Sentiment Analysis Methods for Politics and Hate Speech Contents in Spanish Language: A Systematic Review

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Abstract—**The political debate in social networks, and its derivatives such as hate speech, has surfaced at the top of the social agenda due to its impact on public opinion and, consequently, in the communication strategies of political parties, public institutions, media corporations, and lobbies. The scientific community has been working to respond to the demand for tools that allow studying the political attitude of citizens in these networks, focusing on sentiment analysis methodologies. However, their work has been hampered by several significant challenges, such as the absence of standardized investigation methodologies, the filtering of content created by bots and spammers, or the interpretation of slang and other conventionalisms that are specific to microblogging platforms. In addition to these challenges and the generic problems related to the interpretation of human language, researchers from the Spanish-speaking community have found themselves with the additional problem of developing strategies and methodologies suitable for Spanish text, in a scenario dominated by research aimed at the English language. In this paper, we present a systematic review that describes the state of the art in sentiment analysis methods for politics and hate speech contents in the Spanish language, by systematically reviewing the relevant papers available.**

Index Terms— **hate speech, machine learning, opinion mining, politics, sentiment analysis, twitter**

I. Introduction

A. Contextualization

Sentiment Analysis is a technique used to discern opinions and sentiments in text [1]. The process that encompasses Opinion Mining (OM) and Sentiment Analysis (SA) is defined as the task of detecting, extracting and classifying opinions on a subject, involving Natural Language Processing (NLP by its acronym in English) to track the public's mood on a specific topic [2]. We could also define SA more generically as the study of people's sentiments towards certain entities [3]. Some authors propose a broader view, including the observation of people's actions that can be captured using their facial and verbal expressions, music and movements [4].

In a 2016 research, Ribeiro et al. reference up to twenty four sentiment analysis methods available in the scientific literature (sentence-level methods) [5], of which six combine lexicon and machine learning. Since then, new methods currently under development and discussion have appeared. However, most of the available works related to the mining of emotions in social networks, and particularly in Twitter, refer to the English language [4]. In recent years Mandarin Chinese [6] [7] [8] and, to a lesser extent, Arabic have gained special strength [9] [10]. Although the roots of sentiment analysis go back to the 90s, 99% of the bibliographic production on the subject has been published after 2004 [11]. Research aimed specifically to Spanish content begins later. Therefore, we are facing a very narrow time frame from a world-wide point of view, and even narrower from the point of view of the Spanish language.

Sentiment analysis based on artificial intelligence techniques is a methodology applied in various fields of research. Among other areas, the works carried out in Education stands out. There is a growing interest in the impact of social networks in the educational community, such as inclusive education [12], policies and laws [13][14] . Beyond this discussion, the use of social networks as tools for the service of students has also been studied in depth [15]. Sentiment analysis has also been widely studied with a marketing orientation, fundamentally focused on user opinions about products and brands [3][16][17][18]. Another important field of study for researchers focused on sentiment analysis is Healthcare [19]. This domain implies a large area of opportunity, such as obtaining information about the patients' mood, diseases, adverse drug reactions, and epidemics, among others [20].

With the proliferation of misleading content, fake news is a troubling trend with potential political and social consequences, which concern the scientific community and society. To mitigate this threat, a broad range of approaches have been designed [21]. Specifically, to address the issue of fake news detection, numerous studies have been proposed, based on supervised and unsupervised learning methods [22].

Politics has been, since the birth of social networks, one of the main focuses of attention of the research community. In 2013, Bakliwal already identified "a growing interest in political sentiment in order to predict the outcome of elections" [23]. After several controversial electoral processes since 2016, and as a result of society's growing awareness of hate speech, this interest has increased considerably, with an acceleration in the frequency of publication as of 2018, as we will see later in this review.

If we look specifically at research for Spanish language, a considerable amount of literature has accumulated in the last few years, focused on various areas of interest apart from politics, such as education [24][25][26], health [27][28], and Covid-19 pandemic [29][30][31]. The first sentiment analysis work related to politics for Spanish language was published in 2014, a decade later than the first paper for English language. In addition to this accumulated delay, the production of papers referring to the Spanish language in this domain has grown at a slower rate to the present day.

The research community in Spain and Latin America has developed a great diversity of methods and even specific tools. In recent years, the subdomain of hate speech has focused much of the attention of Spanish-speaking researchers, in response to growing social concern and various initiatives promoted by governments and institutions. To the best of our knowledge, there is no systematic review in the literature that refers specifically to Politics and Hate Speech in the Spanish language.

B. *Structure*

This paper is structured as follows: firstly, we define our methodology, in such a way that it can be reproduced in the same terms, with identical results; second, we plan and conduct the review with a very systematic approach, extracting data according to a previously established criteria, focusing on our research questions. In the next step we analyse all the information collected and, finally, we reflect on the conclusions of the research to establish a framework for further discussions. The results are presented structured in tables to facilitate the systematic understanding of the key aspects.

