

Evaluating Graph Attention Networks as an Alternative to Transformers for ABSA Task in Low-Resource Languages

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Abstract

Opinions toward subjects and products hold immense relevance in business to guide decision-making processes. However, due to the increase in user-generated content, manual analysis is unrealistic. Techniques such as Sentiment Analysis are paramount to understanding and quantifying human emotion expressed in text data. Aspect-Based Sentiment Analysis aims to extract aspects from an opinionated text while identifying their underlying sentiment. Graph-based text representations have been shown to bring benefits to this task, as they explicitly represent structural relationships in text. While studies have demonstrated the effectiveness of this representation for Aspect-based Sentiment Analysis using Graph Neural Networks in English, there is only sparse evidence of improvement using these techniques for low-resource languages such as Portuguese. We develop a straightforward Graph Attention Network model for the Aspect-Based Sentiment Analysis task in Brazilian Portuguese. The proposed approach achieves a Balanced Accuracy score of 0.74, yielding competitive results and ranking third place in the ABSAPT competition. Furthermore, by leveraging sparse graph connections our model is less computationally demanding than a Transformer architecture in terms of training and inference.

Introduction

Opinions toward subjects and products hold immense relevance in business, as they provide insights into the customer bases and remain a solid approach to general market research to guide the decision-making process. Considering the increase in user-generated content, manually examining this data is costly and unrealistic in the ever-expanding digital landscape (Liu 2012).

Techniques such as Sentiment Analysis (SA) are paramount to understanding and quantifying human emotion expressed in text data. Sentiment Analysis is a fundamental task in Natural Language Processing (NLP) and can be understood as the process of computationally analyzing and identifying the emotional tone conveyed by the authors of a piece of text. In practice, Sentiment Analysis asserts

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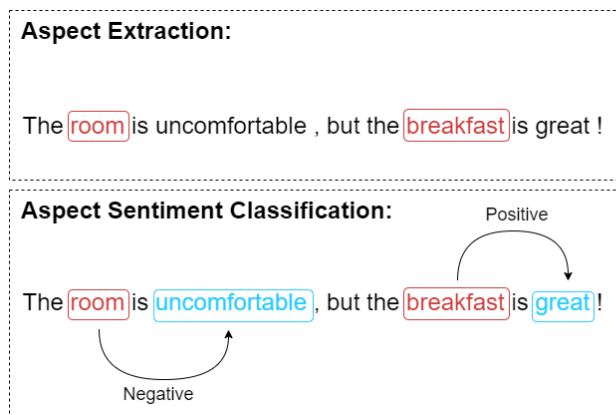


Figure 1: ABSA comprises (1) Aspect Extraction, where aspects are identified in the corpus; and (2) Aspect Sentiment Classification, where sentiment polarities are attributed to aspects.

whether the opinion of a text is positive, negative, or neutral. The significance of such techniques is evident as their applications are diverse, spanning various domains including brand management, political analysis, healthcare, social media monitoring, and much more.

Opinionated texts often express multiple conflicting sentiments regarding different subjects in the same sentence (i.e. in the context of hotel reviews, an author may provide positive feedback about the bed and negative feedback about the breakfast). Identifying these aspects and their sentiments is often more valuable than extracting the overall sentiment tone of an entire document. Aspect-based Sentiment Analysis (ABSA) is based on the idea that all opinions consist of a sentiment polarity and its target (Liu 2012). ABSA subtasks are evidenced in Figure 1.

Historically, traditional Sentiment Analysis often relied on the use of predefined lexical dictionaries listing words associated with positive or negative values indicating their sentiment polarities. These dictionaries were frequently manually compiled and their words would have assigned scores based on perceived emotional connotations. This process is also known as rule-based Sentiment Analysis and involves matching the words in a given document with those

in the dictionaries to compute an overall sentiment score. Assuredly, this kind of approach has several drawbacks including limited vocabulary coverage, lack of context understanding, and difficulty handling polysemy (i.e. words with multiple meanings could be misinterpreted).

Connectionist techniques such as Neural Networks overcame several limitations of rule-based Sentiment Analysis by capturing complex patterns in text data. Unlike previous approaches, they can automatically learn relevant features from data, dismissing the necessity for a prior curated dictionary. This enables them to adapt to various domains, addressing partial vocabulary coverage issues. Furthermore, by distinguishing between the nuanced meanings of words in different contexts, such methods are capable of contextual understanding, making them better equipped to handle polysemy. Expectedly, Neural Networks generally outperform rule-based systems in terms of accuracy.

