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Strategies for Automatic Detection of Fallacious Arguments in Political Speeches during Electoral Campaigns in Mexico

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Abstract. This study proposes a machine learning approach to automatically detect "appeal to emotion" fallacies. The objective is to establish a set of elements that enable the application of fallacy mining. Our method uses a lexicon of emotions to distinguish valid arguments from fallacies, employing Support Vector Machine and Multilayer Perceptron models. The Multilayer Perceptron obtained an F1 score of 0.60 in identifying fallacies. Based on our analysis, we suggest using lexical dictionaries to effectively identify "appeal to emotion" fallacies.

Keywords: fallacies; corpus; arguments; appeal to emotions.

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Стратегии автоматического выявления ошибочных аргументов в политических речах во время избирательных кампаний в Мексике

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Аннотация. Для автоматического обнаружения ошибок «обращения к эмоциям» авторами предлагается подход на основе машинного обучения. Цель состоит в том, чтобы сформировать набор элементов, которые позволят построить приложение для выявления ошибок. Чтобы отличить реальные аргументы от ошибочных, наш метод, основанный на моделях опорных векторов и многослойного перцептрона, использует словарь эмоций. При выявлении ошибок многослойный перцептрон получил оценку по метрике F1, равную 0,60. Основываясь на проведенном анализе, мы предлагаем использовать лексические словари для эффективного выявления ошибок «обращения к эмоциям».

Ключевые слова: ложные высказывания; корпус; аргументы; обращение к эмоциям.

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1. Introduction

Existing research on fallacy identification in several types of texts has provided the types of fallacies committed by political candidates and confirmed their use in political debates and speeches. These studies involve the analysis of texts in the English language. However, these investigations lack a method for identifying fallacies by implementing natural language processing techniques. Although [1] identified some lexical and characteristic syntactic elements of the *Straw man* fallacy and proposed an approximate model of its structure for mining, no method was implemented to automatically identify whether a proposition (argument) is a fallacy. The system developed by [2] and [3] identifies formal fallacies in natural dialogues between two people, but the process used does not allow for the identification of informal fallacies in monological political speeches.

This paper structures the mechanisms for identifying fallacies and presents the main elements to be considered for the development of systems that allow for their identification from unstructured texts. Therefore, our goal is to propose a set of elements that allow for fallacy mining and to discuss the challenges involved in this task. Moreover, this paper assumes that it is possible to implement machine learning-based techniques that allow for the automatic fallacy detection.

This paper presents the identification of emotional appeal fallacies in political speeches in the Spanish language by implementing two machine learning methods: Support Vector Machine, Multilayer Perceptron, and the use of two features: affective terms and lexical diversity. In addition, the conceptualizations of the "fallacy" term are structured, the mechanisms for their identification are presented, a set of elements to consider for the development of systems that allow for fallacy mining is proposed, and the challenges involved in this task are discussed.

2. Motivation

The fallacies have received little attention from the linguistic community. There is insufficient characterization of their form and determination, involving semantic, pragmatic, and communicative analysis. It is important to emphasize that the same reasoning error in arguments can be classified into different types of fallacies. Although there are diverse taxonomies, there is no certain and unique taxonomy. The complexity of classifying them arises from the absence of precise rules that determine absolutes regarding errors in reasoning, and even from the intrinsic problem of the definition, purpose, meaning, or effects of fallacies on the audience or readers [29].

To implement machine learning techniques, a collection of labeled data is required to validate the performance of any implemented technique [51]. Within the literature, there are few corpora available in Spanish language to experiment with methods for identifying fallacies [30]. Corpus have been created with specific objectives and are hardly adaptable to identify arguments that have no valid basis.

Moreover, it is important that criteria identification could be implemented with machine learning techniques. The criteria established to identify fallacies through manual analysis may not be processable through a computational method. Additionally, these criteria may vary according to the types or categories of informal fallacies to be processed.

If we take the example of fallacies by appealing to emotions, emotional appeals can arise in any context as people advocate for what they feel is important, but there are contexts in which they are inappropriate [30]. Similarly, two propositions considered irrelevant to each other in one context, may be considered relevant in another, and there may be references to emotions that are not a fallacy in an argument.

3. Fallacies

There have been numerous attempts to establish concepts that enable an understanding of the term "fallacy" in any argumentation theory [4]. This Inconsistency and disagreement have led to the emergence of several approaches and definitions of the term fallacy.

According to [5], the term "fallacy" is not precise due to its ambiguity and can refer to: "(a) a type of error in an argument, (b) a type of error in reasoning (including arguments, definitions, explanations, among others), (c) a false belief, or (d) the cause of any of the above errors".

In our case, similar to [5], but based on the monological, dialogical, and rhetorical models for argumentation analysis presented in [6], as well as the conceptualization of the term fallacy in the field of formal and informal logic presented in [7], a fallacy can refer to:

1. A type of error in argument form: Fallacies can be defined as arguments that have errors in their form by infringing on any of the deductively valid structures [7, 8] or identifiable instances of invalid logical forms [9].
2. A type of error in the argument reasoning: Fallacies are arguments that contain errors in their content due to mishandling of their propositions [9], or they are an invalid, failed, or fraudulent argumentation [9, 10].

