ABSTRACT

Recent advances in Artificial intelligence (AI) have leveraged promising results in solving complex problems in the area of Natural Language Processing (NLP), being an important tool to help in the expeditious resolution of judicial proceedings in the legal area. In this context, this work targets the problem of detecting the degree of similarity between judicial documents that can be achieved in the inference group, by applying six NLP techniques based on transformers, namely BERT, GPT-2 and RoBERTa pre-trained in the Brazilian Portuguese language and the same specialized using 210,000 legal proceedings. Documents were pre-processed and had their content transformed into a vector representation using these NLP techniques. Unsupervised learning was used to cluster the lawsuits, calculating the quality of the model based on the cosine of the distance between the elements of the group to its centroid. We noticed that models based on transformers present better performance when compared to previous research, highlighting the RoBERTa model specialized in the Brazilian Portuguese language, making it possible to advance in the current state of the art in the area of NLP applied to the legal sector.

Keywords legal · natural language processing · clustering · transformers

1 Introduction

The recent history of the Brazilian Justice shows relevant transformations regarding having all its procedural documents in digital format. In 2012, the Brazilian Labor Court implemented the Electronic Judicial Process (acronym in Portuguese for “Processo Judicial Eletrônico” - PJe), and since then, all new lawsuits have become completely digital, reaching 99.9% of cases in progress on this platform in 2020 [1].

Knowing the limitation of human beings analysing, in an acceptable time, a large amount of data, especially when such data appear not to be correlated, it is possible to help them in the patterns’ recognition context through data analysis, computational ans statistical methods. Assuming that textual data has been exponentially increasing, patterns’ examination in court documents is becoming pronouncedly challenging.

To optimize the procedural progress the Brazilian legal system provides for ways, such as the procedural economy, the principle of speed, due process in order, and the principle of the reasonable duration of a case to ensure the swift handling of judicial proceedings [2]. Hence, one of the major challenges of the Brazilian Justice is swiftly meeting the growing judicial demand. Thus, using a process grouping mechanism, it was possible to assist with the allocation
of work among the advisors of the office for which the process was drawn with a good rate of similarity between the documents analysed. Furthermore, it contributed to the search for case-law for the judgment of the cases in point, guarding the principle of legal certainty. According to Gomes Canotilho [3], the general principle of legal certainty aims to ensure the individual the right to trust that the legal rulings made of their issues are based upon current and valid legal norms.

Hence, this legal management tool allowed reducing the length of the judicial process, generating positive impacts such as the decrease of the operational costs of a lawsuit based on the lower allocation of the resources necessary for its judgment.

Recent studies have shown that machine learning algorithms are critical tools capable of solving high-complexity problems using Natural Language Processing (NLP) [4]. To this end, it is possible to highlight the works of [5] [6] [7] [8] [9] [10] [11], which, taking into account the context of words, apply techniques of word-embeddings generation, a form of vector representation of names, and consequently of documents. The use of word-embeddings is essential to analyze a large set of unstructured data as presented in court.

At present, a specialist triages the documents and distributes the lawsuits to be judged among the team members, configuring a deviation from the main activity of the specialist, which is the production of the draft decisions. This occurrence reinforced a further increase in the congestion rate (an indicator that measures the percentage of cases that remain pending solution by the end of the base-year) and to the decrease in the supply of demand index (acronym in Portuguese for “Índice de Atendimento à Demanda” - IAD - an indicator that measures the percentage of downtime of processes compared to the number of new cases) [1].

This work aims, therefore, to use as a baseline the results discussed by the research “Clustering by Similarity of Brazilian Legal Documents Using Natural Language Processing Approaches” [12] comparing them with the degree of similarity between the judicial documents achieved in the inferred groups through unsupervised learning, through the application of six techniques of Natural Language Processing, which are: (i) BERT (Bidirectional Encoder Representations from Transformers) trained for general purposes for Portuguese (BERT pt-BR); (ii) BERT specialized with the corpus of the Brazilian labor judiciary (BERT Jud); (iii) GPT-2 (Generative Pre-trained Transformer 2) trained for general purposes for Portuguese (GPT-2 pt-BR); (iv) GPT-2 specialized with the corpus of the Brazilian labor judiciary (GPT-2 Jud); (v) RoBERTa (Robustly optimized BERT approach) trained for general purposes for Portuguese (RoBERTa pt-BR); and (vi) RoBERTa specialized with the corpus of the Brazilian labor judiciary (RoBERTa Jud).

