PTT5: Pretraining and validating the T5 model on Brazilian Portuguese data

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Source code: https://github.com/unicamp-dl/PTT5
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Abstract

In natural language processing (NLP), there is a need for more resources in Portuguese, since much of the data used in the state-of-the-art research is in other languages. In this paper, we pretrain a T5 model on the BrWac corpus, an extensive collection of web pages in Portuguese, and evaluate its performance against other Portuguese pretrained models and multilingual models on the sentence similarity and sentence entailment tasks. We show that our Portuguese pretrained models have significantly better performance over the original T5 models. Moreover, we showcase the positive impact of using a Portuguese vocabulary. Our code and models are available at https://github.com/unicamp-dl/PTT5.

1 Introduction

Pretrained language models have been employed successfully in various NLP tasks [4, 15, 10]. Recent works demonstrate that monolingual pretrained models perform better on tasks in that same language than models pretrained on multilingual corpora [20, 22, 11, 3, 23, 2, 14, 1, 8, 12].

For Portuguese tasks, BERT models have already shown improved performance when pretrained on a Portuguese corpus [20]. One of the motivations to perform a similar pretraining but using the T5 model [15] is its capability to generate text. Thus, it can perform tasks that a BERT model cannot, such as summarization, abstractive question answering, and translation.

In this work, we improve the original T5 model on Portuguese language tasks by pretraining it on BrWac [24], a large corpus of web pages in Brazilian Portuguese. We call this model PTT5. We validate our pretraining on Portuguese sentence similarity and entailment tasks and show that monolingual pretraining significantly improves the model’s performance.

2 Data

We use two Brazilian Portuguese datasets: BrWac [24] for pretraining and ASSIN 2 [16] for fine-tuning and evaluating our pretrained models.

2.1 BrWac

The BrWac corpus [24] was built after crawling more than 60 million web pages, filtered down to 3.5 million pages after applying quality control filters, resulting in a dataset with 2.7 billion tokens.
We construct input examples for the pretraining task by concatenating sentences until we reach 512 words. If the last sentence does not fit in the 512 words, we move it to the next example, i.e., we do not split sentences. Any sentence larger than 512 words, which is rare, is truncated to 512 words and added as a separate input example, truncated to 512 words. We use the ftfy library \cite{ftfy} to fix encoding problems. The resulting dataset has 15.6 GB of text and a mean of 360 words per document, as shown in Table 1. We use Python’s split function to count words.

| Processed BrWac Statistics |
|----------------------------|
| Number of documents        | 7,361,359 |
| Total number of words      | 2,656,275,093 |
| Mean number of words per doc | 360 ± 169 (std) |

Table 1: Statistics of BrWac text after pre-processing.

These input examples go through a tokenizer that can vary from using the original T5 vocabulary or our custom Portuguese vocabulary (Section 3.1).

2.2 ASSIN 2

ASSIN 2 \cite{assin2} consists of two Portuguese tasks: semantic similarity and entailment prediction. In the semantic similarity task, given a pair of sentences, a model has to predict a number between 1 and 5, representing how semantically close the two sentences are. The entailment prediction task consists of classifying if one sentence implies the other. It is thus a binary classification task whose classes are “entail” or “none”. The dataset consists of short sentence pairs, with 6500 pairs for training, 500 for validation, and 2448 for testing.

3 Methodology

We now describe our methodology, including creating the custom Portuguese vocabulary, unsupervised pretraining, and fine-tuning and evaluation on ASSIN 2.

3.1 Portuguese Vocabulary

The original T5 vocabulary uses the SentencePiece library \cite{sentencepiece} using English, German, French, and Romanian web pages from Common Crawl\cite{commoncrawl}.

We use a similar procedure to create our Portuguese vocabulary: we train a SentencePiece model on a corpus of 2 million sentences randomly chosen from the Portuguese Wikipedia. We use the Unigram language model as in \cite{t5} and a predetermined vocabulary size of 32,000 wordpieces.

We use the same control tokens (padding, end-of-sequence, and unknown) and vocabulary size of the original T5 to start pretraining from the original T5 checkpoints without significant changes in the model architecture and overall pretraining process.

3.2 Unsupervised Pretraining

The unsupervised pretraining was performed with a denoising objective, which can be implemented in a few different ways. The main idea is to train the model in an unsupervised way, feeding the model with corrupted versions of the original token sequence, and training it to reconstruct the original sequence \cite{t5}.

