Sentiment Analysis of Anti-LGBTQ+ laws in Brazil using Comparative Analysis Models

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Sentiment Analysis of Anti-LGBTQ+ laws in Brazil using Comparative Analysis Models

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Abstract

Social media has become an important platform when it comes to expressing opinions, which means it can be used as a valuable tool for understanding critical points regarding political sentiment. This research wants to explore the sentiment analysis on online discussions related to anti-LGBTQ+ laws being released around the world and the potential impact in Brazilians opinions since past events involving homophobia and prejudice. This study uses data analysis techniques, such as web scraping, machine learning and deep learning models to collect, analyse the sentiments and find insights based on translated comments about anti-LGBTQ+ laws videos circulating in the news channels on YouTube. The literature review shows the studies around sentiment analysis using machine learning and use of multilingual approaches and the challenges faced. The results of the research shows that the negative and positive classes are well labelled by the models but struggles with the neutral due to spam comments and not enough labelled data.

Keywords – Sentiment analysis, anti-LGBTQ+ laws, YouTube comments, machine learning, data analysis.

1 Introduction

With the explosion of social media content, the world has become more connected than ever, with data being created every second containing opinions and feelings about all kinds of events. Groups with different ages and mindsets that became linked by social media have shown the discrepancy between generations and its showing the impact of this throw comments created, posts and discussions on different political topics. One example of this is the discussion online about anti-LGBTQ+ laws released in the United States in last years in states with conservative authorities (Soesanto et al.; 2023). Since the USA is currently a power house about economics and social decisions for other countries, its decisions and policies are often being analysed and discussed all around the globe, influencing debates and opinions.

With the support of data science techniques, this research investigates sentiment analysis to be aware of emotions and opinions expressed online, putting its focus on discussions about anti-LGBTQ+ laws around the world and its repercussions on Brazil, even though being known as a festive and happy people country around the world, its numbers regarding homophobia have increased and take more attention of social media number such as in 2017, 445 LGBTQ+ Brazilians died as victims of homophobia, which mean 1.22 citizens were killed every day by prejudice [1]. Previous studies on LGBTQ+

[1] Violent deaths of LGBT people in Brazil hit all-time high — Brazil — The Guardian

debate are explored in the literature section of this paper to show the importance around the topic these days. As most studies apply sentiment analysis techniques to classify opinions and compare algorithms, a couple of articles had close goals as this research. The first one verified the sentiments of LGBTQ+ in the USA (Soesanto et al.; 2023), while the second one explored Indonesian opinions on anti-LGBTQ+ laws (Fitri et al.; 2019). In spite of that, this research aims to analyse the opinions of Brazilians regarding the upcoming anti-LGBTQ+ laws being discussed for governments from all around the world, providing understanding regarding the population approval or disapproval if similar laws were to be introduced in Brazil.

1.1 Research Question

The research question this research wants to explore is: "How sentiment analysis about anti-LGBTQ+ laws in other countries can impact the relevance of this topic in Brazil?". The significance of this question is divided in two points.

- First, it performs machine learning models and investigates its efficiency and accuracy around sentiment analysis about the topic in Portuguese comments. Previous studies has shown that it is possible to perform sentiment analysis using classifiers, such as Decision Tree, Naïve Bayes, Random Forest, Support Vector Machine and Logistic Regression, but this research will focus its investigation in two models which its structures and literature indicate a good fit when analysing text classification, and at the end, compare the models and select which has a better performance (Giachanou and Crestani; 2016).

- The last part of the question is about investigate how the opinions expressed around anti-LGBTQ+ laws can impact the political decisions in Brazil. By exploring media news content, checking dates of publications and amount of comments generated by these laws it is possible to visualise the repercussion around Brazilians and with the application of sentiment analysis, the classification of opinions about the support for these kind of laws.

This research will use Random Forest and Naïve Bayes techniques to perform sentiment analysis on YouTube comments and achieve the classification of opinions.

The paper is divided in 6 parts, the first one being the Introduction just read. In Section 2, an exploration of the literature review breaking down in five points that describe how previous studies have been done similar applications around comment extraction, data validation, data translation, sentiment analysis around LGBTQ+ topics and challenges faced when applying those steps. In Section 3, the method is explained with a complete description of the procedures used. Section 4 is the implementation and design specifications with a deep explanation of the data used, how it was collected, how the data validation and translation was performed, and the explanation about the machine learning algorithms applied to perform the sentiment analysis. In Section 5, the evaluation around the results of the models applied and selection of most accurate to find the sentiment in Brazilian comments and the visualisations to identify possible insights. In Section 6, the conclusions and future research directions based on the findings of the research.