II. Methodology

A. *Definition of Systematic Review*

In our review, we are applying a specific formal procedure to conduct bibliographic research. The aim is to define a very specific question/subject which is relevant to the research community, in order to describe the state of the art and to identify gaps and current challenges in the current research.

By applying the procedure described in this methodological section, we aim to:

- Systematically review all the relevant papers available
- Present reproducible results, by means of a very strict and detailed methodology.

B. *Methodology Procedure*

1) *Stages*

Our review has involved three major stages, based on the methodology introduced by Kitchenham and Charters [32]: planning, conducting and discussing.

We have chosen this methodological approach because it is specifically oriented to the domain of software engineering.

2) *Planning stage*

In the planning stage, the needs of the review, the format, the relevant bibliographic datasets, and the research questions (RQs) are specified, as well as search terms, selection criteria and extraction strategy.

For the information flow, we followed the statements in PRISMA Flow Diagram from Moher et al. [33] . The PRISMA Statement consists mainly of a four-phase flow diagram. The aim of the PRISMA Statement is to help authors improve the reporting of systematic reviews and meta-analyses, and its use is widespread among the scientific community.

3) *Conducting stage*

The search terms are applied, and the results (papers) are filtered according to the selection criteria. Finally, the relevant information from papers, according to the aim of the systematic review, is extracted and analysed.

The extraction and analysis processes will be carried out by reading and coding / categorizing the contents, to be able to work systematically on common attributes and relevant concepts, aligned with the research questions.

4) *Discussing stage*

The results are systematically discussed, highlighting the most relevant aspects according to the objectives of the research and presenting a framework that serves as a basis for future debate.

III. Planning

As our first step in the field, the planning stage, we conducted the following activities:

A. *Initial Examination ¿Systematic Review or Systematic Mapping?*

If, during the initial examination of a domain, it is discovered that very little evidence is likely to exist or that the topic is too broad, then a systematic mapping study may be a more appropriate exercise than a systematic review [32] . This is not the case in this paper. After our initial examination of the domain, we concluded that our review is suitable for a systematic approach/methodology:

- Very specific topic with sizeable volume of publications found
- Rapid growth in the number of publications per year and remarkable citation ratio (7,69 average citations).

B. *Answer the Question "Need For a Review?"*

A preliminary survey in SCOPUS and WoS databases, later confirmed in the conduction stage of our research, reveals that there is no systematic review available for Sentiment Analysis methods focused on politics (nor hate speech) for the Spanish language, despite being an essential aspect of opinion mining in the Spanish-speaking countries (580 million people speak Spanish in the world, 7.6% of the world's population [34]). Thus, we may consider that our review would be of great help to the research community.

C. *Define Research Questions*

We have defined the following RQs for our review:

- RQ1 - What are the aim and topics that concentrate the interest of the research community?
- RQ2 - What tools and methods are used?
- RQ3 - What are the data sources?
- RQ4 - What unresolved challenges lie ahead?

D. *Identification of Relevant Bibliographic Databases*

In order to find the relevant studies for the review, we selected the databases that cover the majority of papers published in the field of computer science:

- Scopus [35]
- Web of Science [36]

E. *Definition of the Search Expression:*

After discarding several options (too restrictive or too broad) our search expression is:

(TITLE-ABS-KEY ("sentiment analysis" OR "opinion mining") AND TITLE-ABS-KEY ("spanish") AND TITLE-ABS-KEY ("politics" OR "political" OR "hate speech"))

Additional filters and date range restrictions were not applied, thus being consistent with the systematic nature of the review. The search was carried out in June 2022.

F. Selection Criteria

We defined the criteria to exclude papers for the purpose of this review.

- Duplicated papers
- Publications that do not focus specifically in our subject
- Non-scientific materials (i.e., informal publications for informational or commercial purposes)
- Contents limited to presentations, abstracts, and editorials
- Posters and infographics
- Publications hosted in services with restricted access and not accessible

To determine whether one paper is acceptable or not for the purpose of this review, the reading was performed in the following order: title & keywords, abstract and, finally, introduction.