In all pretraining experiments, we use one of the strategies explored in the original T5 paper: each token in the input sequence has a predefined probability of being replaced by a mask token. The model is fed with this masked token sequence, and trained to produce the original sequence. For example, given the input sequence “Que $<$M$>$ para $<$M$>$ sobre o $<$M$>$ PTT5!”, the model
is trained to produce the sequence “Que belo dia para aprendermos sobre o maravilhoso PTT5!”,
where “<M>” is a mask token. Note that this is an illustrative example. In practice, the tokens in
the sentence are subword units.

In the pretraining experiments, we use the cross-entropy loss as a cost function and the Adafactor
optimizer \cite{21}. Training always starts from the corresponding original T5 checkpoints released by
Raffel et al \cite{15}. We use Google Cloud TPU v3-8’s and T5’s official implementation in TensorFlow.

In addition to updating all model weights during pretraining, we also experiment with updating
only the vocabulary embeddings and freezing the remaining weights. The model then has fewer
weights to be learned during pretraining, which leads to faster convergence times. Hence, this could
be a more economical pretraining strategy than the widely adopted strategy of pretraining the whole
model.

3.3 ASSIN 2 Training and Validation

For the ASSIN 2 tasks, the input to T5 is formatted as “ASSIN sentence1: {sentence 1} {eos}sentence2:
{sentence 2} {eos}”, where {sentence 1/2} corresponds to the strings of the sentences and {eos} is
the end-of-sequence token. We experimented with two ways for producing the scores in the sentence
similarity task: For the first approach, we follow Raffel et al.’s strategy for regression tasks and train
the model to output the literal string representing the score. We limit this generation to 5 tokens,
which is then converted to a floating-point number. In the second approach, we feed the mean
over the sequence length of the last hidden state of T5’s encoder to a linear layer with a sigmoid
activation. Since scores are between 1 and 5, we rescale the scalar output $y$ of the sigmoid layer
by doing $4y + 1$. The loss function consists of Mean Square Error (MSE), which is also one of the
the similarity tasks’ main metrics. For the entailment task, we feed the last hidden state of the T5
encoder to the linear layer with two neurons in the output followed by a softmax. We fine-tune the
models using the cross-entropy loss with the RAdam \cite{9} optimizer.

4 Experiments and Discussion

Our experiments comprise two main phases: unsupervised pretraining on the BrWac corpus, and
fine-tuning and evaluating on the ASSIN 2 tasks.

4.1 Unsupervised Pretraining

The experiments with unsupervised pretraining (Figure \ref{fig:pretrain}) were conducted following the methodology
described in Section 3.2. The corruption rate for the input tokens was 15\%, which is the same used
by the original T5 model. Input and output sequence token lengths follow T5’s maximum of 512.
Larger sequences are truncated, and shorter sequences are padded with a special padding token.
The learning rate was constant and equal to 0.003. All models were pretrained for four epochs.

Table \ref{tab:pretrain} shows a summary of all pretraining experiments performed. Each row represents a
specific combination of model size, batch size, and pretraining strategy (whole model vs. vocabulary
embeddings only) and comprises two experiments: one for multilingual vocabulary and another for
the Portuguese vocabulary (see Section 3.1 for more details).

As expected, larger models show lower loss levels. Using the Portuguese vocabulary resulted in
higher loss values for the same model size. A hypothesis for the cause of this behavior is that, since
the weights were initialized using checkpoints from models trained with the original T5 vocabulary,
the model has to adapt to the new Portuguese vocabulary. Evidence for this is the initial high loss
for models starting with the Portuguese vocabulary.

For base and large models, we observed a decrease in approximately 20\% on time spent per epoch
when training only the vocabulary embeddings versus training the whole model.

\url{https://github.com/google-research/text-to-text-transfer-transformer}
Figure 1: Pretraining cross-entropy loss for different model sizes and vocabularies. a) training the whole model; b) training vocabulary embeddings only.

4.2 ASSIN 2 Experiments

Here we describe our experiments in our target task: ASSIN 2. Unless noted otherwise, the learning rate for fine-tuning is 0.0001; the batch sizes are 32, 2, and 1 for the small, base, and large models, respectively. The small batch sizes for the base and large models are due to memory limitations in our GPU. We found that 128 sequence length is enough to accommodate ASSIN 2’s sentence pairs by looking at the tokenized training and validation data. The maximum number of epochs in the reported experiment plots is 50. We used a patience of 5 epochs for the similarity task and 10 epochs for the entailment task.