2 Literature Review

When performing sentiment analysis the objective must be extraction and analysis of people's opinions. Although sentiments and opinions are linked, sentiments are described as emotions related to a fact, while opinion is a point of view (Sarlan et al.; 2014). Sentiment analysis goal is to classify sentiment polarities like negative, neutral or positive. This literature review explains parts of the research that are performed to reach the goal of this project. Here it will be shown past studies that have used YouTube comments as raw data and how it was extracted and used for. The data validation methods identified in previous literature and system set up used, updating to fit to the goal of this project. It also mentions about multilingual techniques to translate text and use it since great part of the studies performing sentiment analysis are in English. Then comes the machine learning introduction where the past papers regarding sentiment analysis focused in LGBTQ+ topic are analysed and compared. Lastly, the challenges are mentioned and shown how many papers have faced the same problems.

2.1 Comment Extraction

The objective of (Thant et al.; 2020) are to extract and prepare YouTube comments written in Myanmar language and to check the effect of multiple pre-processing approaches in extracting musical opinions by using information gain. The dataset used was prepared manually by collecting original unprocessed comments from YouTube using a comment scraper tool, which unfortunately was not further explained by the authors and it would have enriched their work since there is a lack of approaches in the literature. The authors applied machine learning algorithms for opinion extraction and sentiment analysis in different stages of the preparation of the dataset to verify which step impacted the most in accuracy in case of information gain, which increased when added replacement and translation steps. The challenges addressed by the authors were use of slang, sarcasm, negation handling and spam opinion detection, and this issues were suggested as points to be investigate as future work. Although there were missing further explanations regarding the data collection, (Thant et al.; 2020) the pre-processing steps to achieve a better accuracy in the dataset proved to be essential and are being used in this project, also slang detection and spam comments are being treated by performing extra steps in the data cleaning process explained in Section 4.

The objective of (Pradhan; 2021) is to identify the sentiment of viewers regarding videos on YouTube and provide insights to creators to improve the quality of their content and understand the community's acceptance of videos and channels. The extraction of the data was performed by using YouTube Data API v3 which is the interface provided by the company that allows developers to access and interact with data. The author shortly explains the steps performed to collect the dataset using the API, which was objective and precise considering it is the most common data extraction found in the literature for this case. For sentiment analysis, the author used the Natural Language Toolkit and VADER (Valence Aware Dictionary and Sentiment Reasoner) lexicon to determine the sentiments of the text, no further explanation for the approach used or other options to achieve better results were discussed which could have enriched the study. The conclusion section showed the number of positive comments and negative comments identified by the sentiment performed. The author did not mention the challenges faced but suggested that the application of sentiment analysis in a context of decision making is proposed as our future work since YouTube data extraction has proved to be a huge source of public opinion.

2.2 Data Preparation

The study made by (James; 2023) had its objective to perform a sentiment analysis focusing on the capability of the application of Random Forest as machine learning and ANN with comparison to the NLTK. The steps mentioned by the author are very similar to the ones performed in this study since it is the most common practice in the literature when discussing data validation. (James; 2023) explained that the raw data collected from Twitter should be cleaned and processed to get the proper data extraction of features and the stages that were used for the cleaning process include the removal of unwanted special characters and blanks paces, converting words to lowercase to keep a standard, handling emojis converting them to words with the emoji library, using the stop word library to remove the unmeaningful words from the corpus, the empty spaces removal and translating slangs and correcting misspell. All those steps were also applied to paper since its flexible applicability in multiple types of datasets and popularity among researchers due to its convenience.

(Sai et al.; 2023) proposed a system to analyse fake news and detection of hatred news using text analysis and data mining. One of the essential phases to perform an accurate data pre-processing is the step of putting raw data into a format that is comprehensible. Before using machine learning or data mining methods, the data's quality should be examined. The steps of data pre-processing performed by the authors are lower casing, which guarantees correlation inside the function set and addresses the sparsity issue, removal of stop word, which are tiny words used to structure language grammar but are useless for text mining, verification for prepositions, conjunctions, pronouns, and common terms like a, the, an, by, from, to and about. The last is tokenization, that is the technique of dividing prolonged textual content series into tokens. All those steps require a higher coding expertise and time of application, which is why they were not applied to study, but it has brought good results to (Sai et al.; 2023), which means it could be beneficial for this paper as an improvement of the data validation process as future work.

