

# Light and Fast Language Models for Spanish Through Compression Techniques

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# Overview

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# Motivation

# Motivation

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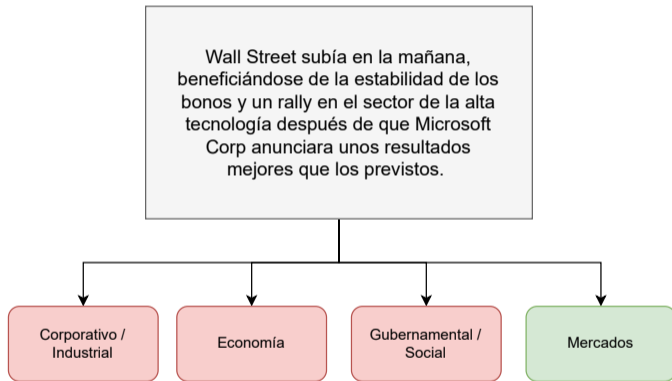



Figure: An example of document classification. Taken from the MLDoc [42] dataset.

# Motivation

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En su lugar entró el chileno Iván Luis Zamorano



**PER**

Figure: An example of named entity recognition. Taken from the CoNLL2002 NER [46] dataset.

# Motivation

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Figure: An example of question answering. Taken from the SQAC [20] dataset.

# Motivation

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# Problem



## Problem

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As **models grows** in size and computational complexity, it's **di cult** to put them in **production** for real time applications or the use of them in hardware restricted devices like mobile phone

## Problem

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And even **more difficult** for the **Spanish** language because of the lack of Spanish-specific resources and models.

# Hypothesis and Objectives

# Hypothesis

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Adopting more parameter-efficient model architectures and employing knowledge distillation techniques to transfer knowledge from large models to smaller ones can significantly enhance model compactness and inference speed, while maintaining most of the performance exhibited by larger models on Spanish NLP tasks.

## General Objective

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To develop **Spanish language models** that are more **compact** and **computationally efficient** while maintaining high levels of task-performance.

# Specific Objectives

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1. To measure the size and inference speed of pre-trained Spanish language models that are currently available.
2. To develop models for the Spanish language that are more parameter-efficient by utilizing weight-shared model architectures.
3. To train models for Spanish that are more inference-efficient by applying task-specific knowledge distillation on Spanish NLP tasks.
4. To evaluate the mentioned techniques on a diverse set of Spanish NLP tasks.
5. To evaluate how the model size impacts the task performance while using these techniques.
6. To release those models publicly as a resource for further research.

# Background and Related Work

# Background - BERT

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Bidirectional Encoder  
Representations from  
Transformers [17].  
Transformer-encoder.  
Pre-training on MLM and  
NSP.  
Fine-tuning on  
downstream tasks.  
base(110M) and large  
(330M).

**Figure:** The masked language modeling (MLM) task used by BERT as pre-training task.



# Background - ALBERT

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A Lite BERT [24].

Transformer-encoder.

Embedding factorization  
and Parameter-sharing.

Pre-training on MLM and  
SOP.

Fine-tuning on  
downstream tasks.

base(12M) to xxlarge  
(235M).

**Figure:** A design comparison of BERT and ALBERT, focusing on the parameter utilization strategy adopted by each model.

# Background - Multilingual and Monolingual Models

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## Multilingual models:

Models that are trained simultaneously using data from several languages.

Examples: mBERT (104 languages), XLM-R (100 languages).

Generally, larger vocabularies, to be able to represent all languages.

## Monolingual models:

Models trained on a single language.

CamemBERT [29] and FlauBERT [25] for French, BERTje [14] and RobBERT [15] for Dutch, FinBERT [49] for Finish, BETO [10] for Spanish.

Generally outperform multilingual models.

# Background - Compression Techniques

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Methods to reduce the overall size or computational complexity of a model.

Pruning: aims to reduce the number of connections (weights) in a neural network by identifying and removing redundant connections.

Quantization : compresses the original network by reducing the number of bits required to represent each weight.

Knowledge Distillation : transfers the knowledge from a big model (teacher) to a smaller model (student) by training the student to imitate the teacher.

# Background - Knowledge Distillation

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**Figure:** The figure provides a visual representation of the Knowledge Distillation [21] framework applied in this work.

# Background - Knowledge Distillation

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Two models, the teacher model,  $M_T$ , and a student model,  $M_S$ . We train  $M_S$  to imitate  $M_T$ . We define the distillation objective as  $L_{KD}$ :

$$L_{KD} = L_O(M_T(x); M_S(x))$$

Where  $L_O$  is a loss function that works on the logits of  $M_T$  and  $M_S$ . The most common choices for this loss are the cross entropy loss, the KL-divergence loss and the mean-squared error loss.

Also, we can include the gold labels from the training dataset. The complete loss, accounting these labels can be seen as:

$$L = L_{CE} + (\lambda) L_{KD}$$

Where  $L_{CE}$  is the traditional cross-entropy loss against gold labels and  $\lambda \in [0; 1]$  defines the weight of each loss.

