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STUDYING DISHONEST INTENTIONS IN BRAZILIAN PORTUGUESE TEXTS

A PREPRINT

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ABSTRACT

Previous work in the social sciences, psychology and linguistics has shown that liars have some control over the content of their stories, however their underlying state of mind may "leak out" through the way that they tell them. To the best of our knowledge, no previous systematic effort exists in order to describe and model deception language for Brazilian Portuguese. To fill this important gap, we carry out an initial empirical linguistic study on false statements in Brazilian news. We methodically analyze linguistic features using the Fake.Br corpus, which includes both fake and true news. The results show that they present substantial lexical, syntactic and semantic variations, as well as punctuation and emotion distinctions.

Keywords: deception detection, linguistic features, natural language processing.

1 Introduction

According to the standard philosophical definition, lying is saying something that you believe to be false with the intent to deceive [Fallis, 2009]. For deception detection, the FBI trains its agents in a technique named statement analysis, which attempts to detect deception based on parts of speech (i.e., linguistics style) rather than the facts of the case or the story as a whole [Adams, 1996]. This method is employed in interrogations, where the suspects are first asked to make a written statement. In [Newman et al., 2003b], the authors report an example proposed by [Adams, 1996] of a man accused of killing his wife. In this statement, the accused consistently refers to “my wife and I” rather than “we”, suggesting distance between the couple. Thus, for [Newman et al., 2003b], linguistic style checking may be useful in the hands of a trained expert who knows what to look for and how to use language to reveal inconsistencies.

In this context, the deception spread through fake news and reviews is a relevant current problem. Due to their appealing nature, they spread rapidly [Vosoughi et al., 2018]. Nevertheless, what makes fake content a hard problem to solve is the difficulty in identifying unreliable content. Fake news detection is defined as the prediction of the chances of a particular news article being intentionally deceptive [Rubin, 2017] and fake reviews or opinion spam are inappropriate or fraudulent reviews [Ott et al., 2011].

The psychologists and other social scientists are working hard to understand what drive people to believe in fake news. Unfortunately, there is not yet a consensus on this issue. As claimed by [Pennycook and Rand, 2019], much of the debate among researchers falls into two opposing camps. One group claims that our ability to reason is hijacked by our partisan convictions. The other group claims that the problem is that we often fail to exercise our critical faculties: that is, we are mentally lazy.

[Pinney, 2015] calls attention to a lack of non-laboratory studies. In [Mann and Vrij, 2001], the authors comment that their study, examining the deceptive and truthful statements of a convicted murderer, was, at the time, the only known study of its type in a “high-stakes realistic setting”. Moreover, as believed by [Meibauer, 2018], we do not know much
about the embedded lies in texts or discourses. With the notable exception of a paper published by Galasiński [2000] and several studies proposed by Meibauer and Dynel [2016] dealing with fictional discourse in the American television show, there is a lack of empirical research.

Therefore, in this paper, we present a pioneering empirical linguistic study for Brazilian Portuguese language on false statements in texts. We methodically analyze linguistic features from the Fake.Br corpus, which includes both fake and true news. The goal in the linguist approach is to investigate predictive deception clues found in texts. In particular, in this paper, we aim to provide linguistically motivated resources and computationally useful strategies for the development of automatic deception detection classifiers for the Portuguese language.

The remainder of this paper is organized as follows. In Section 2, we present the main related work. Section 3 describes an overview of our data. In Section 4, we show the entire empirical linguistic-based study. In Section 5, final remarks and future works are presented.

2 Related Work

DePaulo et al. [2003b] defines deception as a deliberate attempt to mislead others. There are relatively few studies that have focused, specifically, on deceptive language recognition with speech or writing style, specially for Portuguese. Most of the available works have been used to aid in authorship attribution and plagiarism identification Cristani et al. [2012]. Recent studies have been valuable for detecting deception, especially in the Fake News classification.