2.3 Multilingual Methods

(Abdulla et al.; 2014) proposed an approach for text translation for Arabic language to English comparing two approaches often mentioned in the literature about text translation. The first approach is the manual lexicon creation, where the authors translated from English to Arabic 300 seed words and assigned polarity scores. Then it was added to their dictionary synonyms, emoticons, slangs using a Term-Frequency (TF) weighting scheme and words from various Arabic dialects. The second approach is the automatic, where the authors divided into two possible methods, the direct translation or corpus based. The direct translation uses web based machine translation services, such as Google, Microsoft and IBM Translator. Corpus based is a labelled balanced dictionary of positive and negative comments. For the translation from Portuguese language to English, this paper will be using the direct translation with Google Translator API further explained in Section 4. When making the comparison of accuracy, the authors found that the automatic techniques performed better than the manual technique, where the corpus-based approach produced much better results compared with the direct based. Although the results show which model has performed better, the study did not explain why such differences happened and what actions to achieve more accuracy could have been done, which while analysing their study, the application of direct based involved less data to support the model than the corpus based, if both were combined, the model might have had an increase of accuracy.

2.4 Sentiment Analysis applied into LGBTQAI+

Analysing comments collected in the United States of America, (Soesanto et al.; 2023) tested five algorithms such as TextBlob, XGBoost, Naive Bayes, Logistic Regression and Linear Support Vector Machine using pre-processed to classify the sentiments of people about LGBTQ+ content. The study had the goal to understand how LGBTQ+ is treated by the USA which is directly related to the goal of this paper which is to understand the reaction of Brazilians considering the news applied to other countries regarding the same topic. The main difference between both studies, the authors used an online labelled dataset and this study is taking updated comments directly from the platform which is unlabelled. The results found by the authors are that most comments achieved status neutral, followed by positive and then negative, which confirms an accepting ideals about LGBTQ+ content. About the performance of the algorithm applied, Logistic Regression showed the highest accuracy compared with the others, but all of them achieved a satisfactory result, reaching up to 59 percent.

(Fitri et al.; 2019) performed a study about anti-LGBTQ+ opinion for Twitter user in Indonesia. The goal of the authors is to understand opinions and find which algorithm performed the best. They used Naïve Bayes, Decision Tree, and Random Forest as techniques to perform the sentiment analysis in a dataset they have collected from the social media platform, which unfortunately has not been mentioned how. The authors briefly explained the processes used, such as processing the data, applying the algorithm, classifying the categories and evaluating the performance of the models. The results show that most social media users in Indonesia has neutral sentiments about the anti-LGBTQ+ . The best technique found by the authors was Naïve Bayes. Even though the study missed the explanation of crucial parts such as collection of data, and quickly explained the process in general, the study performed brought the idea to identify if in Brazil, the analysis of social media could be benefic for future government decisions since it gives a structure of the population's idea and opinions about the topic.

2.5 Challenges

(Zimbra et al.; 2018) focused their study to evaluate the state-of-the-art in Twitter sentiment analysis, where they conducted a search on 28 academic papers to understand its motives and challenges, which are represented in Table 1. For this particular study, the challenges faced also included sarcasm detection, small comments that lead to polarity of the text and comments out of context that confuse the machine.

While many authors have performed sentiment analysis in social media content, most of them have used Twitter API to collect the data, which now has changes and it is not a possible option for those who would like to run analysis about social media opinion. [2]This

[2]Twitter just closed the book on academic research - The Verge: `https://www.theverge.com/2023/5/31/23739084/twitter-elon-musk-api-policy-chilling-academic-research`

project aims to show another way to collect data using another social media platform. Another point relevance for the importance of this project is the analysis of this comments with focus in prevent or understand a population opinion based in the laws applied in other countries. No other study was found that its goal is to analyse current data to take constitutional decision. In the next section, the steps of this project will be explained a complete description of the research procedure.

Table 1: Sentiment Analysis Challenges

Challenge	**No. of studies**
Sentiment Information Propagation	8
Feature Representation Expansion	5
Specific Preprocessing	20
Specific Features	14
Training Set Expansion	14
Multiple Classifier Methods	9
Sentiment Topic Models	7
Stream-Based Classifiers	5

3 Methodology

This research methodology brings the four main steps (Figure 1) which shows the big picture of the plan to perform the main objective of this these: to understand how sentiment analysis about anti-LGBTQ+ laws in other countries can impact the decisions in Brazil. Those four steps are broke down into actions which are explained in the Design and Implementation section (Agüero-Torales et al.; 2021).