## Related Work

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Tang et al. [44] uses KD to transfer the knowledge from BERT to lighter RNNs.

Turc et al. [47] proposes pre-training compact BERT models and then using task-specific KD to achieve better results.

Sanh et al. [41] introduces a task-agnostic scheme where KD is used on the pre-training task.

Wang et al. [50] and Jiao et al. [22] proposed different methods exclusive for Transformers, to directly distill the knowledge from the self-attention layers of the teacher model to the student model.

# Preliminaries: Evaluation Tasks and Baselines

# Evaluation Tasks

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## 1. Text Classification

Document Classification.  
Natural Language Inference.  
Paraphrase Identification.

## 2. Sequence Tagging

Named Entity Recognition.  
Part-of-Speech Tagging.

## 3. Question Answering

Dataset Name	Task Type	Number of Categories	Train Size	Validation Size	Test Size
MLDoc [42]	Text Classification	4	9458	1000	4000
PAWS-X [52]	Text Classification	2	49401	2000	2000
XNLI [11]	Text Classification	3	392702	2490	5010
POS [45]	Sequence Tagging	18	14305	1654	1721
NER [46]	Sequence Tagging	9	8324	1916	1518
MLQA [27]	Question Answering	-	81810	500	5253
SQAC [20]	Question Answering	-	15036	1864	1910
TAR / XQuAD [6, 2]	Question Answering	-	87595	10570	1190

Table: Details of the datasets used to evaluate our proposed models.



# Inference Metrics

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## Metrics

Size: Number of Parameters.

Speed: Multiply-accumulate Operations (MACs).

## Conditions

Batch size = 1.

Max. sequence length = 512.

# Pre-trained Models for Spanish

## Aim

Include all publicly available Transformer-encoder based models trained on Spanish general domain corpora as baselines.

Model Name	Architecture	Size	Vocab Size	Vocab Types	Max Seq Length	Parameters	Domain	Availability	Reference
Included									
BETO	BERT	base	32K	uncased, cased	512	110M	General	Public	[10]
DistilBETO	DistilBERT	base	32K	uncased	512	67M	General	Public	[18]
RoBERTa-BNE base	RoBERTa	base	50K	cased	514	125M	General	Public	[20]
RoBERTa-BNE large	RoBERTa	large	50K	cased	514	355M	General	Public	[20]
BERTIN	RoBERTa	base	50K	cased	514	125M	General	Public	[12]
Not Included									
GPT-2-BNE base	GPT-2	base	50K	cased	512	124M	General	Public	[20]
GPT-2-BNE large	GPT-2	large	50K	cased	512	773M	General	Public	[20]
RigoBERTa	DeBERTa	base	50K	-	512	-	General	Private	[43]
RoBERTuito	RoBERTa	base	30K	uncased, cased, deaccented	130	109M	Social Media	Public	[34]
BSC-Bio	RoBERTa	base	50K	cased	514	125M	Biomedical	Public	[7]
RoBERTalex	RoBERTa	base	52K	cased	514	126M	Legal	Public	[19]
Longformer-BNE	Longformer	base	50K	cased	4098	149M	General	Public	-

Table: Summary of pre-trained Transformer models for Spanish.

# Proposed Spanish NLP Resources: ALBETO and Speedy Gonzales

# ALBETO: Light models for Spanish

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ALBETO: a series of 5 lightweight models that follow the ALBERT architecture and are pre-trained exclusively on Spanish corpora with sizes that range from 5M to 223M of parameters.

# ALBETO: Model Architecture

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ALBERT architecture.

31K lowercase subword tokens.

Model	Parameters	Layers	Hidden	Embedding
ALBETO tiny	5M	4	312	128
ALBETO base	12M	12	768	128
ALBETO large	18M	24	1024	128
ALBETO xlarge	59M	24	2048	128
ALBETO xxlarge	223M	12	4096	128

**Table:** The configurations of each ALBETO model trained in this work.

# ALBETO: Training Process

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**Figure:** A broad overview of the process involved in the creation of ALBETO models. Sub-processes relevant to distinct stages are portrayed outside the main frame.

# ALBETO: Evaluation

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Fine-tuning on downstream tasks.

Tasks: text classification, sequence tagging and question answering.

Hyperparameter search:

All models:

Batch size: 16, 32, 64.

Epochs: 2, 3, 4.

BETO, DistilBETO, RoBERTa-BNE, BERTIN, ALBETO<sub>tiny</sub> and base

Learning rate: 1e-5, 2e-5, 3e-5, 5e-5.

ALBETO<sub>large</sub>, xlarge and xxlarge

Learning rate: 1e-6, 2e-6, 3e-6, 5e-6.

# Speedy Gonzales: Fast Models for Spanish

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Speedy Gonzales: a collection of fast task-specific language models based on ALBETO, which were trained using Task-specific Knowledge Distillation.



# Speedy Gonzales: Approach

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**Figure:** The first stage of our approach, which involves fine-tuning a set of candidate models on a specific dataset, followed by the selection of the best-performing model as the teacher model for that dataset.