The most common way to input text data into Neural Networks is to adapt it into vectorized representations using embeddings. There have been noticeable advances in terms of the embedding representations themselves, such as deep contextualized word representations (Sarzynska-Wawer et al. 2021), the bidirectional attention mechanism (Devlin et al. 2018), and multiple optimization proposals for them (Dao et al. 2022; Liu et al. 2019). While embeddings are certainly capable of retaining significant amounts of text information, it is possible to add supplementary information with the intent of explicitly capturing structural relationships in text data. Graphs are a suitable type of representation to model relationships in data and we argue that leveraging them to present syntactical connections to the model could potentially improve its performance in downstream tasks. For text data, we can assume words as nodes, whereas their syntactic relations are edges, thus explicitly modeling an additional layer of information that can be added to the embedding rather than using the text alone.

Graph Neural Networks (GNNs) are Neural Networks that utilize graphs as input data. The most common method for leveraging the connected information inherent in the graph structure is through the use of the Message-Passing Mechanism (MPM). This process is akin to a convolution and operates as follows: for each node, the connected nodes are identified; subsequently, an aggregation function is applied between the focal node and its neighboring nodes, to update the focal node (Cai et al. 2021). Various types of aggregation functions can be employed for this task, with each type being better suited for specific problem domains.

In recent years, the Transformer architecture (Vaswani et al. 2017) has garnered increasing attention from researchers in the field of NLP. This type of technique has achieved state-of-the-art results in various text-related tasks. One of the key factors contributing to its success is the utilization of Self-Attention mechanisms. This type of mechanism aims to establish dynamic connections between tokens during the encoding process of each token. In a sense, it provides the capability for a token to aggregate context information from its neighborhood.

However, this architecture is computationally expensive as it assumes connections between all tokens within a con-

text window, resulting in higher computational complexity for training and inference, requiring more powerful hardware and, consequently, incurring higher costs.

We believe that the use of graphs can address this issue. By assuming sparse graphs with key connections between nodes, we can alleviate the computational complexity associated with the Transformer technique, making our model faster for training, requiring less hardware, and still achieving comparable results in terms of quality. Graph Attention Networks (Veličković et al. 2018) (GATs) implement the Self-Attention mechanism for graphs and have shown excellent performance in node classification tasks.

Some well-known works explore the use of GATs for ABSA, with a focus on the English language (Wang et al. 2020). However, to the best of our knowledge, there are no other studies that evaluate this approach for the Brazilian Portuguese language. Because of this, this work proposes a GAT model to approach the Aspect Sentiment Classification task for ABSA in Brazilian Portuguese.

Background

This section provides essential background information on Sentiment Analysis granularity and Graph Neural Networks. It covers ABSA and explores its subtasks, followed by an overview of GNNs and their role in processing graph-structured data.

Aspect-based Sentiment Analysis

Sentiment Analysis is generally performed using either one of three granularity levels: The most coarse level, (1) Document-level Sentiment Analysis takes into account an entire body of text (usually referred to as a document in NLP) and extracts its overall sentiment polarity; Alternatively, (2) Sentence-level Sentiment Analysis breaks the document into sentences and operates on each sentence separately to extract their sentiment polarities; Finally, (3) Aspect-based Sentiment Analysis identifies the aspects contained in a text before deducing a sentiment polarity for each one of them. The latter mentioned is the finer-grained analysis format. Such fine-level approaches for Sentiment Analysis are frequently useful since most scenarios present documents and sentences expressing distinct opinions.

ABSA is a low-granularity sentiment analysis task that aims to analyze the opinion expressed toward any individual aspect of an entity (da Silva et al. 2022). This aspect-level granularity allows a better understanding of the SA problem since it concentrates on sentiments rather than the text language structure (Nazir et al. 2022).

ABSA can be broken into two main sub-tasks: (1) Aspect Extraction (AE), which determines the aspects of a given entity that must be considered in a text, and (2) Aspect Sentiment Classification (ASC), which classifies the polarity for each of the extracted aspects of the entity (da Silva et al. 2022). Some works also include the Sentiment Evolution (SE) sub-task as part of the ABSA processing phases (Nazir et al. 2022). In this work, we focus on the ASC task since a large amount of the aspects contained in our dataset has already been annotated.