3. A violation of rules and/or criteria: Reference is made to rules or criteria that must be followed in speech or argument construction. In this context, fallacies are characterized by infringing on the critical discussion rules and interrupting the resolving a dispute process [11, 12]; They are arguments that lead to error by infringing one of the rules or criteria for constructing good arguments [13, 14] or are considered arguments lacking in solidity [8].
4. Something implausible: Unlike the previous ones, non-linguistic aspects are considered, and reference is made to the argument persuasive intention and the effects it produces on the audience [10, 15].

Regardless of their definition, fallacies are grouped into formal and informal. Informal fallacies are speeches that pretend to be good argumentation [10] and are found in everyday language. This type of fallacy is analyzed in definitions 2, 3, and 4. Formal fallacies arise from errors in their structure and are independent of the content they deal with [7] or the context in which they arise [16], as specified in 1, and are typically presented in syllogisms.

4. Identification of fallacies

4.1 Related works

During electoral campaigns, argumentative strategies are used to persuade and manipulate citizens with the aim of obtaining their vote. One of these strategies is the use of fallacies, which are commonly presented in structured political speeches such as debates, press conferences, position papers, among others, to offer apparently coherent and solid positions [17].

Most of the research on identifying fallacies has focused on analyzing texts written in the English language. In 1986, [18] demonstrated that fallacies are common in political speeches by identifying more than 40 types of fallacies in two presidential debates, including *Ad Populum* and *Ad Hominem*. [16] found 25 fallacies in a presidential debate, with the most frequent being *Straw Person* and *Ad Hominem*. And in [20], 550 texts (press releases and journalistic articles) were analyzed, and almost one-third (32.5%) of the texts included at least one fallacious argument, with fallacies appearing more frequently in press releases than in journalistic articles.

In [4], a set of stages was described for resolving a critical discussion, where violating one of these stages results in a fallacy. According to these stages, [21] analyzed four political debates and found a concentration of fallacies in the argumentation and confrontation stages of the debates, with *Ad Hominem* being the preferred fallacy by politicians in the confrontation stage and *Ad Misericordiam* in the argumentation stage.

In [22], the criteria for a good argument were used to identify fallacies in four presidential debates. The relevance and acceptability criteria were violated most frequently, appearing in 12 of the 32 identified fallacies. The most frequent fallacy was *False Alternatives*, which occurred 10 times.

Another way to identify erroneous arguments in debates was by using the 10 rules of reasoning described in [12]. Considering these rules, [23] analyzed a presidential debate and concluded that politicians most frequently violate rule four (relevance of arguments), which was present in 25% of the data.

Unlike previous works, in addition to identifying fallacies, [24] also obtained the structure and pragmatic strategies of a fallacy. The pragmatic structure was established in three stages: Starting Point, Argument, and Endpoint. In the argument stage, they found that 60% of the arguments in the speeches appealed to self-interest, 20% to fear, 10% to commitment, 10% to flattery, and 0% to reciprocity and authority.

In [25], a taxonomy of fallacies was obtained through an analysis of arguments about security. The authors assumed that security arguments do not contain causal fallacies or emotional appeals, and based on these assumptions, these types of fallacies were excluded. In [26], students' ability to identify fallacies was examined, taking into account their argumentative context, where an argument can be considered fallacious in certain types of contexts only. In [27], the critical thinking skills of 25 students were measured to detect six types of fallacies. The 25 students were able to correctly identify and name three of the six fallacies: *Irrelevant Authority*, *False Dilemma*, and *Ad Hominem*. In the analysis conducted in [28] of a social debate on religion, the *Ad Hominem* fallacy was found to occur most frequently.

In [29], fallacies were identified using a set of nine presidential speeches in Spanish. Seventeen types of fallacies were identified in the opening and closing campaign speeches of presidential candidates. Among the most relevant fallacies in terms of frequency were *False Dichotomy*, *Ad Populum*, *Argumentum in Terrorem*, *Ad Hominem*, and *False Attribution*.

Regarding the approach to automatic identification of fallacies through machine learning algorithms, [1] identified some lexical and syntactic characteristic elements of the *Straw Man* fallacy. Based on the analysis performed, an approximate model of the structure of the *Straw Man* fallacy was proposed for its detection without implementation using Natural Language Processing (NLP) techniques. In [30], a baseline was proposed for the fallacies identification by emotional appeal using three machine learning models: Support Vector Machine, Logistic Regression, and Decision Trees. A set of 601 arguments obtained from 80 political speeches in Spanish was used. As a result, an F-score of 0.55 was obtained using textual similarity between the components of the argument and 0.62 by combining similarity with the affective terms used in the arguments.