# Speedy Gonzales: Approach

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**Figure:** The second stage of our approach, which employs the selected teacher model to train a set of student models using knowledge distillation.

# Speedy Gonzales: Approach

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## Candidate teacher models:

All publicly available Transformer-encoder based models trained on Spanish general domain corpora.

BETO, DistilBETO, RoBERTa-BNE, BERTIN and ALBETO.

## Student models:

ALBETO tiny.

A collection of faster models based on ALBETObase

Models that follow the ALBETObase configuration, but with less layers.

Noted as ALBETObase- $n$  ( $n \in \{2, 4, 6, 8, 10\}$ ).

# Speedy Gonzales: Evaluation

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First stage:

- Same as ALBETO evaluation.

- Selected best teacher models.

Second stage:

- Task-specific Knowledge Distillation on downstream tasks.

- Tasks: text classification, sequence tagging and question answering.

- KL-Divergence loss,  $\beta = 0$  and  $T = 1$ .

- Cached teacher predictions.

- Hyperparameter search:

  - Batch size: 16, 32, 64.

  - Learning rate:  $5e-5$ ,  $1e-4$ .

  - Epochs: 50.

  - Early stopping with tolerance of 10 epochs of no improving.

# Results and Discussion

# Task Performance - Text Classification

Model	MLDoc	PAWS-X	XNLI
Fine-tuning			
BETO uncased	96.38	84.25	77.76
BETO cased	96.65	89.80	81.98
DistilBETO	96.35	75.80	76.59
ALBETO tiny	95.82	80.20	73.43
ALBETO base	96.07	87.95	79.88
ALBETO large	92.22	86.05	78.94
ALBETO xlarge	95.70	89.05	81.68
ALBETO xxlarge	96.85	89.85	82.42
BERTIN	96.47	88.65	80.50
RoBERTa BNE base	96.82	89.90	81.12
RoBERTa BNE large	97.00	90.00	51.62
Task-specific Knowledge Distillation			
ALBETO tiny	96.40	85.05	75.99
ALBETO base-2	96.20	76.75	73.65
ALBETO base-4	96.35	86.40	78.68
ALBETO base-6	96.40	88.45	81.66
ALBETO base-8	96.70	89.75	82.55
ALBETO base-10	96.88	89.95	82.26

**Table:** Models evaluated on sentence or two sentences classification tasks, results are measured using accuracy on the test set of each dataset.

# Task Performance - Sequence Tagging

Model	POS	NER
Fine-tuning		
BETO uncased	97.81	80.85
BETO cased	98.95	87.14
DistilBETO	97.67	78.13
ALBETO tiny	97.34	75.42
ALBETO base	98.21	82.89
ALBETO large	97.98	82.36
ALBETO xlarge	98.43	83.06
ALBETO xxlarge	98.43	83.06
BERTIN	99.02	85.66
RoBERTa BNE base	99.00	86.80
RoBERTa BNE large	61.83	21.47
Task-specific Knowledge Distillation		
ALBETO tiny	97.36	72.51
ALBETO base-2	97.17	69.69
ALBETO base-4	97.60	74.58
ALBETO base-6	97.82	78.41
ALBETO base-8	97.96	80.23
ALBETO base-10	98.00	81.10

**Table:** Models evaluated on sequence tagging tasks, results are measured using the F1 Score on the test set of each dataset.

# Task Performance - Question Answering

Model	MLQA	SQAC	TAR, XQuAD
Fine-tuning			
BETO uncased	64.12 / 40.83	72.22 / 53.45	74.81 / 54.62
BETO cased	67.65 / 43.38	78.65 / 60.94	77.81 / 56.97
DistilBETO	57.97 / 35.50	64.41 / 45.34	66.97 / 46.55
ALBETO tiny	51.84 / 28.28	59.28 / 39.16	66.43 / 45.71
ALBETO base	66.12 / 41.10	77.71 / 59.84	77.18 / 57.05
ALBETO large	65.56 / 40.98	76.36 / 56.54	76.72 / 56.21
ALBETO xlarge	68.26 / 43.76	78.64 / 59.26	80.15 / 59.66
ALBETO xxlarge	70.17 / 45.99	81.49 / 62.67	79.13 / 58.40
BERTIN	66.06 / 42.16	78.42 / 60.05	77.05 / 57.14
RoBERTa BNE base	67.31 / 44.50	80.53 / 62.72	77.16 / 55.46
RoBERTa BNE large	67.69 / 44.88	80.41 / 62.14	77.34 / 56.97
Task-specific Knowledge Distillation			
ALBETO tiny	54.17 / 32.22	63.03 / 43.35	67.47 / 46.13
ALBETO base-2	48.62 / 26.17	58.40 / 39.00	63.41 / 42.35
ALBETO base-4	62.19 / 38.28	71.41 / 52.87	73.31 / 52.43
ALBETO base-6	66.35 / 42.01	76.99 / 59.00	75.59 / 56.72
ALBETO base-8	67.39 / 42.94	77.79 / 59.63	77.89 / 56.72
ALBETO base-10	68.29 / 44.29	79.89 / 62.04	78.21 / 56.21

Table: Models evaluated on question answering datasets, results are noted as F1 Score / Exact Match on the test set of each dataset.



