing on

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ontology-based approaches for SA. Furthermore, most applications and tests used in affective computing in Brazil employ automatic translations from English to Portuguese, whose linguistic structure differs from Brazilian-Portuguese [4].

According to Gruber [6] [7], many contributions applying ontologies in the area of Artificial Intelligence (AI) and information sciences exist. Advances in Machine Learning (ML) developed many statistical solutions to solve SA and Natural Language Process (NLP) issues. However, no statistical classification process could solve semantic and linguistic relations in the same way as human thinking.

Da Silva Conrado et al. [4] observed that many scientific contributions in NLP in Brazil are lexicons, excluding more holistic and semantic approaches, as we present in Table 1 (Section 3). Also, according to Cambria et al.[5], NLP and SA should not be treated as merely classification problems. In addition, our studies verify that, globally, most ontology-based approaches for SA focus on specific domains, such as smartphones or diseases. Unlike most studies, SenticNet is one of the unusual cases where SA was not applied to a specific domain but still uses an ontology-based approach.

Senticnet [8] is a publicly available opinion mining resource using Semantic Web and AI approaches. It deduces the polarity connected to common sense ideas. The framework represents it in a semantically informed manner by generating a collection of commonly used common sense "polar concepts" with relatively strong positive or negative polarity. SenticNet 6 SA classification output is based on a semantic NLP level rather than just syntactic [8]. Its knowledge-based onto-pair structure, in OWL, represents well how its semantic network is built [8].

This paper holds a brief review of ontological methodologies for SA, but we will not exhaust ourselves on domain ontologies due to the wide variety of subjects. We also tested SenticNet 6 in Portuguese to check the need for new technical ontology-based solutions for Brazilian-Portuguese. We hope to raise more discussions about possible expansion strategies for the SA area and reflections on taking a deeper look at the Brazilian scenario. We believe our studies might contribute to the future development of new tools capable of solving complex semantic problems.

Our research was conducted in Scopus and Scielo databases limited to the period 2016-2021. The search string ((“sentiment analysis”) AND (ontology) AND (Portuguese)) only found three articles. Later, we expanded our research to ((“sentiment analysis”) AND (ontology)), leading us to different solutions that could be applied in the Brazilian-Portuguese scenario. the backward snowballing methodology helped locate other relevant works. The research articles were chosen based on: (a) ontology-based approaches for SA; (b) language of the *corpora*; (c) the possibility of domain adaptation, especially in works within English datasets.

2. Ontologies and Sentiment Analysis

Currently, the use of ontologically structured systems has gained prominence in the field of AI, as they help in the sharing and reuse of formal knowledge acquired between AI systems [6], [9], [10], [11]. Statistical or ML techniques have solved the problem of constructing ontologies from texts, although the most significant challenge still lies in the semantics [12].

Many authors rely on simple relations between the classes, attributes, and other members of automated extracted ontologies that depend on advanced NLP techniques and human judgment. However, high-performance sentiment ontologies require many synonyms and relationships [13].

From a semiotical point of view, human beings always use natural language and their social and cultural knowledge of the world, or domain, to understand messages [14]. Likewise, ontologies also use formal language representations to describe document domains [15].

The Suggested Upper Merged Ontology (SUMO) is an upper ontology with general concepts independent of any domain. Its structure could be used to create domain-specific ontologies related to sentiments. Niles et al. [16] mapped SUMO concepts to semantically equivalent words, named synsets, from WordNet [16]. According to Saranya and Jayanthy [9], a solution for emotion classification problems would be an ontological approach based on a given domain, bringing semantic meaning and relationship between the terms. For Jiang et al. [17], an ontological framework could perform better than pre-existing SA lexical approach. For the researchers, the most efficient ontologies use solutions that combine polarity analysis and ML.

Hence, ontology learning and ML techniques for knowledge acquisition are fundamental in developing research in the semantic web [10]. In addition, the use of NLP toolkits and lexical databases for synsets analysis, *i.e.*, a pre-existing synonym base, such as Wordnet, should be considered when developing a SA tool with ontological structure [9].

According to Liu et al. [10], domain ontologies create relationships between a given domain and its concepts. Therefore, the answer to solving possible classification failures in SA in specific contexts could lie in them. An ontological approach might solve sentiment classification problems based on a given domain due to semantic meaning and relations in the *corpus* [9]. Therefore, they could fix possible classification failures, such as ambiguation problems [10].

