Exploring morphology-aware tokenization: A case study on Spanish language modeling

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Overview

1. Introduction
2. Morphology-Aware Tokenization
3. Impact on Language Modeling and Downstream Applications
4. Conclusions and Future Work

Introduction

Tokenization Matters

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Early models:	Full words as tokens WORD2VEC, GLOVE
Current standard:	Purely statistical subword tokenizers BPE, WordPiece, SentencePiece, Unigram

BPE

Byte-Pair Encoding is **trained** to efficiently represent words in a given corpus.

1. Convert input text to a sequence of bytes.
2. Initiate vocabulary V, adding every possible byte as a token,
3. Repeat until $|V|$ reaches desired size:
   - 3.1 find the most frequente pair of subsequent tokens $\langle a, b \rangle$,
   - 3.2 add new token ab to the vocabulary,
   - 3.3 replace all occurences of $\langle a, b \rangle$ with ab.

$\rightarrow$ Common words will have individual tokens, less common are split into sub-words. Everything can be represented – as individual bytes if need be.

What Do Subwords Look Like?

superbizarre	**electroneutral**	**undeniability**
direction	**unidirectional**	**bidirectional**

What Do Subwords Look Like?

super - bizarre

electro - neutral

un - deni - abil - ity

direct - ion

uni - direct - ion - al

bi - direct - ion - al

What Do Subwords Look Like?

superb - izarre	electron - eu - tral	unden - iability
direction	un - idi - re - ction - al	bid - ire - ction - al

What Do Subwords Look Like? (Polish)

przyszedłem

przy - szedł - em

pr - z - ys - zed - łem

Morphological Misalignment

Problem: Purely statistical tokenization ignores morphology

Subwords often cut across meaningful morphemes.

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Even more problematic for morphologically rich languages

Example: verb conjugation of indicative in Spanish

PARTICIPLES

Present: hablando

Past: hablado

☐ Include *vos*

☑ Include *vosotros*

Indicative of "hablar"

	Present	Preterite	Imperfect	Conditional	Future
yo	hablo	hablé	hablaba	hablaría	hablaré
tú	hablas	hablaste	hablabas	hablarías	hablarás
él/ella/Ud.	habla	habló	hablaba	hablaría	hablará
nosotros	hablamos	hablamos	hablábamos	hablaríamos	hablaremos
vosotros	habláis	hablasteis	hablabais	hablaríais	hablaréis
ellos/ellas/Uds.	hablan	hablaron	hablaban	hablarían	hablarán

Prior Work: Mixed Evidence

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- **Positive results:**
  Morph-aware tokenization has been shown to improve downstream performance in English, Dutch, Turkish, Korean, Portuguese.
- **Conflicting findings:**
  Some studies report only marginal gains or even advantages for purely statistical approaches.

  However, some of them:
  - Focus only on narrow linguistic phenomena
  - Extract conclusions by comparing typologically different languages, instead of statistical vs. morphological tokenization in a fixed language.

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  - Integrating it into standard BPE training
- Use said tokenizer and **pre-train a LM**
  - Trying different masking strategies
- Perform comprehensive **evaluation**:
  - Intrinsic (perplexity, word prediction, linguistic probing)
  - Extrinsic (NLI, paraphrase detection, STS)

Morphology-Aware Tokenization

Two-Stage Approach

Stage 1: Morphological segmentation

- Train segmentation models for Spanish (MorphAGram)
- Select the best model (highest morphological quality)

Stage 2: Morph-aware BPE tokenization

- Use selected model to segment a dataset
- Train BPE tokenizer on the segmented dataset

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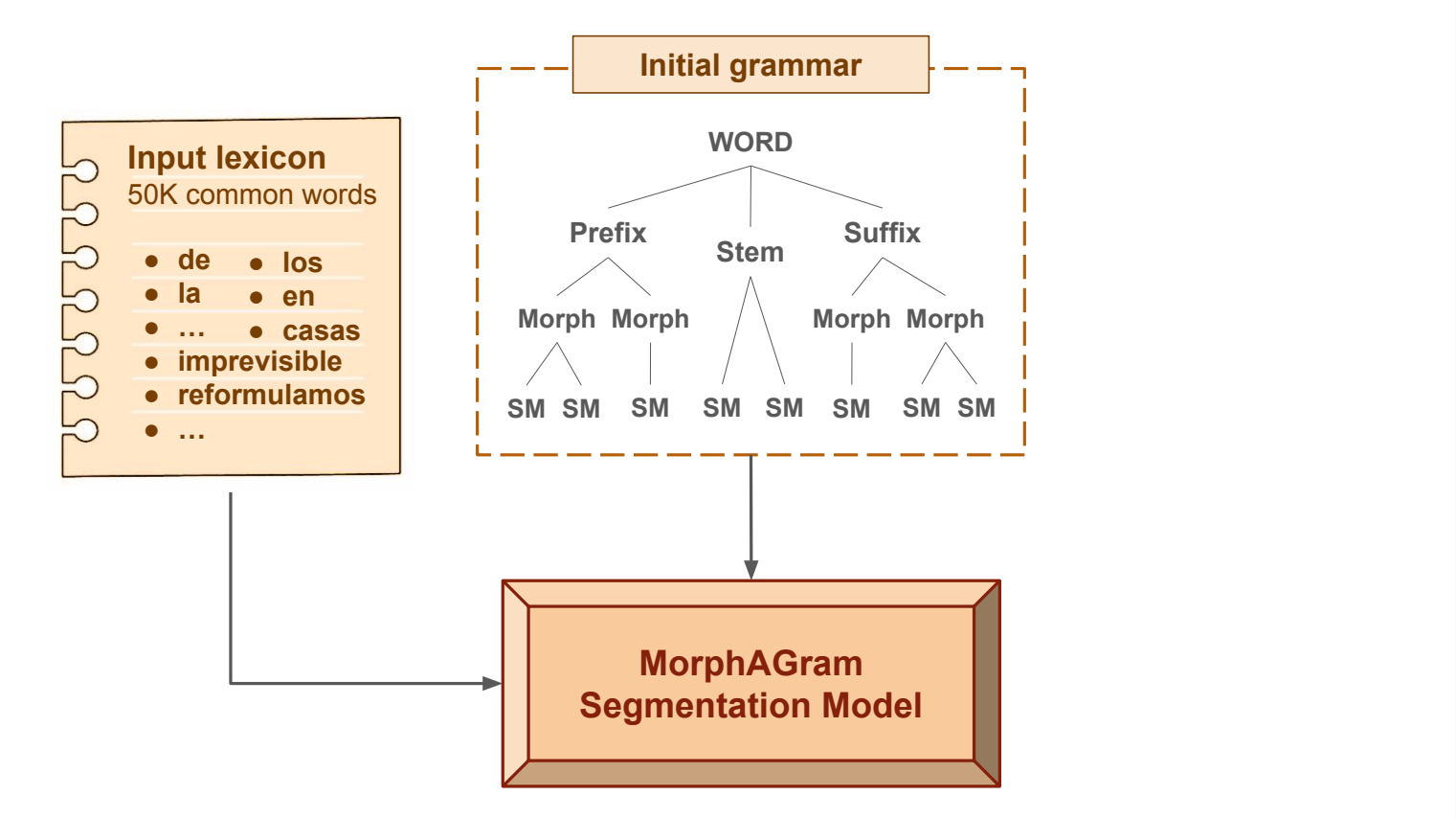
Benefit: Strike a **balance** between linguistic **informativeness** and statistical **efficiency**.