Newman et al. [2003c] examined lying in written communication, finding that deceptive utterances used more total words but fewer personal pronouns. The linguistic-based features have been employed for fake news detection. In Newman et al. [2003a], the authors listed a set of linguistic behaviors that predict deception, as tones of words, kinds of preposition, conjunctions and pronouns. In addition, the deception linguistic style includes weak employment of singular and third person pronouns, negative polarity and frequent use of movement verbs. DePaulo et al. [2003c] also presents a long study on clues to deception. For Nahari et al. [2019], the basic assumption is that liars differ from truth tellers in their verbal behaviour, making it possible to classify the news by inspecting their verbal accounts. Accordingly, they present insights, decisions, and conclusions resulting from deception research conference at legal and criminologist psychology society. In Conroy et al. [2015], the authors proposed a set of features using several linguistic analysis levels. They employed lexical, syntax, semantic and discourse linguistic features. In the lexical level, the authors explored bag-of-words approach using bi-grams. In the syntax level, a probability context free grammar was implemented. For semantic analysis, the context information (such as profile content) has been incorporated. To model discourse features, the authors used the Rhetorical Structure Theory (RST) Mann and Thompson [1987] analytical framework.

Specifically for Brazilian Portuguese, Monteiro et al. [2018] and Silva et al. [2020] created the Fake.Br corpus and proposed classifiers for fake news detection. They have also performed a superficial linguistic analysis of the corpus. However, to the best of our knowledge, no previous systematic empirical linguistic study exists on dishonest intentions and language-based deception detection for the Brazilian Portuguese.

3 Data Overview

To provide a linguistic analysis on false statements in texts, the first challenges concentrate on the data. The identification of reliable corpora for each language is a relevant task. Most of the research has developed computational linguistic resources for English. In general, few resources are available for Portuguese. As we commented before, for Brazilian Portuguese, we have Fake.Br Monteiro et al. [2018], which includes fake and true news in Brazilian Portuguese. An overview of this corpus is shown in Tables 1, 2 and 3.

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The Fake.Br corpus was composed in a semi-automatic way. The fake news were collected from sites that gather such content and the true ones were extracted from major news agencies in Brazil, as G1, Folha de São Paulo and Estadão portals. A crawler searched in the corresponding web pages of these agencies for keywords of the fake news, which were nouns and verbs that occurred in the fake news titles and the most frequent words in the texts (ignoring stopwords). The authors have performed a final manual verification to guarantee that the fake and true news were in fact subject-related.
Table 1: Corpus Overview: Fake.Br

| Subjects                  | Number of Texts | %   |
|---------------------------|-----------------|-----|
| Politics                  | 4,180           | 58.0|
| TV & celebrities          | 1,544           | 21.4|
| Society & daily news      | 1,276           | 17.7|
| Science & technology      | 112             | 1.5 |
| Economy                   | 44              | 0.7 |
| Religion                  | 44              | 0.7 |

Table 2: Number of tokens

| News | Tokens | % |
|------|--------|---|
| Fake | 796,364| 50.80 |
| True | 771,510| 49.20 |

Table 3: Number of news texts

| News | Number of Texts | % |
|------|-----------------|---|
| Fake | 3,600           | 50.0 |
| True | 3,600           | 50.0 |

4 Linguistic Features

Most of the false statements present linguistic features that are different in relation to the true statements. According to Conroy et al. [2015], most liars use their language strategically to avoid being caught. In spite of the attempt to control what they are saying, language “leakage” occurs with certain verbal aspects that are hard to monitor, such as frequencies and patterns of pronouns, conjunctions, and negative emotion word usage Feng and Hirst [2013].

In this section, we aim at understanding relevant linguistic properties of fake and true statements in Brazilian news. We used Python 3.6.9 and the spaCy library to automatically annotate the corpus. We divided our analysis in two main groups: word-level and sentence-level analyses. In the first group, we analyzed the occurrence patterns of (i) sentiment and emotion words, (ii) part-of-speech tags, (iii) pronoun classification, (iv) named-entity recognition and (v) punctuation behavior. In the second group, we evaluated the number of sentences in fake and true news and the average of words for each sentence. We also analyzed the occurrence of clausal relations in syntactical dependency trees on fake and true statements. We present the results in what follows.