# Model Efficiency and Inference Speed

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# Inference Speed on Common Hardware

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Model	Inferences per second	
	CPU	GPU
Fine-tuning		
BETO uncased	3.96	107.19
BETO cased	4.26	109.02
DistilBETO	9.12	217.40
ALBETO tiny	32.53	539.61
ALBETO base	4.50	108.62
ALBETO large	1.29	33.62
ALBETO xlarge	0.35	11.72
ALBETO xxlarge	0.14	6.60
BERTIN	3.99	109.39
RoBERTa BNEbase	3.82	107.77
RoBERTa BNElarge	1.18	33.65
Task-specific Knowledge Distillation		
ALBETO tiny	32.53	539.61
ALBETO base-2	31.08	625.30
ALBETO base-4	15.16	319.32
ALBETO base-6	10.45	213.53
ALBETO base-8	6.82	160.66
ALBETO base-10	6.01	128.38

Table: The number of inferences per second of models on two different hardware settings, CPU and GPU.

# Results - Summary

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Model	Parameters	Speedup	Score
Fine-tuning			
BETO uncased	110M	1.00x	81.02
BETO cased	110M	1.00x	84.82
DistilBETO	67M	2.00x	76.73
ALBETO tiny	5M	18.05x	74.97
ALBETO base	12M	0.99x	83.25
ALBETO large	18M	0.28x	82.02
ALBETO xlarge	59M	0.07x	84.13
ALBETO xxlarge	223M	0.03x	85.17
BERTIN	125M	1.00x	83.97
RoBERTa BNEbase	125M	1.00x	84.83
RoBERTa BNElarge	355M	0.28x	68.42
Task-specific Knowledge Distillation			
ALBETO tiny	5M	18.05x	76.49
ALBETO base-2	12M	5.96x	72.98
ALBETO base-4	12M	2.99x	80.06
ALBETO base-6	12M	1.99x	82.70
ALBETO base-8	12M	1.49x	83.78
ALBETO base-10	12M	1.19x	84.32

**Table:** The summary of results of every evaluated model in terms of parameters, inference speedup and overall score across tasks. The speedup is relative to BETO models. The score column shows the average of the metrics on all tasks.

# Conclusions

# Summary of Contributions

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We introduced ALBETO and Speedy Gonzales, which are **two novel resources** for the **Spanish NLP** community that were created to **improve** two key aspects of machine learning models, namely **model size** and **inference speed**.

# Summary of Contributions

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## ALBETO:

Language models that were pre-trained exclusively for the Spanish language, with different sizes: tiny, base, large, xlarge, and xxlarge

Successfully utilize the weight-shared strategy to achieve greater efficiency in terms of model parameters.

The basemodel, which is an uncased model, outperforms the uncased version of BETO while having significantly less parameters and is marginally inferior to other base-sized models with a case-based vocabulary.

The xxlarge model outperforms all other models.

# Summary of Contributions

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## Speedy Gonzales:

Collection of fast task-specific models trained using Task-specific KD.

Task-Specific KD is effective in transferring knowledge from a larger model to a lighter and faster model.

Speedy Gonzales models achieve comparable task performance to most base-sized models while exhibiting enhanced inference speed.

There exists a trade-off between inference-efficiency of the model and task performance, as observed in the evaluation of the Speedy Gonzales models derived from the ALBERTO basemodel.

Some tasks benefit from the use of larger and more computationally complex models (e.g. QA), while other tasks can be effectively handled by lighter and faster models (e.g. POS, MLDoc).

# Limitations and Future Research Directions

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We only evaluated our models on a limited set of tasks.

Our KD method can be further improved to produce more efficient task-specific language models:

- Explore alternative KD approaches, such as distilling intermediate layers of the teacher model, in addition to its output.

- A multi-teacher approach could be studied, in which the models learn from a collection of teacher models rather than just one.

- Combine with other compression techniques, such as parameter-pruning or quantization.

There exists a trade-off between model size, inference speed, and task performance, making it challenging to choose an appropriate model without context. It is important to develop metrics to formally assess this balance.



# Outcomes

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Two publications:

1. ALBETO and DistilBETO: Lightweight Spanish Language Models

Cañete et al. [5]

Proceedings of the 13th Edition of The Language Resources and Evaluation Conference (LREC), Marseille, France.

[Paper](#), [Code](#)

2. Speedy Gonzales: A Collection of Fast Task-Specific Models for Spanish

Cañete and Bravo-Marquez [9]

Under review.

[Code](#)

Models:

Over 140 models (between pre-trained, fine-tuned and distilled models) publicly available to the research community.