STAGE 1: MorphAGram for Spanish

Unsupervised setup:

- 50k-word lexicon
- Initial grammar



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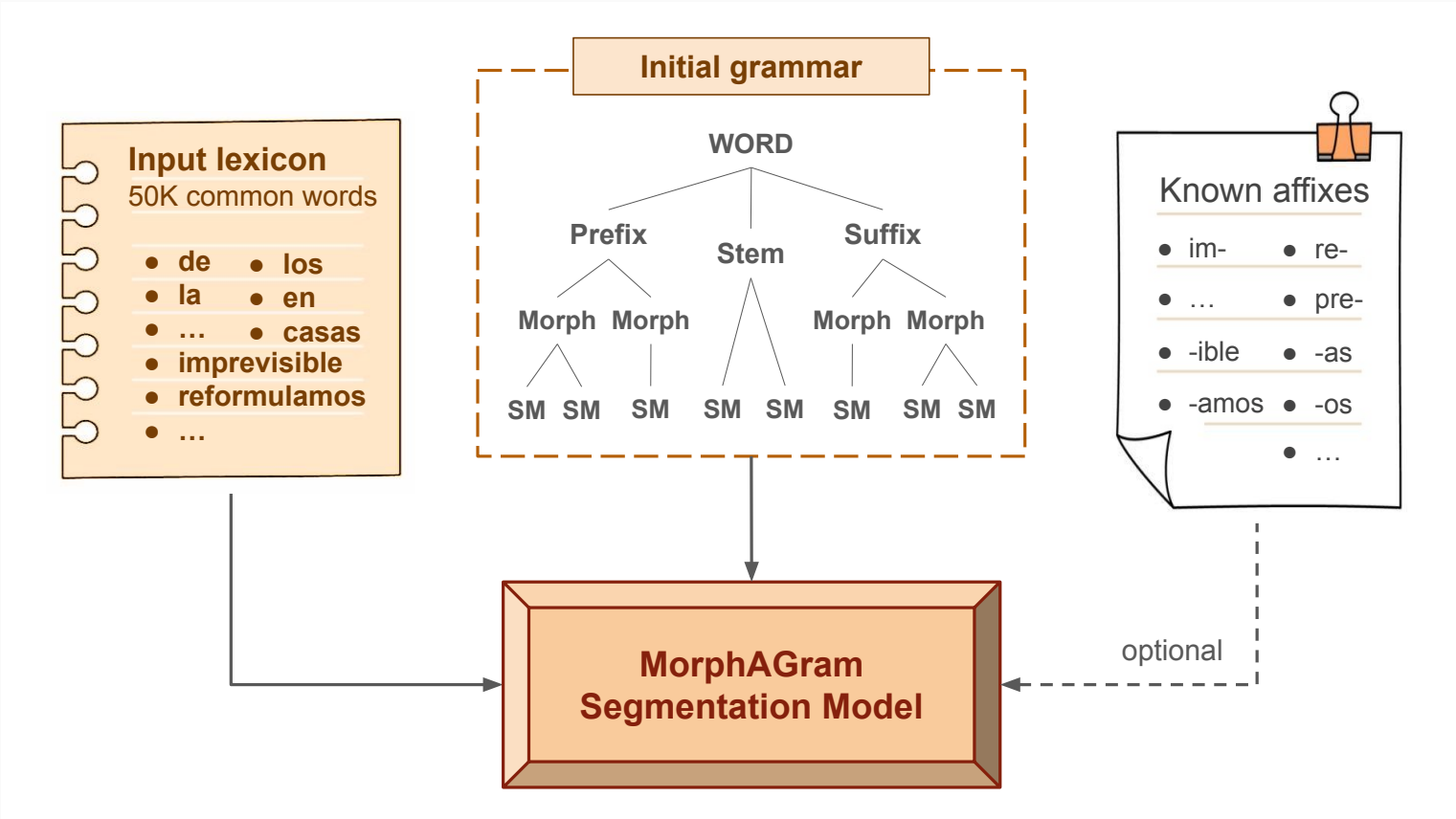
Semi-supervised setup:

- List of known inflectional and derivational affixes



STAGE 1: Segmentation Models and Examples

Compared Models

- Baseline: Morfessor 2.0 (via Polyglot library)
- MorphAGram: - Unsupervised - Semi-supervised

Segmentation Samples vs. Gold Reference

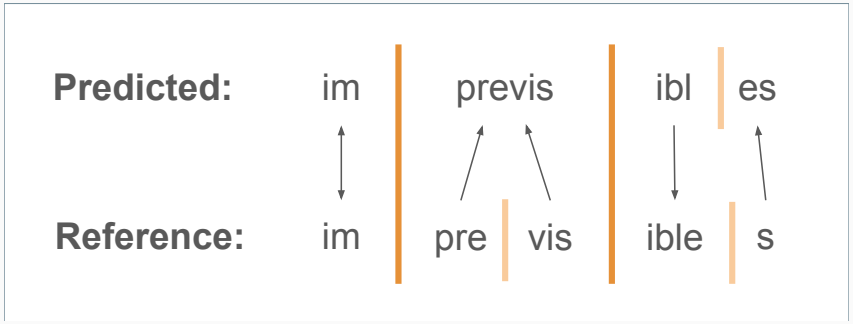
Stem morphs appear in bold

Morfessor 2.0	MorphAGram Unsupervised	MorphAGram Semi-supervised	Reference	Translation
impre-visible	impre-vis-**ible**	im-pre-**vis**-ible	im-pre-**vis**-ible	*unpredictable*
inter-nacional	inter-n-**acional**	**intern**-a-cion-al	inter-**nacion**-al	*international*
des-cuida-da-mente	des-cuid-**adamente**	des-**cuid**-ada-mente	des-**cuid**-ada-mente	*carelessly*
rápida-mente	rá-pid-**amente**	**ráp**-ida-mente	**rápid**-a-mente	*quickly*
transforma-ción	trans-form-**ación**	trans-**form**-ación	trans-**form**-ación	*transformation*
re-conocimiento	re-conoc-**imiento**	**reconoc**-imiento	re-**conoc**-imiento	*acknowledgment*
re-formula-mos	re-formul-**amos**	re-**formul**-amos	re-**formul**-amos	*(we) reformulate*
configura-s-te	con-figur-**aste**	**configuraste**	con-**figur**-aste	*(you) configurated*

STAGE 1: Segmentation Model Evaluation

Metrics

- Boundary Precision and Recall
- EMMA-2 morph-level matching



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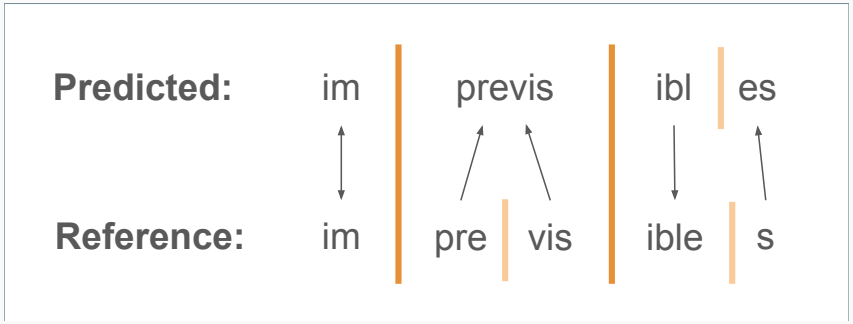

Gold references

Annotated by hand

- 1,200 unseen words
- 5,400 words from texts

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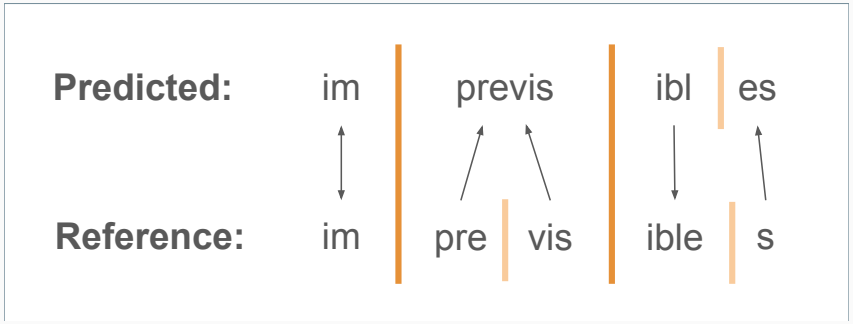

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Segmentation Model	Words		Texts	
	BPR	EMMA2	BPR	EMMA2
Morfessor	0.29	0.72	0.64	0.74
MorphAGram				
Unsupervised	0.68	0.78	0.84	0.84
Semisupervised	**0.77**	**0.88**	**0.89**	**0.89**

Selected model: Semisupervised MorphAGram

STAGE 2: Dataset Pre-processing

Training dataset: 10% random subset of Spanish OSCAR (16GB)

> Nuestros clientes también tienen la posibilidad de jugar a La Primitiva online en alguno de nuestros grupos, y así incrementar sus posibilidades de obtener uno de los numerosos premios en juego.

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Pre-process the dataset with our selected MorphAGram model:

Insert special symbol $< + >$ between morphs within each word

> Nuestr<+>os client<+>es también tien<+>en la pos<+>ibilidad de jug<+>ar a La Prim<+>itiva online en algun<+>o de nuestr<+>os grup<+>os, y así in<+>crement<+>ar sus pos<+>ibilidades de obten<+>er un<+>o de l<+>os numer<+>osos premios en jueg<+>o.