In addition, research has focused on identifying informal fallacies to verify their use, understanding student's abilities to identify fallacies, understanding the fallacies relationship with populist communication, and the strategic and/or manipulative use made of them in debates, political speeches, and other media. Among the most common fallacies that appear most frequently in political speeches are *Ad Hominem*, *Ad Misericordiam*, and *Ad Populum* [17, 19, 18, 21, 22, 24, 29].

In comparison to the referenced paper [30], the present article provides a study on related works regarding fallacy identification, as well as the elements and features to be considered for the implementation of machine learning models. In fallacies identification by appealing to emotions, emotional traits and lexical diversity are employed as argumentative patterns to distinguish valid arguments from fallacies. The Multilayer Perceptron neural network is implemented.

4.2 Features

There are several features that can be used to analyze arguments or documents in order to identify fallacies in valid arguments. Here, we will focus on describing the most common features that frequently appear in a political argumentation context and are centered on the identification of fallacies by appealing to emotions.

In fallacies by appealing to emotions (*Ad Populum* argument), the support given to the argument's conclusion is an inappropriate appeal, because instead of evidence and a rational argument, it relies on expressive language and other mechanisms designed to provoke an emotion in the audience. This type of fallacy incorporates the *Ad Misericordiam* fallacy: a fallacy where the argument relies on *generosity*, *altruism*, or *pity* [7]. Other authors refer to *Ad Populum* as "the speaker appeals to the support that a large number of people give to the presented theses" [29].

Each research presents a proposal of features. For example, argumentative patterns were used in [18, 20, 29]; critical discussion resolution rules were used in [23]; and construction of good arguments criteria were used in [22].

Argumentative patterns are related to the expressive language used in premises to justify the argument's conclusion [7]. For example, the *Ad Misericordiam* fallacy can be identified by the use of words that allow taking advantage of the audience's sympathy or pity [20]. Some patterns are established according to the axes for emotion reconstruction in speech: involved people, intensity/quantity, and time [31].

Other features based on criteria have been established that allow for the development of good arguments, such as the criteria of acceptability, truth, relevance, and sufficiency. When one or more of these criteria are violated, the argument is considered fallacious [32]. Of these criteria, only the acceptability, relevance, and sufficiency criteria were considered in [14], and the refutation structure and effectiveness criterion were included, with relevance being the criterion used for the identification of fallacies by appealing to emotions (FAE). In [33], acceptability, relevance, and sufficiency were proposed as the three main aspects that should be examined to determine if an adequate basis is provided for accepting the conclusion given in the argument; otherwise, the argument is an FAE. Finally, in [34], two of these criteria, relevance and sufficiency, were established to evaluate the argument's components (premise and conclusion) and determine which arguments are fallacious.

Among other features, it includes analyzing arguments through critical questions or considering rules for constructing good arguments. Questions help to distinguish legitimate strategies for supporting the assertion in the argument. For the identification of the *Ad Populum* argument, the questions evaluate whether the arguer has relied on any kind of evidence and whether the appeal is relevant to the conclusion in the context of the argument. In the case of *Ad Misericordiam*, the questions evaluate the appeals in the argument context, as well as the relationship between the premise and conclusion through relevance [35]. Both fallacies can also be identified through the rules established for constructing good arguments [13].

Other criteria have been established that judge arguments within a dialogue structure or systematically evaluate the movements or sequences of the argument in the dialogue context. Under this context, three criteria of a good argument were established in [32]: anticipating an objection to a premise, anticipating other criticisms, dealing with alternative positions; two criteria were established in [34]: Dialectical Relevance and Dialectical Shift; and a set of rules for resolving a critical discussion was established in [11,12].

Based on these rules or criteria, an argument is considered fallacious if it violates one or more of them. The three features can be used in a dialogic speech, unlike the criteria used to evaluate the internal argument structure, which focus more on monologic speeches [24].

According to [26], informal fallacies can be detected by examining the argument's context. In argumentation, the context can be defined using the dimensions suggested by [36], as cited by [26]: initial situation that motivates the dialogue, method of dialogue, and the objective of the dialogue. These dimensions differentiate types of dialogue, which in turn from the argumentative context.

Finally, a critical evaluation of the argument can be performed in two steps to determine whether the approach is fallacious. First, the argument is reconstructed from the speech. Once the argument has been obtained, the three sources of objective evidence are evaluated: the speech text, the dialogue context, and the abstract model of dialogue. These steps involve an evaluation of both the argument structure and the dialogue in which the argument is presented [37].

The set of features is grouped into two categories based on [32] and [34], as cited by [24]. One category groups the features that analyze the dialogue structure, and the other evaluates only the propositions of the argument, that make up the argument structure (Table 1).

Table 1. Features used in the identification of informal fallacies

Dialogue structure	**Argument structure**
Rules for resolving a critical discussion	Argumentative patterns
Dimensions of the context	Rules for constructing good arguments
Dialectical relevance and Dialectical shift	Criteria of a good argument
Sources of objective evidence	

While both categories allow the identification of fallacies, the process for selecting the features depends on their definition or approach. The first category can be used to evaluate arguments from a dialectical approach, and the second from a logical approach. In the case of rhetoric, the acceptability criterion [32], space [31], or any non-linguistic features can be used.

