Building an Expert Annotated Corpus of Brazilian Instagram Comments for Hate Speech and Offensive Language Detection

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Abstract

The understanding of an offense is subjective and people may have different opinions about the offensiveness of a comment. Moreover, offenses and hate speech may occur through sarcasm, which hides the real intention of the comment and makes the decision of the annotators more confusing. Therefore, providing a well-structured annotation process is crucial to a better understanding of hate speech and offensive language phenomena, as well as supplying better performance for machine learning classifiers. In this paper, we describe a corpus annotation process proposed by a linguist, a hate speech specialist, and machine learning engineers in order to support the identification of hate speech and offensive language on social media. In addition, we provide the first robust dataset of this kind for the Brazilian Portuguese language. The corpus was collected from Instagram posts of political personalities and manually annotated, being composed by 7,000 annotated documents according to three different layers: a binary classification (offensive versus non-offensive language), the level of offense (highly offensive, moderately offensive, and slightly offensive messages), and the identification regarding the target of the discriminatory content (xenophobia, racism, homophobia, sexism, religious intolerance, partyism, apology to the dictatorship, antisemitism, and fatphobia). Each comment was annotated by three different annotators and achieved high inter-annotator agreement. The proposed annotation approach is also language and domain-independent nevertheless it is currently customized for Brazilian Portuguese.

1 Introduction

In recent years, the use of social media has increased and brought a lot of advantages for society, as virtual human interactions that enable people from anywhere to connect with anyone (Leite et al., 2020). Nevertheless, society has also been affected in negative ways, such as the spread of offenses and hate speech. Therefore, the identification of offensive, aggressive, and other kinds of abusive language has attracted interest from institutions and become an important research topic (Çöltekin, 2020a; Leite et al., 2020).

Offensive language is used to insult, attack or disrespect a reader. The content of an offense may be characterized in different ways, such as abusive (Steimel et al., 2019; Mubarak et al., 2017), cyberbullying (Rosa et al., 2019) and hate speech content (Schmidt and Wiegand, 2017; Fortuna et al., 2019).

Recent cases show the impact of offensive language in social media around the world. As observed in Figure 1, the “hate speech” term has become very common over the last years.

Figure 1: Occurrence of the term “Hate Speech” in English-language publications indexed in Google Books Ngram Viewer

Nockleby (2000) defines hate speech as “any communication that disparages a person or a group based on some characteristic such as race, color, ethnicity, gender, sexual orientation, nationality, religion or other characteristics”. More recently, Fortuna and Nunes (2018) adopted the following hate speech definition: “language that attacks or diminishes, that incites violence or hate against groups, based on specific characteristics such as...
physical appearance, religion, descent, national or ethnic origin, sexual orientation, gender identity or other, and it can occur with different linguistic styles, even in subtle forms or when humour is used”. For Brugger (2007), the international law consistently allows or prohibits hate speech, depending on the country: such speech is sometimes protected (with varying tolerance levels), sometimes not.

In the United States and South America, hate against minorities or based on party options (also called partyism) has caused serious events of violence. Westwood et al. (2018) showed that, in USA, affective polarization\(^2\) based on the political party is as strong as the polarization caused by skin color and, consequently, party-based discrimination is so profound that outweighs discrimination based on skin color. Sunstein (2016) argues that partyism is real and growing, currently revealing itself to be even worse than racism by provoking consequences to the governmental spectrum. In Brazil, some notorious cases have also recently occurred.

Given the relevance of the topic, the existence of annotated corpora is essential to carry out experiments on automatic offensive language and hate speech detection. Nevertheless, the annotation process is intrinsically challenging. The identification of offensive language requires well-defined context and its absence may lead to a difficult label choice. Another challenge is the presence of sarcasm, which hides the real intention of the comment and makes the decision of the annotators more confusing. The understanding of an offense is also subjective and people may have different opinions about the offensiveness of a comment.

Consistency and quality of the data are directly related to the performance of the Machine Learning classifiers. In Natural Language Processing (NLP), subjective tasks, such as offensive language and hate speech detection, present high complexity and several challenges. Therefore, a definition of an annotation schema is relevant, mainly because a reliable annotation approach offers an adequate characterization of particularities for subjective tasks, which, consequently, improves the quality of the annotated data.