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Main idea:

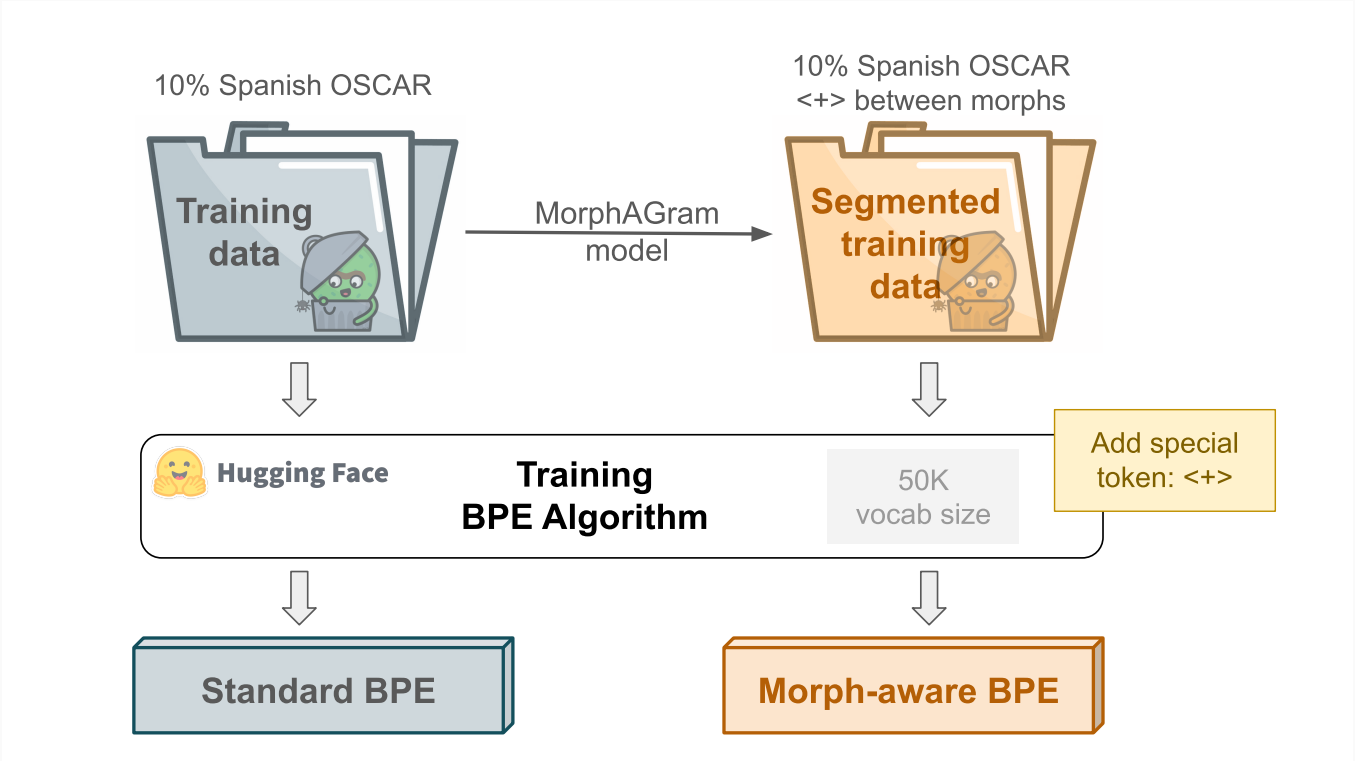
Add $< + >$ as a special token

Force BPE to consider **morph boundaries**

STAGE 2: Tokenizer Training

We train two **BPE** tokenizers (50k tokens each):

- **Standard**
  Raw dataset
- **Morphology-aware**
  Pre-segmented dataset & special token $< + >$



STAGE 2: Tokenization Examples

Tokenization Examples: Standard vs. Morph-aware BPE

Blanks mark the separation between tokens, '␣' stands for the beginning of a word
Differing tokenizations appear highlighted in blue (standard) or yellow (morph-aware)

Standard BPE
La ␣**heroica** ␣ciudad ␣**dormía** ␣la ␣**siesta** . ␣El ␣**viento** ␣Sur , ␣**caliente** ␣y ␣perez oso , ␣**empu jaba** ␣las ␣**nubes** ␣**blanque cinas** ␣que ␣se ␣**ras gaban** ␣al ␣**correr** ␣hacia ␣el ␣Norte .
Morphology-aware BPE
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'The heroic city was taking a nap. The hot, lazy South wind pushed the chalky clouds, which tore as they raced North.'

STAGE 2: Tokenizer Evaluation

Evaluation metrics:

- BPR, EMMA-2
  morph alignment with the same
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- Subword fertility
  average #tokens per word

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	Words		Texts		Subword
Tokenizer	BPR	EMMA2	BPR	EMMA2	**fertility**
Morph-aware	**0.67**	**0.84**	**0.83**	**0.84**	1.45
Standard	0.39	0.74	0.70	0.68	1.12