Some of the research in the literature has used features focused on the analysis of the argumentative structure [18, 29, 30]. We consider that this type of feature can be implemented to some extent using natural language processing techniques, especially argumentative patterns. For example, the patterns found in the identification of fallacies by appealing to emotions are based on emotive language that allows for the justification of the assertions made in the speeches.

4.3 Taxonomy of fallacies

Several taxonomies have been established in the literature to group some of the informal fallacies. However, existing taxonomies differ in their length, categories, sets, and names (Table 2). For example, fallacies used to win an argument were grouped together [38]. Other taxonomies were established according to the criteria that are violated in the construction of a good argument [14], or based on the most common types of reasoning errors [7]. When any of these criteria or errors are violated, the argument is considered fallacious. Lists of fallacies that involve types of errors committed in the content of the reasoning or in the structure of the argument are also presented [5], or fallacies found in security documents were grouped [25].

Some investigations have grouped together a set of fallacies without defining a taxonomy as such. Here, fallacies were grouped that break some of the rules presented in the stages through which the resolution of a dispute must pass in a critical discussion [12]. Also, the types of fallacies that occur when the premises of an argument are irrelevant or when its conclusions are based on faulty analogies were grouped together [39].

Table 2. Taxonomy of fallacies. TF represents the number of fallacies proposed by the taxonomy

Ref.	TF	Categories
[5]	224	A list of uncategorized fallacies is established
[7]	15	Relevance, faulty induction, presupposition, and ambiguity
[12]	34	Opening, confrontation, argumentation, and closing
[14]	60	Structure, relevance, acceptability, sufficiency, and effectiveness of refutation
[25]	33	Circular reasoning, divergent arguments, fallacious appeals, mathematical fallacies, unfounded claims, anecdotal arguments, omission of key evidence, and linguistic fallacies
[38]	64	Linguistic factors, relevance of omission, relevance of intrusion, and relevance of presumption
[39]	32	Irrelevance and analogy

The list of different types of fallacies is extensive, and the features that distinguish them from one another are quite varied. Attempting to address the problem of identifying fallacies using a general method and taxonomy would be inadequate, due to the variety of fallacies, concepts, rules, and criteria established by different authors. For instance, the categories proposed in [7, 38, 14] are oriented towards evaluating arguments from a logical approach, while the categories proposed in [12] are based on a pragmadialectical approach.

5. Elements of identification

Discourse analysis consists of a set of strictly related tasks designed to distinguish good arguments from fallacies. Considering that a fallacy is an argument with an error in its content due to mishandling of its propositions [7], or a claim that has a reasoning error [29], and according to research in literature, a set of elements was obtained to consider in fallacy identification (Fig. 1). These elements are grouped into two sections: Argument Mining and fallacy identification.

5.1 Argument Mining

The main goal of Argument Mining (AM) is to "automatically extract arguments from generic textual corpus, in order to provide structured data for computational models" [6]. The AM systems implement a pipeline architecture, process unstructured documents, and produce a set of annotated arguments as a result.

Research on AM in the literature is characterized by the use of English language texts [6, 40, 41, 45, 46, 50], and few studies have processed Spanish language texts [30, 42, 43, 44].

The tasks involved in systems developed for argument extraction from plain text begin with text segmentation, and the boundary of the text that is considered argumentative (argumentative sentence) is defined. Subsequently, these segments are classified according to their function (premise or conclusion) within the argument (classified sentences), and links between segments (support or attack) are predicted to build the argument structure. Finally, the relationships between the existing arguments in the text are inferred (Fig. 1).

5.2 Identification of fallacies

In literature, the argumentative sentences identification and the components classification stages in AM are used as an initial stage in identifying fallacies [24, 29, 30]. Subsequently, the fallacy concept to be used and the selection of fallacies to be identified are determined. From this, features are selected or searched that allow for the determination of whether a sentence or argument is a fallacy. Therefore, once the arguments or sentences are extracted from the texts, an analysis is carried out for each of them, considering the type of fallacy to be identified. The analysis can be carried out by considering the relationship between argument components: evaluating the justifications present in the premises that support the statement given in the conclusion (inference); by considering the relationship between arguments by evaluating them within the dialogue structure; or by evaluating the arguments in relation to their acceptance in the audience (Fig. 1).

This paper focuses on identifying fallacies automatically by appealing to emotions through the analysis of argumentative components using affective terms (patterns) and measuring the lexical diversity of each component.