[Models at the HuggingFace Hub](#)

# Light and Fast Language Models for Spanish Through Compression Techniques

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# Machine Learning

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Machine Learning is a sub field of Computer Science that studies the question on how to build algorithms that can automatically improve through experience [23].

Two paradigms: unsupervised and supervised.

Unsupervised: According to Jordan and Mitchell [23], is "the analysis of unlabeled data under assumptions about structural properties of the data (e.g., algebraic, combinatorial, or probabilistic)." A common example is Clustering.

Supervised: We use a set of data samples with the form  $(x, y)$ , where  $x$  is called an example and  $y$  is called its label. The goal is to learn a parameterized function  $f(x)$  that maps from  $x$  to  $y$  and that generalizes to unseen pairs  $(x, y)$ .

# Representation Learning

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In classical Machine Learning, the input examples were represented as feature vectors, which were manually engineered, in a process called "feature engineering", by domain experts who possessed knowledge on the specific task at hand.

More recently, not only a function  $f(x)$  is learned but also a rich and useful representation  $x$  is learned from a simpler representation of the data.

# Transfer Learning

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Key idea: reuse the knowledge (or the representation) learned in one very general task, to another more specific task.

In Computer Vision (CV), a model is initially trained on a vast labeled dataset with distinct categories known as ImageNet [16, 40, 39]. The model is then fine-tuned or re-trained to perform other tasks or classify objects in categories not present in ImageNet.

In Natural Language Processing (NLP), where a model is pre-trained for tasks like Language Modeling [36, 37, 4] or Masked Language Modeling [17, 24, 28]. Subsequently, the pre-trained model is fine-tuned for several other tasks like sentiment analysis, question answering, and document classification.

# Representations of Text

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Word Embeddings are a mathematical mapping from a word (a discrete symbol) to a continuous vector of dimensionality  $d$ .

First, sparse vectors. More recently, learned dense vectors. (e.g. Word2Vec [30], GloVe [33], FastText [3]).

One major limitation: Polysemy. They are fixed vectors, meaning that a word is represented identically, regardless of its context.

To overcome this limitation, contextual word representations are used nowadays. These representations not only used a fixed embedding layer, but also deep neural networks, to account for the complete context of a text in the calculation of a representation of a word.

The first contextual representations used RNNs [35] as neural network architecture and then were replaced in favor of Transformers [17].

# Transformer

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## Scaled Dot-Product Attention

$$W^Q \in \mathbb{R}^{d_{\text{model}} \times d_q}, W^K \in \mathbb{R}^{d_{\text{model}} \times d_k}, W^V \in \mathbb{R}^{d_{\text{model}} \times d_v}.$$
$$Q = XW^Q, K = XW^K, \text{ and } V = XW^V.$$

$$\text{Attention}(Q; K; V) = \text{softmax}\left(\frac{QK^T}{d_k}\right)V$$

$$\text{MultiHeadAttention} = \text{Concat}(\text{head}_1; \dots; \text{head}_h)W^O$$

$$\text{Where, } \text{head}_i = \text{Attention}(XW_i^Q; XW_i^K; XW_i^V) \text{ and } W^O \in \mathbb{R}^{hd_v \times d_{\text{model}}}.$$

# Evaluation Tasks - Document Classification - MLDoc

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Assigning a document to a specific category based on its underlying semantic meaning.

The primary objective of Document Classification is to facilitate efficient information retrieval and management.

Spanish subset of MLDoc [42]

A comprehensive multilingual dataset comprising documents in eight languages. It is derived from the widely used Reuters Corpus [26].

Four distinct categories: Corporate/Industrial, Economics, Government/Social, and Markets.



# Evaluation Tasks - Document Classification - MLDoc - Example

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Figure: An example of document classification. Taken from the MLDoc [42] dataset.

# Evaluation Tasks - Paraphrase Identification - PAWS-X

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Determine whether two given sentences possess the same underlying semantic meaning.

Spanish subset of PAWS-X [52]

It is a translation of the PAWS [53] dataset in six different languages.

The training set of PAWS-X has been machine translated, while the validation and test sets were professionally translated by human experts.

# Evaluation Tasks - Paraphrase Identification - PAWS-X - Example

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Figure: An example of the paraphrase identification task. Taken from the PAWS-X [52] dataset.

# Evaluation Tasks - Natural Language Inference - XNLI

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Determining the logical relationship between two given sentences, namely a "premise" and an "hypothesis". Specifically, the task requires inferring whether the premise entails, contradicts, or is neutral to the hypothesis.

## Spanish subset of XNLI [11]

It is a translation of the MultiNLI [51] to 15 different languages.

Offers a machine-translated training set while the validation and test sets have been professionally translated.

# Evaluation Tasks - Natural Language Inference - XNLI - Example

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Figure: An example of natural language inference. Taken from the XNLI [11] dataset.

# Evaluation Tasks - Part-of-Speech Tagging - POS

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Task that aims to assign each word in a sentence its corresponding syntactic category.

The syntactic categories are based on the grammatical function of the word and include, among others, nouns, verbs, adjectives, adverbs, and pronouns.