1.1 Contributions of this paper

In this paper, we present the first robust corpus and its expert annotation process for offensive language and hate speech detection in Brazilian Portuguese. The corpus was collected from different accounts of political personalities on Instagram. The political context was chosen due to the identification of several types of offenses and hate attacks in different groups. The entire annotation process was guided by a linguist, which is NLP specialist, a hate speech skilled, and machine learning engineers, as well as guidelines and training steps have been proposed in order to ensure the same understanding of the tasks and bias minimization, resulting in greater reliability of the annotation and quality of the proposed data to be used in automatic classification tasks.

More specifically, the main contributions of this paper are: (i) a new corpus with 7,000 documents in Brazilian Portuguese, which possess three different layers of annotation (a. offensive versus non-offensive comments; b. offensive comments sorted into highly offensive, moderately offensive, and slightly offensive levels; c. nine hate groups: xenophobia, racism, homophobia, sexism, religious intolerance, partyism, apology to dictatorship, antisemitism, and fat phobia); (ii) the definition of an expert annotation process for hate speech and offensive language detection on social media, which is language and domain-independent (although it has been evaluated for Brazilian Portuguese).

The remainder of the paper is structured as follows. In Section 2, we introduce the most relevant related works. Section 3 describes the corpus development process, as well as our annotation approach. Sections 4 and 5 show the corpus statistics and its evaluation. In Section 6, final remarks and future works are presented.

2 Related Work

Most of hate speech and offensive language corpora are for English (Davidson et al., 2017; de Gibert et al., 2018; Waseem and Hovy, 2016; Gao and Huang, 2017; Jha and Mamidi, 2017; Fersini et al., 2018; Basile et al., 2019; Golbeck et al., 2017). However, Chung et al. (2019) and Ousidhoum et al. (2019) constructed corpora of Facebook and Twitter data for Islamophobia.

\(^2\)According to Westwood et al. (2018), affective polarization consists of the tendency to negatively identify opposing supporters, while co-supporters are positively identified. This affective separation is the result of a classification of opposing supporters as an external group and co-supporters as internal group members.
bia, sexism, homophobia, religion intolerance and disability detection in French language. Germans Bretschneider and Peters (2017) provides an anti-foreigner prejudice corpus with 5,836 Facebook posts hierarchically annotated for slightly and explicitly/substantially offensive language with six targets: foreigners, government, press, community, other, and unknown. For Arabic, Albadi et al. (2018) proposed a dataset with 6,136 twitter posts, which is annotated in religion subcategories. Ljubešić et al. (2018) provides a large-scale dataset composed of 17,000,000 posts, with 2% of abusive language on the 24sata website3 for Slovene and Croatian Moderated News Comments. For Greek, Pavlopoulos et al. (2017) and Pitenis et al. (2020) contributed with datasets of Twitter and Gazeta posts for flagged content detection. For Indonesian language, Alfina et al. (2017) and Ibrohim and Budi (2018) provided a dataset from Twitter. For Italian, Spanish, Polish, Slovene and Turkish, see details at (Sanguinetti et al., 2018), (Aragón et al., 2019), (Ptaszynski et al., 2019), and (Çöltekin, 2020b), respectively.

For European Portuguese, Fortuna et al. (2019) adopted the definition of hate speech proposed by (Fortuna and Nunes, 2018), and proposed a new dataset using a hierarchy of hate to identify social groups of discrimination. For Brazilian Portuguese, de Pelle and Moreira (2017) provided a dataset of offensive comments, as well as classification results achieved by standard classification algorithms, which represent the current baseline for offensive comments detection in Brazilian Portuguese.

### 3 Corpus Development

In this section, we describe our approach to build an annotated corpus for offensive language and hate speech detection on social media. Moreover, we provide a new robust dataset for the Brazilian Portuguese language. The entire process of annotation training took approximately 6 months, and it was guided by a linguist, which is NLP specialist, and a hate speech skilled, as well as supported by annotation guidelines. In addition, the annotators used an offensive lexicon, which it was constructed from Brazilian Portuguese social media texts. The Multilingual Offensive Lexicon (MOL) (Vargas et al., 2021) is composed of 1,000 explicit and implicit offensive and swearing expressions of opinion in context. Each expression was annotated with the following binary classes: context-dependent and context-independent offensive. Three different annotators labeled each expression, and obtained high human inter-annotator agreement (73% Cohen’s Kappa).

#### 3.1 Data Acquisition

The dataset was collected by scraping data from the social network Instagram. Instagram is a representative platform for showcasing digital influencers, making it a powerful option for mass media. According to the Statistical portal [December/2020]4, Brazil occupies the third position in the worldwide ranking of Instagram’s audience with 95 million active Brazilian users. Each person has an account with shared photos and it is possible for others to like, comment, save and share this information. Our data collection focused on the comments of the posts.