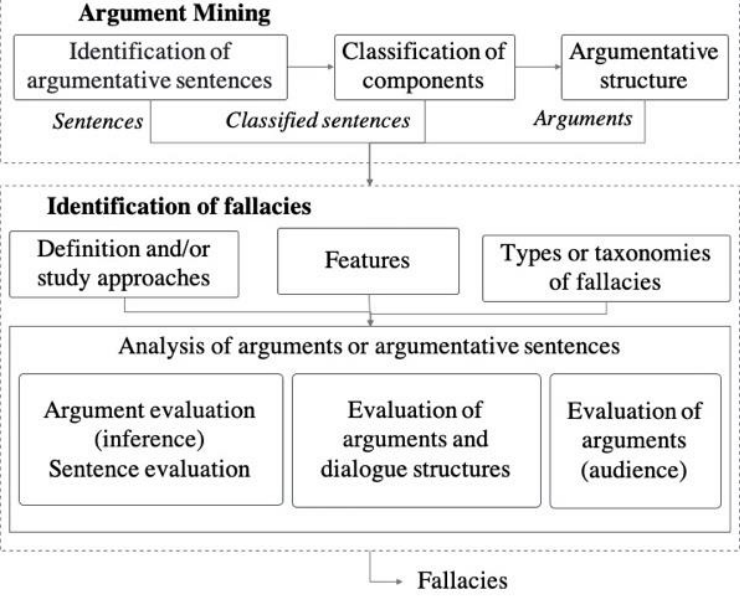

Fig. 1. Elements for fallacy identification

6. Identification of fallacies by appeal to emotions

6.1 Data

The appeal to emotion fallacy corpus consists of arguments obtained from a set of political speeches [30]. The corpus contains 601 arguments labeled according to their argumentative structure (premise and conclusion) and classified into fallacies by appealing to emotions and valid arguments:

1. (*Premise*) Aunque existen otros asuntos, el principal tema de la agenda con el gobierno estadounidense tiene que ser la migración, por todo lo que aquí se ha dicho. (*Premise*) Los flujos migratorios masivos y el creciente rechazo en la frontera constituyen una de las principales fuentes de fricción entre las dos naciones. (*Conclusion*) Por ello, hoy más que nunca es necesaria la cooperación entre ambos gobiernos para buscar soluciones de fondo que atemperen y ordenen el fenómeno migratorio. (*Valid*)
2. (*Premise*) No se puede gobernar un país en un mar, en un océano de desigualdad. (*Premise*) Esto se debe de entender: No vamos a tener seguridad pública, si sigue habiendo tanta desigualdad social. (*Premise*) Esto conviene a todos. (*Conclusion*) Por eso cuando planteamos que “Por el bien de todos, primero los pobres”, no estamos proponiendo imponer las cosas, sino convencer y persuadir. (*Fallacy*)

For argumentative component classification, an agreement with Cohen's Kappa index (kc) of 0.692 and an agreement with Fleiss' Kappa index (kf) of 0.648 were obtained; both results with a substantial agreement degree. In identifying fallacies, a *kc* of 0.442 and a *kf* of 0.282 were obtained [30].

6.2 Feature Selection

The fallacies by appealing to emotions are characterized by the use of emotive language to support an opinion or position in an argument or as a resource to achieve a goal. This type of language is presented in arguments in a positive or negative manner and includes words that serve only to manipulate emotions [7, 13]. Emotive language can be detected through certain argumentative patterns. For instance, words that appeal to emotions [7]:

1. (*Premise*) Somos un país de gente alegre, ingeniosa y trabajadora; de mujeres y hombres que luchan, que están de pie y que saben salir adelante. (*Conclusion*) Por eso, por todos ustedes, aquí hoy les digo: México va a estar mejor y México va a cambiar.

The affective terms can be classified as having either a positive or negative polarity (iSOL lexical dictionary) [47] or according to the type of emotion they convey (SEL dictionary) [48] (Table 3). Some terms in SEL dictionary are classified with more than one type of emotion (TE), and the difference lies in the frequency of use in each TE.

Table 3. Sample of affective terms found in the iSOL and SEL dictionaries

Term	Polarity	Type of emotion	Frequency of use in TE
Abandon	Negative	Sadness	0,898
Admirable	Positive	Happiness	0,764
Admirable	Positive	Surprise	0,73
Abysmal	Negative	-	-
Torment	-	Anger	0,365
Torment	-	Sadness	0,53

There is another way to express emotional language, which is through the use of words that convey emotional features [31]:

2. Nosotros, en la Alianza por México, tenemos un *gran compromiso*, porque en el año 2000 nuestro país tomó el camino de una *aventura política,* que hoy está viviendo nuestro país

las consecuencias, un país sin rumbo, un país sin dirección, un país en donde las cosas están al revés, donde la *inseguridad crece* y los *delitos aumentan* y las víctimas nadie las defiende.

These affective traits are classified into three axes [31]:

1. Involved individuals. The discourse either focuses on the speaker or involves the audience.
2. Intensity/Quantity. It affects categories such as distance, time, or the quality of people through quantitative modulation.
3. Time. It focuses on the description of the period in which the events being narrated occur.

Other traits that do not fall into these axes are also considered, and for these types of terms, a general class was determined (Table 4).