The dataset used was AnCora [45] which is included on the Spanish part of Universal Dependencies [13] Treebank.

# Evaluation Tasks - Part-of-Speech Tagging - POS - Example

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Figure: An example of the Part-of-Speech tagging task. Taken from the AnCora [45] dataset.

# Evaluation Tasks - Named Entity Recognition - NER

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Involves identifying and classifying named entities within a text according to their corresponding types.

It is essential in NLP as it enables computers to extract relevant information from unstructured text data, which can be used for a range of downstream applications.

Named entities are typically classified into categories such as people, places, organizations, or miscellaneous entities.

Entities may consist of multiple words. This complexity requires the adoption of the BIOES-style annotation scheme in NER datasets, where each word is labeled as either the beginning (B) of an entity, inside (I) an entity, or outside (O) of any entity.

Spanish subset of the CoNLL-2002 shared task dataset [46].



# Evaluation Tasks - Named Entity Recognition - NER - Example

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Figure: An example of named entity recognition. Taken from the CoNLL2002 NER [46] dataset.

# Evaluation Tasks - Question Answering - MLQA - SQAC - TAR/XQuAD

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Extractive Question Answering: which aims to extract a span of words from a given context text that fully answers a question posed about that context.

Spanish subset of MLQA [27]

Multilingual dataset, created by translating English QA instances into 6 languages. The dataset provides a validation and a test set for each language, as well as a machine-translated version of the SQuAD v1.1 [38] as a training set.

TAR [6] + XQuAD [2]

TAR [6] is another machine-translated dataset from SQuAD v1.1 to Spanish. XQuAD [2] provides a test set that was obtained from SQuAD v1.1 and professionally translated into 11 different languages, including Spanish.

Following the setup proposed by [10], we combined the train and validation sets from TAR and the Spanish test set from XQuAD as a single evaluation dataset.

SQAC [20]

May offer a more valuable resource for addressing Spanish language-related challenges since it is the only one specifically designed for the Spanish language.

# Evaluation Tasks - Question Answering - MLQA - SQAC - TAR/XQuAD - Example

---

Figure: An example of question answering. Taken from the SQAC [20] dataset.

# Evaluation Metrics - Accuracy

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Accuracy is a metric that calculates the ratio of correct predictions to the total number of predictions made by a model. It can be expressed mathematically as:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{All Predictions}}$$

# Evaluation Metrics - F1 Score

---

In the context of binary classification, Precision is defined as the proportion of examples classified as positive that are truly positive. This can be expressed as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall is defined as the proportion of truly positive examples that are correctly classified. This can be expressed as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

The F1 Score is then defined as the harmonic mean of Precision and Recall, given by:

$$\text{F1 Score} = \frac{2 \text{ Precision Recall}}{\text{Precision} + \text{Recall}}$$

# Evaluation Metrics - Exact Match

---

In the case of Question Answering, the Exact Match metric compares the predicted answer string  $p_s$ , with the correct answer string  $c_s$ . The Exact Match for a single example is defined as:

$$\text{Exact Match}_{\text{single}} = \begin{cases} 1; & \text{if } p_s == c_s \\ 0; & \text{otherwise} \end{cases}$$

The Exact Match for a collection of pairs  $(p_s; c_s) \in A$  is then defined as the average of the Exact Match for a single example, expressed as:

$$\text{Exact Match} = \frac{\sum_{(p_s; c_s) \in A} \text{Exact Match}_{\text{single}}(p_s; c_s)}{|A|}$$

# ALBETO - Dataset - SUC

---

General domain corpora.

Same corpus [8] used on BETO [10].

300M lines, 3B tokens, 18.4B chars.

Sources: Spanish Wikis (dump of April 2019), Books, News, Subtitles, European Parliament, TED Talks, etc.

# ALBETO - Preprocessing

---

Identical to BETO [10] and very simple.

Removing URLs and listings.

Removing multiple whitespaces.

Lowercase.



# ALBETO - Pre-training Details

---

MLM and SOP.

Single TPU v3-8 for each model.

A maximum sequence length of 512 was used for pre-training, and the largest multiple of 64 that fit in the TPU memory was selected as the batch size.

We experienced divergence in the loss on large and xlarge models, this issue forced to stop the training and restart it from an earlier checkpoint with a slightly lower learning rate.