As proposed in [12], the degree of similarity indicates the performance of the model and was a result of the average similarity rate of the documents groups, which was based on the cosine similarity between the elements of the group to its centroid and, comparatively, by the average cosine similarity among all the documents of the group.

To delimit the scope of this research and make a coherent comparison same data as in [12] was applied. Thus, the data set extracted contained information from the Ordinary Appeal Brought (acronym in Portuguese for “Recurso Ordinário Interposto” - ROI) of approximately 210,000 legal proceedings [3]. The Ordinary Appeal Brought was used as a reference, as it is regularly the type of document responsible for sending the case to trial in a higher court (2nd degree), hence creating the Ordinary Appeal (acronym in Portuguese for “Recurso Ordinário” - RO). It serves as a free plea, an appropriate appeal against final and terminative judgments proclaimed at first instance, which seeks a review of the court decision drawn up by a hierarchically superior body [13].

For the present work, a literature review on unsupervised machine learning algorithms applied to the legal area was performed, using NLP, and an overview of recent techniques that use Artificial Intelligence (AI) algorithms in word embeddings generation. Then, applying some methods until obtaining results, comparing them, and finally, proposing future challenges.

2 State-of-the-Art Review

More recent research maintain that machine learning algorithms have great potential for high complexity problem-solving. These machine learning algorithms categories can be: (i) supervised; (ii) unsupervised; (iii) semi-supervised; and (iv) via reinforcement [14]. This research context reviewed the literature in search of the most recent productions for the period from 2017 to 2021, through the databases (i) Google Scholar; (ii) Science Direct; and (iii) IEEE Xplorer, on unsupervised machine learning algorithms or clustering applied to the legal area using NLP.

The research revealed that, so far, few productions are dealing with the subject, which proves its complexity. We highlight the research conducted by Oliveira and Nascimento [12] that sought to detect the degree of similarity between

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1 A legal term meaning a set of previous judicial decisions following the same line of understanding.

2 https://www.doi.org/10.5281/zenodo.6399973
the judicial documents of the Brazilian Labor Court through unsupervised learning, using NLP techniques such as (i) inverse frequency of the term document frequency (TF-IDF); (ii) Word2Vec with CBoW (Continuous Bag of Words) trained for general purposes for the Portuguese language in Brazil; and (iii) Word2Vec with Skip-gram trained for general purposes for the Portuguese language in Brazil.

Expanding the research for the use of Natural Language Processing applied to the judicial area, a systematic review of the literature of the challenges faced by the system of trial prediction was found, which can assist lawyers, judges and civil servants to predict the rate of profit or loss, time of punishment and articles of law applicable to new cases, using the deep learning model. The researchers describe in detail the Empirical Literature on Methods of Prediction of Legal Judgment, the Conceptual Literature on Text Classification Methods and details of the transformers model [15].

Therefore, we then sought to expand the research by removing the restriction for the legal area, which revealed some publications. [16] Discusses using a content recommendation system based on grouping, with k-means, in similar articles through the vector transformation of the content of documents with the TF-IDF [17]. In [18], the authors performed an automatic summarization of texts using TF-IDF and k-means to determine the sentence groups of the documents used in creating the summary. It concludes that these studies used TF-IDF as the primary technique to vectorize textual content and that k-means is the most commonly used algorithm for unsupervised machine learning.

We assume that choosing the best technique of generating word embeddings requires research, experimentation and comparison of models. Many recent studies prove the feasibility of using word embeddings to improve the quality of the results of AI algorithms for pattern detection and classification, among others.

