This paper presents the Spanish RoBERTa-base and RoBERTa-large models, as well as the corresponding performance evaluations. Both models were pre-trained using the largest Spanish corpus known to date, with a total of 570GB of clean and deduplicated text processed for this work, compiled from the web crawlings performed by the National Library of Spain from 2009 to 2019.

1 Introduction and Previous Work

In recent years, the language-specific modeling literature has been quite prolific [1]. In the case of Spanish, BETO [2], a Spanish BERT [3], outperformed a strong multilingual baseline, mBERT. BETO was trained with a collection of existing corpora, such as the Spanish Wikipedia. Nevertheless, there aren’t many high-quality Spanish-specific models available.

In this work, we:

1. process the largest clean Spanish corpus based on the web crawlings performed by the National Library of Spain from 2009 to 2019,
2. train RoBERTa-base [4] and RoBERTa-large (the largest Spanish-specific model to date) models with these data[1]
3. conduct a complete evaluation on a diverse set of tasks.

*Equal contribution.

Publicly available at https://huggingface.co/BSC-TeMU/roberta-base-bne and https://huggingface.co/BSC-TeMU/roberta-large-bne.
In Section 2, we describe the new dataset and how we generated it. In Section 3, we compute word embeddings as a simple baseline for future experiments. Then in Section 4, we describe the new RoBERTa models. In Section 5, we evaluate the new models and compare their results with strong monolingual (BETO) and multilingual (mBERT) models. In addition, we compare it to the BERTIN model produced in the Flax/Jax Community Week. Finally, we present our conclusions and suggest future work, in Section 6.

2 Data

The National Library of Spain (Biblioteca Nacional de España) crawls all .es domains once a year. Besides this massive crawl, the library performs selective crawls that can be classified into three categories: themed based (this includes 15 different thematic collections, from fine arts to universities, feminism and politics), relevant events (that is, events of special relevance for the Spanish society, and of special significance for future research on Spanish history, society and culture) and domains at risk of disappearing. The data used for training the language models derive from these selective crawls, carried out from 2009 to 2019.

Due to the size of the data, the Library ran the first data extraction from WARC formatted files using the Selectolax Python library in its own premises. This process generated 59TB of JSON files containing some metadata along with the text extracted from the WARC files, namely: paragraphs, headers, keywords and links’ texts.

To ensure the quality of the data, we developed a cleaning pipeline which splits data into sentences, detects the language, removes noisy and ill formed sentences (based on some heuristics), deduplicates and eventually outputs the data with their original document boundaries. The pipeline is inspired by the heuristics proposed in Virtanen et al. For this cleaning process, we used 100 nodes with 48 CPU cores of MareNostrum 4 during 96h. At the end of the process we were left with 2TB of clean data at the document level. Finally, to remove repetitive content, we concatenated the entire corpus and deduplicated again, obtaining a total of 570GB of high quality data.

3 Embeddings

We computed both CBOW and Skip-gram word embeddings with 300 dimensions using FastText and are available on Zenodo:

- CBOW
- Skip-gram

With the clean data at document level mentioned on the Corpora section, the processing took around 20 days on a HPC node equipped with an AMD EPYC 7742 (@ 2.250GHz) processor using the 128 threads.

4 Models

The architecture and training procedure (masked language modeling without next sentence prediction) selected for our models was RoBERTA, in base and large sizes (following the standard BERT nomenclature). Both models were pre-trained for a single epoch as proposed in Komatsuzaki, following recent trends. Following the mentioned literature, we do not use dropout to increase convergence speed taking into account that the model will not overfit to a large dataset in a single pass, but keep weight decay to 0.01 because it has been proven to still be beneficial in single-epoch regimes. As vocabulary, we use Byte-Level BPE as in the original RoBERTa, trained with our train corpus. For training, we use the Fairseq library, and for fine-tuning, Huggingface Transformers.

5 Evaluation

We compare our RoBERTa base and RoBERTa large models with the mBERT, BETO and BERTIN models.
The BERT multilingual base model cased (mBERT) is a BERT language model with 12 self-attention layers, 12 attention heads each, a hidden size of 768, and a total of 110M parameters. It was pretrained on 104 languages with the Wikipedia dataset.