Ontology-based approaches could be of great value when applied in different areas for user review analysis from various sectors of society. However, until the writing of this article, few studies using ontologies for SA were developed, especially in the Brazilian scenario.

3. Sentiment Ontology Approaches

There are seldom ontologies addressed to the sentiment domain for text classifications. However, we found some ontology-based sentiment opinion mining methods from different and specific domains. We highlight some of them in this section.

English is usually the most common language for SA. In contrast to other idioms, ontology-based approaches using English *corpus* are predominant. Some of them could influence new works in different languages.

Kontopoulos et al. [18] created a prototype of a SA ontology focused on concept discovery. The *corpus* consisted of English tweets covering the smartphone domain. The ontology uses ML techniques and has hierarchical relationships and classes between concepts. As *tweets* are composed of representative words and have syntactic content, text-based sentiment classifiers are generally inefficient in their analysis due to the imposed character limit [18]. Hence, the authors developed an onto-based technique whose sentiment scores are assigned to distinct notions in the text. Its architecture identifies different sentiments in a single tweet.

Ceci et al. [19] developed a camera ontology domain based on Amazon text reviews. The authors used the Movie Ontology for term classification purposes and *sentiment learning on product reviews* with *sentiment ontology tree* [19]. Support Vector Machine (SVM) and Naïve Bayes were employed for classification with the case-based reasoning approach. Ceci et al. [19] analyzed the sentiment of product rating.

Based on Plutchik's emotion wheel [20], the goal of Visual Sentiment Ontology (VSO) was to design an ontology of semantic concepts related to emotions frequently shared on Flickr or YouTube. Currently, the tool has more than 3,000 concepts composed of adjective-noun pairs, in English, such as "beautiful sky" [21].

The Emotion Ontology (MFOEM) [22] is a subpart of the Basic Formal Ontology (BFO) and the Ontology of Mental Functioning (MF). They include information and relations between data types such as neuroimaging, pharmaceutical studies, behavior monitoring, etc. Despite its immense scientific contribution, MFOEM will not classify sentiments at the sentence level. However, its rich emotional vocabulary can be used to detect mentions of particular sentiments through text mining approaches.

Ontology-based frameworks in English could be tested or even trained for other languages. Senpy is a framework in Python that analyzes sentiments with a plugin architecture. It offers a semantic web approach using semantic vocabularies. Senpy contains knowledge bases and lexicons, including Vader, SenticNet, and Wordnet Affect. Despite recognizing languages, the tool does not support Portuguese [23].

OntoSenticNet [24] is an ontological approach application for SA based on fuzzy ontology methods and polarity verification of primitive concepts [11]. The tool is a feature of SenticNet, a semantic repository with 100,000 terms in multiple languages. One central differential and characteristic of Senticnet and OntoSenticNet is their conceptual hierarchical relationship, whose properties relate to concepts and sentiment values. The tool also uses linguistic and statistical analysis methods, deep learning and symbolic and subsymbolic AI. SenticNet can extract Primitives using ML algorithms such as LSTM. The deep learning model allows the automatic discovery of clusters of semantically related concepts sharing similar lexical functions [25]. Its primary language is English, but the tool has multilingual support, including Portuguese.

Asian countries, especially China and India, have improved new research on ontologies applied to SA. From entity extraction to the reuse of upper ontologies, there are remarkable works in development in Asia. For Liu et al. [10], labeling product reviews with attributes and their corresponding sentiment structure would be a way to perform SA. Hence, the authors proposed a fuzzy domain ontological tree algorithm combined with a sentiment ontology mechanism. It enabled the automatic building of a domain ontology tree based on product reviews. Their method includes the sentimental terms extraction, product features, and their relation. The *corpus* consisted of reviews from the Chinese website 360buy.com. According to Liu et al. [10], their experiments improved the accuracy of polarity predictions.

Jung et al. [13] constructed their domain based on competency questions. The concepts and their terminologies were collected from clinical practice guidelines, literature, and social media posts about teenage depression. Also, the concept classes, hierarchy, and relationship-mapped concepts are extracted from frequently asked questions (FAQ) answers. The ontology super classes connect to the BFO with Protégé. The ontology application was in English, and its dataset was in South Korean, whose terminology had 1,682 synonyms in the 443 classes.