Mikolov et al. proposed in 2013 Word2Vec Skip-gram and CBoW, two new architectures to calculate vector representations of words considered, at the time, reference in the subject [6]. Then, Embeddings from Language Models (Elmo) [19], Flair [20] and context2vec [21], libraries based on the Long Short Term Memory Network (LSTM) [22] created distinct word embeddings for each occurrence of the word, context-aware, which allowed the capture of the meaning of the word. The LSTM models were used widely for speech recognition, language modelling, sentiment analysis and text prediction, and, unlike Recurrent Neural Network (RNN), have the ability to forget, remember and update information, thus taking a step ahead of the RNNs [23].

As of 2018, new techniques for generating word embeddings emerged, with emphasis on (i) Bidirectional Encoder Representations from Transformers (BERT) [9], a context-sensitive model with architecture based on a Transformers model [24]; (ii) Sentence BERT (SBERT) [25], a “Siamese” BERT model proposed to improve BERT’s performance when seeking to obtain the similarity of sentences; (iii) Text-to-Text Transfer Transformer (T5) [26], a framework for treating NLP issues as a text-to-text problem, i.e. template input as text and template output as text; (iv) Generative Pre-Training Transformer 2 (GPT-2), a Transformers-based model with 1.5 billion parameters [10]; and (v) Robustly optimized BERT approach (RoBERTa), a model based on the BERT model, which was trained longer and used a higher amount of data [11].

With this analysis, it was possible to advance in the current state of the art of NLP applied to the legal sector. By conducting a comparative study and implementation of Transformers techniques (BERT, GPT-2 and RoBERTa), using models for generic purpose in Brazilian Portuguese (pt-BR) and specialized models in the labor judiciary, to carry out the grouping of labor legal processes in Brazil using the k-means algorithm and cosine similarity.

## 3 Methodology

In this section, the protocol necessary to reproduce the results achieved and to analyze them comparatively is presented. For the implementation of the routines used in this study, we used the Python programming language (version 3.6.9) and the same libraries used in the study by Oliveira and Nascimento [12].

The processing flow (pipeline) was composed of the phases: (i) data extraction; (ii) data cleaning; (iii) generation of word embeddings templates; (iv) calculation of the vector representation of the document; (v) unsupervised learning; and (vi) calculation of the similarity measure, of which phases (i), (ii), (v) and (vi) followed the same steps described by Oliveira and Nascimento [12] and the other phases are detailed in sections to be follow.

### 3.1 Generation of word embeddings templates

The usage of vector representation of words, whose numerical values indicate some relationship between words in the text, is an essential technique in the machine learning problem-solving process when the data used by the model is textual.
Thus, in this research, word embeddings generated and shared for the Portuguese language were used, such as (i) BERT (large) model generated based on brWaC corpus [27], composed of 2 billion and 700 thousand tokens, and published in the article BERTImbau: Pretrained BERT Models for Brazilian Portuguese [28]; (ii) GPT-2 (Small) model generated based on texts extracted from Wikipedia in Portuguese, and published in article GPorTuguese-2 (Portuguese GPT-2 small): a Language Model for Portuguese text generation (and more NLP tasks...) [29]; and (iii) RoBERTa (Base) model generated based on texts extracted from Wikipedia in Portuguese, entitled roberta-PT-BR and published in Hugging Face [30].

In addition to these pre-trained models in the Portuguese language, the most recent literature suggests that using embeddings adherent to the context of the problem proposed to be solved may bring a better result. Thus, using the 210,000 documents extracted, two embedding generation techniques were applied, namely, (i) specialization of the BERTImbau model; (ii) specialization of the GPorTuguese-2 model; and (iii) specialization of the roberta-pt-br model, which will be detailed below.

### 3.1.1 Specialization of Transformers models

Recent studies show the benefits of applying for learning transfer on generalist models, which, in recent years, has significantly improved the results, reaching the state-of-the-art in NLP [31]. For the specialization of Transformers models, in addition to cleaning the data, it is also necessary to adjust the data to make the most of its benefits. Of the adjustments made, two deserve highlights: (i) definition of the sentence slot; and (ii) definition of the strategy of “disguising” or masking (MASK) of the sentences’ tokens, which are detailed below.