Graph Neural Networks

GNNs are a type of Neural Network designed to process graphs as input. A graph consists of a collection of nodes and edges representing entities and relationships, respectively. The most common graph representations are the dependency matrix and adjacency lists. Creating dependency matrices involves constructing a matrix of size $N \times N$, where N corresponds to the number of nodes. In this representation, the value indexed by row i and column j represents the edge value between the nodes i and j . However, this representation may present an inefficient memory usage whenever graphs are sparse, as many of their connection values are null. Adjacency lists are a common alternative to address this problem. This type of representation is more suitable for sparse data as it only creates a vector of size N (number of nodes) that contains other vectors with nodes related to the index.

GNNs exploit graph associability through the Message-Passing Mechanism algorithm. This mechanism corresponds to a convolution and applies an aggregation function to each node in a graph. This function updates node features based on the information from all its neighboring nodes, capturing complex relationships and dependencies within the graph. Different types of problems benefit from different types of aggregation functions.

The issue with standard aggregation functions, such as the mean, median, and sum, is that they treat all edges equally, assigning the same weight to each one. This approach might not be appropriate as the edges may represent relationships with varying significance levels in many scenarios. Alternatively, the usage of the novel GAT architecture (Veličković et al. 2018) addresses this problem to a degree. This type of architecture employs a multi-head self-attention mechanism to create different weights for types of node connections (Wang et al. 2020), thus generating a specific interpretation per edge.

Attention mechanism has demonstrated good results for NLP tasks. This type of methodology aims to discover underlying connections between tokens in a semantic form, and encodes this information to the hidden representation of the input, increasing the amount of context given to the classifier. In other words, the embedding created of each token in the input carries information about their semantic relationships with other tokens.

Related Works

This section provides an overview of the state of current research in ABSA for Portuguese and explores the application of GNNs in these tasks.

Approaches for ABSA in Portuguese

The Artificial Intelligence Innovation Hub at the Federal University of Pelotas¹ held the Aspect-Based Sentiment Analysis in Portuguese (ABSAPT) competition in 2022, where the participants had to develop systems capable of extracting aspects and classifying their sentiment in texts

¹<http://ia.ufpel.edu.br>

(da Silva et al. 2022). The provided dataset for the competition contains reviews of hotel services written in Portuguese, derived from the corpora developed by Freitas (2015) and Corrêa (2021).

Twelve teams participated in the competition, submitting predictions and technical reports of their strategies for each task. Among the methods considered, some participants used rules and lexicon systems, traditional machine learning techniques, and Transformer-based deep learning models (the latter of which achieved the best-performing solutions in the competition (da Silva et al. 2022)).

Research involving transformer-based methodologies has become increasingly common in several areas and ABSA is no exception. In Lopes et al. (2022) the authors explore the performance of BERT (Devlin et al. 2018) models for Portuguese tasks. They used BERTimbau (Souza, Nogueira, and Lotufo 2020), a version of the base BERT model pre-trained in Portuguese data. The evaluation experiments consist of the ASC task using a Portuguese dataset unseen during the pre-training of the model. The dataset is composed of hotel reviews, all annotated from the TripAdvisor² website. With 194 reviews in Portuguese, the corpora also comprises 17 different aspects in its annotations.

Finally, its authors argue that the use of a post-training dataset (Xu et al. 2019) improves the prediction capabilities of the resulting model, precisely because of the additional training with another corpus in the same domain as the target task data. Their post-training dataset consists of 8,067 TripAdvisor reviews from New York, Las Vegas, and Paris hotels. The approach taken by the authors to train the model involves a sentence-pair classification task, in a question-answering format: Two sentences are used as input to the model, the first sentence is the text review and the second is a question regarding a specific polarity of one aspect. Considering the annotated polarities possibilities are either positive, neutral, or negative, this approach generates three inputs for each annotation. Using the described methodology, the authors achieved an F1-Score and a Balanced Accuracy score of 0.77.

Graph Neural Network-Based ABSA

The application of GNNs is an emerging paradigm for accomplishing the ABSA task (Luo, Zhang, and Zhao 2021). GNNs are capable of modeling linguistic structures like dependency trees, building connections between non-adjacent keywords and improving their interactions. This characteristic is advantageous for ABSA solutions since the aspect word may be distant from the opinion keyword in the text (Huang et al. 2020).

Several works propose novel methods to improve ABSA solutions for the English language using GNNs, focusing especially on the Graph Convolutional Network (GCN) architecture (Tian, Chen, and Song 2021; Zhu et al. 2023; Li et al. 2021). The GAT architecture (Veličković et al. 2018) has earned significant acclaim within the academic community as well, showing promising results for ABSA tasks (Huang et al. 2020; Huo, Jiang, and Sahli 2021).