4.1 Word-Level Analysis

In the word-level analysis, our goal is to identify differences among word usage behavior and variations in fake and true news.

4.1.1 Sentiment and Emotion Words

According to Zipitria et al. [2017], deception language involves negative emotions, which are expressed in language in terms of psychological distance from the deception object. The psychological distance and emotional experience reflect an attempt to control the negative mental representation. Therefore, we have identified the incidence of sentiment and emotion words in fake and true statements. We used the sentiment lexicon for Portuguese Sentilex-PT and WordNetAffect.BR to account for the sentiment words. Table 4 shows the results. Note that the incidence of sentiment and emotion words in fake news overcame the ones in true news, except for surprise emotion.

Table 4: Word-level sentiment and emotion occurrence

| Sentences | True News | Fake News |
|-----------|-----------|-----------|
| Positive  | 103,376   | 115,260   |
| Negative  | 102,54    | 115,431   |
| Joy       | 4,941     | 5,657     |
| Sadness   | 2,596     | 3,347     |
| Fear      | 1,757     | 1,895     |
| Disgust   | 1,561     | 1,667     |
| Angry     | 2,865     | 3,232     |
| Surprise  | 423       | 419       |
| Total     | 642,636   | 665,489   |

[1] https://spacy.io/
[2] https://spacy.io/api/annotation
In the fake news, we have observed a difference of 11.49% and 12.57% in positive and negative sentiment when compared to the true news; for joy, sadness, fear, disgust, angry and surprise emotions, the difference amounts to 14.49%, 28.92%, 7.85%, 6.79%, 12.80% and 0.95% when compared to the true news. Therefore, we evidence that in our corpus the fake statements presented more negative and positive sentiments and emotions than true statements, confirming what some relevant literature [DePaulo et al., 2003a; Conroy et al., 2015; Newman et al., 2003b] have found, i.e., that dishonest texts have more negative than positive sentiments and emotions.

4.1.2 Part-of-Speech

The growing body of research suggests that we may learn a great deal about people’s underlying thoughts, emotions, and reasons by counting and categorizing the words they use to communicate. For Newman et al. [2003b], several aspects of linguistic style, such as pronoun usage, preposition and conjunctions that signal cognitive work, have been linked to a number of behavioral and emotional outcomes. To exemplify, in Ye and Chua [2006], the authors identified that poets who use a high frequency of self-reference but a lower frequency of other-reference in their poetry were more likely to commit suicide than those who showed the opposite pattern.

In this present study, we extracted the frequency of part-of-speech in our corpus in order to examining the grammatical manifestations of false behavior in text. The obtained results for part-of-speech occurrence is shown in Table 5. The results show an impressive increase on the number of interjections in fake news compared to the true news. We must also point out that, for many authors, it is clear that interjections do not encode concepts as nouns, verbs or adjectives do. Interjections may and do refer to something related to the speaker or to the external world, but their referential process is not the same as that of lexical items belonging to the grammatical categories mentioned, as the referents of interjections are difficult to pin down [Padilla Cruz, 2009]. Similarly, the use of space character has shown a relevant occurrence difference. We found 25,864 spaces in fake news and 3,977 spaces in true news. Furthermore, in true statements, the use of the NOUN category is 9.79% larger than in fake statements. The verbal use is also 13.81% more frequent in the true statements.