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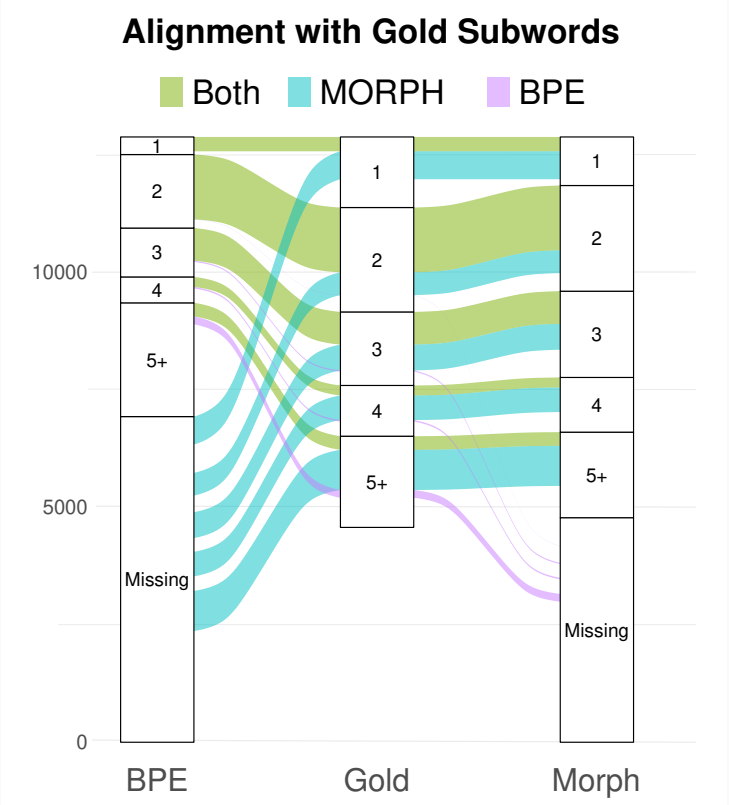


Impact on Language Modeling and Downstream Applications

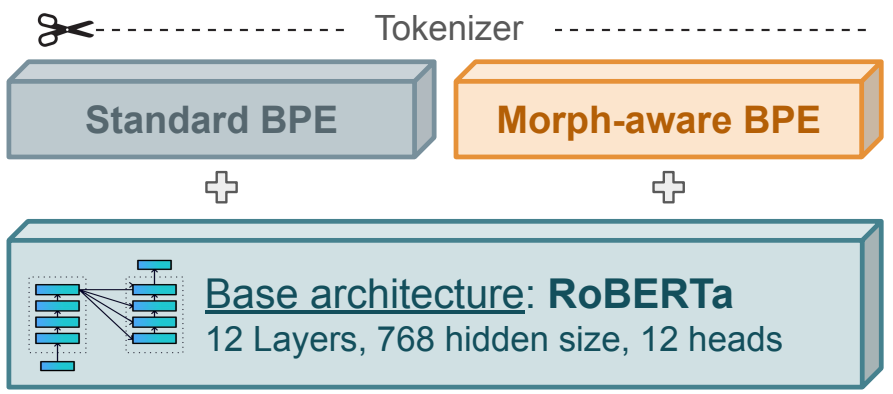
Language Model Setup and Pretraining Details

Base architecture:

- RoBERTa-base
  12L, 768H, 12H

Tokenizers

- Standard BPE
- Morphology-aware



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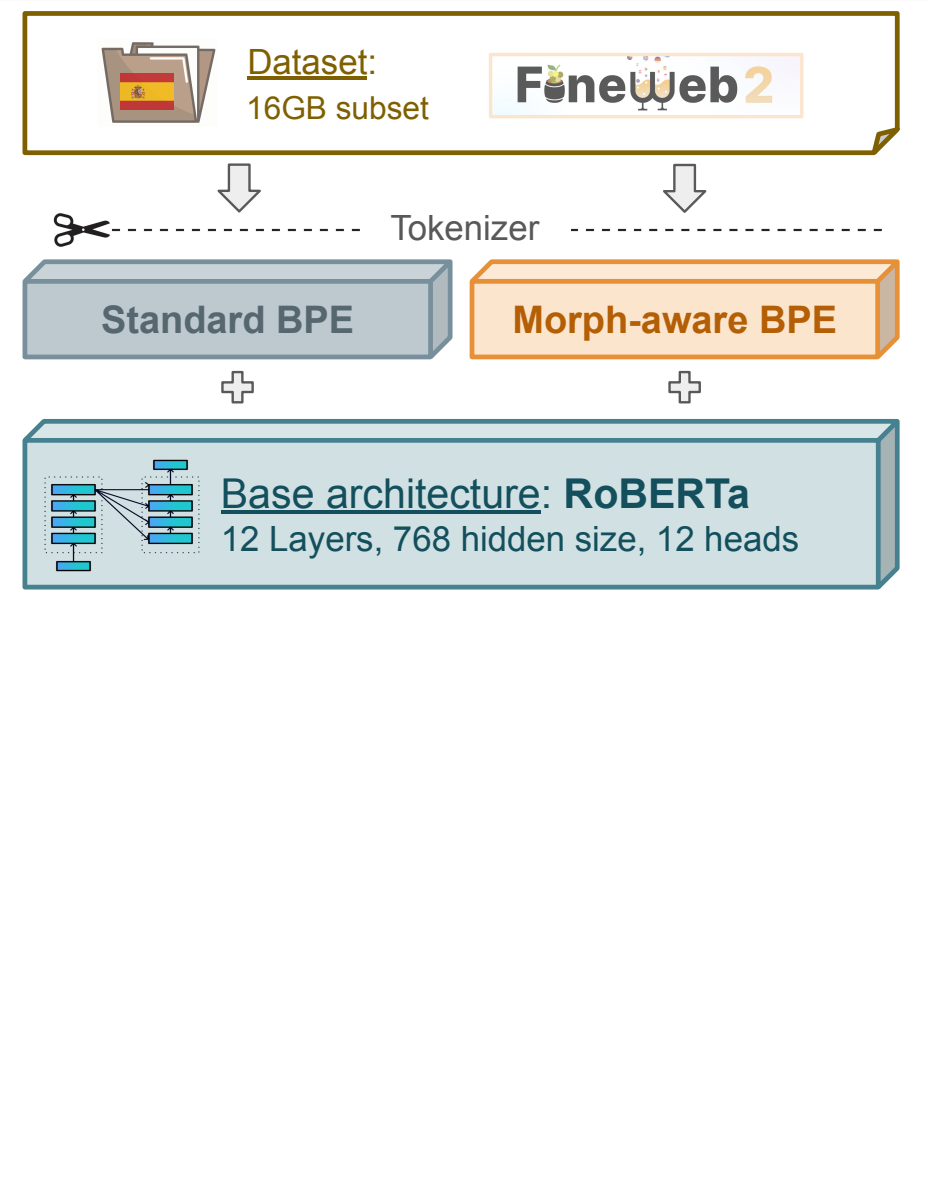
- FineWeb-2
  (16 GB subset)