The Spanish-BERT model (BETO) has 12 self-attention layers, 16 attention heads each, a hidden layer of 1024 as hidden size, and a total of 110M parameters. It was pretrained with text from different sources: all the Spanish data from Wikipedia and the Spanish portion of the OPUS Project[^10].

The BERTIN model is a RoBERTa-large model with 24 layers, 16 attention heads each, hidden size of 1024, and a total 355M parameters. It was trained from scratch on the Spanish portion of mC4.

We fine-tuned each model in the following tasks:

- The Cross-lingual Adversarial Dataset for Paraphrase Identification (PAWS-X) [13].
- The Multilingual Document Classification Corpus (MLDoc) [14, 15].
- Named Entity Recognition from the Capitel Corpus (Capitel-NER) [11].
- Part of Speech from the Capitel Corpus (Capitel-POS) [12].
- Semantic Textual Similarity (STS) from 2014 [16] and 2015 [17].
- Part of Speech from Universal Dependencies (UD-POS).
- The Cross-Lingual NLI Corpus (XNLI) [18].
- Named Entity Recognition from Conll2002 (Conll-NER) [19].

For all models and tasks, we conduct a small grid search and pick the best value for each model:

- Batch size: 16, 32.
- Weight decay: 0.01, 0.1.
- Learning rate: 1e-5, 3e-5, 5e-5.
- Epochs: The best (as per the validation set) out of 5 epochs.

Table 1 summarizes the results with the best configurations for all models and tasks. Then, tables 8, 7, 5, 4, 6, 2, 9, and 3 report the best hyperparameters for each model for PAWS, MLDoc, Capitel-NER, Capitel-POS, STS, UD-POS, XNLI, and Conll-NER, respectively.

We note that these are preliminary results and that the final evaluation is subject to change, especially in terms of the RoBERTa-large fine-tuning, for which we have encountered some numerical instability due to the difficulty of training large models.

| Dataset      | Metric | RoBERTa-b F1 | RoBERTa-l F1 | BETO F1 | mBERT F1 | BERTIN F1 |
|--------------|--------|--------------|--------------|---------|----------|-----------|
| UD-POS       | F1     | **0.9907**   | 0.9901       | 0.9900  | 0.9886   | 0.9904    |
| Conll-NER    | F1     | **0.8851**   | 0.8772       | 0.8759  | 0.8691   | 0.8627    |
| Capitel-POS  | F1     | 0.9846       | **0.9851**   | 0.9836  | 0.9839   | 0.9826    |
| Capitel-NER  | F1     | 0.8959       | **0.8998**   | 0.8771  | 0.8810   | 0.8741    |
| STS          | Combined | **0.8423**  | 0.8420       | 0.8216  | 0.8249   | 0.7822    |
| MLDoc        | Accuracy | 0.9595       | 0.9600       | 0.9650  | 0.9560   | **0.9673** |
| PAWS-X       | F1     | **0.9035**   | 0.9000       | 0.8915  | 0.9020   | 0.8820    |
| XNLI         | Accuracy | 0.8016       | 0.8130       | 0.7876  | 0.8130   | WiP       |

Table 1: Evaluation table of models.

[^10]: https://opus.nlpl.eu/
[^11]: https://sites.google.com/view/capitel2020#p_CbqX2kG3XE1p
[^12]: https://sites.google.com/view/capitel2020#p_eFfF6UC3XFMc
[^13]: https://universaldependencies.org/
| Model      | Batch Size | Weight decay | Learning rate | Eval F1   | Test F1  |
|------------|------------|--------------|---------------|-----------|----------|
| RoBERTa-b  | 16         | 0.10         | 5e-5          | 0.9907    | **0.9907** |
| RoBERTa-l  | 32         | 0.10         | 3e-5          | 0.9910    | 0.9901   |
| BETO       | 16         | 0.01         | 3e-5          | 0.9907    | 0.9900   |
| mBERT      | 32         | 0.10         | 5e-5          | 0.9892    | 0.9886   |
| BERTIN     | 8          | 0.10         | 5e-5          | 0.9898    | 0.9904   |