- Getting into the topic: the question being raised after so many laws about anti-LGBTQ+ being raised in the USA and realising how much content it was being share in social media about other countries debating and commenting those decision. To support the question, a deep article search was performed to understand if academics had already applied sentiment analysis in Brazilians comments about the topic, although it has been performed in Indonesia, it was not in Brazil (Fitri et al.; 2019).

- Dataset search: since it is a new questioning, the data required for the analysis was not available or labelled, which means the author had to verify in the literature was to extract unlabelled data directly from the social media platform. YouTube has been chosen as the source since most news in Brazil release videos about events around the whole and it gets interactions from all different generations [3].

- Validation and Translation: after collecting the dataset from YouTube, the author had to perform a cleaning and validation of the data, since inside the comments it is found special character, hashtags, emojis and slangs that can mislead the model's results. After removing and changing the slangs, a translation from Portuguese to English was performed, since most of the libraries perform using English language (Mercha and Benbrahim; 2023).

[3] YouTube for Press (blog.youtube)

- Sentiment Analysing using machine learning models: after the unlabelled data has been cleaning and maintained, the application of Random Forest and Naive Bayes models to understand which one has performed better and why, the author made visualisations to explain its findings and which insights could been taken to answer the research question raised.

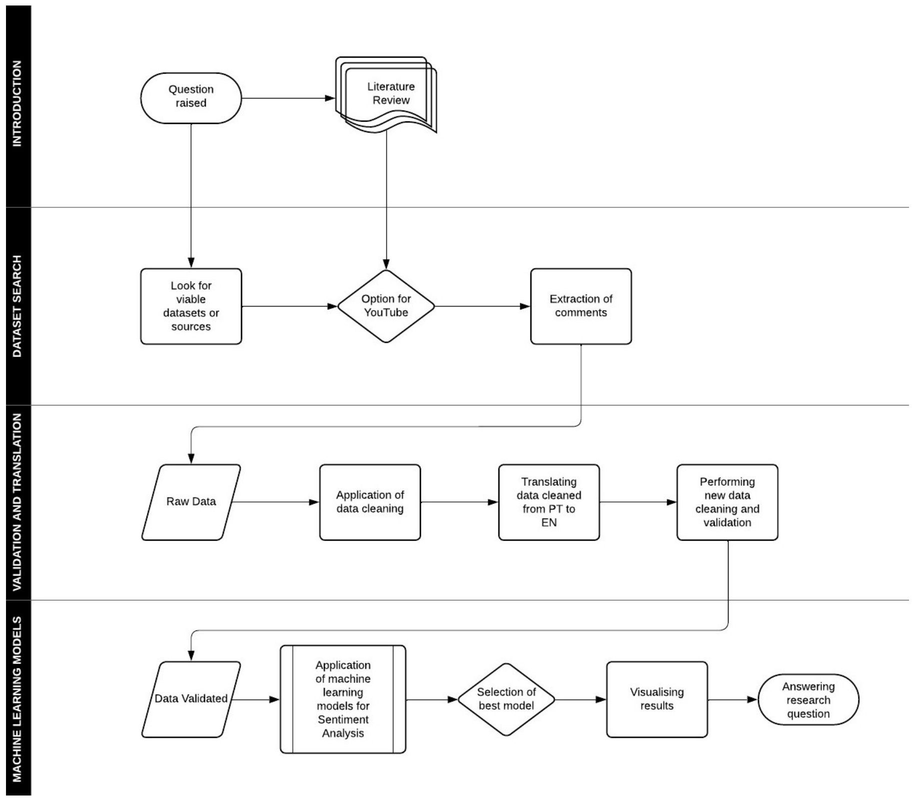

Figure 1: Big picture of tasks performed for this research

The next section of this research intend to explain in details which step performed, showing the challenges faced and how they were defeated. It also will bring explanations of decisions taken.

4 Design Specification and Implementation

The application of two machine learning models to perform a sentiment analysis of Anti-LGBTQ+ laws in Brazil are applied and investigated if its performance is satisfactory to make decisions towards political strategies. The components and implementation of the whole process to achieve this are divided into the four subsections below.