G. Information Extraction Strategy

In order to collect the information and answer our research questions, our extraction strategy was planned as follows:

- Register bibliographical data
- Read the full text of every paper (the ones accepted in the selection phase)
- Identify and collect all the relevant pieces of information related to our RQs, with special focus on:
    - Specific topics which are discussed
    - Specific matters which are pointed out as "controversial", "challenging" or "not resolved"
    - Techniques which are used or discussed

IV. Results: Conducting the Review

We conducted the review in three steps: searching datasets, Screening – Eligibility, and Results.
We also performed two additional procedures aimed to enrich the results and contextualizing our work:

- While screening the returned papers, we tried to identify additional records not found in the datasets, as suggested by the PRISMA statement [33] . In this case, we check the bibliography referenced by authors in the papers that were found, just to be sure that no relevant document was missing (sentiment analysis works specifically dealing with politics or hate speech in the Spanish language that meet the acceptance criteria expressed in section III – F).
- We performed a quantitative parallel search with a broader view, for statistical contextualization.

A. Searching the Bibliographic Datasets

The first step of our systematic review in the "conduction stage" was the application of the search expression in each bibliographic dataset, in July 2022, which resulted in:

- 47 returned papers from Scopus
- 40 from WOS (Web of Science)

Thus, a total of 87 papers were found (including duplicates). The second step was the searching of relevant works, if any, cited in the returned papers but not found in the bibliographic datasets under our search expression (possibly because of inadequate tagging or any other indexing issue).
Thanks to this prevention, seven additional relevant works was found, for a final 94 papers to be screened.

B. Screening-Eligibility

In this phase, after the removal of 30 duplicate studies, 64 papers where screened. 18 records were excluded in the screening (74% not relevant and 26% conference presentations), resulting in 46 papers. One of the documents was not accessible in full text, which leaves us with a final total of 45 papers to be included in the extraction phase (Fig. 1).

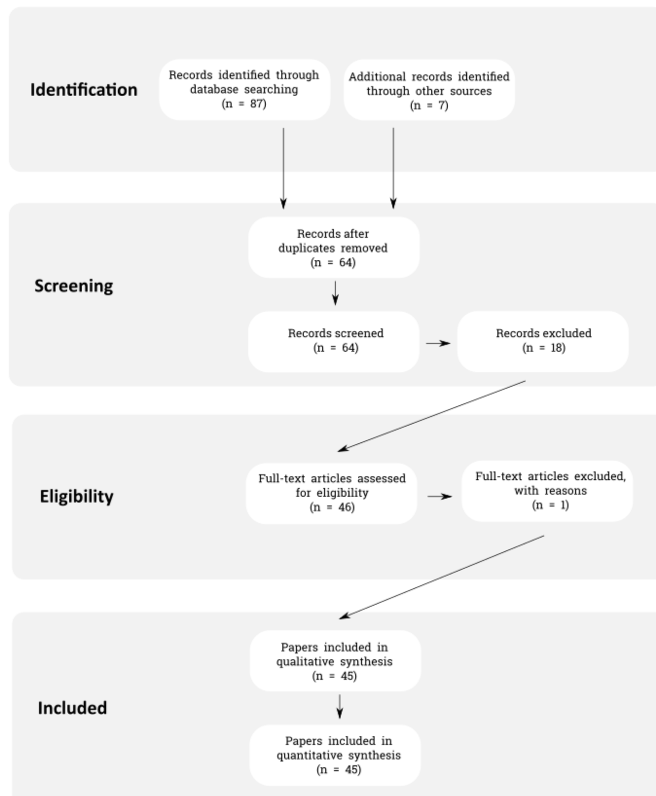

Fig. 1. Information flow. PRISMA Flow Diagram from Moher et al. [33] (adapted).

C. Selected Papers

1) Papers list (RQ1)

Table I summarize published and analysed works, indicating authors, year of publication and citations, which will be expanded and analysed later.

2) Contextualization

The first work focused on Spanish language was published in 2014 (Fig. 2). A parallel search without the term "Spanish" reveals that the first paper published on this domain (English language) was released in 2004.