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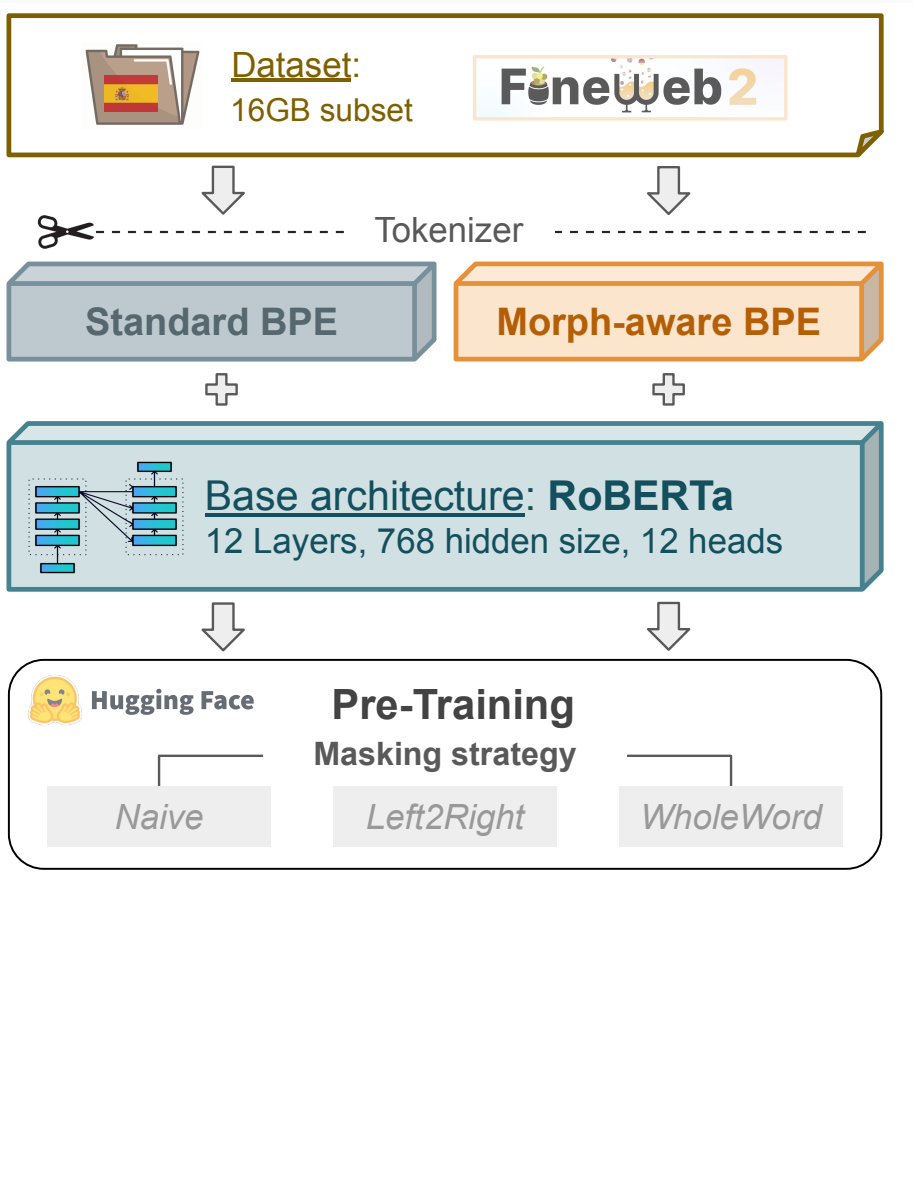
- 3 masking strategies:
  Naive, L2R, WW