4.1 YouTube Comment Extraction

To perform this step, the author had to search for ways to extract the comments in a quick and automated way, since the amount of time to make this project is short. Web scrape has been an easy tool to achieve this goal (Mahto and Singh; 2016), especially if it does not break any rule established by the platform [4]. Using Python code language and libraries such as 'Selenium', 'Scrapy' and 'Webdriver manager (chrome)', the script initialises a web bot that reads the list of URLs video links containing the news channels in Brazil covering the Anti-LGBTQ+ laws being released in other countries. The bot opens each YouTube video URL in a Chrome browser, scrolls down the page and extracts the information respecting the delays requested by the platform. The extracted data is then saved into a CSV file.

Around 100 videos about Anti-LGBTQ+ laws in Brazil were watched and checked but only 44 were selected, due to misinformation or fake news, the videos selected were from well known news channels from Brazil, which can bring more confidence about the information being transmitted and seriousness of the comments. More than 11,500 comments were collected from 14 news channels Figure 2.

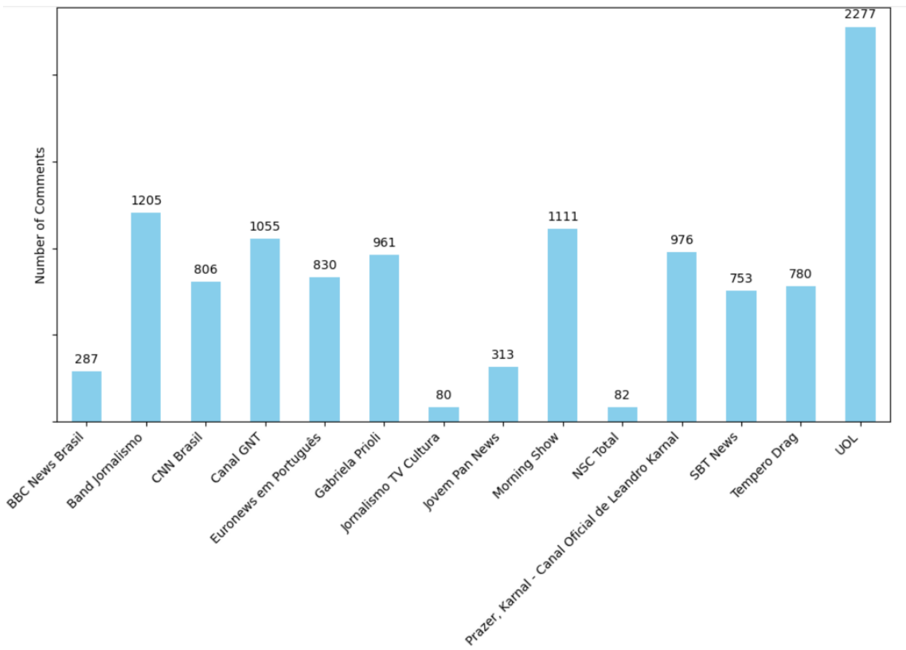

Figure 2: Comments by News Channels

After collecting the comments, to understand how the comments are, it was used the library 'wordcloud' and 'matplotlib' to visualise the most used words in the comments. Since this is raw data, the result shows slangs, stop words such as 'the', 'to', 'and' Figure 3. This brings the next subsection, which is the data cleaning.

4.2 Data Cleaning

Since the raw data needs to be fixed before translating to avoid misleads for the sentiment analysis, using Python libraries like 'Pandas' and 'SpellChecker', first it was removed blank lines and duplicate rows, then tokenization to convert the words and help the further analysis (Vijayarani et al.; 2016). Due the comments are being made in a social media platform, the sentences or words might be misspell or used as slang, to fix the mistakes and catch the slangs, it was used 'Spell Checking'[5] , which its algorithm uses a

[4]YouTube for Press (blog.youtube)
[5]https://pypi.org/project/pyspellchecker/

Figure 3: Comments by News Channels

extensive dictionary containing different languages, it verifies the comments and correct the words, it also provide the list of words that it was not able to correct, the authors went throw this list and corrected manually since most of it were slangs. A dictionary of slang was created and replaced in the file.

After the slangs were replaced, the next step of the data cleaning was to rename or remove emojis. These emojis can bring important meaning to the comment, for example if it is a vomit face, means the person is disgusted by the topic or a clapping hand is agreeing with the news [6]. For this, a few emojis were replaced by the meaning and the rest was removed. The emojis replaced are shown in the Table 2

Table 2: Emojis replaced

Short Name	Code
Nauseated face	U+1F922
Vomiting face	U+1F92E
Partying face	U+1F973
Worried face	U+1F61F
Slightly frowning face	U+1F641
Frowning face	U+2639
Loudly crying face	U+1F62D
Thumbs up	U+1F44D
Thumbs down	U+1F44E
Clapping hands	U+1F44F

The final cleaned dataset is saved to a new csv file. This step is crucial for the translation which is the following subsection of this paper, a high quality dataset with clear words and meanings provide a better chance of correct translation and so a accurate sentiment classification (Kumar and Khosla; 2018).