| N. | Label | Definition | True News | Fake News |
|----|-------|------------|-----------|-----------|
| 1  | NOUN  | noun       | 140,107   | 127,609   |
| 2  | VERB  | verb       | 86,256    | 98,168    |
| 3  | PROPN | proper noun| 109,501   | 98,757    |
| 4  | ADP   | adposition | 109,613   | 92,166    |
| 5  | ADJ   | adjective  | 33,433    | 32,535    |
| 6  | DET   | determiner | 77,660    | 83,169    |
| 7  | ADV   | adverb     | 25,384    | 31,534    |
| 8  | SPACE | space      | 3,977     | 25,864    |
| 9  | PRON  | pronoun    | 20,994    | 24,348    |
| 10 | AUX   | auxiliary  | 13,529    | 16,999    |
| 11 | CCONJ | coordinating conjunction | 17,263 | 16,352 |
| 12 | NUM   | numeral    | 16,951    | 12,596    |
| 13 | SCONJ | subordinating conjunction | 8,870 | 12,392 |
| 14 | SYM   | symbol     | 10,065    | 9,458     |
| 15 | OTHER | other      | 2,684     | 3,113     |
| 16 | INTJ  | interjection | **66** | **220** |
| 17 | PART  | particle   | 29        | 23        |

4.1.3 Pronouns

Several studies on deception show that the use of the first-person singular is a subtle proclamation of one’s ownership of a statement. In other words, liars tend to distance themselves from their stories and avoid taking responsibility for their behavior [Friedman and Tucker, 1990]. Therefore, deceptive communication should be characterized by fewer first-person singular pronouns (e.g., I, me, and my) Newman et al. [2003b]. In addition, when people are self-aware, they are more “honest” with themselves [Carver and Scheier, 1981; Duval and Wicklund, 1972; Vorauer and Ross, 1999] and self-reference increases [Davis and Brock, 1975].

In accordance with deception literature, we investigate the pronoun behavior in our corpus. We identify the occurrence for first, second and third persons of singular and plural pronouns. Table 6 exhibits the results. Surprisingly, the pronoun occurrence in fake news overcame the ones in true news, except in the 3rd person singular (tonic oblique). An unusual
behavior, considering the literature on deception, may be noted on the 1st person singular (subject). In fake statements, there has been a jump in the occurrence of the “eu” pronoun (1,097) related to true statements (495). 3rd person singular (subject) and 3rd person singular (unstressed oblique) represent 34.16 % and 42.80 % respectively on the total occurrence of pronouns in the corpus for the fake news. Differently, for true news, the 3rd person singular (subject) and 3rd person singular (unstressed oblique) represent 36.88% and 47.74 % respectively. In other words, the 3rd person occurrence in true news overcame fake news considering the total occurrence of pronouns in the corpus.

Table 6: Pronoun occurrence

| N. | Pronoun Classification                      | Example  | True News | Fake News |
|----|---------------------------------------------|----------|-----------|-----------|
| 1  | 1st person singular (subject)               | eu       | 495       | 1,097     |
| 2  | 1st person singular (unstressed oblique)    | me       | 233       | 447       |
| 3  | 1st person singular (tonic oblique)         | mim      | 39        | 87        |
| 4  | 2nd person singular (subject)               | você, tu | 390       | 683       |
| 5  | 2nd person singular (unstressed oblique)    | te       | 4         | 24        |
| 6  | 2nd person singular (tonic oblique)         | ti, contigo | 2   | 2        |
| 7  | 3rd person singular (subject)               | ele, ela | 3,344     | 4,006     |
| 8  | 3rd person singular (Unstressed oblique)    | se, o, a, lhe | 4,329 | 5,019     |
| 9  | 3rd person singular (tonic oblique)         | si, consigo | 44   | 41        |
| 10 | 1st person plural (subject)                 | nós       | 52        | 71        |
| 11 | 2nd person plural (subject)                 | vocês    | 7         | 26        |
| 12 | 3rd person plural (subject)                 | eles, elas | 128  | 222       |

We must also point out that we found that the occurrence differences of 2nd person plural (unstressed oblique) and (tonic oblique) pronouns in fake and true news are statistically irrelevant.

4.1.4 Named-Entity Recognition

According to [Meibauer 2018], most scholars in the field of deception research seem to accept standard truth-conditional. In addition, semantic assumptions on deception are rarely made explicit [Zimmermann 2011]. Moreover, the implicit content extraction is a hard task in natural language processing area, as [Vargas and Pardo 2018] comments. Nevertheless, we propose a superficial semantic analysis based on named-entity recognition categories. Table 7 shows the results.