²<https://www.tripadvisor.com.br/>

Notably, Gomes, Corrêa, and Freitas (2023) employs a GNN-based solution using DualGCN (Li et al. 2021) for the ABSA task in Portuguese. They achieve competitive results compared to Transformer-based strategies in the ABSAPT competition. To our knowledge, published works have yet to apply GAT-based models for ABSA problems in Portuguese.

Methodology

This section outlines the methodology adopted for this study, encompassing data selection, graph transformation, text embedding generation, and GAT construction. We cover relevant challenges and project decision-making aspects of our approach.

Data

We selected the same corpus used in the ABSAPT Competition (da Silva et al. 2022) to assess our methodology. This choice stems from the scarcity of resources for Brazilian Portuguese in NLP, particularly in terms of corpora. This dataset stands out as one of the few well-documented annotated datasets for ABSA in Portuguese. Moreover, we have access to the competition rankings, which serve as a baseline for our work.

The corpus contains reviews written in Brazilian Portuguese by various hotel guests. These reviews were sourced from the TripAdvisor website and consist of a minimum of 300 characters each. They encompass reviews from destinations such as New York, Las Vegas, Paris, and Porto Alegre. Table 1 presents the size of the dataset in terms of annotations, reviews, and aspects. It is also noteworthy that a single review may appear several times in the dataset, as one review often addresses multiple aspects. Therefore, an annotation represents a pairing of a review and its aspect.

Attribute	Amount
Annotations	3797
Reviews	1031
Aspects	77

Figure 2 denotes the class distributions, with almost 70% examples belonging to the positive class. This entails a need for robust evaluation metrics, such as the Balanced Accuracy score.

Graph Transformation

The initial stage of our methodology involves graph transformation. We opt to employ a dependency parser to establish the syntactic connections among words, necessitating the tokenization of our data.

For tokenization and dependency parsing, we utilize the spaCy library³, specifically leveraging the `pt_core_news_lg`

³<https://spacy.io/>

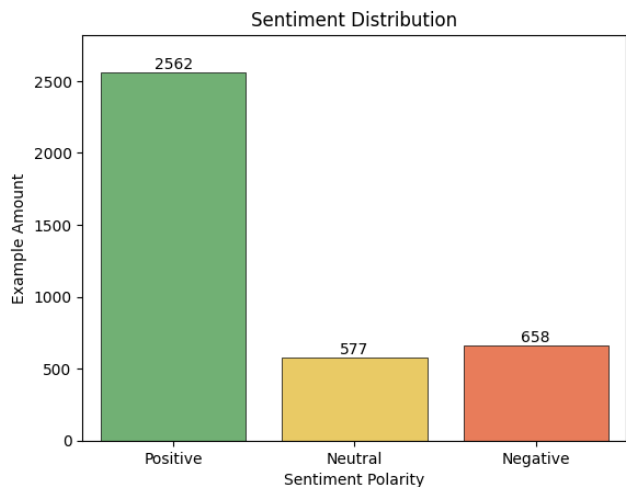


Figure 2: Polarity Sentiment label distribution.

model. This model is widely utilized for Portuguese dependency parsing, primarily due to its accessibility and ease of installation as a public resource.

In Figure 3, we show an example of a dependency tree generated by this tool, and how it resembles a graph. After the tokenization and parsing of the connections between the words, we save these two lists and move to the next step.

Embeddings

To generate embeddings for the review texts, we employ the BERTimbau Large model (Souza, Nogueira, and Lotufo 2020), a variant of BERT fine-tuned for the Portuguese language. The encoding of our text information utilizes the hidden state vectors from the four last layers concatenated, following the methodology outlined in the original BERT paper (Devlin et al. 2018).

Differences in tokenization present a challenge when exploring alternative models for text encoding. spaCy operates at the word level, whereas BERTimbau operates at the subword level. This leads to divergent tokenization patterns, particularly for certain characters.

To overcome this disparity, we adopt a methodology akin to that employed by DualGCN (Li et al. 2021). This involves extending the syntactic relationships of the root word to its subword components. Consequently, our graph operates at the subword level, with subword nodes mirroring the values and edges of the original word.