We collected 15,000 comments from six public Instagram accounts of the Brazilian political domain (see Table 1). We selected three liberal-party accounts and three conservative-party accounts, being four women and two men (see Table 2).

Table 1: Data Collection Information

| Data/Account | Total |
|--------------|------|
| Extracted Comments | 15,000 |
| Posts | 30 |
| Accounts | 6 |

Table 2: Account Profiles

| Profile | Description |
|---------|-------------|
| Gender | 4 women and 2 man |
| Political | 3 liberals and 3 conservative |

Posts were selected at random, regarding any subject, not just political, arranged throughout the second half of 2019 (see the subjects of these posts in Table 3). The choice of influencers aimed at balancing variables such as sex and political nature; therefore, men and women were chosen, representing the two main Brazilian political strands with more than 500 thousand followers. We removed comments that contained only

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324sata (lit. “24hours”) is the leading media company in Croatia.

4https://www.statista.com/statistics/578364/countries-with-most-instagram-users/
emotes, laughs (kkk or hahah or hshhs), and accounts (e.g., @namesomeone). In Figure 2, we have an overview of the corpus construction with detailed steps of the data collection process. The resulting corpus was named “HateBr”.

Table 3: Topics

| Topics      | Total | %   |
|-------------|-------|-----|
| Politics    | 16    | 61.54 |
| Fake News   | 2     | 7.69 |
| Crimes      | 2     | 7.69 |
| Sexism      | 2     | 7.69 |
| Racism      | 1     | 3.85 |
| Economy     | 1     | 3.85 |
| Harassment  | 1     | 3.85 |
| Environment | 1     | 3.85 |

3.2 Concepts

Recent papers addressed the detection of hate speech on social media focusing on different aspects. The main aspects are (i) detecting hate groups, such as racism (Hasanuzzaman et al., 2017), antisemitism (Jikeli et al., 2019), and cyberbullying (Van Hee et al., 2015); (ii) filtering pages with hate and violence (Liu and Forss, 2015); (iii) offensive or abusive language detection (Gao et al., 2020); and (iv) toxic comment detection (Guimarães et al., 2020). For a comprehensive survey of NLP techniques in order to detect hate speech, see (Schmidt and Wiegand, 2017). For multilingual approaches, see (Steimel et al., 2019).

This paper contributes to tasks of offensive language detection and detecting hate groups. In our approach, in addition to offensive and non-offensive comments, we identified flaming-levels for offensive language, as well as groups of hate. In order to achieve that, we distinguish offensive terms or expressions from swearing and hate speech. Therefore, for annotation theory or concept, we evaluate three main dictionary definitions on offense and swearing, as well as the most commonly shared literature definition for hate speech, and we adopted the following concepts for offenses, swearing and hate speech annotation.

3.2.1 Offenses

Term or expression that intends to undermine or disparage any of the following social aspects: moral, appearance, physical and psychological health, sexual behavior and orientation, intellectual, economic, religious, and political aspects.

3.2.2 Swearing

Swearing words or expressions are used to convey a hateful opinion, with high aggressive value and great potential to generate negative reactions to the interlocutor.

Table 4 shows examples of annotation for each offense and swearing labels.

Table 4: Offenses, Swearing Terms and Expressions

| Type      | Term/Expression | Translation          |
|-----------|-----------------|----------------------|
| Swearing  | Vai Tomar no Cú | Go Fuck Yourself     |
| Swearing  | Vergonha na Cara| Get Your Shit Together|
| Swearing  | Vai para o Inferno| Go to Hell           |
| Swearing  | Filho da Puta   | Motherfucker         |
| Swearing  | Foda-se          | Fuck it              |
| Offenses  | Mentiroso        | Lier                 |
| Offenses  | Vagabunda        | Bitch                |
| Offenses  | Canalha          | Jerk                 |
| Offenses  | Desgraçado       | Bastard              |
| Offenses  | Facista          | Fascist              |

3.2.3 Hate Speech

Hate speech is a language that attacks or diminishes, that incites violence or hate against groups, based on specific characteristics such as physical appearance, religion, descent, national or ethnic origin, sexual orientation, gender identity, or other, and it may occur with different linguistic styles, even in subtle forms or when humor is used (Fortuna and Nunes, 2018).