Table 7: Named-entity occurrence

| Named-Entity | Label | True News | Fake News |
|--------------|-------|-----------|-----------|
| Person       | (PER) | 19,398    | 22,151    |
| Localization | (LOC) | 19,232    | 15,250    |
| Organization | (ORG) | 9,503     | 8,851     |
| Miscellaneous| (MISC)| 8,427     | 9,119     |

Based on the obtained results, one may see that the true statements present larger number of localization occurrences (LOC) than fake statements. Otherwise, the fake statements overcome in larger number of person occurrences (PER) when compared to the true statements. Organization (ORG) has occurred more frequently in true statements, while miscellaneous (MISC) in fake statements.

4.1.5 Punctuation

[DePaulo et al. 2003a] assumes that punctuation pattern could distinguish fake and true texts. Consequently, the punctuation behavior would be a “clue to deception”. We evaluate the occurrence of each punctuation mark. The obtained data is shown in Table 8. In agreement with the literature, our results show a noticeable change among the punctuation setting in fake and true news. Note that in fake statements there has been a expressive use of interrogation, exclamation, end point, double quotes, two points, three consecutive points, square brackets, bar and asterisks. For the true news, we observed the larger use of comma, single trace, single quotes and two consecutive points. We also point out that the “Error” label consists on annotation mistakes.

4.2 Sentence-level Analysis

According to the standard philosophical definition of lying, the intention to deceive is an important aspect of deception [Augustine 1952, Kupfer 1982, Williams 2002, Bok 1978]. In order to provide an initial understand on dishonest
intents in text, we analyze the sentence structure in true and fake statements. In order to achieve that, we evaluate the number of sentences and the average number of words, which is shown in Table 9.

Table 9: Sentence-level analysis

| Sentences | True News | Fake News |
|-----------|-----------|-----------|
| Total     | 43,066    | 50,355    |
| Avg of words | 15.45    | 13.24     |

Based on data displayed by Table 9, we may note that, in fake statements, there are 14.47% more sentences than in true statements. It is interesting to realize that, despite the greater number of sentences in fake news, the average number of words by sentence is smaller than in true news.

According to Conroy et al. [2015], analysis of word usage is often not enough for deception prediction. Deeper language structure (syntax) must also be analyzed to predict instances of deception. Therefore, in order to investigate anomalies or divergences in syntactic structure of false and true statements, we also analyzed the dependency relation occurrences in our corpus. We present the results in the Table 10.

A dependency tree, according to Jurafsky et al. [2009], is a syntactic structure corresponding to a given natural language sentence. This structure represents hierarchical relationships between words. Figure 1 shows a dependency tree example. Notice that the relations among the words are illustrated above the sentence with directed labeled arcs from heads to dependents. According to Jurafsky and Martin [2009], we call this a typed dependency structure because the labels are drawn from a fixed inventory of grammatical relations. It also includes a root node that explicitly marks the root of the tree, i.e., the head of the entire structure. For the interested reader, the Universal Dependencies project Nivre et al. [2016] provides an inventory of dependency relations that are cross-linguistically applicable.

Figure 1 shows the syntactical dependency structure for the following sentence extracted from our corpus: *Eu acho que não tem nenhuma razão ele continuar no governo.* (“I think there is no reason for him to remain in the government”). The NSUBJ relation identifies the subject; CCOMP identifies the complement of the main verb; ADVMOD identifies the adverb modifier; MARK is the word introducing a finite clause subordinate to another clause; OBJ identifies the direct object; DET identifies determinants; AMOD exhibits the adjectival modifier of a noun phrase (NP); and XCOMP consists of an open clausal complement for a verb.5

Based on the obtained results (see Table 10), in an initial analysis, we found a relevant difference among the syntactic structures in fake and true news. For example, one may notice a significant difference on the occurrence of CASE, OBJ, OBJ, and XCOMP.
OBL, NMOD, ROOT, DET, ADVCL, AUX, FLAT:NAME, CSUBJ and PARATAXIS structures. In the future, we intend to perform a deeper syntactical analysis of the dependency trees, looking for argument structure differences, for instance.