Table 2: Best configurations for the eval UD-POS dataset with F1 score for eval and test.

| Model      | Batch Size | Weight decay | Learning rate | Eval F1   | Test F1  |
|------------|------------|--------------|---------------|-----------|----------|
| RoBERTa-b  | 32         | 0.01         | 5e-5          | 0.8870    | **0.8851** |
| RoBERTa-l  | 32         | 0.01         | 1e-5          | 0.8882    | 0.8772   |
| BETO       | 16         | 0.10         | 3e-5          | 0.8710    | 0.8759   |
| mBERT      | 16         | 0.10         | 3e-5          | 0.8727    | 0.8691   |
| BERTIN     | 16         | 0.01         | 5e-5          | 0.8690    | 0.8627   |

Table 3: Best configurations for the eval CoNLL-NER dataset with F1 score for eval and test.

| Model      | Batch Size | Weight decay | Learning rate | Eval F1   | Test F1  |
|------------|------------|--------------|---------------|-----------|----------|
| RoBERTa-b  | 32         | 0.10         | 5e-5          | 0.9848    | 0.9846   |
| RoBERTa-l  | 16         | 0.01         | 1e-5          | 0.9854    | **0.9851** |
| BETO       | 32         | 0.10         | 5e-5          | 0.9839    | 0.9836   |
| mBERT      | 16         | 0.10         | 5e-5          | 0.9835    | 0.9839   |
| BERTIN     | 16         | 0.10         | 5e-5          | 0.9835    | 0.9826   |

Table 4: Best configurations for the eval Capitel-POS dataset with F1 for eval and test.

| Model      | Batch Size | Weight decay | Learning rate | Eval Combined Score | Test Combined Score |
|------------|------------|--------------|---------------|---------------------|---------------------|
| RoBERTa-b  | 32         | 0.01         | 5e-5          | 0.9134              | **0.8423**          |
| RoBERTa-l  | 32         | 0.01         | 3e-5          | 0.9117              | 0.8420              |
| BETO       | 16         | 0.01         | 3e-5          | 0.9017              | 0.8216              |
| mBERT      | 16         | 0.01         | 3e-5          | 0.9122              | 0.8249              |
| BERTIN     | 32         | 0.01         | 5e-5          | 0.8612              | 0.7822              |

Table 6: Best configurations for the eval STS dataset with Combined Score for eval and test.

| Model      | Batch Size | Weight decay | Learning rate | Eval Accuracy | Test Accuracy |
|------------|------------|--------------|---------------|--------------|---------------|
| RoBERTa-b  | 32         | 0.10         | 3e-5          | 0.9750        | 0.9595        |
| RoBERTa-l  | 16         | 0.01         | 1e-5          | 0.9710        | 0.9600        |
| BETO       | 32         | 0.01         | 5e-5          | 0.9720        | 0.9650        |
| mBERT      | 16         | 0.01         | 1e-5          | 0.9670        | 0.9560        |
| BERTIN     | 32         | 0.10         | 3e-5          | 0.974         | **0.9673**    |

Table 7: Best configurations for the eval MLDoc dataset with accuracy for eval and test.
### Table 8: Best configurations for the eval PAWS-X dataset with F1 for eval and test.

| Model   | Batch Size | Weight decay | Learning rate | Eval F1 | Test F1 |
|---------|------------|--------------|---------------|---------|---------|
| RoBERTa-b  | 32         | 0.01         | 3e-5          | 0.9030  | 0.9035  |
| RoBERTa-l  | 32         | 0.10         | 1e-5          | 0.9015  | 0.9000  |
| BETO      | 16         | 0.01         | 3e-5          | 0.9035  | 0.8915  |
| mBERT     | 16         | 0.10         | 3e-5          | 0.9020  | 0.9020  |
| BERTIN    | 16         | 0.01         | 3e-5          | 0.8765  | 0.8820  |