Latin American countries contribute little to the state-of-the-art Spanish and Portuguese idioms. We found only two works for the Brazilian-Portuguese language using ontologies applied to SA. García-Díaz et al. [26] developed a SA method based on ontological aspects. Their goal was to classify the polarity of emotions evoked by the epidemics of Dengue, Zika and Chikungunya in Latin America. The *corpus* was compiled from Twitter and later labeled by volunteers as positive, negative, and neutral. The proposed ontology collected its knowledge from Disease Ontology (DO) and Infectious Diseases Ontology (IDO). The DO and IDO do not have Spanish versions. Therefore, the terms were manually included, which was highly time-consuming. Due to domain specificity, the authors dealt with many term ambiguity issues. Despite manual translations, García-Díaz et al. [26] failed to solve disambiguation problems effectively.

Freitas and Vieira [27] developed a tool to identify features in the hotelier domain. The authors also noted the lack of resources for the Portuguese language. Thus, the work needed several evaluation stages for its conclusion. The dataset consists of 194 TripAdvisor reviews published from March 2010 to May 2014. HOntology has 282 concepts categorized into 16 higher-level concepts.

KBRS is a knowledge-based recommendation system with an emotional health monitoring application to detect users' depression and stress. Depending on the monitoring results, the KBRS, based on ontologies and SA, is activated to send motivational messages [28]. Recurrent neural networks are responsible for identifying sentences with depressive and stressful contexts. According to Rosa et al. [28], experimental results suggest that the proposed KBRS achieves a rating of 94% of satisfied users compared to 69% for recommendation systems without sentiment and ontology metrics.

The assemblage of those works leads us to think that research using ontology-based approaches is not the primary option for sentiment classification. As stated in Section 1, da Silva Conrado et al. [4] already observed that most scientific contributions in SA in Brazil are lexicons that treat SA as a classification problem, regardless of the *corpus* semantic relations in the sentences, therefore, excluding more holistic analysis in their approaches. Traditionally, lexicons are a set of words in a given language. From a computational SA perspective, such groups of words are related, presenting different labels for possible sentiments they may express.

Table 1 lists some of the most important studies in Brazilian-Portuguese. The table indicates if the study applied a translation or if it was originally developed in Portuguese. Nineteen significant studies with a focus on SA were discovered. Of 10 ontologies-based works, only two had an SA focus. Nine works were SA lexicons-based. The Table shows the title of the study, its approach and original language, treatment of language problem, sentiments or other specific domains, and the year of the study. As SenticNet is a multilanguage tool without Portuguese research, we did not include it in Table 1.

4. Experiments

Our preliminary tests aimed to support the validation of further research in the field of SA with ontological and semantic approaches. As SenticNet is a multilingual open-source framework with support for the Portuguese language, we employed it to evaluate the effectiveness of automatic translations for emotion classification and the performance of its ontological pairs. In

SenticNet, each concept c is associated with a Polarity value P for c, *i.e* a floating value between $[-1, 1]$, representing its polarity.

We tested four datasets in Portuguese: MQD [29], SADT [30], TOPIE [31] and TweetSentBR [32]. SenticNet recommends not preprocessing the *corpus* before input. The tests were performed in Python. Senticnet 6 results for English datasets were greater than 80% [25], our Portuguese tests outcome were *circa* 30%: MQD [29] (37%), SADT [30] (32%), TOPIE [31] (31%), and TweetSentBR [32] (36%). The tests exposed the relatively low accuracy for automatic Portuguese translations applying Senticnet 6. This fact raises the discussion about the differences in idiomatic structures, especially when dealing with semantic relations.

Table 1
A comparison between lexical and onto-based approaches for Affective Computing in Brazil According to Original Language and Domain (*EN = English; PT = Portuguese; BPT = Brazilian Portuguese)

Study Title	Approach	Original Language*	Type	SA Approach	Domain	Year
ANEW BR [33]	Lexicon	EN	Translation	X	N/A	2011
LIWC [34]	Lexicon	EN	Translation	X	N/A	2007
LIWC 2015pt [35]	Lexicon	EN	Translation	X	N/A	2015
Wordnet AffectBR [36]	Lexicon	EN	Human Translation	X	N/A	2003
Opinion lexicon [37]	Lexicon	EN	API Translation	X	N/A	2011
Wordnet AffectBR_adapt [38]	Lexicon	EN	Human Translation	X	N/A	2011
Reli Lexicon [39]	Lexicon	PT	Brazilian Idiomatic Matrix	X	N/A	2013
Personalitem Lexicon [40]	Lexicon	BPT	Brazilian Idiomatic Matrix	X	N/A	2015
Unilex [41]	Lexicon	BPT	Brazilian Idiomatic Matrix	X	N/A	2017
Linguateca [42]	Ontology	PT	Brazilian and European Idiomatic Matrix		Linguistics	1998
TEXTQUIM/ITEXTECC [43]	Ontology	BPT	Brazilian Portuguese		Chemistry/Medicine	2003
NANOTERM [44]	Ontology	BPT	Brazilian Portuguese		Nanotechnilogies	2006
OntoLP [45]	Ontology	BPT	N/A		Semi-Automatic Ontology Builder	2008
Bio-C [46]	Ontology	BPT	Brazilian Portuguese		Bio-Fuel	2009
e-Termos [47]	Ontology	BPT	Brazilian Portuguese		Electronics	2009
TermiNet [48]	Ontology	BPT	Human Translation		Linguistics	2009
Hontology [27]	Ontology	BPT	Brazilian Portuguese	X	Accomodation Sector	2012
TOPTAX [49]	Ontology	BPT	Brazilian Portuguese		Chemistry, Computing, Physics, IFM	2013
KBRS [50]	Ontology	BPT	Brazilian Portuguese	X	Depression and Stress	2018