TABLE I
SELECTED PAPERS

Ref	Authors	Year	Citations
[37]	Cuesta et al. 2014	2014	22
[38]	Pla & Hurtado 2014	2014	42
[39]	Agulló et al. 2015	2015	0
[40]	Vilares et al. 2015	2015	45
[41]	Cerón-Guzmán et al. 2016	2016	18
[42]	Castro et al. 2017	2017	13
[43]	Singh et al. 2017	2017	9
[44]	Arcila-Calderón et al. 2017	2017	14
[45]	Gomez-Torres et al. 2018	2018	0
[46]	Criado & Villodre 2018	2018	7
[47]	Hidalgo et al. 2018	2018	1
[48]	Gil-Vera & Montoya-Suarez 2018	2018	9
[49]	Pérez & Luque 2019	2019	10
[1]	Pereira-Kohatsu et al. 2019	2019	54
[50]	Vega et al. 2019	2019	8
[51]	Bohorquez-Lopez et al. 2019	2019	0
[52]	Franco-Riquelme et al. 2019	2019	5
[53]	Baviera et al. 2019	2019	6
[54]	Baviera et al. 2019	2019	3
[55]	Almatarneh et al. 2019	2019	7
[56]	Cignarella 2020	2020	0
[57]	Sanchez-Nunez et al. 2020	2020	0
[58]	Grimaldi et al. 2020	2020	4
[59]	Pamungkas et al. 2020	2020	0
[60]	Arcila-Calderón et al. 2020	2020	15
[61]	Blasco-Duatis & Coenders 2020	2020	2
[62]	Pastor-Galindo et al. 2020	2020	8
[63]	Arcila et al. 2020	2020	12
[64]	Ramon-Hernandez et al. 2020	2020	1
[65]	Plaza-Del-Arco et al. 2021	2021	1
[66]	Plaza-del-Arco et al. 2021	2021	24
[67]	Córdoba-Cabú et al. 2021	2021	0
[68]	Andrade-Segarra et al. 2021	2021	2
[69]	Tamayo et al. 2021	2021	0
[70]	Uzan & HaCohen-Kerner 2021	2021	0
[71]	Romero-Vega et al. 2021	2021	1
[72]	Sanchez-Junquera et al. 2021	2021	3
[73]	Jain et al. 2021	2021	1
[74]	Gómez-Zaragoza & Pinto 2021	2021	1
[75]	Huertas-García et al. 2021	2021	0
[76]	Arcila-Calderón et al. 2021	2021	5
[77]	Rodriguez-Ibanez et al. 2021	2021	1
[78]	Cervero 2021	2021	0
[79]	Rendon-Cardona et al. 2022	2022	0
[80]	Robles et al. 2022	2022	0

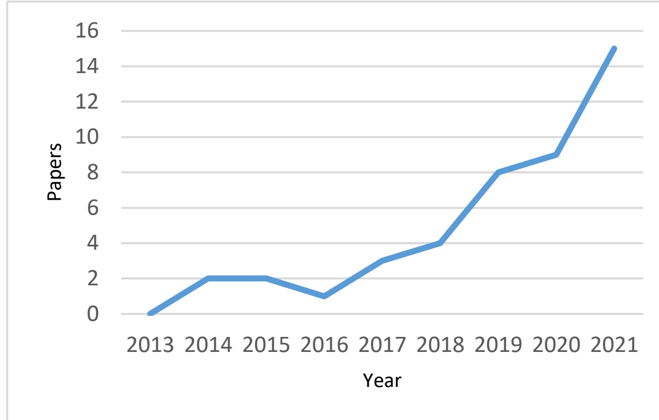

Fig. 2. Papers to be included in the extraction phase, per year of publication.

Apart from time gap, as we see in Fig. 3, paper production in this domain is growing at a lower rate for Spanish language.

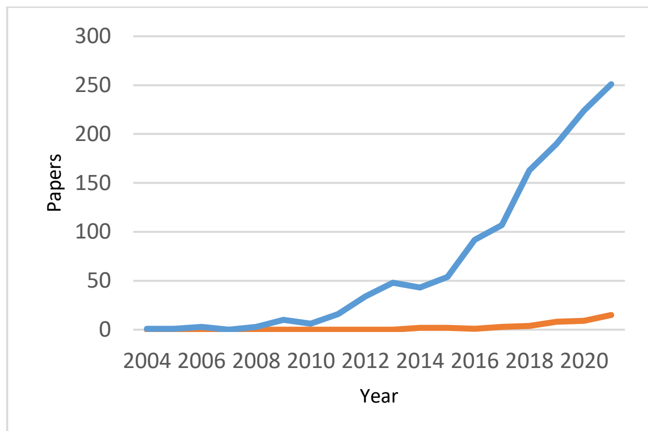

Fig. 3. Published papers related to sentiment analysis methods for politics and hate speech contents in Spanish language (orange), compared to TOTAL articles published worldwide (blue).

D. Extraction

Once the 45 papers included in the review have been accessed for analysis, we focused our extraction on the identification and classification of all the relevant features concerning to our RQs. To be more specific:

- Analysis tools / Methods
- Research type
- Research aim / topic
- Text sources and datasets
- Unsolved challenges, future developments, and controversial aspects.

E. Analysis

1) Aim and topics (RQ1)

In recent years, a clear preference towards the hate speech subdomain can be verified. Until 2019, only 4 papers on hate speech were published, 20% of the documents analysed in this review for the period. However, as of 2020 we have seen a considerable increase in works on hate speech, with 15 papers, 60% of the total for this late period. Considering the entire time span, hate speech accounts for 42% of the researchers' attention. In this regard, Fig. 4 presents a panoramic view of the works published since 2014.