Defining the sentence slot is a fundamental step to enable the usage of specialized data in the learning transfer from a pre-trained model. Therefore, inspired by the strategy proposed in the article Transformers: State-of-the-Art Natural Language Processing [32] that, for each batch of 1,000 documents, as presented in Figure 1, all content is concatenated and sentences of 128 tokens created, if the last “sentence” of this lot is less than 128 tokens this “sentence” is disregarded, other detailed approaches have been tested later.

| token 1 | ... | token 128 | token 129 | ... | token 256 | ... | token 1025 | ... | token 1100 |
|---------|-----|-----------|-----------|-----|-----------|-----|------------|-----|------------|
| 1       | ... | 128       | 129       | ... | 256       | ... | 1025       | ... | 1100       |

Figure 1: Slot N - generation of “sentences” with 128 tokens

In order to reduce the loss of context of words at the edges of the sentence, the proposed approach, entitled Slot N/K, generated “sentences” with N tokens from the concatenation of 1,000 documents, as detailed below and illustrated in Figure 2.

- Initial Slot: “sentence” formed by the first N tokens;
- Intermediate slots: “sentence” formed by N tokens counted from the N-K token of the previous “sentence”, where K is the number of return tokens;
- Final Slot: “sentence” formed by the last N tokens.

From the above-detailed approach, simulations performed with the settings (i) Slot 128/16; (ii) Slot 128/32; (iii) Slot 128/64; (iv) Slot 256/64; (v) Slot 512/64; and (vi) Slot 64/16, comparing them with each other and with the approach proposed by [32]. The Slot 128/32 approach was selected for achieving the best performance in the specialization of the Transformers model in Portuguese with the corpus of the judiciary (Figure 3).
For learning transfer, depending on the Transformers model used, a token masking strategy for each sentence is applied, using Masked Language Models (MLM) for BERT and Causal Language Models (CLM) models for GPT-2 models. While the CLM is trained unidirectionally in order to predict the next word based on the preceding words [33], the MLM has a two-way approach to predict the masked words of the sentence.

Hence, for the transfer of learning of BERT models, inspired by the article Transformers: State-of-the-Art Natural Language Processing [32] that used the masking rate of 15%, simulations were performed using the masking rate of 15% and the masking rate of 25%, reaching, with the rate of 15%, the best result in the specialization of the BERT model in Portuguese with the corpus of the judiciary.

3.2 Calculation of the vector representation of the document

Vector representation techniques of words (word embeddings) such as (i) BERT; (ii) GPT-2; and (iii) RoBERTa need to undergo a transformation in order to, from the word embeddings, calculate the vector representation of the document (document embeddings).

It is initially necessary to detail how to obtain word embeddings for Transformers techniques. One of the advantages of Transformers techniques over previous word embeddings techniques, such as Word2Vec, is the ability to capture the vector representation of the word according to the global context, meaning that the same word can have more than one vector representation. It becomes more evident when highlighting the word “bank” (banco in Pt-BR) in the following two sentences (i) I go to the bank (banco in Pt-BR) to withdraw money; and (ii) I will sit on the bench (banco in Pt-BR) of the square; where, with Word2Vec, the vector representation of the word “bank” is unique regardless of the phrase and with BERT, GPT-2 and RoBERTa word embeddings are different.

Therefore, for Transformers templates, it is necessary to “divide” the entire document into “slots” of sentences. Considering that, unlike the GPT-2 model, the BERT and RoBERTa models have a limitation of up to 512 tokens per sentence and require that the first and last tokens be special, respectively [CLS] and [SEP], the slot size has been set at 510 tokens per sentence.

Thus, we developed strategies to obtain all the word embeddings of the document, whose words of the generated sentences kept the context according to the complete file. These approaches consist, similar to that presented in Figure 2, in bringing about sentences with 510 tokens as detailed below:

- Initial Sentence: “sentence” formed by the first 510 tokens;
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- Intermediate sentences: “sentence” consisting of 510 tokens counted from token N - K of the previous “sentence”, where K was set empirically to value 64;
- Final Sentence: “sentence” formed by the last 510 tokens;

Therefore, the sentences generated from each document have coincident tokens chosen to ensure greater adherence to the token context in the file. To this end, we tested two different approaches: (i) averages of word embeddings of coincident tokens; and (ii) use of the first 32 coincident tokens of the previous sentence and the last 32 coincident tokens of the current sentence, which showed better results in the simulations performed.