5. Final Remarks

This paper reviewed ontologies applied to SA and raised some reflections about possible expansion strategies for the SA field in Brazil. Although there are novel ontology approaches, with highlights to the work of [28] and [27], most research for Brazilian Portuguese focus on lexicon approaches that reduce NLP and SA to a simple classification problem. Several studies abroad, especially in English, have already testified that more elaborate linguistic structures require more robust text-mining tools [10].

This research is still under development, but we hope this Brazilian ontology review will evoke new concerns and studies on the NLP and SA Brazilian academic field. For future works, we expect to develop a sentiment ontology prototype based on the research of [51], and [28] and then conduct new experiments.

References

[1] D. N. Nguyen, T. T. Phan, P. H. Do, Embedding knowledge on ontology into the corpus by topic to improve the performance of deep learning methods in sentiment analysis, Scientific Reports 11 (2021).

[2] J. Reis, P. Gonçalves, M. Araújo, A. Pereira, F. Benevenuto, Uma abordagem multilíngue para análise de sentimentos, in: Anais do IV Brazilian Workshop on Social Network Analysis and Mining, SBC, Porto Alegre, RS, Brasil, 2015. URL: https://sol.sbc.org.br/index.php/brasnam/article/view/6767. doi:10.5753/brasnam.2015.6767.

[3] IBGE, Ibge divulga estimativa da população dos municípios para 2020, , 2020. Acessado: 22 nov. 2020.

[4] M. da Silva Conrado, A. D. Felippo, T. A. S. Pardo, S. O. Rezende, A survey of automatic term extraction for brazilian portuguese, Journal of the Brazilian Computer Society 20 (2014). doi:10.1186/1678-4804-20-12.

[5] E. Cambria, S. Poria, A. Gelbukh, M. Thelwall, Sentiment analysis is a big suitcase, IEEE Intelligent Systems 32 (2017) 74–80. doi:10.1109/MIS.2017.4531228.

[6] T. R. Gruber, Towards principles for the design of ontologiesn used for knowledge sharing, in: N. Guarino, R. Poli (Eds.), Formal Ontology in Conceptual Analysis and Knowledge Representation, Kluwer Academic Publishers, Deventer, The Netherlands, 1993.

[7] T. Gruber, Ontology, , 2009. Acessado: 18 fev. 2021.

[8] E. Cambria, A. Hussain, Sentic Computing: Techniques, Tools, and Applications, Springer Publishing Company, Incorporated, 2012.

[9] K. Saranya, S. Jayanthy, Onto-based sentiment classification using machine learning techniques, volume 2018-January, 2018, pp. 1–5. doi:10.1109/ICIIECS.2017.8276047.

[10] L. Liu, X. Nie, H. Wang, Toward a fuzzy domain sentiment ontology tree for sentiment analysis, in: 2012 5th International Congress on Image and Signal Processing, 2012, pp. 1620–1624. doi:10.1109/CISP.2012.6469930.

[11] M. Dragoni, S. Poria, E. Cambria, Ontosenticnet: A commonsense ontology for sentiment analysis, IEEE Intelligent Systems 33 (2018) 77–85. doi:10.1109/MIS.2018.033001419.

[12] A. Stavrianou, P. Andritsos, N. Nicoloyannis, Overview and semantic issues of text mining, SIGMOD Record 36 (2007) 23–34. URL: www.scopus.com.

[13] H. Jung, H.-A. Park, T.-M. Song, Ontology-based approach to social data sentiment analysis: Detection of adolescent depression signals, Journal of Medical Internet Research 19 (2017) e259. doi:10.2196/jmir.7452.