- **Partyism**: Westwood et al. (2018) demonstrated that partyism and partisan affect influence behaviors and non-political judgment.
According to the professor at Harvard University, “partyism” is a form of hostility and prejudice that operates across political lines (Sunstein, 2016). In our corpus, the most relevant occurrence of hate speech consist of partyism, as the following example shows: *Os petralhas colocaram sua corja em todos os lugares, não salva ninguém, que tristeza... Esquerda parasita liso.* “The petralhas put their crowds everywhere, no one can be saved, how sad. They are parasite and trash”.

- **Sexism:** Sexism behavior is mostly related to patriarchy, which, according to Walby (1990), consists of a system of social structures that are related to each other and that allow men to exploit women. Nonetheless, Delphy (2000) complements that women are seen as objects of sexual satisfaction of men, reproducers of heirs, labor force, and new breeders. An example found in our corpus shown: *Cala esse bueiro de falar merda sua vagabunda safada.* “Shut that manhole to talk shit you dirty slutmachi”.

- **Religious Intolerance:** As maintained by (Altemeyer, 1996), theoretical constructs loom large in the literature on religiosity and intolerance: namely, religious fundamentalism, which is consistently associated with high levels of intolerance and prejudice toward out-groups. An example follows: *Aqui na Bahia se chama "crente do cu quente".* “Here in Bahia it is called “Christian of the hot ass””.

- **Apology to Dictatorship:** According to the Brazilian Penal Code, apology to dictatorship consists of comments that incite the subversion of the political or social order, the animosity between the Armed Forces or between them, and the social classes or civil institutions. An example follows: *Intervenção militar já!!! Acaba STF não serve pra nada mesmo...* “Military intervention now !!! It’s over STF is of no use at all ...”.

- **FatPhobia:** Robinson et al. (1993) defines fatphobia as negative attitudes towards and stereotypes about fat people. An example follows: *Velha barriguda d bem folgada, heim? Porca rosa, peppa! “Old bellied and very loose, huh? Pink Nut, peppa!”.

- **Homophobia:** According to for Fundamental Rights FRA (2009), homophobia is an irrational fear of, and aversion to, homosexuality and to lesbian, gay and bisexual people based on prejudice. An example follows: *Quem falou isso deve ser um global que não sai do armário :) :( e tem esse desejo :( :( nessa hora que tinha que intervir aqui e botar um merda desse no pau. ...Dá muito o cú.* “Whoever said that must be a global who does not come out of the closet :( :( and has that desire :( :( at that time they had to intervene here and apply the law against them. ... It gives the ass a lot”.

- **Racism / Racial Segregation:** According to Wilson (1999), racism consists of the “an ideology of racial domination”. In addition, Clair and Denis (2001) argues that racism presumes biological or cultural superiority of one or more racial groups, used to justify or prescribe the inferior treatment or social position(s) of other racial groups. Through the process of racialization, perceived patterns of physical difference, such as skin color or eye shape – are used to differentiate groups of people, thereby constituting them as “races”; racialization becomes racism when it involves the hierarchical and socially consequential valuation of racial groups. In our corpus, we found many offenses such as “monkey” and “cheetah”, as well as another offenses related to racial segregation. An example follows: *E uma chita ela né! Opssss, uma chata.* “And she is a cheetah right! Oopssss, a boring”.

- **Antisemitism:** The definition of antisemitism adopted by the IHRA in 2016 states that “Antisemitism is a certain perception of Jews, which may be expressed as hatred toward Jews. Rhetorical and physical manifestations of antisemitism are directed toward Jewish...”

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5The Brazilian Penal Code, Decree-Law No. 2,848 / 1940, is formed by a set of systematic rules with a punitive character. Its purpose is the application of sanctions in conjunction with discouraging the practice of crimes that threaten the social fabric.

6International Holocaust Remembrance Alliance (IHRA) unites governments and experts to strengthen, advance, and promote Holocaust education, research, and remembrance, as well as to uphold the commitments of the 2000 Stockholm Declaration.
or non-Jewish individuals and/or their property, toward Jewish community institutions and religious facilities. Manifestations might include the targeting of the state of Israel, conceived as a Jewish collectivity". An example follows: Que escroto caquético! É a velha hipocrisia judaica no mundo dos pilantras monetários. Judeu dos infernos! “What a cachectic scrotum! It’s the old Jewish hypocrisy in the world of monetary hustlers. Jew from hell!”.