Table 4. Sample of emotional traits in arguments

Involved individuals	Intensity/ Quantity	Time	General
Democrats.	Many, more, most	Two months	Real change
Mexicanos	Minimum, huge	Future	Single mothers, widows
Veracruzanos	Millions, hundreds, thousands	Present	Disability
People	Marginalized Mexico	Half a century	Lack
	Very serious situation	Past generations	Criminal acts

Expressive language is related to the lexical diversity of the argument. Lexical diversity measures whether a text uses a wide range of terms or is limited to recycled lexical items [49]. The simplest measure of diversity is the type/token ratio (TTR). This diversity expresses the ratio of types (word forms) to the ratio of tokens (continuous words) in the text (Eq. (1)). The interpretation is based on these two parameters, the greater the number of word forms relative to the number of all words in the text, the more lexically varied the text or corpus.

$$TTR = \frac{no.\ type}{no.\ tokens} \quad (1)$$

The affective terms are used in argument components to justify or establish the idea and topic discussed in the argument. This can result in a decrease in the number of different lexical elements used in the argument. Therefore, if the affective terms are removed or repeated (Argument 5 and 6), diversity decreases. Hence, the argument is considered a fallacy when it has lower lexical diversity and a higher number of affective terms.

1. *(Conclusion) D*ebemos estar unidos de cara a la nación, *(Premise)* porque sólo unidos podremos vencer a quienes son nuestros verdaderos *enemigos:* la *pobreza*, la *delincuencia*, el *desempleo*, la *desigualdad*. *(Premise)* Divididos perderíamos la fuerza que necesitamos para construir un *México mejor.*
2. *(Premise)* No se puede *manipular*, como se hacía antes, ya no se puede pensar poner vino nuevo en botellas viejas. *(Premise)* Puede seguir la misma estructura de poder, la misma estructura de control y de *manipulación*, pero es otra la mentalidad de nuestro pueblo. *(Premise)* El pueblo de México no es *tonto*, *tonto* es el que piensa que el *pueblo* es *tonto*. (*Conclusion*) Por eso no les va a funcionar su estrategia. *(Premise)* Ellos tienen el dinero, mucho dinero para comprar espacios en la televisión, en la radio, para *difamarnos*, pero no tienen lo mero principal, no tienen el apoyo de la *mayoría* de la gente, eso se los puedo asegurar.

6.3 Features analysis

Emotive traits were not found in the iSOL and SEL dictionaries. These texts are represented as syntagms in the arguments, primarily as nominal syntagms (NS) or adjective syntagms (S-ADJ). A dictionary of emotive features was made with 1,093 syntagms classified as affective and non-affective (Table 5). The labeling was performed by groups of two and three annotators. An agreement of 0.2478 was obtained with Cohen's Kappa index and 0.2302 with Fleiss' Kappa index (Table 6).

Table 5. Sample of nominal and adjective syntagms

Nº	Emotive traits	Classification
1	a failed strategy	Affective
2	a political adventure	Affective
3	foreign policy	Non-Affective
4	an exacerbated presidentialism	Affective
5	economic policies	Non-Affective

Table 6. Inter-annotator agreement for labeling emotive traits

Group	Affective	Non- Affective	Total	*k*
A1 – A2	459	147	606	0,2240
A1 – A3	670	65	735	0,2123
A2 – A3	486	133	619	0,2478
A1 – A2 – A3	436	61	497	0,2302

There is a set of 601 arguments. Each argument (ARG) has a structure with a conclusion (CO) and one or more premises (PRE). The argumentative structure was analyzed using three dictionaries: type of emotion (TE), polarity (PO), and emotive traits (ET), along with the lexical diversity of each component and the argument itself (Table 7).

Table 7. Sample of the features obtained in the arguments.

#ARG	Lexical Diversity			Affective Terms		
	CO	PRE	ARG	TE	PO	ET
1	0,695	0,654	0,658	15	10	3
2	0,799	0,772	0,648	15	10	3
3	0,652	0,631	0,675	2	7	3
4	0,421	0,401	0,446	3	9	2
5	0,781	0,752	0,812	3	3	1

The relationship between lexical diversity and affective terms indicates that arguments use a limited vocabulary and frequently employ affective language. Compared to [30], using the emotional features dictionary, most fallacies contain at least one affective term (Fig. 2 and 3). However, the number of affective terms increases in both fallacies and valid arguments (Fig. 4 and 5).

7. Results

The identification of fallacies is carried out through the analysis of argumentative components. The corpus contains classification of arguments, which is the first element of Argument Mining to initiate the identification of fallacies. Affective terms and lexical diversity of each component are used in the analysis, and the result of these features is evaluated using Support Vector Machine (SVM) and Multilayer Perceptron (MLP) methods. The MLP network has three layers, and the number of neurons in input and hidden layer depends on the number of features to be evaluated. x_n are the features used for fallacy identification, while y represents the classes (valid argument and fallacy). The logistic sigmoid function was used in the network (Fig. 6).