Model	Learning Rate	Batch Size	Warmup Ratio	Warmup Steps	Total Steps	Training Time (days)
ALBETO tiny	1.25e-3	2,048	1.25e-2	125,000	8,300,000	58.2
ALBETO base	8.83e-4	960	6.25e-3	53,333	3,650,000	70.4
ALBETO large	6.25e-4	512	3.12e-3	12,500	1,450,000	42.0
ALBETO xlarge	3.12e-4	128	7.81e-4	6,250	2,775,000	64.2
ALBETO xxlarge	3.12e-4	128	7.81e-4	3,125	1,650,000	70.7

**Table:** Training details of all ALBETO models, which were trained using a single TPU v3-8 each one.

# ALBETO - Training Loss - tiny

---

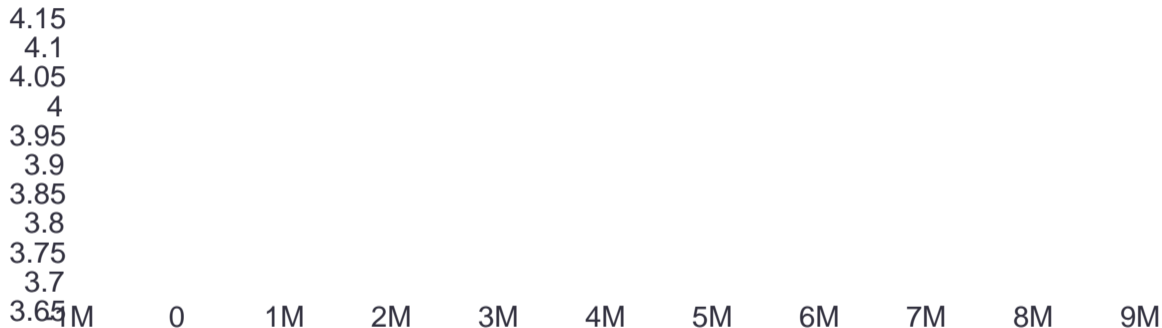


Figure: The progression of the training loss on the ALBETO tiny model.

# ALBETO - Training Loss - base

---

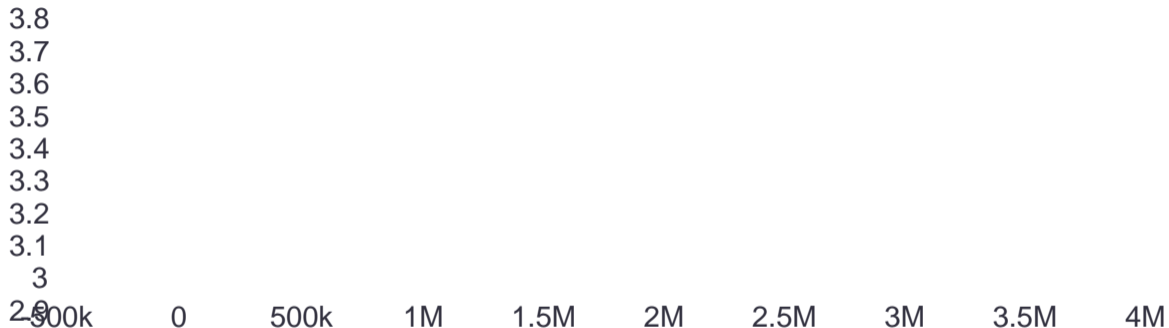


Figure: The progression of the training loss on the ALBETO base model.

# ALBETO - Training Loss - large

---

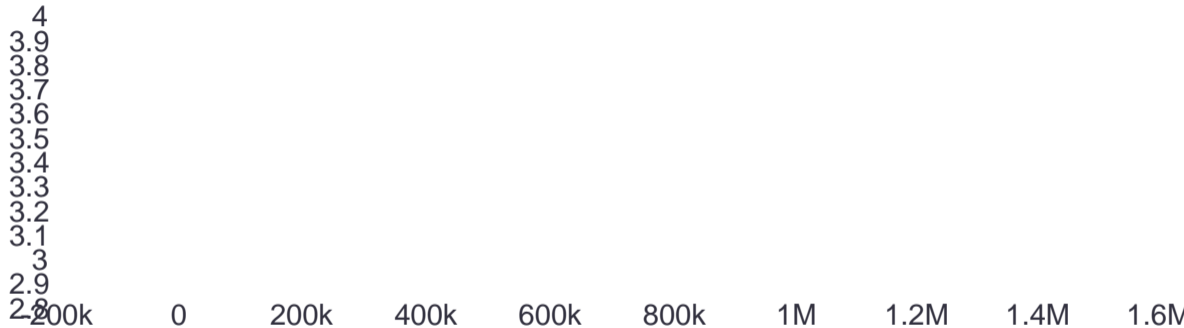


Figure: The progression of the training loss on the ALBETO-large model.

# ALBETO - Training Loss - xlarge

---

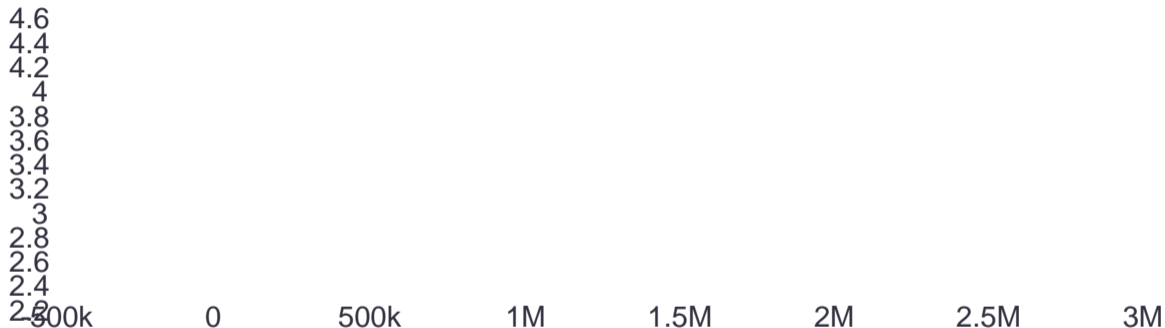


Figure: The progression of the training loss on the ALBETO xlarge model.