Additionally, we introduce spaces between punctuation marks to align with the tokenization approach of BERTimbau. This adjustment is necessary as spaCy tokenization merges punctuation marks with adjacent words lacking intervening spaces. Thus, we insert spaces before and after each punctuation mark to ensure compatibility with the tokenization scheme seen in BERTimbau.

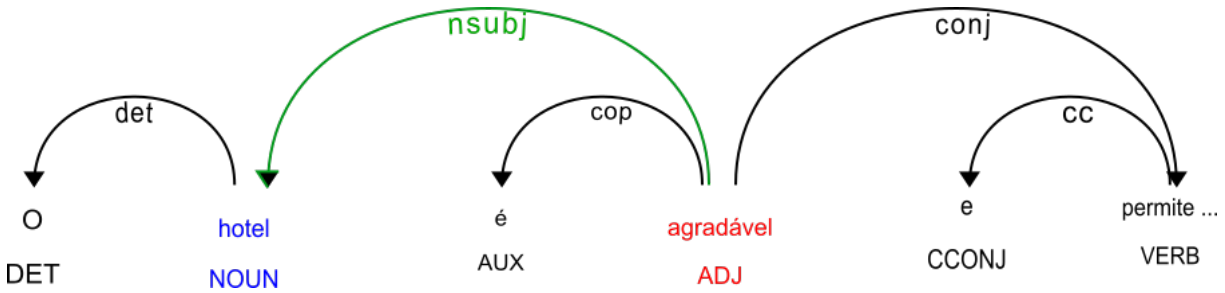


Figure 3: Dependency Tree example generated by spaCy. Source: (Corrêa 2021)

Graph Attention Network

To construct the GAT within our methodology, we utilize the PyTorch Geometric framework⁴. This framework facilitates the integration of PyTorch with graph structures by offering pre-implemented layers, various function aggregators, and auxiliary functions.

Our architecture comprises two Graph Attention Layers, each producing output vectors with the same dimensions as the input features, set at 4,096. We opt for retaining the original feature vector size from the BERTimbau embeddings and exclusively apply Multi-Head Self-Attention to the graph.

Subsequently, we implement a straightforward linear layer to classify aspect nodes into one of three polarities: positive, neutral, or negative. The input vector size of this linear layer is six times 4,096. This choice stems from our analysis, which revealed that after BERTimbau tokenization, the largest aspect consists of six tokens. Accordingly, we design a linear layer to accommodate this maximum input size, applying padding for smaller aspects.

Evaluation Metrics

We utilize a set of descriptive metrics to assess the performance of models, such as F1-Score, Precision, Recall, and Balanced Accuracy. We select these metrics because they are frequently used in ABSA studies and facilitate comparison with existing research. Employing multiple complementary metrics is standard practice, as it helps us assess the effectiveness of our models across different aspects of classification tasks.

The F1-Score offers a balanced measure by considering both precision and recall (seen in Equation 1). It provides insight into the overall performance of the model in correctly classifying positive and negative instances. A high F1-Score indicates robust performance across both precision and recall, signifying a well-balanced model. We present the Macro F1-Score, which calculates the average F1-Score across classes. TP, FP, FN, and FN stand for True Positives, False Positives, False Negatives, and False Negatives, respectively.

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \quad (1)$$

Precision measures the proportion of true positive predictions relative to all positive predictions (seen in Equation 2). A high precision score indicates a low false positive rate (i.e. depicts how well the model identifies positive instances). Recall calculates the ratio of true positive predictions to all actual positive instances (seen in Equation 3), indicating the sensitivity of the model to identifying positive class samples (i.e. high recall scores suggest that the model effectively captures most positive instances).

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

Balanced Accuracy (seen in Equation 4) addresses the issue of class imbalance within the dataset by computing the average accuracy across all classes. This metric ensures that each class contributes equally to the final evaluation, providing a fair assessment of the overall performance of models. It is particularly useful in scenarios where the dataset contains imbalanced class distributions, ensuring that the evaluation remains unbiased across all classes.

$$Bacc = \frac{Sensitivity + Specificity}{2} \quad (4)$$

Sensitivity (or Recall) is also referred to as the True Positive Rate, whereas Specificity is the True Negative Rate.

Results

The ABSAPT competition (da Silva et al. 2022), organized by the Artificial Intelligence Innovation Hub at the Federal University of Pelotas in 2022, was a competition for the ABSA tasks. Divided into two subtasks (Aspect Extraction and Aspect Sentiment Classification) with publicly available datasets for training and testing. We use their dataset in this work because, to our knowledge, it is the biggest corpus for ABSA tasks available in Portuguese.