[14] N. Guarino, D. Oberle, S. Staab, What Is an Ontology?, 2009, pp. 1–17. doi:10.1007/978-3-540-92673-3_0.

[15] S. K. Narayanasamy, K. Srinivasan, S. Mian Qaisar, C.-Y. Chang, Ontology-enabled emotional sentiment analysis on covid-19 pandemic-related twitter streams, Frontiers in Public Health 9 (2021). URL: https://www.frontiersin.org/article/10.3389/fpubh.2021.798905. doi:10.3389/fpubh.2021.798905.

[16] I. Niles, A. Pease, Linking lexicons and ontologies: Mapping wordnet to the suggested upper merged ontology (2004).

[17] X. Jiang, A. H. Tan, Mining ontological knowledge from domain-specific text documents, 2005. doi:10.1109/ICDM.2005.97.

[18] E. Kontopoulos, C. Berberidis, T. Dergiades, N. Bassiliades, Ontology-based sentiment analysis of twitter posts, Expert Systems with Applications 40 (2013) 4065–4074. URL: https://www.sciencedirect.com/science/article/pii/S0957417413000043. doi:https://doi.org/10.1016/j.eswa.2013.01.001.
[19] F. Ceci, R. Weber, A. Goncalves, A model for sentiment analysis based on ontology and cases, IEEE Latin America Transactions 14 (2016) 4560. doi:10.1109/TLA.2016.7795829.
[20] R. Plutchik, A psychoevolutionary synthesis, Harper Row, Publishers (1980).
[21] D. Borth, R. Ji, T. Chen, T. Breuel, S.-F. Chang, Large-scale visual sentiment ontology and detectors using adjective noun pairs, in: Proceedings of the 21st ACM International Conference on Multimedia, MM '13, Association for Computing Machinery, New York, NY, USA, 2013, p. 223–232. URL: https://doi.org/10.1145/2502081.2502282. doi:10.1145/2502081.2502282.
[22] J. Hastings, W. Ceusters, B. Smith, K. Mulligan, The emotion ontology: Enabling interdisciplinary research in the affective sciences, volume 6967, 2011, pp. 119–123. doi:10.1007/978-3-642-24279-3_1.
[23] J. F. Sánchez-Rada, C. A. Iglesias, I. Corcuera, Araque, Senpy: A pragmatic linked sentiment analysis framework, in: 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA), 2016, pp. 735–742. doi:10.1109/DSAA.2016.79.
[24] SenticNet, Senticnet, , 2022. Accessed: 26 Jul. 2022.
[25] E. Cambria, Y. Li, F. Z. Xing, S. Poria, K. Kwok, Senticnet 6: Ensemble application of symbolic and subsymbolic ai for sentiment analysis, in: Proceedings of the 29th ACM International Conference on Information Knowledge Management, CIKM '20, Association for Computing Machinery, New York, NY, USA, 2020, p. 105–114. URL: https://doi.org/10.1145/3340531.3412003. doi:10.1145/3340531.3412003.
[26] J. A. García-Díaz, M. Cánovas-García, R. Valencia-García, Ontology-driven aspect-based sentiment analysis classification: An infodemiological case study regarding infectious diseases in latin america, Future Generation Computer Systems 112 (2020) 641–657. URL: https://www.sciencedirect.com/science/article/pii/S0167739X2030892X. doi:https://doi.org/10.1016/j.future.2020.06.019.
[27] L. A. Freitas, R. Vieira, Ontology based feature level opinion mining for portuguese reviews, in: Proceedings of the 22nd International Conference on World Wide Web, WWW '13 Companion, Association for Computing Machinery, New York, NY, USA, 2013, p. 367–370. doi:10.1145/2487788.2487944.
[28] R. L. Rosa, G. M. Schwartz, W. V. Ruggiero, D. Z. Rodríguez, A knowledge-based recommendation system that includes sentiment analysis and deep learning, IEEE Transactions on Industrial Informatics 15 (2019) 2124–2135. doi:10.1109/TII.2018.2867174.
[29] G. d. Azevedo, G. Pettine, F. Feder, G. Portugal, C. O. Schocair Mendes, R. Castaneda Ribeiro, R. C. Mauro, F. Paschoal Júnior, G. Guedes, Nat: Towards an emotional agent, in: 2021 16th Iberian Conference on Information Systems and Technologies (CISTI), 2021, pp. 1–4. doi:10.23919/CISTI52073.2021.9476326.
[30] C. F. da Silva Nascimento, R., G. P. Guedes, Identificando sintomas depressivos: um estudo de caso no youtube, Anais do VIII Brazilian Workshop on Social Network Analysis and Mining (2019).
[31] E. Souza, T. Alves, I. Teles, A. L. I. Oliveira, C. Gusmão, Topie: An open-source opinion

mining pipeline to analyze consumers' sentiment in brazilian portuguese, in: J. Silva, R. Ribeiro, P. Quaresma, A. Adami, A. Branco (Eds.), Computational Processing of the Portuguese Language, Springer International Publishing, Cham, 2016, pp. 95–105.