Table 3 shows results on the test set using the official ASSIN 2 evaluation script. We compare with fine-tuning from the original T5 weights and fine-tuning from PTT5. We also compare our results to BERTimbau, a BERT model also pretrained on BrWac [20], mBERT, a multilingual training of BERT, and the top models from the official ASSIN 2 leaderboard.

In general, PTT5 Base achieves competitive performance with BERTimbau, with the Portuguese vocabulary largely contributing to the results. Despite the largest BERT model achieving the best performance (BERTimbau Large), our PTT5 Base was better than PTT5 Large. PTT5 Base achieves top MSE, which can be due to optimization with MSE loss. It is noticeable how ASSIN 2’s test dataset is different from its validation set. PTT5 consistently outperforms the original T5 model on both tasks. This result aligns with our initial hypothesis that Portuguese denoise pre-training might improve performance when fine-tuning on Portuguese tasks. The use of the custom Portuguese vocabulary also consistently improved results.

https://sites.google.com/view/ASSIN2

| Size | Batch size | Trainable parameters (all weights / emb. only) | Hours/epoch (all weights / emb. only) |
|------|------------|-----------------------------------------------|--------------------------------------|
| Small| 256        | 60M / 16M                                     | 3.3 / 3.4                            |
| Base | 128        | 220M / 25M                                    | 8.4 / 6.6                            |
| Large| 64         | 740M / 32M                                    | 39.5 / 32.3                          |
| Large| 128        | 740M / (not performed)                        | 38.9 / (not performed)               |

Table 2: Batch size and approximated training time per epoch on a TPU v3-8 for each PTT5 model size (total amount of trainable parameters) on unsupervised pretraining experiments. We show numbers for pretraining the whole model versus pretraining the vocabulary embeddings only.
| Team/Method                  | Team/Method                  | Pearson | MSE   | Accuracy | F1   |
|-----------------------------|-----------------------------|---------|-------|----------|------|
| Deep Learning Brasil [17]   | IPR [18]                    | 0.785   | 0.59  | 88.3     | 88.3 |
| Stilingue [5]               | mBERT [20]                  | 0.817   | 0.47  | 86.6     | 86.6 |
| BERTimbau Base [20]         | BERTimbau Large [20]        | 0.836   | 0.58  | 89.2     | 89.2 |
| T5 Small                    | T5 Base                     | 0.757   | 0.61  | 83.9     | 83.9 |
| T5 Base                     | T5 Large                    | 0.780   | 0.60  | 82.3     | 82.1 |
| T5 Large                    | PTT5 Small, T5 vocab        | 0.776   | 0.65  | 84.7     | 84.7 |
| PTT5 Base, T5 vocab         | PTT5 Large, T5 vocab        | 0.793   | 0.63  | 84.4     | 84.4 |
| PTT5 Large, PT vocab        | PTT5 Small, PT vocab        | 0.811   | 0.51  | 85.8     | 85.8 |
| PTT5 Base, PT vocab         | PTT5 Base, PT vocab, emb. only | 0.762   | 0.67  | 85.1     | 85.0 |
| PTT5 Large, PT vocab        |                             | 0.819   | 0.53  | 88.0     | 88.0 |

Table 3: Test results on ASSIN 2 using the official evaluation code.

4.2.1 Ablation: Output Strategy

Figure 2 compares the validation loss in semantic similarity task and the validation accuracy in the entailment task between the two output strategies: string generation and linear layer over the last hidden states. For the string generation approach, accuracy is used in Figures 2b and 2d. These experiments used the original T5 vocabulary and weights. We use the linear layer approach in all other experiments due to its faster convergence and higher stability.

4.2.2 Ablation study: Portuguese Vocabulary vs. Original T5 Vocabulary

Figure 3 shows validation losses when varying the size of the initial PTT5 weights, with and without our custom Portuguese vocabulary on the semantic similarity task (Figures 3a, 3c, and 3e) and entailment task (Figures 3b, 3d, and 3f). We notice that the Portuguese vocabulary helps PTT5 achieving better results and convergence on ASSIN 2. Additionally, we notice that larger models converge faster in the fine-tuning step.

4.2.3 Ablation: Additional Hyperparameter Tuning

Table 4 shows the best validation MSE loss for the similarity task and best validation cross-entropy loss for the entailment task, for each model. All PTT5 models were pretrained for 4 epochs. PTT5 base with the Portuguese vocabulary achieved the lowest MSE (0.0387). PTT5 Large with the Portuguese vocabulary achieved the lowest cross-entropy (0.1420). However, as shown in Table 3, the large model achieved a lower Person correlation than the base model.