We compare the results of our approach with the four highest-ranked works in the Aspect Sentiment Classification

⁴<https://pyg.org>

task in ABSAPT. The table 2 summarizes the results of our approach against other methodologies.

Table 2: Results in the Test Data.

Approaches	BAcc	Precision	Recall	F1-Score
Gomes et al. (2022)	0.82	0.81	0.82	0.81
Neto et al. (2022)	0.78	0.76	0.78	0.77
<i>GAT-PT (ours)</i>	0.74	0.70	0.74	0.72
Assi et al. (2022)	0.62	0.65	0.62	0.61
Heinrich and Marchi (2022)	0.62	0.65	0.62	0.61

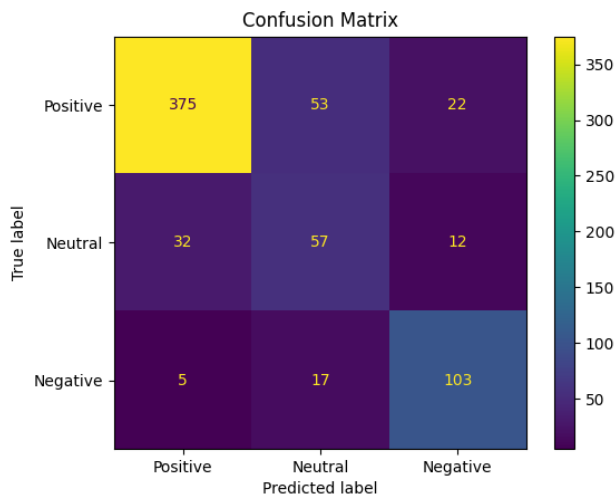


Figure 4: Confusion Matrix. Source: The authors.

The best results in each metric are depicted in bold font. Our model outperforms the third (Assi et al. 2022) and fourth-place (Heinrich and Marchi 2022) models, which employ techniques based on the BERTimbau model.

Furthermore, the authors Heinrich and Marchi (2022) noted that their approach could have achieved superior results if it were not for the significant time required for training the model, as indicated by their testing.

All models utilize Transformers for model creation, including our methodology. However, unlike others, ours is not fine-tuned during training; it is solely used for embedding creation. This entails a quicker training process for the GAT model, and reduced hardware requirements.

Figure 4 presents the Confusion Matrix for our approach in the test dataset. We can observe that the neutral class achieved fewer correct predictions than the others, possibly due to its status as the smallest class. It is also important to note that neutral aspects may have a somewhat subjective interpretation since they lack a clear associated sentiment.

Regarding the model that secured the first place in the competition, although its predictive capability is notably

higher than our proposed model, it is composed of an ensemble of PTT5 (Carmo et al. 2020) models, which are T5 (Raffel et al. 2020) large models pre-trained in Portuguese. This approach is considerably more computationally expensive than ours, requiring a larger budget for its utilization.

The second-place competitors (Neto et al. 2022) face a similar issue: the authors fine-tune the BERTimbau model for the sentence classification task, using the aspect as an auxiliary sentence. This approach yields slightly better results than our work albeit at the cost of higher computational requirements.

Conclusion

In this study, we developed a straightforward Graph Attention Network model for the Aspect-Based Sentiment Analysis task in Brazilian Portuguese. The proposed approach offers competitive results, ranking third place in the ABSAPT competition. Furthermore, by leveraging sparse graph connections our model is less computationally demanding than a transformer architecture in terms of training and inference.

There are various methodological alternatives future studies could explore. Investigating alternative architecture parametrization beyond the basic two-layer Graph Attention model (which may be insufficient for the complexity of the ABSA task) could provide more insight into how the performance of GATs relates to transformer implementations. Notably, this includes a more thorough analysis regarding their performance score and computational cost trade-offs.

Testing different dependency parsers, beyond the included in spaCy, is also relevant, particularly because limited information is available regarding its suitability for use in GNNs. Different tree parsing approaches will significantly affect the graph connections and ultimately potentially impact downstream task performance. Moreover, dedicating attention to the evaluation of embedding models, particularly those surpassing BERTimbau, holds promise for further enhancing Brazilian Portuguese approaches to sentiment analysis.

By demonstrating competitive performance and reduced computational demands compared to Transformer architectures, we hope to inspire further research and exploration of GATs for Sentiment Analysis. Continued exploration in this domain offers a compelling avenue to advance state-of-the-art research in natural language understanding.

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