Hence, as shown in Figure 4, the return tokens that are coincident between the current and previous sentences are used as follows: (i) the first 32 coincident tokens of the previous sentence (for example, tokens 446 to 477 from Slot 1 exemplified in Figure 4), and (ii) the last 32 coincident tokens of the sentence in question (for example, Tokens 478 to 510 from Slot 2 exemplified in Figure 4). It is worth noting that the last sentence slot must contain 510 tokens, as well as the others, and coincident tokens tapped as follows: (i) the first half of the coincident tokens of the previous sentence (for example, tokens 590 to 773 from Slot 2 exemplified in Figure 4), and (ii) the second half of the coincident tokens of the sentence in question (for example, tokens 774 to 956 from Slot 3 exemplified in Figure 4).

![Figure 4: Word embeddings generation strategy](image)

After obtaining the word embeddings, the same technique used in the research by Oliveira and Nascimento was chosen to generate the document embeddings, that is, the average of the word embeddings of the words in the document, weighting them with the TF-IDF.

Consequently, to enable an overview, Table 1 summarizes the parameters used for training the six models used in this research.

| Model     | BERT imbau | BERT Jud. | GPortuguese-2 | GPT-2 Jud. | roberta-pt-br | RoBERTa Jud. |
|-----------|------------|-----------|---------------|------------|----------------|-------------|
| Data for training | brWac corpus | 210,000 ROIs | Wikipedia in Portuguese | 210,000 ROIs | Wikipedia in Portuguese | 210,000 ROIs |
| Tokenization type | word-piece | byte-level BPE | 12-layer, 768-hidden, 12-heads, 117M parameters | byte-level BPE | 12-layer, 768-hidden, 12-heads, 125M parameters |
| Model details | 24-layer, 1024-hidden, 16-heads, 340M parameters | 12-layer, 768-hidden, 12-heads, 117M parameters | 12-layer, 768-hidden, 12-heads, 125M parameters |
| Token mask type | Masked | Masked | Causal |

Moreover, in order to allow the graphic representation in two dimensions of the vector representation of the documents, the technique of reduction of T-Distributed Stochastic Neighbor Embedding (t-SNE), which minimizes the divergence...
Brazilian court documents clustered together using transformer-based models between two distributions, measuring the similarities between pairs of input objects and the similarities between pairs of the low dimension points corresponding in the incorporation [34].

4 Results and Discussions

Applying the methodology as previously detailed, this research shows how natural language processing techniques in conjunction with machine learning algorithms are paramount in optimizing the operational costs of the judicial process, such as the aid of document screening and procedural distribution. It grants working time optimization since it allows the experts time to be devoted to their core activity.

In order to use the unsupervised learning algorithm, k-means, it was necessary to select the best K to achieve the best result for each NLP technique studied. This way, the elbow method was applied based on the calculated inertia of each of the 31 K tested, as shown in Figure 5.

Figure 5: Inertia charts constructed by using the elbow method for determining the best number of clusters for each approach
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From obtaining the best K, the k-means template was trained and, with the grouping performed by the model, we calculated (i) the average similarity between the documents of each group, thus allowing an overview of the distribution of documents in the groups generated by each NLP technique; and (ii) the mean similarity between the group’s documents and their centroid, making possible to indicate which technique achieved the best performance.

To demonstrate the progress brought by this research, Table 2 presents the results extracted from the study [12], which established a baseline for research on the use of NLP techniques applied to the legal environment for the same purpose. We highlight the Word2Vec Skip-gram pt-BR technique, which presented itself, in that research, as the best option for generating word embeddings aiming to group judicial documents of the Ordinary Appeal Brought type.