4.3 Data Translation

Using Python language and Google Cloud Translation API to translate the cleaned dataset from Portuguese comments to English [7] . The first step is setting the environment for

[6]Full Emoji List, v15.1 (unicode.org)
[7]Cloud Translation API — Google Cloud

Google Cloud credentials, which it is needed to have a Google account that provides you a key to use its tools. The libraries used for this step are 'os', 'Pandas' and 'Google Cloud'. The cleaned dataset is loaded and the translation script uses a function to handle the language process. The code takes around one hour to finish but finishes and saves the new translated file (De Vries et al.; 2018). This script shows the translation capabilities of the Google Cloud Translation API and exemplifies best practices in error handling, making it a great solution for multilingual text processing in any language. Figure 4 shows now the most commented words, note that the stop words are not being considered due to the cleaning process and the words are all in English.

Figure 4: Most used translated words

4.4 Sentiment Analysis

Since our dataset was collected directly from YouTube, the text is not classified with sentiments, since the machine learning algorithms this study is evaluating needs a labelled file to train and then apply the model in the unlabelled data, to fix this, the author selected 5% of the dataset and labelled manually. In order to have a base of knowledge of how the machine would interpret the comments, a pre-built sentiment analysis tool called the Sentiment Intensity Analyzer (SIA) and VADER (Valence Aware Dictionary and Sentiment Reasoner) from the Natural Language Toolkit (NLTK) is applied. The NLTK is a library used to import the SIA which calculates sentiment scores for each comment in the translated data. This type of sentiment analysis is based on a heuristics model (Vencer et al.; 2023). After running this sentiment model, the results show a similar division of comments between the classes, with the positive getting a bit higher (Figure 5).

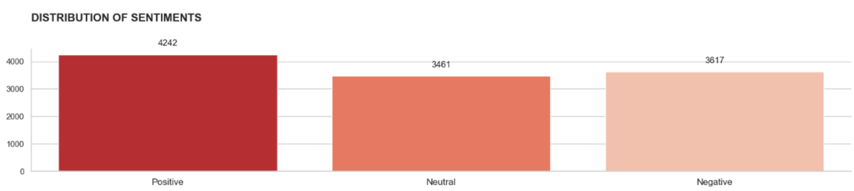

Figure 5: Comments by Sentiment

Note that, when the sentiment is positive, it means that people are agreeing with the news being reported and negative for people disagreeing. Figure 6 shows that people against the laws being reported have written better comments, which means they might be giving opinions and explaining why to go against it instead of just celebrating. When

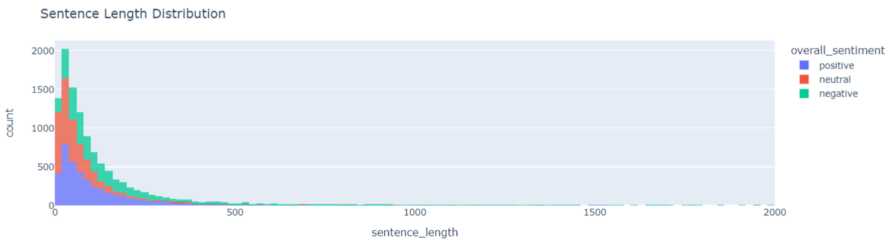

Figure 6: Sentence Length Distribution by Sentiment

creating the labelled file to perform the machine learning models, the author selected a part of the original dataset and labelled and compared with the comments classified by this algorithm. The match accuracy was 68%, which can be considered a good result considering that only 5 percent of the original dataset was used. In Figure 7 it shows the words most used by class.

Figure 7: Most used words by Sentiment

4.4.1 Random Forest Classifier

The first machine learning model chosen to perform the sentiment analysis is Random Forest Classifier, since it uses an ensemble learning method that creates multiple decision trees during training and joins the predictions to get the accurate result (Karthika et al.; 2019). The model uses the labelled dataset created to train and test and understand the patterns of the comments. After the model is trained and tested, it is applied to the original unlabelled dataset and a confusion matrix is made to understand the performance of the model.