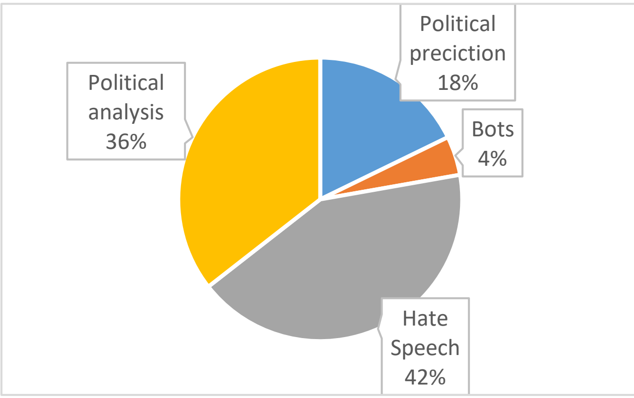

Fig. 4. Topics of analysed papers.

It is significant to note that prior to 2019 there was not a single paper on sentiment analysis for the Spanish language specifically dedicated to hate speech. The growing interest in hate speech detection from 2020 is directly aligned with the social concerns about the possible negative impact that these messages can have on individuals or on the society [1].

We have been able to identify four different aims in the works published on hate speech: analysis of the phenomenon (past events), detection (identify hate), monitoring (real time detection) and, more recently, profiling.

Unlike the usual orientation of works focused on elections and other aspects of politics, in the case of hate speech, a component of social practicality is added to the mere academic-methodological debate. This intention is especially reflected in the HaterNet tool created by Pereira-Kohatsu et al. an intelligent system currently being used by the Spanish National Office Against Hate Crimes of the Spanish State Secretariat for Security, that identifies and monitors the evolution of hate speech on Twitter [1].

If we take a broader perspective and consider all the works published since 2014, we observe that most of the works (58%) are focused on political generalities (predominantly electoral processes) aimed to experimental method discussions and comparative method analysis, in some cases related to specific case studies. The lack of consensus in the research community on the most suitable methods, together with the constant renewal of the state of the art, force researchers to continuously prospect different approaches and tools.

Of 26 works on politics, 30% are oriented to the prediction of electoral results. Another topic of growing interest is political bots. Pastor-Galindo et al. clearly demonstrated not only a non-negligible number of social bots on Twitter participating in the Spanish elections (2019) but also a relevant number of interactions and traffic volume [62]. This collection of false opinions has an obvious impact on all subdomains if they are not detected and discarded in the datasets.

We found that only 3 papers [39][42][52] deals specifically with Geolocation, all of them with limited results, due to several reasons as described below. This represents less than 7% of the total number of papers. Franco-Riquelme et al. [52] found in their research that most of the tweets did not indicate their location. This is a well-known problem, as less than 1% of tweets are geolocated (geo-tagged) and the information available from the "location" field in users' profiles is unreliable [81]. Castro et al. [42] just discarded all not-geotagged tweets (no indication of volume) in their work. To overcome this issue, the solution proposed by Franco-Riquelme et al. [52] consists in merging the extracted tweets with the data retrieved from each user profile, leading to a 40% of geolocated tweets from the entire dataset. Castro et al. propose a reverse geocoding process with Google Maps API, interpolating geographic points (latitude, longitude) to a readable place name [42]. The experimental tool created by Agulló et al. [39] performs a two-steps checking: first, the geolocation info is searched in the user's profiles; second, if this info is not available in the corresponding field, the system looks for the geo-tagging info (it it has been enabled by the user). There is no info in this paper about the percentage of tweets which are discarded by the application of this procedure, but according to experiences of Franco-Riquelme et al., it should be very high. Instead of reverse geocoding, Agulló et al. use Google Maps API directly as a mean of graphical presentation.

Of the 45 papers studied, only four have real-time monitoring as their objective, that is, less than 9% of the total. In this context, "real time" means a continuous monitoring of opinions as they are produced, as opposed to an analysis performed on a collection of messages in a given time range. Pereira-Kohatsu et al. [1] , Arcila et al. [44], Vilares et al. [40] and Ramón-Hernández et al. [64] are the only papers which deals with real-time monitoring challenges. While Arcila et al. And Vilares et al. Focuses on a better understanding of political conversation phenomena on Twitter, Pereira-Kohatsu et al. Presents a powerful framework (HaterNet) dedicated to identifying and monitor hate speech in Twitter. 84% of works describe procedures aimed to analyse past events, either to validate hypotheses or to propose new methodologies, but there is also a very significative interest on prediction (16%). For this predictive approach, all the authors apply a very similar view: they analyse past opinions on Twitter (ad hoc datasets) in a given period of time and then apply the proposed analysis method to obtain a prediction, which is compared with the actual results of the elections. As a baseline reference, they use different prediction methods available, like poll-based data [41] or other Twitter prediction performances [58].

Fig. 5 summarizes the aim of all the studies analysed.