Table 10: Clausal dependency relations occurrence

| N. | Label           | Definition                               | True News | Fake News |
|----|-----------------|------------------------------------------|-----------|-----------|
| 1  | CASE            | case marking                             | 106,964   | 89,177    |
| 2  | DET             | determiner                               | 71,070    | 78,013    |
| 3  | AMOD            | adjectival modifier                      | 29,486    | 29,580    |
| 4  | NMOD            | nominal modifier                         | 62,406    | 50,913    |
| 5  | ROOT            | root                                     | 43,055    | 50,035    |
| 6  | FLAT:NAME       | flat multiword expression (name)         | 45,955    | 40,025    |
| 7  | NSUBJ           | nominal subject                          | 43,091    | 49,321    |
| 8  | OBJ             | object                                   | 39,787    | 45,063    |
| 9  | OBL             | oblique nominal                          | 38,901    | 33,550    |
| 10 | ADVMOD          | adverbial modifier                       | 22,741    | 28,834    |
| 11 | CONJ            | conjunct                                 | 21,316    | 20,907    |
| 12 | APPOS           | appositional modifier                    | 21,146    | 20,587    |
| 13 | CC              | coordinating conjunction                 | 18,603    | 17,586    |
| 14 | MARK            | marker                                   | 17,108    | 19,932    |
| 15 | ACL             | clausal modifier of noun (adjectival clause) | 14,239 | 13,072 |
| 16 | NUMMOD          | numeric modifier                         | 10,034    | 8,427     |
| 17 | COP             | copula                                   | 8,767     | 11,359    |
| 18 | ADVCL           | adverbal clause modifier                 | 8,210     | 9,437     |
| 19 | ACL:RELCL       | relative clause modifier                 | 8,177     | 7,720     |
| 20 | CCCOMP          | clausal complement                       | 7,610     | 9,380     |
| 21 | AUX             | auxiliary                                | 6,902     | 9,989     |
| 22 | XCOMP           | open clausal complement                  | 6,208     | 7,411     |
| 23 | AUX:PASS        | auxiliary                                | 5,931     | 6,485     |
| 24 | NSUBJ:PASS      | passive nominal subject                  | 5,574     | 6,014     |
| 25 | DEP             | unspecified dependency                   | 3,017     | 2,357     |
| 26 | EXPL            | expletive                                | 2,139     | 2,874     |
| 27 | NMOD:NPMOD      | nominal modifier                         | 2,055     | 2,093     |
| 28 | OBL:AGENT       | agent modifier                           | 1,329     | 1,084     |
| 29 | COMPOUND        | compound                                 | 1,251     | 1,119     |
| 30 | NMOD:TMOD       | temporal modifier                        | 1,193     | 368       |
| 31 | FIXED           | fixed multiword expression               | 1,135     | 1,259     |
| 32 | PARATAXIS       | parataxis                                | 934       | 1,491     |
| 33 | CSUBJ           | clausal subject                          | 769       | 1,053     |
| 34 | IOBJ            | indirect object                          | 328       | 466       |
| 35 | FLAT:FOREIGN    | foreign words                            | 13        | 15        |
5 Final Remarks and Future Work

We know that language may be used to deceive and confuse people. The current context of social media usage is unique, with diversity in format, and relatively new. However, lying and deceiving have been at play in other forms of human communication for ages [Rubin, 2017]. In this paper, we presented a study on the statements in true and fake news for Brazilian Portuguese. We performed an empirical linguistic-based analysis over the Fake.Br corpus. We automatically annotated a set of linguistic features in order to investigate actionable inputs and relevant differences among fake and true news. Based on the obtained results, we found that fake and true news present relevant differences in structural, lexical, syntactic and semantic levels.

For future work, we intend to deepen our investigation of syntactical behavior and to explore discourse markers and sophisticate machine learning techniques in order to provide deception detection classifiers for different tasks, such as fake news and reviews detection in several languages.