Table 2: Statistical data extracted from the work “Clustering by Similarity of Brazilian Legal Documents Using Natural Language Processing Approaches” [12]

| Type                | Groups | Mean | Std. | Min. | 25%  | 50%  | 75%  | Max. |
|---------------------|--------|------|------|------|------|------|------|------|
| TF-IDF              | 49     | 0.624| 0.172| 0.247| 0.502| 0.586| 0.164| 0.964|
| Word2Vec CBoW ptBR  | 59     | 0.947| 0.063| 0.764| 0.935| 0.979| 0.991| 0.999|
| Word2Vec Skip-gram ptBR | 34   | 0.948| 0.061| 0.796| 0.925| 0.976| 0.992| 0.999|

Consequently, the statistical data of the average similarity between the documents of each group and the average similarity of the group documents for their centroid presented respectively in Table 3 and Table 4, highlighted in bold for the best result value of each metric and projected in the comparative distribution chart (Figure 6 and Figure 7), show that the generalist word embeddings in Portuguese (pt-BR) achieved superior results when compared to the specialized legal corpus word embeddings. The proximity of the results among the generalist models is also noteworthy. However, for the expert model, this proximity was observed only between the BERT Jud models and GPT-2 Jud.

Table 3: Statistics of the cosine similarity between all elements of the group. The best results are highlighted in bold

| Transformer Model | Groups | Mean  | Std. | Min. | 25%  | 50%  | 75%  | Max. |
|-------------------|--------|-------|------|------|------|------|------|------|
| BERT ptBR         | 35     | 0.976 | 0.012| 0.937| 0.967| 0.979| 0.985| 0.991|
| BERT Jud          | 36     | 0.943 | 0.031| 0.853| 0.938| 0.952| 0.960| 0.981|
| GPT-2 ptBR        | 33     | 0.972 | 0.020| 0.906| 0.965| 0.979| 0.985| 0.996|
| GPT-2 Jud         | 36     | 0.952 | 0.034| 0.847| 0.947| 0.964| 0.971| 0.994|
| RoBERTa ptBR      | 34     | 0.976 | 0.023| 0.874| 0.971| 0.985| 0.988| 0.993|
| RoBERTa Jud       | 39     | 0.918 | 0.035| 0.835| 0.927| 0.922| 0.941| 0.980|

Figure 6: Comparison chart of the distribution of the average similarity between the group documents. The more cohesive the boxes and the fewer outliers, the better
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Table 4: Statistics of the cosine similarity of the group elements to the centroids. The best results are highlighted in bold

| Transformer Model | Groups | Mean | Std. | Min. | 25% | 50% | 75% | Max. |
|-------------------|--------|------|------|------|-----|-----|-----|------|
| BERT ptBR         | 35     | 0.987| 0.007| 0.967| 0.983| 0.970| 0.992| 0.995|
| BERT Jud          | 36     | 0.971| 0.016| 0.923| 0.969| 0.976| 0.980| 0.990|
| GPT-2 ptBR        | 33     | 0.985| 0.011| 0.947| 0.985| 0.990| 0.992| 0.998|
| GPT-2 Jud         | 36     | 0.974| 0.021| 0.900| 0.973| 0.980| 0.985| 0.997|
| RoBERTa ptBR      | 34     | 0.987| 0.017| 0.905| 0.985| 0.992| 0.994| 0.997|
| RoBERTa Jud       | 39     | 0.958| 0.019| 0.914| 0.952| 0.960| 0.970| 0.990|

Figure 7: Comparison chart of the distribution of the average similarity of the group documents to their centroid. The more cohesive the boxes and the fewer outliers, the better

When comparing the values presented in Table 3 and Table 4, it is noteworthy that the results in Table 3 are slightly lower in all cases. From this, it is inferable that the measurement of similarity as in Table 3 might reduce the similarity rate since there may be elements positioned altogether opposite in the group. From Figure 6 and Figure 7, it is also possible to verify that the groupings generated by all techniques are very cohesive, especially in the generalist techniques cases, which created fewer groupings in the range of outliers than the expert techniques.

Since most of the techniques achieved results close to each other, we considered it important to present the time spent for the processing of each Transformer technique, with the use of a computer with 40 physical nuclei and 196 GB of memory, in the generation of numerical representation of approximately 210,000 judicial documents of the Ordinary Appeal Brought type. As presented in Table 5, GPT-2 reached an average vectorization of documents per minute much higher than BERT. However, as expected, RoBERTa further outperformed BERT and GPT-2, as performance can be improved when trained for more extended periods, with larger batches, over more data, without using the prediction of the next sentence strategy, in addition to training longer sequences with dynamically changed standard masking.