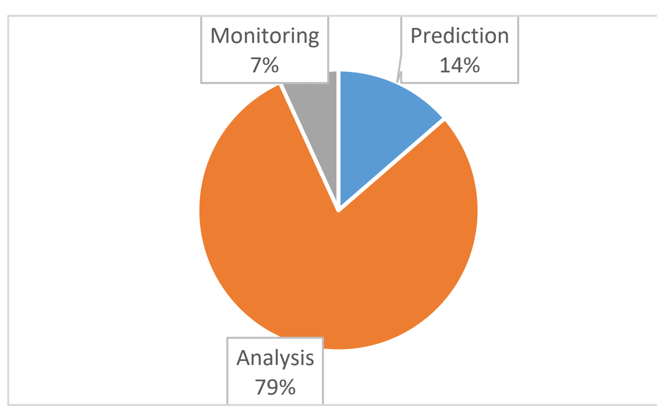

Fig. 5. Different aims in published works.

2) Analysis tools (RQ2)

The mere statistical analysis of the tools used by the authors clearly reflects a scenario where we can identify a lack of methodological consensus and rapid methodological evolution (see Table II), especially if we consider that only 8 years have elapsed between the first study and the last.

TABLE II
MOST FREQUENT RESOURCES DESCRIBED ON ANALYZED PAPERS, PER YEAR

Resource	Papers	%	2014	2015	2016	2017	2018	2019	2020	2021
BERT based	8	18%								8
NLTK	5	11%	1						3	1
Sentistrenght	4	9%		1				2		1
Freeling	3	7%	1		1		1			
SciKit	3	7%			1			1	1	
StanfordNLP	2	4%					2			
LinguaKit	2	4%						1		1
AFINN	2	4%								2

In their works, the selected authors are considering two different approaches to this task:

- Lexicon-based: uses a predefined lexicon to check the occurrence of words in the revised text.
- Machine Learning techniques: uses diverse language model classifiers, applying in some cases techniques based on neural networks (Deep Learning methods).

Lexicon-based and Machine-Learning search for text patterns by means of lexical and syntactical information, making use of different approaches as n-grams, BoW (Bag of Words) and POS (Part of Speech).

Although the range of time that has elapsed since the first publication is very short, barely 8 years, a clear evolution is observed from lexicon-based techniques to approaches centred on machine learning.

The most common lexicon-based tool used in the selected works [53][54][40][76] is SentiStrength. This tool extracts sentiment strength from informal text, using new methods to exploit the de-facto grammars and spelling styles of cyberspace [82]. SentiStrength is basically a framework that compares social media text against a lexicon-based classifier of sentiments, measuring its strength by assigning scores ranging from -5 to +5. Applied to MySpace comments, SentiStrength was able to predict positive emotion with 60.6% accuracy and negative emotion with 72.8% accuracy [82]. The accuracy for negative emotions is better than baseline and a wide range of general machine learning approaches [82].

AFINN [83] is a list of words rated for valence with an integer between minus five and plus five (as SentiStrenght). The author of this dictionary manually labelled postings from Twitter, scored for sentiment. Using a simple word matching he showed that the new word list may perform better than ANEW[1] [84], "though not as good as the more elaborate approach found in SentiStrength" [85]. AFINN dictionary has been used by two authors in this review [77][80]. Rodríguez-Ibañez et al. evaluated and benchmarked AFINN with three other sentiment lexicons widely available in the Spanish language: JAEN [86], Linguakit [87], and SBU [88], concluding that "the higher granularity of AFINN does not add clear benefits, which could be justified based on the very limited number of words included within" [77].

Although we find that most papers in our review are using techniques which involve machine learning, there is a great diversity of methods and tools, and a lack of standardization in sentiment analysis procedures.

NLTK [89] (Natural Language Tool Kit) is used in five papers to build corpora and models out of tweet collections [67][63][60][59][37]. This powerful toolkit is a veteran platform for building programs (Python programming language) to work with human language data. It provides interfaces to over 50 corpora and lexical resources (i.e. WordNet [90]), and a suite of text processing libraries for different tasks: tokenization, stemming, tagging, parsing and classification [89].

Stanford NLP [91] is a well-regarded tool among the research community, but it is hardly used by the selected authors (only two of them [45][47]). Stanford NLP is developed and maintained by the Natural Language Processing Group, at Stanford University. It applies an effective combination of deep linguistic modelling and data analysis with probabilistic, machine learning, and deep learning approaches to Natural Language Processing. Its "core" (CoreNLP [92]) enables users to derive linguistic annotations for text, including token and sentence boundaries, parts of speech, named entities, and sentiment, among other functions. CoreNLP currently supports eight languages: English, Spanish, Chinese, French, German, Italian, Hungarian and Arabic.