### Table 9: Best configurations for the eval XNLI dataset with accuracy score for eval and test.

| Model   | Batch Size | Weight decay | Learning rate | Eval accuracy | Test accuracy |
|---------|------------|--------------|---------------|---------------|---------------|
| RoBERTa-b  | 16         | 0.01         | 3e-5          | 0.8124        | 0.8016        |
| RoBERTa-l  | WiP        | WiP          | WiP           | WiP           | WiP           |
| BETO      | 16         | 0.01         | 1e-5          | 0.8269        | 0.8130        |
| mBERT     | 32         | 0.10         | 1e-5          | 0.8032        | 0.7876        |
| BERTIN    | WiP        | WiP          | WiP           | WiP           | WiP           |

### 6 Conclusions & Future Work

In this work, we have processed the largest clean Spanish corpus to date. Furthermore, the textual richness provided by our dataset should be additive to the ones in the previously used Spanish datasets, because we have not used them (e.g., our models have not seen Wikipedia).

The RoBERTa-base model outperforms the strong BETO, mBERT and BERTIN baselines in most tasks (UD-POS, Conll-NER, Capitel-POS, Capitel-NER, STS and PAWS-X). The RoBERTa-large, despite obtaining better results than BETO and mBERT, struggles to outperform its base counterpart in all but two tasks, which we attribute to the difficulty of the process of optimization of larger models.

As future work, we are planning to 1. combine the new dataset with other sources (such as the Spanish Wikipedia), 2. further investigate the training procedure of RoBERTa-large to get its results to its full potential.

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Appendix I

This Appendix contains a sample of Masked Language Modelling prediction assessments for understanding the models’ predictions.

Agreement

Sentence: "Juana se dejó el libro en el coche porque es muy {mask} con sus cosas."
RoBERTa-base-BNE: ['lista', 'buena', 'cuidadosa', 'estrecha', 'generosa']
RoBERTa-large-BNE: ['cuidadosa', 'pesada', 'tranquila', 'lista', 'ocupada']
BETO: ['cuidadoso', 'sensible', 'buena', 'buena', 'fácil']
mBERT: ['buena', 'feliz', 'bien', 'triste', 'fuerte']
Sentence: "La chica que encontraron en el parque estaba leyendo un libro {mask} en el banco."
RoBERTa-base-BNE: ['sentada', 'sentado', 'tumbado', 'viejo', 'esperando']
RoBERTa-large-BNE: ['sentada', 'sentada', 'tumbado', 'y']
BETO: ['sienta', 'sentado', 'tumbado', 'preparado', 'preparada']
mBERT: ['sé', 'escrito', 'estaba', 'suyo', 'y']
Sentence: "De entre todas, eligieron en el concurso de baile a quién estaba mejor {mask}."
RoBERTa-base-BNE: ['vestida', 'preparada', 'dotado', 'vestido', 'preparado']
RoBERTa-large-BNE: ['vestida', 'vestido', 'preparada', 'formada']
BETO: ['vestida', 'vestido', 'vestidos']
mBERT: ['visto', 'el', 'colocado', 'ubican']
Sentence: "A la chica los pantalones le quedaban cortos porque eran muy {mask} para su edad."
RoBERTa-base-BNE: ['cortos', 'grandes', 'grandes', 'altos', 'pequeños']
RoBERTa-large-BNE: ['cortos', 'altos', 'grandes', 'altos']
BETO: ['cortos', 'pequeños', 'grandes', 'altos']
mBERT: ['grandes', 'populares', 'importantes', 'jóvenes', 'buenas']
Sentence: "Le gustaban mucho, pero no {mask} podía comprárlas porque eran demasiado caras."
RoBERTa-base-BNE: ['las', 'se', 'le', 'la', 'lo']
RoBERTa-large-BNE: ['siempre', 'se', 'tú', 'tú', 'me', 'todos']
BETO: ['se', 'siempre', 'le', 'les', 'las']
mBERT: ['se', 'le', 'leyo', 'sólo', 'lo']