- Xenophobia: Oliveira (2019) describes xenophobia as a form of prejudice, which is manifested through discriminating actions and hate against foreigners. An example follows: Ele está certo. Vai ter um monte de argentino faminto invadindo. “He is right. There will be a lot of hungry Argentines invading the Brazil”.

3.3 Method

In order to achieve a reliable annotation process, we proposed a method that we divided into three main steps. In the first step, we annotated the corpus in two classes: offensive or non-offensive language. In the second step, we selected only offensive comments and classified them into offense-levels. The offense-levels consist of three different classes: highly offensive, moderately offensive, and slightly offensive. Finally, in the third step, we classified the offensive comments according to hate groups. Figure 3 shown our approach.

In order to identify offensive terms and expressions, as well as swearing words, annotators were supported by an offensive lexicon called MOL - Multilingual Offensive Lexicon. The authors describe the entire MOL construction process in (Vargas et al., 2021).

We initially assume that, if in a comment there is any explicit or implicit offensive expression and swear word into offensive lexicon, then this comment has offensive content. If there are no such linguistic markings in the text, this comment is non-offensive. That was our first classification.

In a second step, the set of offensive comments received a new label according to its level of offense. The process consists of the following checkings: [i] if the comment contains at least one explicit swear word or a sequence of explicit and implicit offensive words, this comment is highly offensive; [ii] if the comment contains at least one explicit and strong offensive term or expression, this comment is moderately offensive, and [iii] if the comment does not present the previous issues, this comment is slightly offensive. As the product of this step, we obtained the flaming-levels of offensive comments.

In parallel with the offense-levels annotation, we also annotated the hate speech groups. Nine groups were identified, which were previously described. This activity was built on the set of offensive comments and consists of flagging offenses or/and discrimination against these minority groups.

3.4 Annotators Background

Due to the degree of complexity of the task for offensive language and hate speech detection, mainly because it involves a highly politicized domain, we decided to enroll annotators at higher levels of education. Moreover, in order to minimize bias, we selected annotators from different political orientations, as well as different colors, as shown in Table 5.

| Profile | Description |
|---------|-------------|
| Education | PhD |
| Gender | feminine |
| Political | liberal and conservative |
| Color | white and black |
We selected annotators with higher levels of education. Two annotators have Ph.D. degrees and one is a Ph.D. candidate. Furthermore, we diversified the color and political profile as a bias-minimization strategy.

4 Dataset Statistics

One of the struggles of the annotation process is the difference between the number of comment classes, since there are much fewer offensive comments than non-offensive comments present in randomly sampled data (Schmidt and Wiegand, 2017; Çöltekin, 2020a). Therefore, a large number of comments had to be collected and annotated in order to find a balanced number of offensive and non-offensive instances. From all comments collected in the data acquisition step, a balanced dataset was selected, which contains 7,000 comments sorted into offensive and non-offensive classes, as displayed in Table 6.

Table 6: Binary class: offensive x non-offensive

| Binary Class | Total |
|--------------|-------|
| Non-Offensive| 3,500 |
| Offensive    | 3,500 |
| Total        | 7,000 |

Comments labeled as offensive were selected for a second annotation layer according to the level of offense, which identified 1,678 comments as slightly offensive, 1,044 as moderately offensive, and 778 as highly offensive. Results are shown in Table 7.

Table 7: Offensive levels

| Offense-level Classes | Total |
|-----------------------|-------|
| Slightly Offensive    | 1,678 |
| Moderately Offensive  | 1,044 |
| Highly Offensive      | 778   |
| Total                 | 3,500 |

Furthermore, offensive comments were categorized according to the nine discrimination groups in order to identify the comments that contain hate speech, as presented in Table 8.

5 Evaluation

The entire process of annotation was carried out by three annotators. Each comment was annotated by each one in order to guarantee the reliability of the annotation process. Therefore, we computed inter-annotator agreement, using three different metrics: simple inter-annotator, Cohen’s kappa, and Fleiss’ kappa, which are described below.

- **Simple inter-annotator agreement**
  Calculation of labels marked equally by the annotators. Peer agreement inter-annotator over 0.80 is a good result for subjective tasks (Vargas et al., 2020).

  We obtained, on average, 0.89 of agreement in binary-class annotation, and 0.80 of agreement in the annotation of flaming-levels (Table 9, where each annotator is represented by a capital letter), showing satisfactory results.