# ALBETO - Training Loss - xxlarge

---

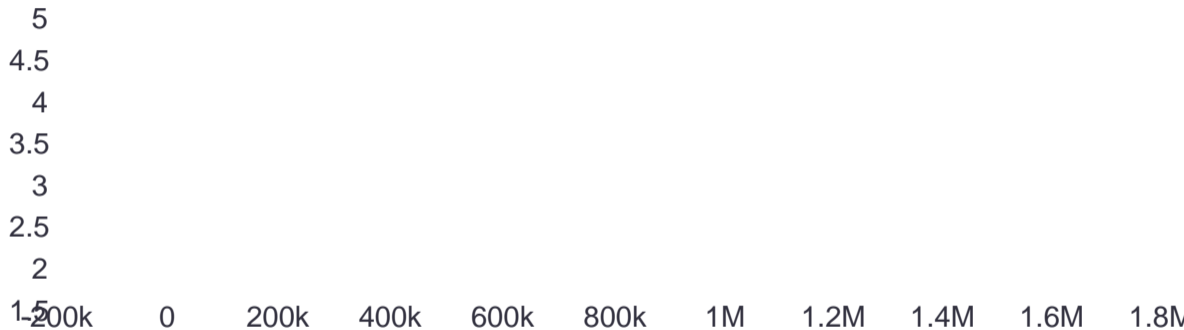


Figure: The progression of the training loss on the ALBETO-xxlarge model.

# ALBETO - Fine-tuning Details

---

We conducted a hyperparameter search on BETO, DistilBETO, RoBERTa-BNE, BERTIN, ALBETO tiny and base exploring combinations of batch size 16, 32, 64, learning rate 1e-5, 2e-5, 3e-5, 5e-5 and number of epochs 2, 3, 4.

For the larger ALBETO models (large, xlarge, and xxlarge), we reduced the learning rates to 1e-6, 2e-6, 3e-6, 5e-6 to mitigate numerical instability issues during training.

These fine-tuning procedures were performed on one to two NVIDIA RTX 3090 GPUs, depending on the model and task.

To fine-tune the largest models on QA, we utilized two NVIDIA A100 GPUs from the Patagon supercomputer [31].

We used gradient accumulation in situations where the GPU memory was insufficient to reach the target batch size.

# Speedy Gonzales: KD Implementation - Text Classification - Single Sentence

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# Speedy Gonzales: KD Implementation - Text Classification - Two Sentences

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# Speedy Gonzales: KD Implementation - Sequence Tagging

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Figure: Implementation of KD for sequence tagging tasks. The tokens marked with the blue color represents the property of being the first token of a word.

# Speedy Gonzales: KD Implementation - Sequence Tagging - Same Vocabulary

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Figure: Implementation of KD for sequence tagging tasks with models that share the same vocabulary.

# Speedy Gonzales: KD Implementation - Question Answering

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Figure: Implementation of KD for question answering datasets. The tokens marked with the blue color represents the property of being the first token of a word.

# Speedy Gonzales: KD Implementation - Question Answering - Same Vocabulary

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Figure: Implementation of KD for question answering datasets with models that share the same vocabulary.

# Speedy Gonzales: Other details

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Our code uses Python and PyTorch [32].

To measure MACs we used the THOR<sup>1</sup> library.

We conducted initial experiments utilizing three distinct loss functions: mean-squared error loss, cross-entropy loss, and KL-divergence loss. We varied the parameters  $\alpha$  and  $T$  across these losses using Optuna [1]. The outcomes of these experiments revealed that the optimal settings were  $\alpha = 0$  and  $T = 1$ . Although all three losses yielded satisfactory outcomes with this configuration, KL-divergence produced marginally superior results.

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<sup>1</sup><https://github.com/Lyken17/pytorch-OpCounter>

# Speedy Gonzales: Selected Teacher Models

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Dataset	Teacher Model
MLDoc	RoBERTa BNElarge
PAWS-X	ALBETO xxlarge
XNLI	ALBETO xxlarge
POS	RoBERTa BNEbase
NER	RoBERTa BNEbase
MLQA	ALBETO xxlarge
SQAC	ALBETOxxlarge
TAR / XQuAD	ALBETO xxlarge

Table: The teacher models selected for each task.

Table 10 presents the teacher models selected for each task. The selection process is based on the lowest validation loss achieved among the candidate teacher models that were ne-tuned for each task.

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# Light and Fast Language Models for Spanish Through Compression Techniques

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