Table 5: Average processed documents per minute for each model highlighted in bold for the best result value

| Transformer Model | Average number of documents processed per minute |
|-------------------|--------------------------------------------------|
| BERT ptBR         | 6.45                                             |
| BERT Jud          | 9.62                                             |
| GPT-2 ptBR        | 29.40                                            |
| GPT-2 Jud         | 29.03                                            |
| RoBERTa ptBR      | **55.31**                                        |
| RoBERTa Jud       | 53.73                                            |
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Given the above, among all the techniques evaluated, the RoBERTa pt-BR technique was the best option for generating word embeddings for judicial documents clustering of the Ordinary Appeal Brought type. Although the BERT pt-BR technique achieved a slightly better result (a difference minor than 0.01), it was computationally inefficient in document processing gpt-2 pt-BR and RoBERTa pt-BR techniques.

It is important to stress that the results of this research (Table 4) showed relevant advances in contrast to the results presented in the previous research (Table 2), in which the best average cosine similarity of the elements of the group to the centroid was, respectively, 0.98 and 0.94.

A fact to be analysed in the results presented is that specialized word embeddings techniques showed slightly worse results. Its occurrence is due to the general techniques in Portuguese being trained with a much larger corpus than the one used to refine the generalist model. This fact is also reported by Ruder et al. [31], featuring a behaviour similar to that found in the present study, in which the corpus of the base model is much larger than the specialized corpus used.

The result achieved by each approach can be visualized in a two-dimensional projection of the groups formed in the six techniques (i) BERT pt-BR; (ii) BERT Jud.; (iii) GPT-2 pt-BR; (iv) GPT-2 Jud.; (v) RoBERTa pt-BR; and (vi) RoBERTa Jud., respectively, shown in Figure 8, Figure 9, Figure 10, Figure 11, Figure 12 and Figure 13. After a qualitative analysis, it is evident in the images that the groups formed from the RoBERTa pt-BR are much better defined, which corroborates the findings previously explained in this study.

![2D Projection of Groups - BERT ptBR](image)

Figure 8: Groups of documents formed by the BERT pt-BR technique projected in two dimensions using the test dataset.
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Figure 9: Groups of documents formed by the BERT Jud technique projected in two dimensions using the test dataset.

Figure 10: Groups of documents formed by the GPT-2 pt-BR technique projected in two dimensions using the test dataset.
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Figure 11: Groups of documents formed by the GPT-2 Jud technique projected in two dimensions using the test dataset.

Figure 12: Groups of documents formed by the RoBERTa pt-BR technique projected in two dimensions using the test dataset.
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Figure 13: Groups of documents formed by the RoBERTa Jud technique projected in two dimensions using the test dataset.

5 Conclusions and Future Works

Applying Artificial Intelligence techniques as a tool for pattern detection in legal documents has been proven, in general, as a viable and effective solution in the scientific and technological environment and very satisfactory in the practice of legal work. In this research, the results presented are considered amply promising for improving the Average Similarity Rate compared to previous research conducted by Oliveira and Nascimento [12].

Of all the techniques evaluated, the RoBERTa pt-BR technique stands out as the best option for word embeddings for clustering legal documents of the Ordinary Appeal Brought type. The BERT pt-BR technique is also in evidence since it presented slightly better quantitative rates than RoBERTa pt-BR, even though it did not reach an execution time as satisfactory as RoBERTa pt-BR. On the other hand, the specialized models with the corpus of the judiciary, in general, did not achieve better results than the generalist models. Despite this, we believe that the specialization of BERT, GPT-2 and RoBERTa with a more robust legal corpus can achieve even better results.

Therefore, for future work, there’s the suggestion of deepening the specialization of BERT, GPT-2 and RoBERTa for the judiciary and evaluating whether the new embeddings generated will improve the overall performance of clustering. In addition, new possibilities arise, such as validating the word embeddings generated for other types of legal documents and using them in other applications, such as the generation of decision drafts and classification of documents and processes. It is also worth delving into techniques for texts transformation into their vector representations faster in their word embeddings.

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