  Table 9: Simple inter-annotator agreement

| Peer Agreement | AB | BC | CA | AVG |
|----------------|----|----|----|-----|
| Binary class   | 0.89| 0.89| 0.90| 0.89 |
| Offense-levels | 0.79| 0.77| 0.84| 0.80 |

When the full agreement is expected, there is an expected decrease in agreement rates, because it is considered a match in three evaluations and not by pairs. In this evaluation, we obtained 0.84 of agreement in binary-class annotation, and 0.70 of agreement in annotation for levels of offense (Table 10), still presenting satisfactory results (Vargas et al., 2020).

Table 10: Full inter-annotator agreement (i.e., when the three annotators used the same label for the same comment)

| Full Agreement | ABC |
|----------------|-----|
| Binary class   | 0.84|
| Offense-levels | 0.70 |

- **Cohen’s kappa**
  Described by Equation 1; where po is the relative agreement observed between raters and
is the hypothetical probability of random agreement, it shows the degree of agreement between two or more judges beyond what would be expected by chance (Cook, 2005; Sim and Wright, 2005).

\[ k = \frac{\rho_o - \rho_e}{1 - \rho_e} \]  

(1)

Kappa values range from 0 to 1, and in Table 11 there are possible interpretations of these values (Landis and Koch, 1977) (although it is known that there may be differences according to the subjectiveness of the evaluated task).

Table 11: Kappa values and strength of agreement according to (Landis and Koch, 1977)

| Kappa values | Strength of agreement |
|--------------|-----------------------|
| 0.00-0.20    | Slight                |
| 0.21-0.40    | Fair                  |
| 0.41-0.60    | Moderate              |
| 0.61-0.80    | Substantial           |
| >0.80        | Almost Perfect        |

In this metric, we obtained, on average, 0.75 of agreement in the binary-class annotation and 0.47 of agreement in the annotation of offensive levels (Table 12). According to 11, binary-class kappa value is considered a Substantial Agreement, and flaming-levels kappa value is considered a Moderate Agreement. These results are satisfactory, and the stratum difference empirically reinforces a greater difficulty activity of annotating levels of offense.

Table 12: Cohen’s kappa

| Peer Agreement | AB  | BC  | CA  | AVG |
|----------------|-----|-----|-----|-----|
| Binary class   | 0.76| 0.72| 0.76| 0.75|
| Offense-levels | 0.46| 0.44| 0.50| 0.47|

• Fleiss’ kappa

It is an extension of Cohen’s kappa for the case where there are more than two annotators (or methods). This means that Fleiss’ kappa works for any number of annotators giving categorical ratings (with binary or nominal scale), for a fixed number of items (Fleiss, 1971). The interpretation for the values of Fleiss’ kappa also follows Table 11.

In Fleiss’ kappa evaluation, we obtained 0.74 of agreement in binary-class annotation, and 0.46 of agreement in the annotation of flaming-levels (Table 13), maintaining the same levels of agreement presented by Cohen’s kappa. Our Fleiss’ kappa value to binary class is in agreement with the literature, mainly with OFFCOMBR-2, so far the only annotation for offensive comments on the Brazilian web. OFFCOMBR-2 labeled 1,250 comments as offensive or not offensive, annotated by three judges and presenting Fleiss’ Kappa equal to 0.71 (de Pelle and Moreira, 2017).

Table 13: Fleiss’ kappa

| Fleiss’ kappa | ABC |
|---------------|-----|
| Binary class  | 0.74|
| Offense-levels| 0.46|

In addition to these evaluation metrics, two steps were taken to account for hate speech groups: [i] the comments flagged by at least two annotators were immediately inserted in the groups, and [ii] the comments flagged by only one annotator passed a new checking, where the three annotators flagged the comment as validated or not. When at least two annotators validated the comment, it was added to the group.

6 Final Remark

Due to the severity of the hate speech and offensive comments in Brazil, and the lack of research in Portuguese, this paper provides a new expert annotation process, as well as the first robust manually annotated dataset for offensive language and hate speech detection in Brazilian Portuguese. The proposed corpus was collected from Instagram and consists of randomly sampled 7,000 comments with 3,500 non-offensive and 3,500 offensive samples. Additionally, comments labeled as offensive were classified according to three offense levels, named as highly offensive, moderately offensive, and slightly offensive. Finally, we also labeled the target of the discriminatory content (xenophobia, racism, homophobia, sexism, religious intolerance, partyism, apology to the dictatorship, antisemitism, and fatphobia). A high human annotation agreement was obtained. The proposed expert annotation process is also language and domain-independent.
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