Polarity agreement

Sentence: "Llegamos muy pronto y no pude hablar con {mask}."
RoBERTa-base-BNE: ['nosotros', 'vosotros', 'yo', 'ella']
RoBERTa-large-BNE: ['el', 'ella', 'ellos', 'yo', 'nadie']
BETO: ['él', 'ella', 'ellos', 'yo', 'nadie']
mBERT: ['ellos', 'el', 'ella', 'nada', 'ellas']
Sentence: "No lo había visto {mask}."
RoBERTa-base-BNE:['nunca', 'antes', 'yo', 'jamas', 'nadie']
RoBERTa-large-BNE: ['nunca', 'antes', 'yo', 'previamente']
BETO: ['antes', 'nunca', 'jamás', 'yo', 'anteriormente']
Lexical selection
Sentence: "Quita las manzanas verdes del cesto y deja solo las {mask}.
RoBERTa-base-BNE: [‘rojas’, ‘naranjas’, ‘verdes’, ‘amarillas’, ‘nueces’]
RoBERTa-large-BNE: [‘manzanas’, ‘de’, ‘naranjas’, ‘hojas’, ‘’]
BETO: [‘semillas’, ‘verdes’, ‘manzanas’, ‘rojas’, ‘malas’]
mBERT: [‘verdes’, ‘flores’, ‘manos’, ‘otras’, ‘mismas’]
Sentence: "Este es un problema para el cual la solución es {mask}.
RoBERTa-base-BNE: [‘sencilla’, ‘simple’, ‘inmediata’, ‘fácil’, ‘clara’]
RoBERTa-large-BNE: [‘sencilla’, ‘!’ ‘fácil’, ‘la’, ‘simple’]
BETO: [‘simple’, ‘sencilla’, ‘fácil’, ‘desconocida’, ‘complicada’]
mBERT: [‘simple’, ‘solución’, ‘problema’, ‘tiempo’, ‘necesaria’]
Sentence: "Tenemos un problema para el cual hay que tomar una decisión y hay que {mask}.
RoBERTa-base-BNE: [‘solucionarla’, ‘hacerlo’, ‘actuar’, ‘hablar’, ‘esperar’]
RoBERTa-large-BNE: [‘actuar’, ‘solucionarla’, ‘hacerlo’, ‘resolver’, ‘…’]
BETO: [‘actuar’, ‘hacerla’, ‘hacerlo’, ‘votar’, ‘tomar’]
mBERT: [‘decidir’, ‘hacerlo’, ‘hacer’, ‘tomar’, ‘pensar’]
Sentence: "Felipe {mask} que Juan conoce a Marta."
RoBERTa-base-BNE: [‘dice’, ‘cree’, ‘asegura’, ‘descubre’, ‘confiesa’]
RoBERTa-large-BNE: [‘dice’, ‘cree’, ‘confiesa’, a firmar’, ‘asegura’]
BETO: [‘descubre’, ‘dice’, ‘sabe’, ‘explica’, ‘revela’]
mBERT: [‘dice’, ‘ordenar’, ‘indica’, ‘de’, ‘a firmar’]
Sentence: "Mi amigo es bastante {mask}.
RoBERTa-base-BNE: [‘bueno’, ‘mayor’, ‘guapo’, ‘listo’, ‘grande’]
RoBERTa-large-BNE: [‘bueno’, ‘guapo’, ‘grande’, ‘interesante’, ‘divertido’]
BETO: [‘bueno’, ‘guapo’, ‘fuerte’, ‘listo’, ‘inteligente’]
mBERT: [‘bien’, ‘fuerte’, ‘popular’, ‘importante’, ‘buen’]
Sentence: "Mi amiga es bastante {mask}.
RoBERTa-base-BNE: [‘buena’, ‘mayor’, ‘mala’, ‘guapa’, ‘lista’]
RoBERTa-large-BNE: [‘buena’, ‘linda’, ‘guapa’, ‘interesante’, ‘grande’]
BETO: [‘buena’, ‘guapa’, ‘bonita’, ‘agradable’, ‘hermosa’]
mBERT: [‘fuerte’, ‘buena’, ‘bien’, ‘regular’, ‘cercana’]
Sentence: "Salió a cazar y mató un {mask}.
RoBERTa-base-BNE: [‘leon’, ‘perro’, ‘toro’, ‘conejo’, ‘gato’]
RoBERTa-large-BNE: [‘leon’, ‘perro’, ‘lobo’, ‘hombre’, ‘oso’]
BETO: [‘oso’, ‘conejo’, ‘zorro’, ‘león’, ‘perro’]
mBERT: [‘hombre’, ‘soldado’, ‘piloto’, ‘caza’, ‘home’]
Sentence: "Una {mask} situada en la región de Alta Normandía."
RoBERTa-base-BNE: [‘villa’, ‘ciudad’, ‘localidad’, ‘isla’, ‘aldea’]
Te voy a contar una {mask} sobre mi prima.