In their research, Gómez-Torres et al. "adapt" the Stanford NLP tool to the Ecuadorian regional language, through the revision of regional expressions, idioms, messages with discordant meanings, abbreviations, among other characteristics of the Spanish language [45].

Introduced in a 2019 paper by Devlin et al. [93], BERT (Bidirectional Encoder Representations from Transformers) is designed to pre-train deep bidirectional representations from unlabelled text. The pre-trained BERT model can be fine-tuned with just one additional output layer to create models for a wide range of tasks, such as language inference, without substantial task-specific architecture modifications [93]. BERT has pushed the GLUE score to 80.5% (which means a 7.7% improvement), MultiNLI accuracy to 86.7% (4.6% improvement), and SquAD v2.0 Test F1 to 83.1 (5.1 point absolute improvement) [93].

Despite its recent development, together with its conceptual novelty (with all that this entails for a research community accustomed to other methods), BERT and its Spanish trained model BETO, have been used to a greater or lesser extent in almost a third of the of the works published since 2020 (for the purposes of this review), which gives us a precise idea of its success.

Word2Vec is used by in just one work [51]. Word2vec is a natural language processing technique published in 2013. The Word2vec algorithm uses a neural network model to learn word associations from a large corpus of text. Once trained, the model can detect synonymous words, and represents each word with a particular vector.

The open source language analysis tool suite Freeling [94] is used by Pla & Hurtado, Cerón-Guzmán et al. y Gómez-Torres et al. [38][41][32] for lexical normalization and other primary tasks. FreeLing project is led by Lluís Padró (Universidad Politécnica de Cataluña – Departamento de Ciencias de la Computación) as a means to make available to the community the results of the research carried out at the UPC natural language processing research group [94]. According to Franco-Riquelme et al., Freeling has been used to perform NLP to support primary analytical tasks and data processing, with certain success [52] (although they discard it for their investigation, claiming the existence of better options).

Franco-Riquelme et al. [52] performs a named entity recognition procedure (NER, also known as entity chunking or entity extraction) using LinguaKit [87]. The authors justify this preferred option, while discarding others, with this statement: "We found that once examined, of all the resources that were necessary for working with our Spanish language database and were considered in the implementation of this research, LinguaKit was the most useful computational tool."

The tool Tweetmotif [95] is used by 2 researchers in this review [38][45], mainly for topic summarization. TweetMotif is an exploratory search application for Twitter. Unlike traditional approaches to information retrieval, this tool groups messages by frequent significant terms – a result set's subtopics. The topic extraction system is based on syntactic filtering, language modelling, near-duplicate detection, and set cover heuristics.

Sánchez-Núñez et al. [57] is the only paper using Viz Tweet Sentiment Visualization [96] . This tool allows to visualize, estimate and measure the feeling of short and incomplete fragments of text as well as its basic emotional properties [45]. It was chosen by the authors because "it provides many more dimensions than can be found in other sentiment analysis applications".

SciKit [97] is mentioned in three papers [41][55][60] as a repository of resources available for Classification, Regression and clustering [97]. Scikit-learn is a Python module with a wide range of machine learning algorithms for supervised and unsupervised problems [98].

3) Text sources and data extraction (RQ3)

87% of woks are related to Twitter as only source. Bohorquez et al. [51] are the only authors working on Facebook opinions, and there is only on study dedicated to politicians speeches [51] (ParlSpeech dataset), media news [64] and college media [79]. In his work on syntactic methodologies, we can deduce that Cignarella uses content from Reddit in one of the two datasets used in his research [56].

In most cases all data collection has been made using the Twitter API, either directly or through some intermediate tool, like Tweepy [99].

For some of the research, the authors used a previously third-party collected set of tweets, like HatEval[2] or PAN (CLEF2021) dataset [3], instead of performing the extraction by themselves. 58% of the studies are based on custom ad-hoc datasets.

4) Specific problems hampering research with current methods (RQ4)

Some authors pose a critical view of the state of the art, beyond the scope of their experimental work. For example, Grimaldi et al. point out some unsolved challenges for future studies: the use of weighting factors to include the "inaudible voice" (the population segment who does not participate in social media debate), the implementation of demographic data (i.e. age and gender) and geolocation, so as to be "at par with the statistical sampling methods" [58].

Singh et al. [43] identify the following weak points to overcome in future research:

- Massive re-tweets
- Multiple tweets from the same person
- Language interpretation issues
- Multiple entities in the same tweet (i.e., more than one party mentioned)
- Sentiment valence issues (positive/negative)

Criado and Villodre [46], concludes that current Machine-learning based systems are still unable to capture all the vicissitudes of the contexts.

According to Pereira-Kohatsu et al., "Surface forms" (lexicon-based and machine learning approaches) have worked remarkably well for many Natural Language Processing problems, but they are not capable of explaining the word semantics [1]. Methods based on word embeddings by training a neural network, make possible to come close to this objective [1].