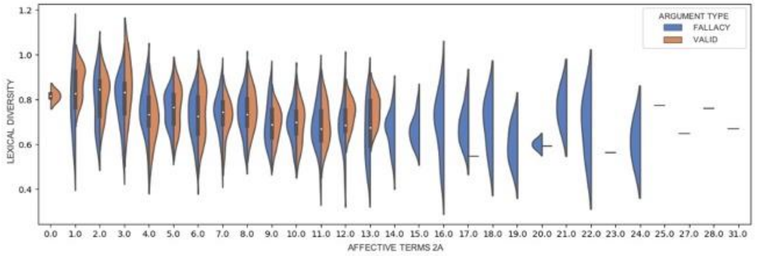

Fig. 2. Data distribution by affective terms and lexical diversity. Affective terms added from the emotional traits dictionary, and considering agreement between two annotators (2A)

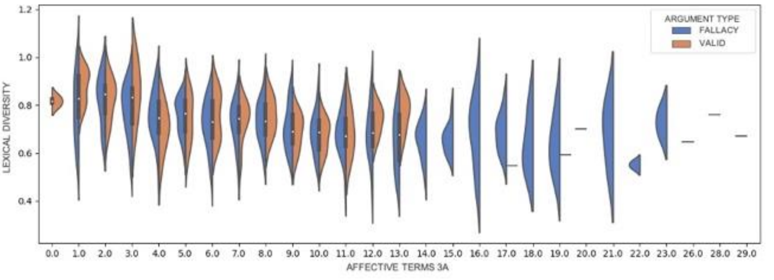

Fig. 3. Data distribution by affective terms and lexical diversity. Affective terms added from the emotional traits dictionary, and considering agreement between three annotators (3A)

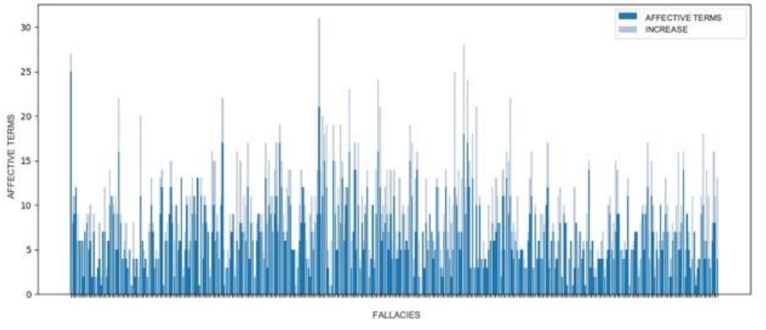

Fig. 4. Increase of affective terms in fallacies with the emotional traits dictionary

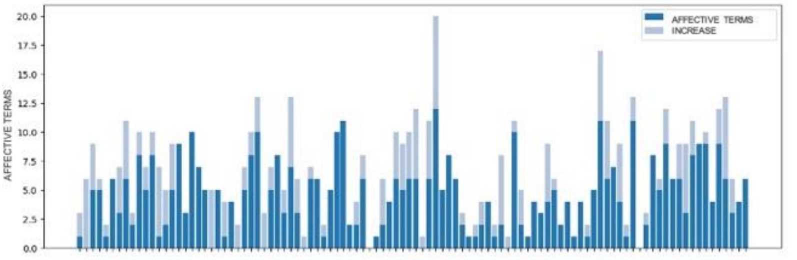

Fig. 5. Increase of affective terms in valid arguments with the emotional features dictionary

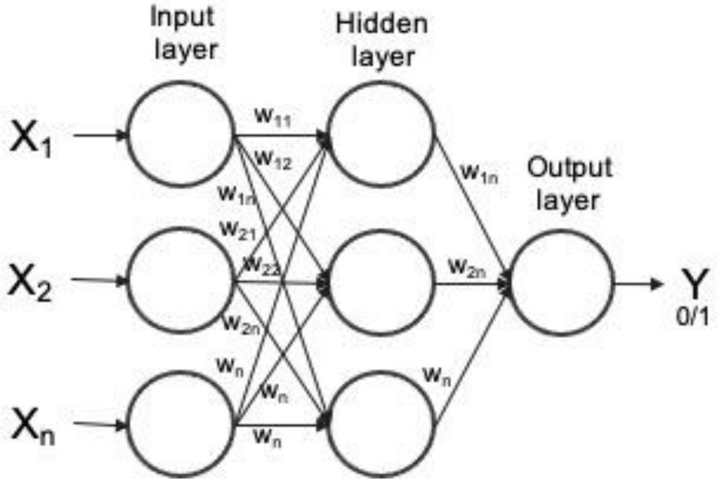

Fig. 6. MLP method architecture

The evaluation of features with SVM and MLP models was performed using a 10-fold cross-validation with 70% of the data for training, and the results are presented using the F1-score metric.

In the experiments, affective terms were evaluated by independently considering the dictionaries and then calculating the information gain (IG) of the affective term (AT) set (Table 8). In this test, a performance of 0.48 was obtained by processing the GI (TA) with the MLP model.