Martin se {mask} para ir a pescar al río.

Llamó a su {mask} porque se encontraba mal.

Llamó a su {mask} porque el coche hacía un ruido ra ro.

Lleva a su {mask} para ir a pescar al río.
Sentence: "Los {mask} también pueden llevar falda."
RoBERTa-base-BNE: ["hombres", "nios", "chicos", "futbolistas", "bebs"]
RoBERTa-large-BNE: ["hombres", "nios", "chicos", "bebs", "perros"]
BETO: ["hombres", "nios", "varones", [UNK]", "perros"]
mBERT: ["caballos", "animales", "hombres", "romanos", "colores"]
Sentence: "El papel de la mujer en la ciencia es {mask}."
RoBERTa-base-BNE: ["fundamental", "imprecindible", "incuestionable", "clave", "crucial"]
RoBERTa-large-BNE: ["fundamental", "el", "esencial", "clave", "crucial"]
BETO: ["fundamental", "relevant", "crucial", "importante"]
mBERT: ["social", "fundamental", "diferente", "importante", "universal"]
Sentence: "El papel de la {mask} en la ciencia es relevante."
RoBERTa-base-BNE: ["ciencia", "empresa", "sociedad", "educacin", "Universidad"]
RoBERTa-large-BNE: ["ciencia", "empresa", "msica", "sociedad", "historia"]
BETO: ["sociedad", "educacin", "politica", "economia", "cultura"]
mBERT: ["sociedad", "mujer", "educacin", "vida", "cultura"]
Sentence: "Lo m s importante para ella es su {mask}."
RoBERTa-base-BNE: ["salud", "familia", "vida", "futuro", "trabajo"]
RoBERTa-large-BNE: ["corazon", "sonrisa", "familia", "marido", "hijo"]
BETO: ["seguridad", "familia", "vida", "felicidad", "trabajo"]
mBERT: ["vida", "trabajo", "amor", "clase", "voz"]
Sentence: "Lo m s importante para ella es su {mask}."
RoBERTa-base-BNE: ["salud", "vida", "familia", "trabajo", "felicidad"]
RoBERTa-large-BNE: ["familia", "sonrisa", "persona", "trabajo", "equipo"]
BETO: ["familia", "seguridad", "trabajo", "vida", "dinero"]
mBERT: ["vida", "amor", "voz", "trabajo", "educacin"]
Sentence: "Los {mask} son groseros y violentos."
RoBERTa-base-BNE: ["comentarios", "insultos", "animales", "hombres", "dos"]
RoBERTa-large-BNE: ["comentarios", "insultos", "nios", "mensajes", "dos"]
BETO: ["hombres", "animales", "nios", "humanos", "adultos"]
mBERT: ["pies", "frutos", "ojos", "postes", "otros"]
Sentence: "No vayas por esa calle, que hay muchos {mask} y te podrías pasar algo."
RoBERTa-base-BNE: ["coches", "sitos", "perros", "problemas", "nios"]
RoBERTa-large-BNE: ["coches", "sitos", "semforos", "peligros", "robos"]
BETO: ["coches", "policas", "robos", "edificios", "nios"]
mBERT: ['nios', 'barrios', 'lugares', 'personas']
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