In Table 3, it shows that while the accuracy of the model is 57%, it performed very well to predict the negative class, with precision (predicted negatives corrects) of 86% and positive class with recall (actual positives were predicted well) of 88%. The neutral class did not achieve a good result in either measures.

This result also can be seen in the ROC Curve showed in Figure 8, where the class Positive (blue line) shows achieved good results in True Positives Ratios while the Neutral class (orange line) was the closest to the dotted line, which is the random classification (0.5).

Table 3: Confusion Matrix Results for Random Forest

	Precision	**Recall**	**F1 Score**
Negative	0.86	0.35	0.50
Neutral	0.29	0.33	0.31
Positive	0.58	0.88	0.70
Accuracy	0.57		

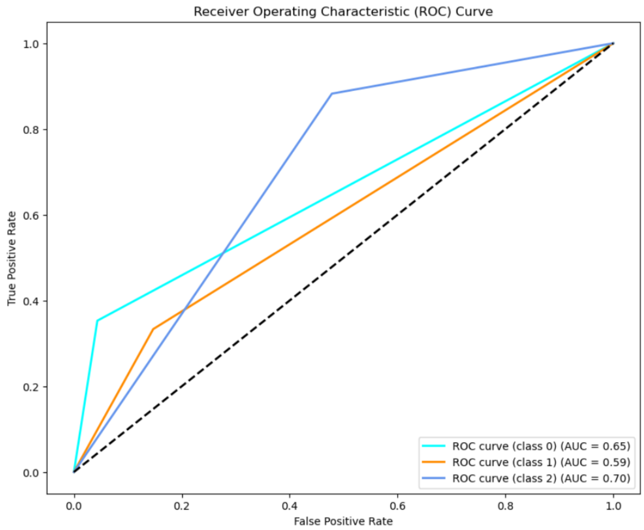

Figure 8: ROC Curve for Random Forest

In Figure 9 shows the words most used by class when performed the sentiment analysis using Random Forest. Note that a few words repeat compared with the SIA and VADER model, such as ’Hungary’ in the positives and ’people’ in the negative.

Figure 9: Most used words by class for Random Forest

4.4.2 Naive Bayes

The second machine learning model chosen to perform the sentiment analysis is Naive Bayes, which strong point is that can be efficient and perform well text classification tasks like sentiment analysis with limited data, which is the case of the labelled data (Mishra et al.; 2022). The model uses the labelled dataset created to train and test and understand the patterns of the comments. After the model is trained and tested, it is applied to the original unlabelled dataset and a confusion matrix is made to understand the performance of the model. In Table 4, it shows that while the accuracy of the model is 60%, it performed very well to predict the negative class, with precision (predicted negatives corrects) of 89% and positive class with recall (actual positives were predicted well) of 94%. The neutral class did not achieve a good result in both measures.

Table 4: Confusion Matrix Results for Naive Bayes

	Precision	**Recall**	**F1 Score**
Negative	0.89	0.47	0.62
Neutral	0.00	0.00	0.00
Positive	0.52	0.94	0.67
Accuracy	0.60		

The result of Naive Bayes also can be seen in the ROC Curve showed in Figure 10, where the class Positive (blue line) shows achieved good results in True Positives Ratios while the Neutral class (orange line) is exactly in the dotted line, which means that its classification was not successful at all.

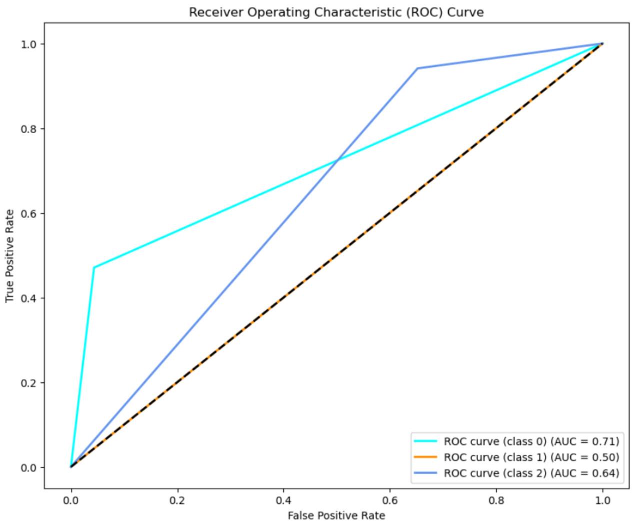

Figure 10: ROC Curve for Naive Bayes

In Figure 11 shows the words most used by class when performed the sentiment analysis using Naive Bayes. Note that a few words repeat compared with the SIA and VADER model and Random Forest, such as 'Hungary' in the positives keep showing up and 'people' in the negative.