Pla and Hurtado identify in their research other not solved problem: "Obtaining the polarity at entity level is a hard problem and introduces additional complexity because the part of the tweet refers to each of the entities must be determined. To resolve this problem, it should make a deep parsing of the tweet and perform a study of such dependencies. This is not a solved problem in NLP even considering normative texts and is further aggravated in Twitter texts" [38].

Spammer accounts and bots are also great challenges for the research community. Robles et al. [80] and Pastor Galindo et al. [100] develop in their work different methodological approaches to overcome this challenge.

If we compare the key aspects of this RQ section with the conclusions of other authors who have carried out reviews on sentiment analysis for the English language, we obtain very significant concordances. For example, in their review of sentiment analysis methods, Giachanou & Crestani [101] mention spamming, bots, word embedding methods, and entity-level polarity among the main lines of work of the international research community. The same authors point out the difficulties related to the interpretation of the context, especially when using lexicon-based tools. Metaxas et al. [102], in their study on the methods of predicting electoral results (mostly focused on US elections), conclude the existence of important unresolved challenges related to statistical representativeness (compared to traditional surveys) and with the distortion produced by spammers and propagandists. Therefore, the most relevant challenges for researchers focused on the Spanish language seem to be aligned with those of the international community as a whole.

V. Discussion

As a result of our analysis, everything seems to indicate that we are at an early stage in the domain of sentiment analysis methods for politics and hate speech contents in Spanish language, with a long way to go, many opportunities for research and a very slow growth curve compared to the English language.

The future challenges in the field of our review are concentrated on several axes:

- Semantic cross-domain challenges in sentiment analysis, such as irony detection and figurative language interpretation.
- Other transversal problems, related to fake content. There are specific hurdles that pose a significant challenge when working with the data, such as bots and spamming, but it is not clear whether the research community can rely on generic solutions valid for other areas, or whether it is necessary to develop specific tools for the field of political debate.
- Geolocation, given the geographical linkage of the electoral processes. In this sense, no proposals have yet been made to overcome the limited information that Twitter offers on the geographic location of its users (would we also have this problem with Facebook?).
- Methodological standardization. There is no standardized analysis procedure agreed upon by the research community (this issue is not exclusive to Spanish-language research, of course), with a great diversity of tools and methodological approaches to the same problems. In this sense, we must highlight the effort of Cuesta et al. for defining a specific framework [37].
- Twitter dependency. We observe an almost exclusive focus on Twitter. Thanks to its powerful API, which makes extraction work extremely easy (and of course, also thanks to the fact that almost all texts are public in this social network), this social media has drawn the attention of researchers, ignoring other sources that have different idiosyncrasies and audiences. Facebook is currently an unexplored field, with the marginal exception of just one paper [51], and this is undoubtedly introducing a great bias in the conclusions obtained, especially if we take into account the widespread implementation of this network throughout the Spanish-speaking world (around 22 million users in Spain, for example [103]). Unfortunately, Facebook does not currently allow scrapping of its content[4]. In addition to this, the absence of other networks makes it impossible to apply a broader vision of sentiment analysis, such as that proposed by Yadollahi et al. [4].
- Growing interest in monitoring hate speech, undoubtedly linked to the (recent) concern of political parties and institutions about this sensitive issue. Hate speech is closely connected to political ideology (and discourse) but has its own semantic dynamics as well as often distinct research goals. This requires specific approaches, very different, for example, from predictive models for electoral processes. The novelty of the "hate speech" subdomain, which could well be considered a domain in its own right, poses significant challenges to the research community.
- Generalized use of machine learning technologies in a broad sense, and the growing relevance of BERT as a state-of-the-art tool, with great future prospects. The emergence of BERT, as we have seen, has recently been a turning point that opens new paths for the research community.

As a corollary to this discussion, it is evident that there are great opportunities for research on all fronts related to Sentiment analysis methods for politics and hate speech contents in Spanish language.

Social interest in studying the attitude of the population in the political sphere, within social networks, is one of the sociological keys in today's world, but the research community has not yet reached a consensus on a methodological framework that allows to solve this challenge. In particular, deep learning technologies, together with geolocation and the incorporation of more networks (especially Facebook), may be the keys that lead us to a final success scenario.

Regarding the methodological debate from a more strategic perspective, the paper by Pereira-Kohatsu et al. related to HaterNet is especially interesting, due to its depth and novelty compared to other works [1]. HaterNet, the system currently being used by the Spanish National Office Against Hate Crimes of the Spanish State Secretariat for Security that identifies and monitors the evolution of hate speech in Twitter, is a novel tool that will undoubtedly be an important source of future works.

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