For the interested reader, more information may be found at the OPINANDO project webpage (at https://sites.google.com/icmc.usp.br/opinando/).

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References

S. H. Adams. Statement analysis: What do suspects' words really reveal? *FBI Law Enforcement Bulletin*, 1(1):12–20, 1996.

S. Augustine. Lying. In R. J. Defferrari, editor, *Treatises on Various Subjects* (*The Fathers of the Church*, volume 16, page 47–110. Catholic University of America Press, 1952.

S. Bok. *Lying: moral choice in public and private life*. Random House, New York, USA, 1 edition, 1978.

C. S. Carver and M. F. Scheier. *Attention and Self-Regulation: A Control-Theory Approach to Human Behavior*. Springer-Verlag, New York, USA, 1 edition, 1981.

N. J. Conroy, V. L. Rubin, and Y. Chen. Automatic deception detection: Methods for finding fake news. In *Proceedings of the 78th ASIST Annual Meeting: Information Science with Impact: Research in and for the Community*, USA, 2015. American Society for Information Science.

M. Cristani, G. Roffo, C. Segalin, L. Bazzani, A. Vinciarelli, and V. Murino. Conversationally-inspired stylometric features for authorship attribution in instant messaging. In *Proceedings of the 20th ACM International Conference on Multimedia*, pages 1121–1124, New York, NY, USA, 2012. ACM.

D. Davis and T. Brock. Use of first person pronouns as a function of increased objective self-awareness. *Journal of Experimental Social Psychology*, 11:381–388, 1975.

B. DePaulo, J. J. Lindsay, B. Malone, L. Muhlenbruck, K. Charlton, and H. Cooper. Cues to deception. *Psychological bulletin*, 129:74–118, 02 2003a.

B. DePaulo, J. J. Lindsay, B. Malone, L. Muhlenbruck, K. Charlton, and H. Cooper. Cues to deception. *Psychological bulletin*, 129:74–118, 2003b.

S. Duval and R. A. Wicklund. *A theory of objective self awareness*. Academic Press, Oxford, England, 1 edition, 1972.

D. Fallis. What is lying? *Journal of Philosophy*, 106(1):29–56, 2009.

V. W. Feng and G. Hirst. Detecting deceptive opinions with profile compatibility. In *Proceedings of the Sixth International Joint Conference on Natural Language Processing*, pages 338–346, Nagoya, Japan, 2013. Asian Federation of Natural Language Processing.

K. L. Finney. Detecting deception through rst: A case study of the casey anthony trial. *Proceedings of the 31st annual NorthWest Linguistics Conference*, 1(1):12–23, 2015.

H. S. Friedman and J. S. Tucker. Language and deception. In *Handbook of language and social psychology*, page 257–270. John Wiley and Sons, 1 edition, 1990.

D. Galasiński. *The Language of Deception: A Discourse Analytical Study*. SAGE Knowledge, SAGE Publications, 2000.
Studying Dishonest Intentions in Brazilian Portuguese Texts

D. Jurafsky and J. H. Martin. *Speech and language processing: an introduction to natural language processing, computational linguistics, and speech recognition*, 2nd Edition. Prentice Hall series in artificial intelligence. Prentice Hall, Pearson Education International, 2009. ISBN 9780135041963.

D. Jurafsky, R. Ranganath, and D. McFarland. Extracting social meaning: Identifying interactional style in spoken conversation. In *Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, pages 638–646, Stroudsburg, PA, USA, 2009. Association for Computational Linguistics.

J. Kupfer. The moral presumption against lying. *The Review of Metaphysics*, 36(1):103–126, 1982.

S. Mann and A. Vrij. Telling and detecting lies in a high-stake situation: The case of a convicted murderer. *Applied Cognitive Psychology*, 15(2):187–203, 2001.