Figure 11: Most used words by class for Naive Bayes

5 Evaluation

This section will present the final interpretation of the results achieved by the two machine learning models applied for the sentiment analysis, Random Forest Classifier and Naive Bayes. For the Random Forest Classifier, the model got accuracy of 57%, it did very well when predicting the negative class, achieving a precision of 86% and a recall of 88% for the positive class. However, the neutral class did not perform well in either precision or recall. The ROC Curve confirmed the same results, even though the True Positives Ratio for the positive class got an very good result, the neutral classification can not be trusted.

Naive Bayes model got a higher accuracy compared with the previous model, with accuracy of 60%. But it did a similar analysis as Random Forest, with high performance in predicting the negative class, with a precision of 89% and a great recall of 94% for the positive class. But, the neutral class did not achieve satisfactory results in both precision and recall.

When comparing both models, they demonstrated well in classifying negative and positive comments, while the performance of neutral sentiments was not good enough. The Naive Bayes model was better than the Random Forest in terms of accuracy. However, it is important to note that the training and testing of both models were conducted on a labeled dataset, representing only 5% of the original data, which without a doubt have influenced in these result but the amount of time and resources to label a bigger part of the dataset were a challenge. Also, another point worth mention is while the author was manually labelling a part of the data, the amount of comments that were out of context and purely spam were huge, this fact might have clouded the models to understand and classify neutral sentiment. Despite these negative points, the models can be improved to achieved better results.

5.1 Ethics Concerns

When applying sentiment analysis using YouTube comments about a sensitive topic such as anti-LGBT laws can raises ethical concerns. As an open platform, YouTube serves as a space for public debate with different voices and opinions (Townsend and Wallace; 2016). It can cause ethical concerns about potential discriminatory narratives or genuine expressions of concern related to dangerous situations. Also, sentiment analysis models may have difficulty classifying feelings or interpret context, which could result in misunderstandings of users' intentions. As anti-LGBT laws are against basic human rights and social justice, there is a risk that the application of sentiment analysis may be biased, reinforcing bad stereotypes or prejudiced points of view. To mitigate these concerns, ethical considerations must guide the application of sentiment analysis tools, including transparency, fairness, and a commitment to addressing potential biases, all while respecting users' right to freedom of expression (Townsend and Wallace; 2016).

6 Conclusion and Future Work

Coming back to the question that raised the curiosity of how sentiment analysis about anti-LGBTQ+ laws in other countries can impact the debate of this topic in Brazil, after the investigation and application of the machine learning models, this research focus in the utilization of YouTube comments as an indicator of public sentiment towards the application of such laws in Brazil, the main objective was to understand if the population would approval or disapproval such laws, providing a possible tool for governments to follow the mindset of its citizens, since as mentioned in the introduction, Brazil is one of the countries that have more fatalities when its about homophobia and prejudice.

The research achieved a few insights about the sentiment analysis tools used, including the Sentiment Intensity Analyzer (SIA) and VADER, along with Random Forest Classifier and Naive Bayes. Apart of the challenges of working with an unclassified dataset, the author manually labeled 5% of the data to train and test the models which has been proved not being enough to prepare the models for a better classification, all though the models did classified well the negative and positive comments. The key findings indicate that people expressing disagreement with those laws tended to articulate and explain more their comments. Also that the polarization of opinions about the topic shows that laws involving such polemic topic might not fall well in the public view about the government.

It is important to acknowledge the limitations of this study. The manual labeling of only 5% of the dataset did not capture the diversity of sentiments present in the entire data, which also involved load of spam comments that cause noise for the model's performance. Additionally, YouTube comments do not represent the broader population, which can be dangerous for biased of opinions if not balanced well. For future work suggestions, the author suggest a deep search of how filter spam comments to prevent one of the challenges dealt by this project. Also, if applied as a indicator for future decision, a way of collection data and separating by regions of the country might provide insights in local cities or states instead of the whole country.

In conclusion, this research addressed the question and objectives by applying sentiment analysis to understand public opinion on anti-LGBTQ+ laws on debated abroad. The findings show the efficacy of the applied models in discerning sentiments. The study's limitations should be considered, emphasizing the need for cautious interpretation of results.

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