In Table 5, we show some additional experiments to explore variations in the batch size, learning rate, and the number of pretraining epochs. We also evaluated the performance of the PTT5 pretrained with vocabulary embeddings only.

Different pretraining methods showed similar performance on the validation set of ASSIN 2. However, on the test set, pretraining all weights achieved far better performance than pretraining the vocabulary embeddings only. These results suggest that the validation set of ASSIN 2 was not the best choice for model selection, probably due to its small size (500 examples) and because metrics were already too high for all models (e.g., Pearson correlations were close to 1). Hence, experiments
Figure 2: Training and validation curves comparing the string generation and linear layer approaches on the similarity and entailment tasks, starting from T5 small (a and b) and T5 base weights (c and d).
Figure 3: Training and validation loss curves on ASSIN 2 tasks, starting from the pretrained PTT5 weights.
### Table 4: Validation loss for each model configuration after fine-tuning on the ASSIN 2 tasks. MSE loss is for the similarity task and cross-entropy loss (CE loss) is for the entailment task. Lower is better.

| Initial Weights | Size | Batch Size | LR   | Vocab | Val. MSE loss | Val. CE loss |
|-----------------|------|------------|------|-------|---------------|--------------|
| T5 Small        | 32   | 1e-4       | T5   | 0.1042| 0.2697        |
| T5 Base         | 2    | 1e-4       | T5   | 0.0626| 0.1865        |
| T5 Large        | 1    | 1e-4       | T5   | 0.0617| 0.1732        |
| PTT5 Small      | 32   | 1e-4       | T5   | 0.0976| 0.2135        |
| PTT5 Base       | 2    | 1e-4       | T5   | 0.0407| 0.1700        |
| PTT5 Large      | 1    | 1e-4       | T5   | 0.0413| 0.1750        |
| PTT5 Small      | 32   | 1e-4       | PT   | 0.0551| 0.1727        |
| PTT5 Base       | 2    | 1e-4       | PT   | 0.0387| 0.1439        |
| PTT5 Large      | 1    | 1e-4       | PT   | 0.0460| 0.1420        |

### Table 5: Additional fine-tuning experiments on ASSIN 2’s similarity task to explore learning rate, batch accumulation, and pretraining vocabulary embedding only. From PTT5 with Portuguese vocabulary checkpoint. PTT5 Large was pretrained with a batch size of 128.

| Pretraining Epochs | Emb. Only? | Size | Batch Size | LR   | Val. MSE Loss | Val. Pearson |
|--------------------|------------|------|------------|------|---------------|--------------|
| 4                  | No         | Base | 2          | 1e-4 | 0.0387        | 0.981        |
| 4                  | No         | Base | 32         | 1e-4 | 0.0514        | 0.976        |
| 4                  | No         | Base | 32         | 1e-3 | 0.0483        | 0.975        |
| 4                  | Yes        | Base | 2          | 1e-4 | 0.0353        | 0.983        |
| 4                  | Yes        | Base | 32         | 1e-3 | 0.0447        | 0.978        |
| 4                  | No         | Large| 1          | 1e-4 | 0.0378        | 0.981        |
| 4                  | No         | Large| 2          | 1e-4 | 0.0393        | 0.980        |
| 1                  | No         | Base | 2          | 1e-4 | 0.0389        | 0.982        |
| 0.1                | No         | Base | 2          | 1e-4 | 0.0367        | 0.982        |
| 1                  | Yes        | Base | 2          | 1e-4 | 0.04525       | 0.978        |
| 0.1                | Yes        | Base | 2          | 1e-4 | 0.0419        | 0.979        |

5 Conclusion

We pretrained T5 models on a large Brazilian Portuguese corpus. The resulting models achieved better performance than the original T5 models on the ASSIN 2’s Portuguese tasks. Moreover, using a Portuguese vocabulary proved to be better than using the original T5 multilingual vocabulary. Finally, for ASSIN 2 tasks, we found that pretraining all weights leads to better performance than pretraining the vocabulary embeddings only. Despite having achieved better results than the top-submissions to the ASSIN 2 leaderboard, our Portuguese T5 model is still a few points below to the state-of-the-art model, a Portuguese BERT Large model (BERTimbau Large).

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