W. C. Mann and S. A. Thompson. *Rhetorical Structure Theory: A Theory Of Text Organization*. 1987.

J. Meibauer. The linguistics of lying. *Annual Review of Linguistics*, 4(1):357–375, 2018.

J. Meibauer and M. Dynel. Empirical approaches to lying and deception. *International Review of Pragmatics*, 8(3), 2016.

R. Monteiro, R. Santos, T. Pardo, T. Almeida, E. Ruiz, and O. Vale. Contributions to the Study of Fake News in Portuguese: New Corpus and Automatic Detection Results, pages 324–334, 01 2018.

G. Nahari, T. Ashkenazi, R. Fisher, P. Granhag, I. Hershkowitz, J. Masip, E. Meijer, Z. Nisin, N. Sarid, P. Taylor, B. Verschuere, and A. Vrij, ‘language of lies’: Urgent issues and prospects in verbal lie detection research. *Legal and Criminological Psychology*, 24:1–23, 01 2019.

M. L. Newman, J. W. Pennebaker, D. S. Berry, and J. M. Richards. Lying words: Predicting deception from linguistic styles. *Personality and Social Psychology Bulletin*, 5(29):665–675, 2003a.

M. L. Newman, J. W. Pennebaker, D. S. Berry, and J. M. Richards. Lying words: Predicting deception from linguistic styles. *Personality and Social Psychology Bulletin*, 5(29):665–675, 2003b.

M. L. Newman, J. W. Pennebaker, D. S. Berry, and J. M. Richards. Lying words: Predicting deception from linguistic styles. *Personality and Social Psychology Bulletin*, 29(5):665–675, 2003c.

J. Nivre, M.-C. de Marneffe, F. Ginter, Y. Goldberg, J. Hajic, C. D. Manning, R. McDonald, S. Petrov, S. Pyysalo, N. Silveira, R. Tsarfaty, and D. Zeman. Universal dependencies v1: A multilingual treebank collection. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16)*, pages 1659–1666, Portorož, Slovenia, 2016. European Language Resources Association (ELRA).

M. Ott, Y. Choi, C. Cardie, and J. T. Hancock. Finding deceptive opinion spam by any stretch of the imagination. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 309–319, Portland, Oregon, USA, June 2011. Association for Computational Linguistics.

M. Padilla Cruz. Might interjections encode concepts? more questions than answers. *Lodz Papers in Pragmatics*, 5:241–270, 12 2009.

G. Pennycook and D. Rand. Why do people fall for fake news? *New York Times Edition*, 1:1–12, 2019.

V. L. Rubin. Deception detection and rumor debunking for social media. The SAGE Handbook of Social Media Research Methods, 2017.

R. M. Silva, R. L. Santos, T. A. Almeida, and T. A. Pardo. Towards automatically filtering fake news in portuguese. *Expert Systems with Applications*, 146:1–14, 2020. ISSN 0957-4174.

F. A. Vargas and T. A. S. Pardo. Aspect clustering methods for sentiment analysis. In *13th International Conference on the Computational Processing of Portuguese*, pages 365–374, Canela, RS, Brazil, 2018.

J. D. Vorauer and M. E. Ross. Self-awareness and feeling transparent: Failing to suppress one’s self. *Journal of Experimental Social Psychology*, 35(5):415–440, 1999.

S. Vosoughi, D. Roy, and S. Aral. The spread of true and false news online. *Science*, 359:1146–1151, 03 2018.

B. Williams. *Truth and Truthfulness: An Essay in Genealogy*. Princeton University Press, Nova Jersey, EUA, 1 edition, 2002.

S. Ye and T.-S. Chua. Learning object models from semistructured web documents. 18(3):334–349, 2006. ISSN 1041-4347.

T. F. Zimmermann. Model-theoretic semantics. In C. Maienborn, K. Heusinger, and P. von, Portner, editors, *Semantics: An International Handbook of Natural Language Meaning*, page 762–802. Berlin: de GruyterTo the best of our knowledge, 1 edition, 2011.
I. Zipitria, B. Sierra, and I. Sopena-Garaikoetxea. Emotion in deceptive language. In Proceedings of the 39th Annual Meeting of the Cognitive Science Society, CogSci 2017, London, UK, 16-29 July 2017, 2017.