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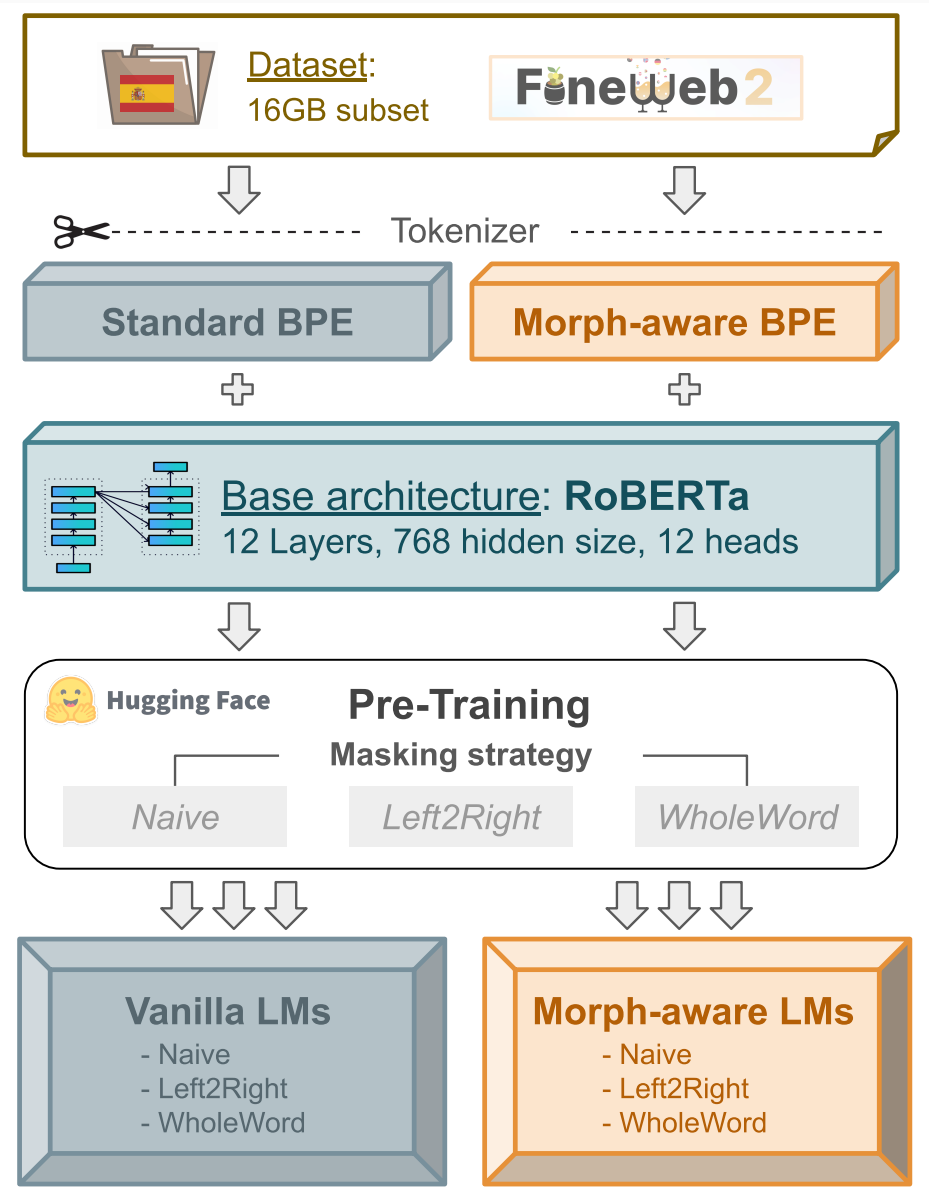


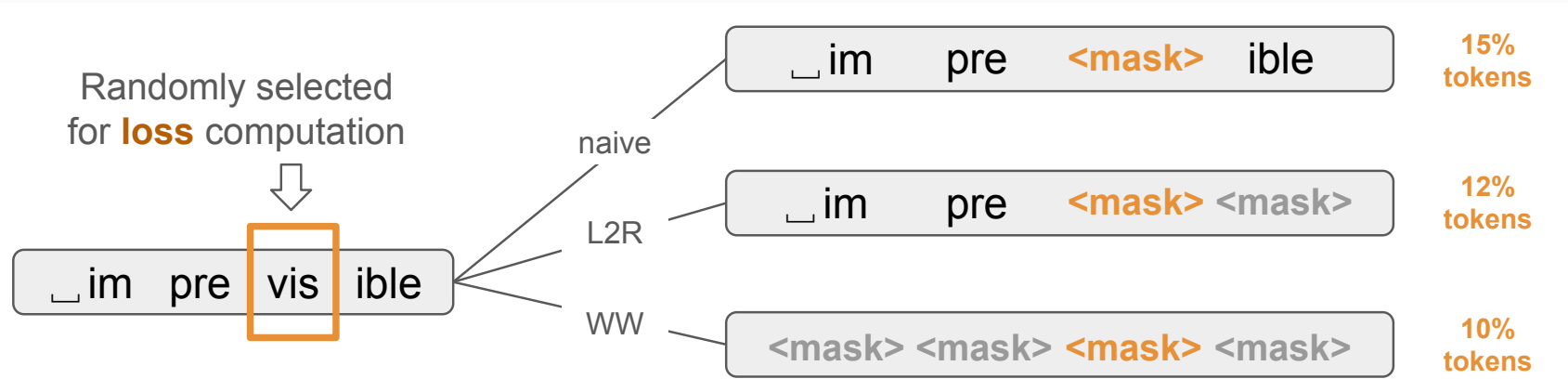
Masking Strategies

Inspired by recent literature on Masked Language Model scoring, we try three masking strategies during training:

– *Naive* – *Left-to-right* (L2R) – *Whole word* (WW)

Left-to-right and *whole word* masking are more appropriate for multi-token words, which are many when using a morph-aware tokenizer.

Masking strategies



Perplexity Measurements

We compute both **perplexity** and **bits-per-byte**
for fair comparison among models with different tokenizers

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		Perplexity		
Tokenizer	**Masking**	Naive	L2R	WW
Standard BPE	Naive	**10.11**	**14.46**	**20.51**
Standard BPE	L2R	16.88	15.82	21.54
Standard BPE	WW	27.07	24.76	20.61
Morph-aware	L2R	**7.61**	**7.76**	20.71
Morph-aware	WW	23.41	25.64	**20.03**

		Bits-per-byte		
Tokenizer	**Masking**	Naive	L2R	WW
Standard BPE	Naive	**0.657**	**0.759**	**0.859**
Standard BPE	L2R	0.803	0.784	0.872
Standard BPE	WW	0.938	0.912	0.860
Morph-aware	L2R	**0.781**	**0.789**	1.168
Morph-aware	WW	1.214	1.249	**1.155**

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Selected models:

Vanilla LM - Standard BPE tokenizer with **naive** masking

Morph-aware LM - Morph-aware tokenizer with **L2R** masking

LAMBADA word prediction

- Task: predict **final** and **random** words in a text

!! Models are bidirectional & target words can be multi-token

- Greedy prediction L2R/R2L
- Accuracy (exact match)

Un segundo después, Sibyl levantó lentamente la vista. Sus rizos rubios caían sin fuerza sobre sus hombros y una sombra embrujada oscurecía sus brillantes ojos azules. Tenía miedo.

random

La chica no mostró sorpresa ante la llegada de Nika, como si la hubiera estado esperando desde el principio.

final

"Ven y siéntate conmigo", dijo Sibyl.