The result increased to an F1-score of 0.56 when processing the set of ATs (Table 9); and when grouping lexical diversity (LD) and ATs with tokens (Table 10). However, the best performance, an F1-score of 0.60, was obtained when grouping the gain of affective terms, lexical diversity, and tokens (Table 10).

Table 8. Result using affective terms and information gain from them

Features	SVM	MLP
ISOL	0,45	0,45
SEL	0,44	0,44
ET	0,43	0,45
IG(AT)	**0,48**	**0,48**

Table 9. Results considering affective terms, lexical diversity and Tokens

Features	SVM	MLP
Tokens	0,54	0,54
AT	0,46	**0,56**
LD	0,48	0,53

Table 10. Results considering groups of features

Features	SVM	MLP
Tokens + IG (AT)	0,54	0,54
AT + *Tokens*	0,52	**0,56**
AT + LD	0,55	0,55
LD + *Tokens*	0,55	**0,56**
LD + IG (AT)	0,48	0,53
Tokens + IG (AT) + LD	0,58	**0,60**
Tokens + AT + LD	0,48	0,53

The obtained result was lower than expected according to [30]. We believe that increasing the affective lexicon and using lexical diversity instead of textual similarity of arguments would improve the results. This is because there is a relationship between diversity and affective terms, i.e., both are evaluated based on the lexical set used in arguments. However, the result obtained is higher when considering only affective terms and increasing the lexical set with noun and adjective syntagms: in [30], an F1-score of 0.42 was obtained with SVM method, while in this study, an F1-score of 0.46 was obtained with SVM and 0.56 with MLP (Table 9).

Arguments contain several affective terms, including valid arguments. By including noun and adjective syntagms, fallacies have at least one affective term, but valid arguments contain more affective terms. This compared to the affective terms set used in [30]. Additionally, lexical diversity slightly decreases when increasing the number of affective terms in arguments (Fig. 2 and 3). Therefore, valid arguments are classified as fallacies (Fig. 7). Although lexical diversity and textual similarity are widely used models in machine learning, and lexical dictionaries are currently little used linguistic resources in automatic identification, obtaining of new affective terms related to political discourse has increased the result obtained in [30].

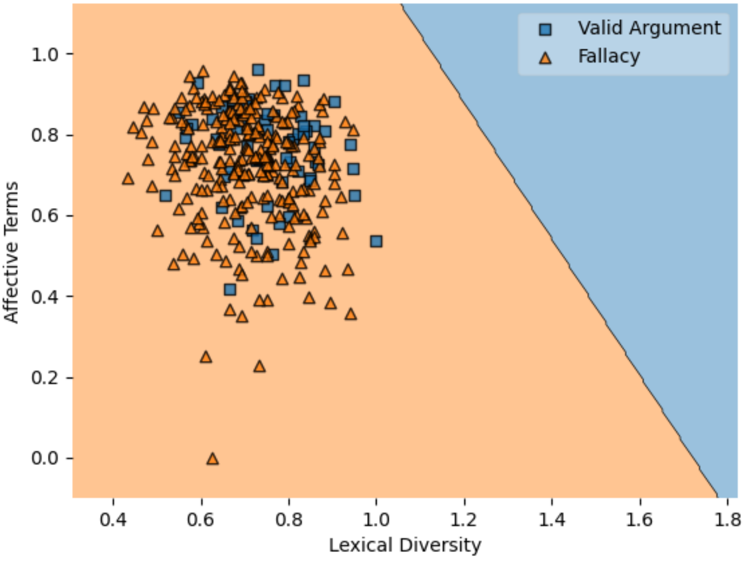

Fig. 7. Plotting the SVM data with affective terms and lexical diversity

8. Conclusions

There is a limited systematic study on fallacies to determine their complexity of treatment from a linguistic perspective and the difficulty this phenomenon poses to Language Technologies. This paper proposes a set of main elements to consider in the development of systems using machine learning methods. We believe that evaluating arguments using a logical perspective and argumentative patterns is the best option for developing systems that allow for fallacy mining.

In fallacy identification, features related to expressive language are used, such as affective terms and lexical diversity of arguments; Two machine learning models were implemented: Support Vector Machine and Multilayer Perceptron. As a result, an F1-score of 0.56 was obtained with affective terms processing, 0.53 using lexical diversity, and 0.60 when grouping the information gain of affective terms, lexical diversity, and argument tokens.

The use of affective terms is considered the main feature to determine if an argument is a fallacy. Despite obtaining low performance with this feature, by obtaining a set of terms used specifically in political speeches, the results increased in relation to previous work. Therefore, affective lexical dictionaries related to political discourse are necessary to identify fallacies by appealing to emotions.

Based on our results, it is proposed to increase the corpus data, get new affective terms, and use conventional neural models such as recurrent networks. Additionally, the topic discussed in the argument should be considered as an additional feature for fallacy identification. This will help to elaborate semantic fields according to the argument's topic, in order to identify and create an affective lexical dictionary related to specific themes. Lastly, perform tests incorporating the textual similarity presented in [30]. Also, balance the corpus data by having an equal number of fallacies and valid arguments.

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