[32] H. B. Brum, M. d. G. V. Nunes, Building a sentiment corpus of tweets in brazilian portuguese, in: International Conference on Language Resources and Evaluation - LREC, European Language Resources Association, 2018.

[33] C. Kristensen, C. Gomes, A. Justo, K. Vieira, Brazilian norms for the affective norms for english words, Trends in Psychiatry and Psychotherapy 33 (2010) 135–146. doi:10.1590/S2237-60892011000300003.

[34] PortLEX, Liwc (2022). Acessed: 26 Jul. 2022.

[35] F. Carvalho, R. Rodrigues, G. Santos, P. Cruz, L. Ferrari, G. Guedes, Avaliação da versão em português do liwc lexicon 2015 com análise de sentimentos em redes sociais, in: Anais do VIII Brazilian Workshop on Social Network Analysis and Mining, SBC, Porto Alegre, RS, Brasil, 2019, pp. 24–34. URL: https://sol.sbc.org.br/index.php/brasnam/article/view/6545. doi:10.5753/brasnam.2019.6545.

[36] P. Pasqualotti, R. Vieira, Wordnetaffectbr: uma base lexical de palavras de emoções para a língua portuguesa, RENOTE 6 (2008). doi:10.22456/1679-1916.14693.

[37] M. Souza, R. Vieira, D. Busetti, R. Chishman, I. M. Alves, F. D. L. Unisinos, Construction of a portuguese opinion lexicon from multiple resources, in: In 8th Brazilian Symposium in Information and Human Language Technology - STIL, Mato Grosso, 2011.

[38] M. T. Longhi, Mapeamento de Aspectos Afetivos em um Ambiente Virtual de Aprendizagem, 2011.

[39] C. Freitas, Sobre a construção de um léxico da afetividade para o processamento computacional do português, 2013, p. 1031=1059.

[40] M. A. S. N. N. T. A. S. P. Antonio A. A. Machado, Magalí T. Longhi, Personalitatem lexicon: Um léxico em portugûes brasileiro para mineração de traços de personalidade em textos, 2015.

[41] K. F. de Souza, M. H. R. Pereira, D. H. Dalip, Unilex: Método léxico para análise de sentimentos textuais sobre conteúdo de tweets em português brasileiro, Abakós 5 (2017). doi:10.5752/p.2316-9451.2017v5n2p79.

[42] F. para a Computação Científica Nacional, Linguateca, , 2022. Accessed: 27 Jul. 2022.

[43] I. de Letras da UFRGS, Textquim, , 2022. Accessed: 27 Jul. 2022.

[44] D. Kasama, C. Zavaglia, G. M. Almeida, Do termo à estruturação semântica: representação ontológica do domínio da nanociência e nanotecnologia utilizando a estrutura quali, Linguamática 2 (2011).

[45] OntoLP, Ontolp portal de ontologias, , 2008. Acessado: 22 nov. 2020.

[46] D. H. P. Pino, Aspectos semânticos da terminologia do biodiesel, 2021.

[47] Embrapa, e-termos, , 2022. Accessed: 27 Jul. 2022.

[48] A. Di Felippo, The terminet project: an overview, Young Investigators Workshop on Computational Approaches to Languages of the Americas (2010) 92–99.

[49] d. S. F. F. R. S. O. Moura, M. F., An experimental comparison of label selection methods for hierarchical document clusters, , 2022. Accessed: 27 Jul. 2022.

[50] R. L. Rosa, G. M. Schwartz, W. V. Ruggiero, D. Z. Rodríguez, A knowledge-based recommendation system that includes sentiment analysis and deep learning, IEEE Transactions

on Industrial Informatics 15 (2019) 2124–2135. doi:10.1109/TII.2018.2867174.
[51] B. Smith, The ontology of emotions (april 2018), , 2018. Acessado:20 January. 2022.