Word Prediction and Linguistic Probing

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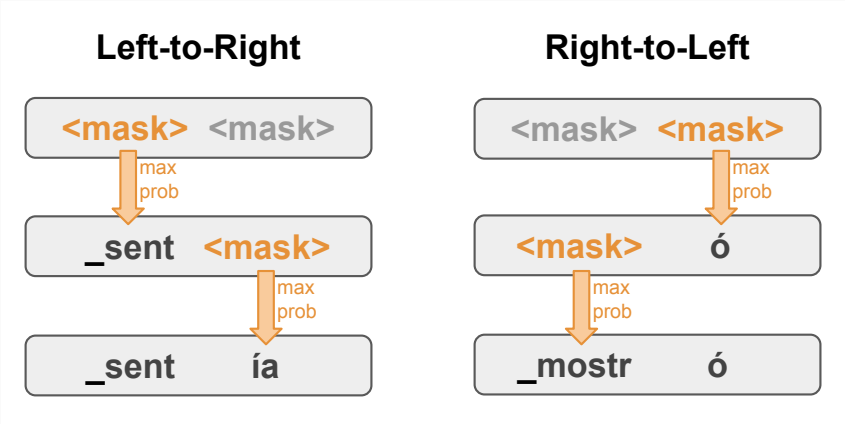
Greedy prediction:



We compute the tokens' joint probability for each word and select the highest among the two

$$p_{L2R}(\_sentia) = p(\_sent|BC) \cdot p(ia|BC + \_sent)$$

$$p_{R2L}(\_mostro) = p(o|BC) \cdot p(\_mostr|BC + o)$$

where BC is the bidirectional context (with the corresponding masks)

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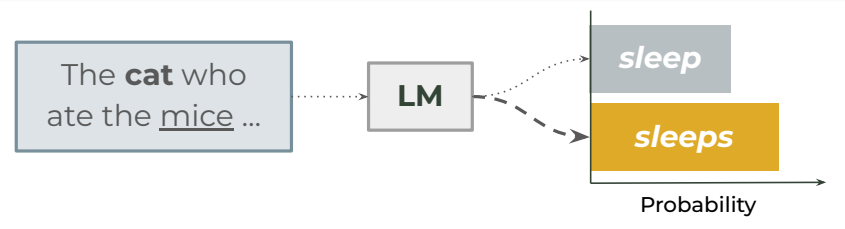
Agreement tests

- Task: assign higher probability to **correctly inflected** target
- Several types of agreement



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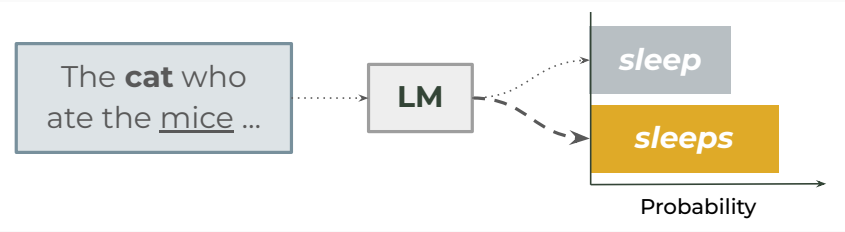
Un segundo después, Sibyl levantó lentamente la vista. Sus rizos rubios caían sin fuerza sobre sus hombros y una sombra embrujada oscurecía sus brillantes ojos azules. Tenía miedo.

La chica no mostró (random) sorpresa ante la llegada de Nika, como si la hubiera estado esperando desde el principio.

"Ven y siéntate conmigo", dijo Sibyl. (final)

Agreement tests

- Task: assign higher probability to **correctly inflected** target
- Several types of agreement



	Model	
Task	Vanilla	Morph-aware
LAMBADA word prediction		
Final word	0.338	**0.400**
Random word	0.393	**0.434**
Morpho-syntactic tests		
Agreement	0.864	**0.926**

Downstream Tasks: Finetuning Details and Results

We fine-tune both models (vanilla vs. morph-aware) on:

- tasks:
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XNLI (Accuracy)	0.733	**0.742**
InferES (Accuracy)	0.656	**0.666**
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Morph-aware model achieves **consistent gains** across tasks

Conclusions and Future Work

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- **Morphological segmentation**
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  - More linguistically meaningful tokens
- **Language Model** improvements:
  - Large gains in morphologically sensitive tasks
  - Consistent (though smaller) gains in general tasks

Concluding Remarks

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- Our approach is **simple but effective**: No need to modify tokenization algorithms or model architectures
- Our approach is **generalizable** to other languages:
  - Best with an available morphological segmenter
  - But MorphAGram's framework provides a good language-agnostic alternative
- Released resources:
  - Segmentation model, reference data, lexicon, affix list
  - Tokenizers and trained models

`https://github.com/Albalbalba/morphtokenizer`

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Thinking outside the box:

Word-level tokenization is not compulsory!

Assess promising alternatives (CANINE, LCM) in morphology-sensitive tasks

Thanks for your attention!

Any questions?